International Journal of Creative Multimedia

An Instructional Design Approach for Adaptive Multimedia e-Content: Integrating Felder-Silverman Learning Styles and Backward Design

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Abstract

This paper proposes a novel approach to designing and developing adaptive multimedia e-content for personalised learning environments, integrating the Felder-Silverman Learning Style Model (FSLSM), backward design principles, and adaptive techniques. The approach aims to address the limitations of single-dimensional learner profiling by considering multifaceted learning preferences across all four dimensions of the FSLSM. At the core of this approach is the recognition that effective e-content should be viewed holistically as a learning object, encompassing learning outcomes, activities, resources, and assessments. The FSLSM is employed to profile learners based on their preferences across the dimensions of Active/Reflective, Sensing/Intuitive, Visual/Verbal, and Sequential/Global. This comprehensive profiling allows for a nuanced understanding of individual learning styles. The backward design process ensures that learning activities, resources, and assessments are aligned with these preferences, creating a pedagogically sound and personalised learning experience. The approach integrates the FSLSM dimensions with backward design principles to design learning activities that cater to both active and reflective learners and are presented in both sequential and global manners.

International Journal of Creative Multimedia (2026) 7, 1, 48-71
doi: https://doi.org/10.33093/ijcm.2026.7.1.3

Published by MMU PRESS. URL: https://journals.mmupress.com/index.php/ijcm

Learning resources are selected to cater to visual and verbal learners and are presented in both sensitive and intuitive styles. Assessments are adapted based on the learner's knowledge level, providing targeted feedback and ensuring appropriate challenges. Content adaptation within this approach is driven by the learner's preferences regarding the type of learning activity, the presentation style of the learning activity, the type of learning material, and the content style of the learning material. By considering these factors, the approach facilitates the creation of a dynamic and personalised learning environment that caters to the unique needs of each learner. This integrated approach offers a robust theoretical foundation for designing and developing adaptive multimedia e-content that promotes personalised learning.

Keywords: Adaptive e-content; Personalised learning; Adaptive techniques; Dynamic content adaptation; Learner profiling; Multimedia instructional design

Received: 9 April 2025, **Accepted:** 24 April 2026, **Published:** 30 April 2026

Introduction

Personalised and adaptive learning represents a transformative educational approach that customises learning experiences to align with the unique needs, preferences, and capabilities of each student. This shift from traditional, uniform educational models leverages multimedia technological advancements to create highly individualised learning pathways, thereby enhancing student engagement and improving learning outcomes. The efficacy of personalised and adaptive learning lies in its capacity to accommodate diverse learning preferences and paces among students. Specifically, adaptive learning systems can dynamically adjust content and delivery based on real time assessments of a student's comprehension and performance, effectively meeting learners at their current level and fostering a more supportive educational environment (Chen, 2023).

Kurniawan and Kusumaningrum (2021) highlight that adaptive learning environments provide personalised information tailored to student needs, significantly enhancing the effectiveness of educational interventions. Furthermore, research indicates that adaptive learning systems can democratise access to educational resources, thereby broadening learning opportunities regardless of a learner's background (Peng et al., 2019). With the advent of technologies such as artificial intelligence (AI) and machine learning algorithms, the integration of these technologies has become a focal point in educational research, positing that such technologies can substantially enhance student performance by offering personalised interactions and support throughout the learning process (Yuan et al., 2023).

In the realm of e-learning, personalised and adaptive learning systems have revolutionised student engagement with content. These systems provide instant feedback, personalised learning plans, and multiple pathways through resources based on individual learner data, thereby fostering collaboration between learners and educators (Anindyaputri et al., 2020). However, these advancements also underscore the critical shortcomings of traditional, static learning models. The inadequacy of one-size-fits-all approaches in e-learning is evident in their failure to address diverse learner needs, often resulting in disengagement and suboptimal academic outcomes (Taylor et al., 2021). Research indicates that the rigidity of conventional e-learning methodologies neglects individual differences in learning, thereby hindering potential educational growth (Wambsganss et al., 2020).

