Adaptive Smart Online Learning System Design (ASOLS)

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Abstract: The COVID-19 pandemic accelerated the global shift toward online learning, proving its necessity in ensuring uninterrupted education. Post-pandemic studies reveal a notable increase in student performance, highlighting the potential of digital platforms. Adaptive learning systems have emerged as a key driver of this progress by tailoring content to individual learner preferences. These systems can leverage established models such as the VAK (Visual, Auditory, Kinesthetic), Felder-Silverman, and David Kolb models to assess learner preferences and behaviours. The VAK model identifies whether students learn best through visual, auditory, or Kinesthetic means, enabling platforms to recommend multimedia content, interactive exercises, or hands-on simulations accordingly. The Felder-Silverman model expands this through dimensions like active/reflective or sensing/intuitive learning, while Kolb's experiential learning cycle focuses on concrete experience versus abstract conceptualization. By integrating these models, adaptive systems can efficiently recommend or adjust course material to fit individual learning styles, thereby maximizing engagement, retention, and outcomes for a diverse global learner population that increasingly prefers—and depends on online education.

Keywords: *Learning Style, Learning Style Model, Online Learning, Smart Online Learning System, Adaptive Learning System, Intelligent Leaning System, Adaptive Learning, Personalized Learning, VAK Model, Felder Silverman Model, David Klob Model.*

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I. INTRODUCTION

Every learner is unique, with distinct learning styles and preferences that influence how they absorb, process, and retain information. Some learners thrive through visual aids, while others learn best through hands-on experiences, auditory input, or reading and writing. These differences highlight the need for flexible and inclusive teaching approaches that cater to a variety of learning needs. However, traditional education systems often rely on a one-size-fits-all method, which can leave some students disengaged or struggling to keep up. This mismatch between teaching styles and individual learning preferences can hinder academic progress and motivation. Addressing this issue is essential to create more effective, personalized learning experiences. The problem lies in adapting educational strategies to support diverse learners and maximize their potential.

In 1920, VAK Learning Style Model, categorizes learners based on their preferred sensory modes of learning: Visual, Auditory, and Kinesthetic [1]. Visual learners absorb information best through seeing—such as diagrams, charts, and written instructions. Auditory learners prefer to hear information and benefit from discussions, lectures, and verbal explanations. Kinesthetic learners, on the other hand, learn most effectively through hands-on activities, movement, and physical engagement. Developed to help tailor teaching methods to individual needs, the VAK model emphasizes that while most people have a dominant style, combining multiple approaches can enhance understanding and retention.

Richard Felder and Linda Silverman [2] introduced Felder-Silverman Learning Styles Model, which categorizes learners based on four dimensions: active vs. reflective, sensing vs. intuitive, visual vs. verbal, and sequential vs. global. Active learners prefer engaging in group work and learning by doing, while reflective learners favour thinking through material individually. Sensing learners focus on facts and practicality, whereas intuitive learners prefer theories and abstract concepts. Visual learners grasp information better through images and diagrams, while verbal learners learn more effectively through words and explanations. Sequential learners understand material in logical steps, while global learners absorb information in large leaps and may grasp the big picture before the details.

In 1984, David Kolb's Learning Style Model [3] outlines a four-stage cycle, which includes Concrete Experience, where the learner actively experiences an event; Reflective Observation, where they reflect on that experience; Abstract Conceptualization, where they form theories or ideas based on their reflections; and Active Experimentation, where they apply those ideas to the world. Kolb emphasizes that effective learning involves engaging in all four stages. This model also identifies four learning styles—Diverging,

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Assimilating, Converging, and Accommodating—based on individuals' preferences within the learning cycle.

The Honey and Mumford Learning Style [4] model, developed in 1982, identifies four distinct learning styles: Activist, Pragmatist, Reflector, and Theorist. These styles were derived from and influenced by Kolb's Experiential Learning Theory, serving as an adaptation and extension of his original framework.

In 1987, N. D. Fleming [5] developed a learning style theory that identifies four main types of learners i.e., Visual (pictures and graphs), Auditory (voice-based instructions), Read/Write (Using words and writing) and Kinesthetic (experience or practical approach) based on how people prefer to take in and process information.

II. RELATED WORK

Yassine Zaoui Seghroucheni and Mohamed Chekou proposed a mobile-specific adaptive learning architecture [6] grounded in the Felder–Silverman Learning Styles Model to customize instructional content per learner preference. Leveraging a Bayesian network, the system dynamically recommends learning objects suited to each user's learning style and device context. It integrates context-awareness such as device constraints to optimize content delivery for on-the-go mobile usage. Overall, the solution extends prior adaptive learning approaches by tailoring both pedagogy and media to learner preferences within a smartphone environment.