Despite the clear advantages of personalised and adaptive learning, significant uncertainty persists among academics regarding the optimal methods for designing effective adaptive learning environments. Several studies suggest that while the efficacy of adaptive learning has been established, the mechanisms for successful implementation and the nuances of creating truly adaptive educational experiences require further exploration (Fadieieva, 2023; Hariyanto & Köhler, 2017). This uncertainty may stem from the complexities involved in accurately profiling learners and dynamically adjusting content in response to their evolving needs (Rodríguez Magaña et al., 2023; Lieber et al., 2018). Therefore, continued research is essential to resolve existing uncertainties surrounding the design and implementation of these systems, aiming to refine adaptive learning systems and optimise their impact across diverse educational contexts.

This paper proposes a conceptual approach that integrates the Felder-Silverman Learning Style Model (FSLSM), adaptive techniques, and backward design principles to develop adaptive multimedia e-content for personalised learning environments. The proposed approach aims to enhance the effectiveness of e-learning by providing tailored learning experiences that can adapt to the unique needs of each learner, thereby improving engagement and learning outcomes.

Literature Review

The Concept of Personalised Learning in Education

The concept of personalised learning (PL) encompasses various dimensions, including assessment, teaching strategies, and curriculum customization. As articulated by Shemshack and Spector (2020), PL extends beyond mere content delivery; it integrates tailored feedback mechanisms and individualised learning objectives based on student performance and preferences. They further highlight PL as a pivotal trend in educational reform, emphasizing its role in addressing diverse student needs. PL is increasingly recognised as a transformative approach in educational systems worldwide, reshaping the dynamics of teaching and learning. PL environments embrace a tailored educational framework that accommodates individual learner characteristics, encompassing diverse needs and preferences.

In higher education settings, PL has demonstrated significant efficacy. Kontrimienė et al. (2021) emphasise that transitioning from traditional teaching paradigms to personalised learning not only enhances student engagement but also necessitates that educators evolve into self-directed learners themselves. This shift is critical for preparing teachers to effectively support personalised practices, thereby linking teacher education with personalised student learning outcomes. The implementation of PL involves various methodologies, tools, and technologies that allow for customization of the learning experience, ultimately aiming to enhance student engagement and improve outcomes.

Personalised learning initiatives are increasingly being adopted in diverse educational contexts, such as vocational education and low-enrollment schools. Zakaria et al. (2024) illustrate that personalised learning can provide equitable quality education to students in challenging environments. Additionally, Fariani et al. (2023) assert that personalised learning approaches not only cater to the diverse academic strengths and weaknesses of students but also address intrinsic motivators, enhancing overall engagement.

However, challenges remain in realizing the full potential of PL approaches. Factors such as educator preparedness, technological barriers, and the need for supportive institutional policies can hinder effective implementation (Major et al., 2021; Ajuwon et al., 2024). Specific pedagogical designs that leverage technology emphasise the importance of adaptability in learning environments to accommodate varied learner profiles. As noted by Gligorea et al. (2023), the integration of AI within instructional frameworks allows for the dynamic adjustment of educational content and pacing, ensuring that digital resources are tailored to the specific cognitive and behavioural needs of diverse student populations.

Critique of Learning Styles and Advocacy for Personalised Learning

The discourse surrounding learning styles and personalised learning has been extensively critiqued by numerous scholars, leading to a consensus that challenges the validity of the "learning styles" concept and promotes a more evidence-based approach in educational practices. The literature underscores significant critiques regarding learning styles while affirming the importance of personalised learning approaches that provide a more tailored educational experience. The consensus emerging from various studies advocates for integrating diverse instructional strategies that cater to individual preferences without being constrained by the largely contested and unsupported concept of fixed learning styles.

Despite the popularity of tailoring instruction to individual preferences, many cognitive and educational psychologists strongly caution against the "meshing hypothesis," citing a significant lack of empirical evidence to support its efficacy (Felder, 2020). Critics argue that learning styles are a conceptually weak construct and suggest that educators should instead prioritise more measurable and impactful characteristics, such as a student's prior knowledge and specific interests (Dinsmorea et al., 2022). This skepticism extends into the realm of personalised e-learning, where the use of learning-style models for system adaptation is frequently questioned; a primary methodological concern is the heavy reliance on self-reported questionnaires, which often produce inaccurate or unstable classifications due to inconsistent or non-authentic learner responses (Ilić et al., 2023).

Moreover, the existence of the "learning styles myth" is pervasive even among educators, with studies revealing a widespread belief in the effectiveness of tailored instruction based on learning styles, despite a lack of supporting evidence (Newton, 2015; Newton & Miah, 2017). Newton and Salvi (2020) synthesised systematic reviews suggesting that not only does the belief in learning styles persist, but it also detracts from the potential for more broadly applicable pedagogical frameworks, which would instead address diverse learning preferences without strict adherence to unvalidated models. Indeed, the pushback against learning styles as a theory grows alongside an understanding that educational strategies should prioritise instructional methods rather than adherence to learning style categorizations (Moussa-Inaty et al., 2019).

In contrast, an emerging consensus advocates for the principles of personalised learning, which is increasingly recognised as a more effective approach in educational contexts. While critics of personalised learning caution that over-individualization may fragment the curriculum or undermine necessary standardisation (Idowu, 2024), proponents maintain that a "one-size-fits-all" model fails to address the diverse cognitive and motivational profiles inherent in any classroom. In inclusive settings, adaptive and flexible methodologies ensure that learning differences are leveraged to improve conceptual understanding and engagement (Selvakumar et al., 2025; Devaki, 2025), often by aligning instructional modes with students' preferred processing styles, such as visual, auditory, or kinesthetic (Madhu & Bhattachryya, 2023; Devaki, 2025). However, contemporary personalisation has evolved beyond simply acknowledging these preferences; it now integrates adaptive technologies and learning analytics to continuously refine instruction based on real-time performance data. Research into intelligent tutoring systems demonstrates that this automated feedback and dynamic adaptation personalise the experience more effectively than static preference-based models, ultimately reinforcing both academic performance and student self-regulation (Lin et al., 2023; Kochmar et al., 2020).

Recent critiques urge a shift towards inclusive pedagogical practices that focus on adaptive learning environments rather than rigid adherence to models categorised by learning styles. For instance, while automated systems may continue to detect learning preferences through online activities, scholars warn against the pitfalls of rigid classification systems without empirical validation, advocating for approaches that leverage technology to enhance personalised learning experiences without solely relying on learning style classifications (Lestari et al., 2024).

Development of Adaptive Personalised Learning Environments

The development of adaptive learning systems utilizing advanced technologies has revolutionised personalised learning environments. Recent literature highlights the effectiveness of these systems in addressing the diverse needs of learners and enhancing the educational experience. The literature supports their efficacy in creating tailored educational experiences that enhance learner engagement and achievement. However, continued exploration and development are essential to fully realise the potential of these systems and address the challenges inherent in their implementation.

Adaptive learning systems are designed to customise educational experiences based on individual learner characteristics, including preferences, competencies, and learning progress. Tekesbaeva et al. (2023) define adaptive learning as a flexible pedagogical approach integrating various forms, methods, and technologies tailored to improve students' self-awareness and learning outcomes. This perspective aligns with the recognition that generic educational approaches, often referred to as the one-size-fits-all model, fail to meet the individualised needs of learners. Al-Abri et al. (2019) argue that personalised learning fosters meaningful engagement by aligning teaching with students' unique requirements.

Technological advancements have played a crucial role in the evolution of adaptive learning systems. Anil and Moiz (2019) propose a personalised dynamic learning plan generator that actively responds to learners' interactions within smart learning environments. Such systems harness real-time data analytics and machine learning algorithms to continually refine educational experiences. Additionally, Temdee (2020) highlights how digital technologies enable the transformation of traditional learning environments into adaptive systems, offering personalised educational experiences. This reflects a broader trend in educational technology that leverages AI to facilitate customised learning pathways, thus promoting learner autonomy and self-directed learning.

Empirical studies support the efficacy of adaptive learning systems. For instance, Zhilmagambetova et al. (2023) explored the impact of personalised adaptive mathematics instruction and found that learners exhibited higher satisfaction and improved outcomes compared to traditional methods. Their use of a mixed-method approach provided valuable insights into learner perceptions and attitudes towards adaptive technologies, validating their role in enhancing educational experiences. Furthermore, research on computer-assisted simulation learning games has demonstrated significant enhancements in social studies students' scholarly learning and engagement, suggesting that interactive and adaptive elements can lead to improved educational outcomes (Obro, 2022).