The authors in [6] propose an integrated adaptive-learning framework that links students' clickstream activity in virtual learning environments (from the Open University Learning Analytics Dataset) to one of three VAK modalities—Visual, Auditory, or Kinesthetic—using semantic mapping based on WordNet. Next, they classify learners using machine-learning classifiers (K-Nearest Neighbors, Support Vector Machine, Logistic Regression, and Random Forest), incorporating semantic associations between activity metadata and VAK categories. Their system not only predicts each learner's VAK style but also recommends the most suitable assessment strategies aligned with that style.

In 2010, Pipatsarun Phobun and Jiracha Vicheanpanya [7] proposed an incorporating Intelligent Tutoring Systems (ITS) to personalize learning based on students' knowledge level, learning style, and behaviour. The system combined ITS with Adaptive Hypermedia (AH) to create a hybrid Adaptive Intelligent Tutoring System (AITS) that adapts both content presentation and problem-solving support. Their conceptual architecture organizes domain knowledge, learner modeling, pedagogical strategies, and navigation personalization into modular components. The AITS framework stores knowledge relationships (e.g. prerequisite, transfer knowledge) in a domain-agnostic way to support adaptability across topics.

Mubaraka Sani Ibrahim and Mohamed Hamada [8] proposed a new adaptive learning system using the Felder-Silverman Learning Style Model (FSLSM) in conjunction with the Index of Learning Styles (ILS) questionnaire. The identified learning styles are then used to recommend personalized course structures. The system also enables instructors to monitor both the learners' styles and the recommended course content. Additionally, the framework incorporates automatic student modeling, which can facilitate future automated detection of learning styles, which are presented to the users on a dashboard.

Jenila Livingston et al. [9] presented an intelligent e-learning framework designed to adapt to individual learner needs. It incorporates learner profiling, knowledge assessment, and customized content delivery to enhance learning effectiveness. The system uses Artificial Intelligence techniques to monitor learner progress and dynamically adjust tutoring strategies. Its goal is to simulate a human tutor by offering personalized feedback, guidance, and learning paths tailored to each student's performance and preferences.

Existing online learning systems have typically been either intelligent or adaptive which was significantly enhanced by integrating both adaptive and intelligent learning capabilities. Furthermore, the proposed approach introduces the identification of new learning styles by using the combination of learning style models, which will serve as a foundation for recommending courses and learning content tailored to individual learners.

III. PROPOSED METHOD

This section presents the proposed method for designing a new Adaptive Smart Online Learning System (ASOLS), illustrated in Fig. 1. The proposed model integrates three well-established learning style theories—VAK (Visual, Auditory, Kinesthetic), Felder-Silverman Learning Style Model, and Kolb's Experiential Learning Theory—to create a comprehensive understanding of an individual's learning preferences. Each model contributes unique dimensions: VAK focuses on sensory input preferences, Felder-Silverman addresses cognitive processing and information organization, while Kolb explores how learners experience and process information through concrete or abstract means. By combining these perspectives, the hybrid model provides a multi-dimensional learner profile that captures both how learners prefer to receive information and how they best engage with and apply it.

The flowchart in Fig. 1 illustrates a hybrid learning style model for a content recommendation system that begins when a learner signs up and completes a diagnostic quiz combining elements from the VAK, Felder-Silverman, and Kolb learning style models. The system begins with a 15-question diagnostic quiz designed to evaluate a learner's preferences across all three models. Questions target sensory input preferences (VAK), cognitive approaches like active vs. reflective learning and sensing vs. intuition (Felder-Silverman), and experiential dimensions such as learning by doing vs. thinking (Kolb). Each response is mapped to corresponding learning style dimensions and based on their responses, the system calculates scores for each model and

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synthesizes them into a unified hybrid profile, capturing sensory preferences, cognitive processing styles, and experiential tendencies. This profile is then used to match the learner with content that is tagged according to format (e.g., video, text, simulation), learning approach (e.g., step-by-step, exploratory), and interaction level.

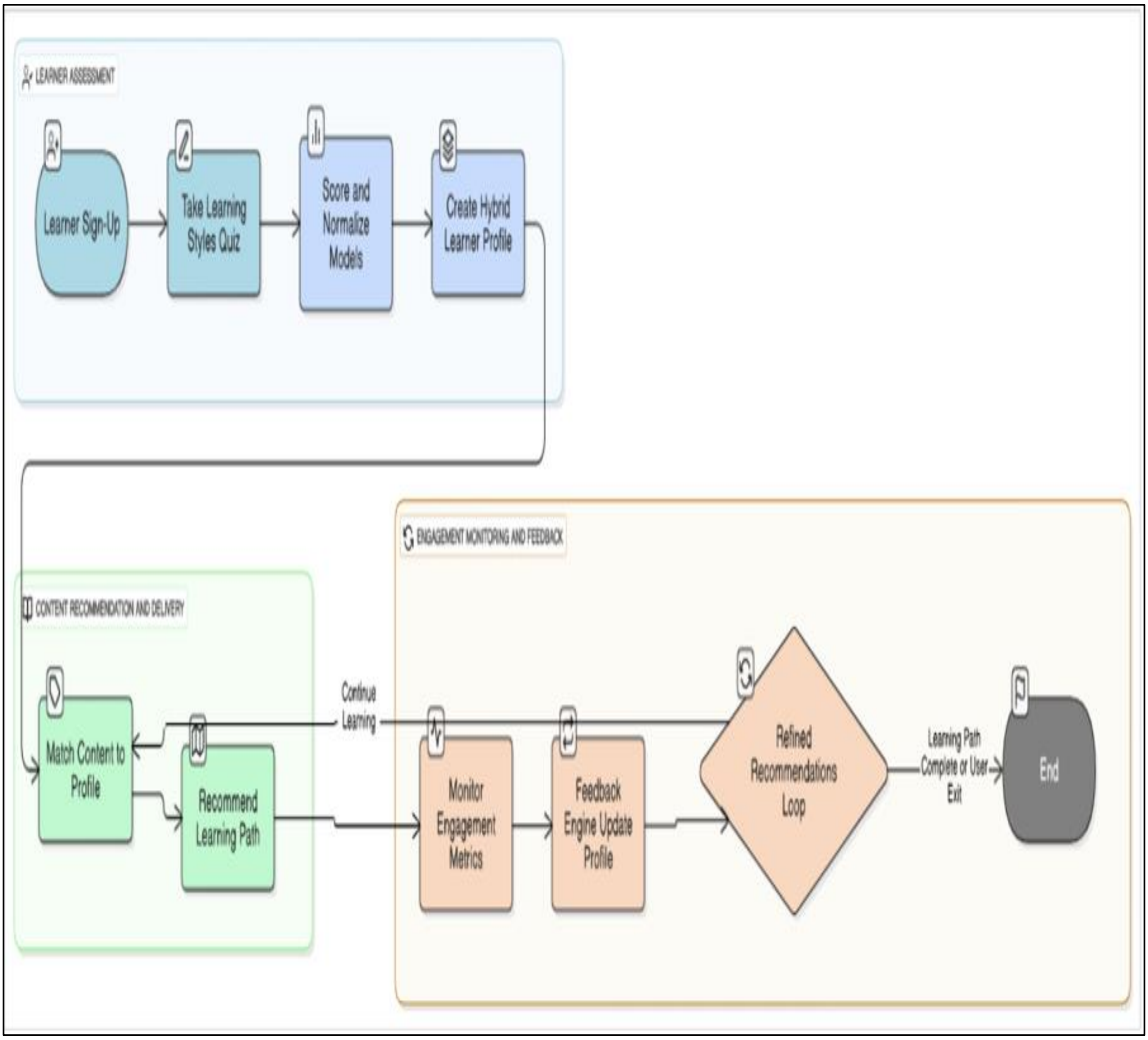

Fig 1 The Proposed Model of the System

Once personalized content is recommended, the system continuously monitors learner behaviour such as time spent, quiz performance, and completion rates—to gather feedback. This data is used in a feedback loop that updates the learner's profile over time, adapting future recommendations to better suit their evolving preferences and performance. The process is iterative, ensuring dynamic personalization and improved learning outcomes as the learner progresses. Thus, by drawing on the strengths of VAK, Felder-Silverman, and Kolb, the system supports diverse learners and improves educational outcomes through targeted content delivery.