Despite these advancements, challenges remain in the widespread implementation of adaptive learning systems. While the promise of personalised education is enticing, educators often face difficulties in understanding the best approaches to design and deploy such systems effectively. Schrum (2021) points out that while interdisciplinary frameworks for applying technology in pedagogical settings offer potential, the successful integration of digital skills within traditional disciplines requires careful planning and execution. Moreover, the complexity of developing adaptive learning systems necessitates ongoing research to refine methodologies and evaluate the long-term impacts of these innovations on student learning (Ghitulescu et al., 2021).

Recent Development in Adaptive Learning Systems

Recent advancements in the implementation of adaptive e-learning systems have significantly benefited from the integration of advanced technologies such as machine learning (ML), learning analytics (LA), and AI. These technologies facilitate the personalization of learning experiences, enhance learner engagement, and improve educational outcomes.

ML is pivotal in customizing learning experiences by analysing learner interactions and optimizing content delivery. Research by Gligorea et al. (2023) underscores that AI and ML can substantially enhance personalised learning paths, increase student engagement, and improve overall academic performance by providing tailored educational content that meets individual learner needs. The incorporation of ML algorithms allows systems to adapt dynamically based on student performance data, thereby facilitating a more responsive educational environment.

Furthermore, Alshammari and Qtaish (2019) highlight that adaptive e-learning systems capable of analysing learning styles and knowledge levels of students are more efficient, fulfilling diverse learner requirements and minimizing information overload. This adaptation not only enhances learner satisfaction but also improves retention rates and engagement. These findings demonstrate the critical role of ML in building responsive learning ecosystems that can adjust to the ever-changing dynamics of educational contexts.

Learning analytics provides essential tools for monitoring and assessing learner performance, thereby supporting the adaptability of e-learning systems. According to Han et al. (2021), learning analytics dashboards can effectively visualise student data, offering insights that enable timely interventions during collaborative learning activities. Such analytics empower educators to understand learning behaviours and adjust content or instructional strategies accordingly, ensuring that individual learner needs are met more effectively.

In the context of adaptive learning objects, Diego et al. (2019) introduce the concept of Adaptive Learning Objects (ALOs), which harness learning analytics to capture contextual information and adapt resources dynamically. This form of responsiveness not only improves engagement but also fosters deeper learning as content is personalised to fit specific learning environments. The ability to gather and analyse student interaction data underscores the necessity of integrating LA into adaptive e-learning frameworks.

AI is at the forefront of revolutionizing adaptive e-learning by enabling more sophisticated personalization techniques. The research conducted by Ristić et al. (2023) emphasises that adaptive e-learning systems incorporating AI facilitate a more meaningful learning process, enhancing flexibility and providing real-time feedback that aligns with individual learning styles. This feature sets the stage for a more interactive learning atmosphere where students feel more connected and supported throughout their educational journey.

Moreover, Apoki et al. (2020) discuss how personalised adaptive learning (PAL) approaches, facilitated by AI, can effectively address the challenges posed by dynamic and multifaceted learning environments. By leveraging AI, these systems can continually assess learner performance and adjust instructional techniques accordingly, ensuring that students receive the support they need to succeed. This capability further emphasises the essential role of AI in personalizing learning experiences in adaptive e-learning systems.

Addressing the Gap in the Need for a Comprehensive Approach Integrating Instructional Design for development of Adaptive Content

The development of adaptive e-content has garnered significant attention from researchers and educators alike due to its potential to enhance the effectiveness of learning experiences. Adaptive e-content adapts educational materials and approaches to meet the individual needs of learners, thereby fostering a more personalised learning experience.

Adaptive e-content has proven to increase the effectiveness of the learning process across various educational settings. Solehuddin et al. highlight that properly implemented adaptive e-learning content significantly enhances learning effectiveness in classrooms, particularly at the elementary level (Solehuddin et al., 2023). Moreover, Bezza et al. assert that there is a strong necessity for e-learning content to be personalised according to individual learner profiles, emphasizing that diverse learner characteristics necessitate a bespoke approach to content delivery (Bezza et al., 2013). This personalization can transform the learning experience by catering to distinct learning preferences and paces, as supported by the findings of Kolekar et al., who discuss the importance of recognizing and integrating learner-specific styles within adaptive e-learning systems (Kolekar et al., 2013).

Despite its potential advantages, developing adaptive e-content presents several challenges. A major hurdle is effectively modelling user profiles to facilitate personalised learning. Bezza et al. explain two methodologies—inductive and deductive—for adapting content to user profiles yet underscore the relative scarcity of systematic research addressing these adaptive techniques (Bezza et al., 2013). Similarly, the literature reveals that capturing diverse learning styles remains complex. Kolekar et al. stress the need for a modified approach to existing literature that reflects actual learner interactions with e-learning platforms to foster adaptation (Kolekar et al., 2013). Furthermore, institutions often face barriers when integrating interactivity—a crucial element for engaging learners in e-learning environments. Bigirwa et al. indicate that interactivity enhances the adoption of e-learning, noting that it is integral to instructional design yet poses significant challenges in implementation (Bigirwa et al., 2020).

To effectively develop adaptive e-content, a comprehensive approach that incorporates sound instructional design principles is essential. Holcomb and Greer emphasise the necessity for standardised processes and templates that can facilitate consistent quality in e-learning design across various contexts (Holcomb & Greer, 2020). Moreover, Zain et al. advocate for integrating 21st-century learning frameworks within instructional design, promoting interactive and collaborative learning strategies that align with contemporary educational needs (Zain et al., 2016). This holistic approach is further supported by Chen and Chen, who highlight the critical role of formative assessments embedded within e-learning frameworks to enhance monitoring and support of student understanding (Chen & Chen, 2023).

Incorporating these design principles not only contributes to the development of effective adaptive e-content but also supports ongoing evaluation and refinement of learning systems, ensuring they remain responsive to learners' evolving needs. The integration of technology within pedagogical frameworks, as discussed by Telli and Altun, emphasises the importance of employing strategies that bolster learning retention and transfer (Telli & Altun, 2023). Furthermore, by adopting these comprehensive instructional design practices, educators can improve the quality of learning experiences and address the diverse requirements of their students (Mahmood, 2024).

Towards an Integrated Theoretical Approach for Adaptive e-Content Development

To support personalised learning environments, this study proposes an integrated theoretical approach for the creation of adaptive e-content. This approach is grounded in major two interconnected theoretical foundations: backward design principles, and the Felder-Silverman Learning Style Model (FSLSM) guided by adaptive techniques or parameters. When combined, these elements provide an instructional design holistic approach to e-content creation, enabling learning management systems (LMS) to incorporate machine learning algorithms for the automated personalization of the content based on the learner profiles of the learners.

Learner Profiling Using FSLSM

The intersection of learning styles and e-learning has generated considerable scholarly attention, particularly regarding the adaptation of educational strategies to meet diverse learner preferences. Theoretical frameworks surrounding learning styles comprise several prominent models, notably the Kolb experiential model, Gardner's multiple intelligences, and Felder-Silverman's learning style model (FSLSM). Among these, FSLSM is frequently cited as particularly advantageous for e-learning environments due to its adaptability and comprehensive structure, which allows it to incorporate various dimensions of learning, including sensory preferences and approaches to processing information (El-

Bishouty et al., 2014; Rajper, 2023). Figure 1 illustrates the four pivotal dimensions of learner profiling: Processing, Perception, Input, and Understanding.