- *Below is the Pseudo Code for the Above-Described Model:*

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```
# Step 1: Collect responses
responses = get_quiz_responses(user_id)

# Step 2: Process individual models
vak_scores = calculate_vak(responses)  # {Visual: 0.7, Auditory: 0.2, Kinesthetic: 0.1}
fslsm_scores = calculate_fslsm(responses)  # {Active: 0.8, Reflective: 0.2, ...}
kolb_scores = calculate_kolb(responses)  # {Assimilating: 0.6, Converging: 0.4, ...}

# Step 3: Create hybrid profile
hybrid_profile = merge_profiles(vak_scores, fslsm_scores, kolb_scores)

# Step 4: Content Matching
matching_content = []
for content in content_repository:
    match_score = content_match_score(content, hybrid_profile)
    if match_score > threshold:
        matching_content.append((content, match_score))

# Step 5: Recommend Top-N Content
recommended_content = sort_by_score(matching_content)[:N]
present_to_user(user_id, recommended_content)

# Step 6: Monitor Feedback
user_interactions = track_interactions(user_id)
# Example: {'video_A': 5 min, 'quiz_B': 90%, 'sim_C': 20 sec}

```

```
# Step 7: Feedback Loop
def update_profile(hybrid_profile, user_interactions):
    weights = calculate_behavioral_shift(user_interactions)
    updated_profile = adjust_weights(hybrid_profile, weights)
    return updated_profile

# Re-loop with updated profile
while True:
    sleep(1 week)
    user_interactions = track_interactions(user_id)
    hybrid_profile = update_profile(hybrid_profile, user_interactions)
    new_recommendations = recommend_content(hybrid_profile)
    present_to_user(user_id, new_recommendations)
```

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➢ *Below is the Analysis Table for the Above-Described Model:*

Table 1 Analysis:

Flowchart Step	Model	Identified Learning Style/Score	Result	Recommended Content
Step 1: Take Quiz	**VAK**	Visual: 70%Auditory: 20%Kinesthetic: 10%	Dominant modality is **Visual**	Infographics, diagrams, video explainers
	FSLSM	Reflective: 60%Intuitive: 70%Visual: 80%Global: 60%	**Reflective, Intuitive, Visual,** Global learner	Theoretical readings, global overviews, mind maps
	Kolb	Assimilating (Abstract + Reflective)	Prefers understanding **theories and logical structure**	Research articles, model-based instruction
Step 2: Score & normalize	All Models	Scores normalized to 0–1 range	All models contribute equally	Enables balanced hybrid profile
Step 3: Hybrid Style Profile	Combined	Visual + Reflective + Intuitive + Assimilating	Aditi is a Visual Theoretical Learner	Drives personalized content mapping
Step 4: Match Content	Metadata Tags	visual, reflective, intuitive, global, assimilating	Matches content metadata with profile	Concept maps, whiteboard explainers, theoretical guides
Step 5: Recommend Learning Path	Hybrid Profile	Blended path with visuals + theories + reflection	Sequenced path for higher retention	**1. Video overview** **2. Concept map** **3. Theory PDF** **4. Reflective journal**
Step 6: Monitor Engagement	Behavioural Data	High time spent on videos + theory Low on hands-on	Profile validation successful	**Reinforce visual-theoretical strategy**
Step 7: Feedback Engine	Updated Profile	Learner prefers slightly more structured flow	Adjust profile to be **Visual + Reflective + Intuitive + Sequential**	Add ordered theory modules and guided paths
Repeat from Step 4	Re-filtered Content	Profile refined via engagement data	Improved personalization	Even better content matches in next iteration

Table 2 Result

Model	Learning Style
VAK	Visual
FSLSM	Reflective, Intuitive, Visual, Slightly Global
Kolb	Assimilating (Abstract + Reflective)

➢ *Summary:*

Learner is a Visual + Theoretical + Reflective learner and prefers structured, abstract content delivered in visual formats and enhanced with reflective activities.

IV. LIMITATIONS

The hybrid model, while comprehensive, relies heavily on static quiz-based profiling, which may not accurately reflect real learner behaviour. It also assumes fixed learning styles and requires extensive content tagging, making scalability and adaptability challenging. Additionally, overlapping dimensions across models can lead to redundancy and confusion in recommendations.

V. CONCLUSION

The hybrid learning style model—integrating VAK, Felder-Silverman, and Kolb—offers a multidimensional approach to understanding learner preferences and personalizing content delivery. By combining sensory, cognitive, and experiential dimensions, it enables more accurate and adaptive recommendations. While limitations exist, especially around static profiling and content scalability, the inclusion of a feedback loop allows the system to evolve based on real learner behaviour. Overall, it provides a strong foundation for building intelligent, learner-centric educational platforms.

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