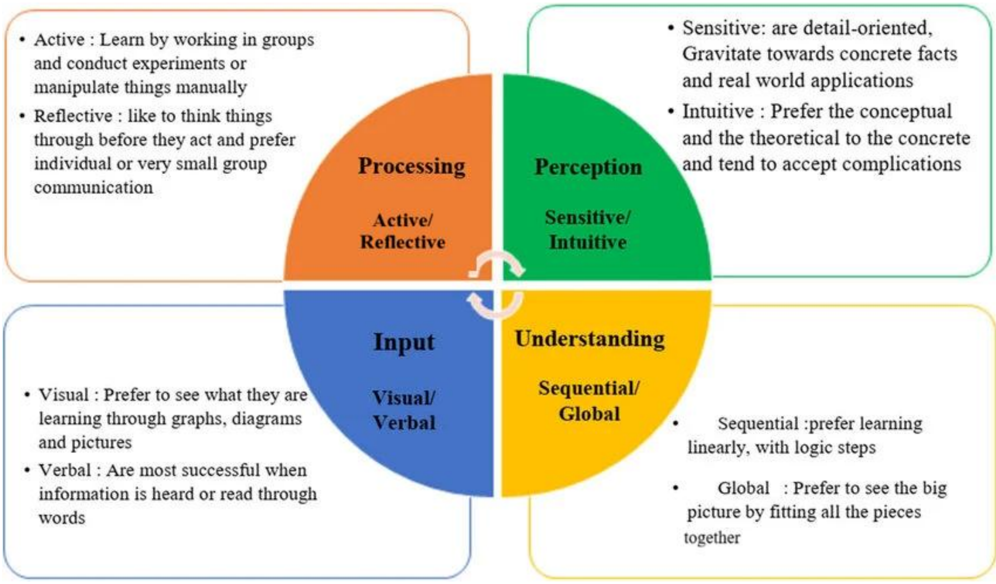

Figure 1. The Felder-Silverman Learning Style Model (FSLSM) Dimensions

Felder-Silverman Learning Style Model (FSLSM) has become a prevalent and relevant discourse in pedagogical research, particularly to cater to diverse learning preferences among students in various educational settings. The FSLSM categorises learning into four pivotal dimensions: Perception (sensing/intuitive), Processing (active/reflective), Input (visual/verbal), and Understanding (sequential/global) (Joseph et al., 2022). This categorical organization enables educators to tailor their instructional strategies to effectively accommodate individual differences in learning preferences, thus facilitating a more inclusive educational environment. Importantly, the input dimension (visual/verbal), together with the processing and understanding dimensions, provides a strong theoretical basis for the design of multimedia and multimodal learning experiences. Rather than relying on single-format content delivery, the application of FSLSM-informed design encourages the integration of diverse content representations, allowing learners to engage with material through formats that align with their preferences and cognitive processing styles.

Research supports the view that incorporating the FSLSM into educational practices leads to improved learning outcomes. For instance, students engaged in learning environments designed to align with their identified learning styles reported higher levels of satisfaction and understanding of the material (Masegosa et al., 2024; Almarwani & Elshatarat, 2022). Kannapiran et al. Kannapiran et al. (2018) assert that modifying instructional methods based on students' learning preferences can significantly enhance the achievement of learning objectives. Similarly, studies reveal that personalised learning approaches built upon FSLSM principles can foster student engagement and improve retention rates (Rashid et al., 2023).

Building on this foundation, the proposed integrated approach adaptive e-content emphasises multimedia-driven adaptive content design, where learning materials are structured to support multiple modes of representation and interaction. This includes the use of videos, infographics, simulations, and interactive elements, alongside textual resources, enabling learners to engage with content in ways that align with their preferences. Furthermore, content is designed in multiple variations, allowing adaptive systems to dynamically present materials based on learner profiles, thereby enhancing both engagement and learning effectiveness.

This approach is theoretically supported by Cognitive Theory of Multimedia Learning, which posits that learning is more effective when information is presented through both verbal and visual channels, facilitating deeper cognitive processing and improved retention (Mayer, 2021). In this context, multimedia is not treated as a supplementary feature but as a core design principle underpinning adaptive learning.

Designing Instruction Through Backward Learning Design

Backward learning design (BLD) and instructional design are critical elements in contemporary educational frameworks, focusing on promoting student engagement and enhancing learning outcomes. The backward design approach emphasises a structured methodology where educational objectives are established first, followed by the delineation of assessments and instructional activities to achieve those goals. As noted by Overson and Benassi, this approach aligns course Student Learning Outcomes (SLOs) with assessment mechanisms and learning activities, ensuring that students achieve intended educational milestones. This intentional alignment is essential for reinforcing content mastery and facilitating the transfer of learning across various contexts, as supported by Gombu et al. (Gombu et al., 2022). Figure 2 delineates the structured methodology where learning outcomes are established before assessments and activities.

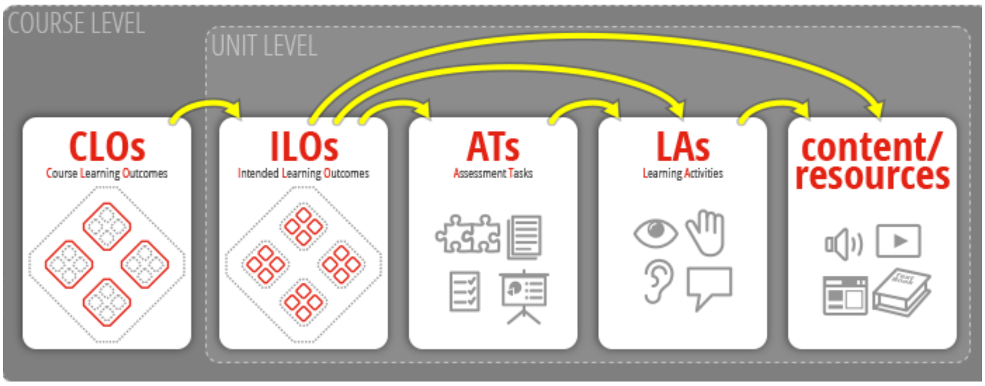

Figure 2. The Backward Learning Design (BLD) Process at Course and Unit Levels

The impact of backward design is not limited to curriculum development but extends into pedagogical strategies that motivate learners. The role of educators in facilitating engaging learning experiences is highlighted by methodologies grounded in backward design. For instance, activating prior knowledge and ensuring that learning objectives resonate with students' experiences can significantly elevate motivation (Dethan & Martha, 2023). In instructional strategies specifically centered around learning enhancement and engagement, backward design serves as a guiding principle that helps educators create more impactful learning environments by starting with the end in mind—the desired competencies students should demonstrate after instruction (Neiles & Arnett, 2021). Consequently, the synthesis of backward design methodologies with active learning tactics enhances the efficiency of instructional design and aligns educational practices with evidence-based teaching frameworks that respond to the demands of 21st-century education (Wisniewski et al., 2024).

Mapping FSLSM with BLD Based on Adaptive Parameters

The innovative aspect of this approach lies in its methodical mapping of FSLSM dimensions to backward design elements, thereby operationalizing adaptive e-content development. The theoretical approach identifies the following key adaptive parameters that guide content personalization and can be operationalised within adaptive learning environments:

- Type of learning activity
- Presentation style of the activity
- Type of learning material
- Content style of the material
- Adaptivity of assessment based on knowledge level

Each FSLSM domain is mapped to a corresponding content element as follows:

- **Learning Activities:** The design and implementation of learning activities (LAs) are guided by the Processing (Active/Reflective) and Understanding (Sequential/Global) dimensions of FSLSM. LAs can be presented in a sequential or global format and are designed to accommodate both reflective and active learners. For example, reflective learners might favour case based analysis or journaling, whereas active learners might participate in cooperative problem-solving or simulations. Similarly, global learners benefit more from comprehensive overviews and interconnected concepts, while sequential learners benefit from stepwise instructional progression.
- **Learning Resources:** The selection and arrangement of learning materials are influenced by the Perception (Sensing/Intuitive) and Input (Visual/Verbal) dimensions. Resources are

curated to accommodate both verbal (textual narratives, audio explanations) and visual (diagrams, infographics, video content) preferences. Additionally, intuitive learners are supported by abstract theories and conceptual models, while sensing learners are provided with tangible examples and real-world applications.

Learner Knowledge Level and Adaptive Assessment

Consistent with the backward design approach, assessment is considered a fundamental part of the learning object. To further enhance personalization, this approach incorporates adaptive testing strategies. These assessments adjust in complexity and depth based on the learner's demonstrated knowledge level, ensuring that feedback is timely, relevant, and constructive. This strategy facilitates a customised learning path, enabling learners to receive the support they need to progress toward the desired outcomes.

Proposed integrated instructional approach for adaptive content design and development

To facilitate the automated generation and delivery of tailored e-content, this integrated theoretical model combines the strengths of FSLSM, backward design, and adaptive learning techniques. By reconceptualizing content as a learning object and aligning instructional components with learner preferences across all FSLSM dimensions. Figure 3 synthesises these elements by mapping FSLSM domains to specific adaptive parameters such as types of learning activities and material styles.

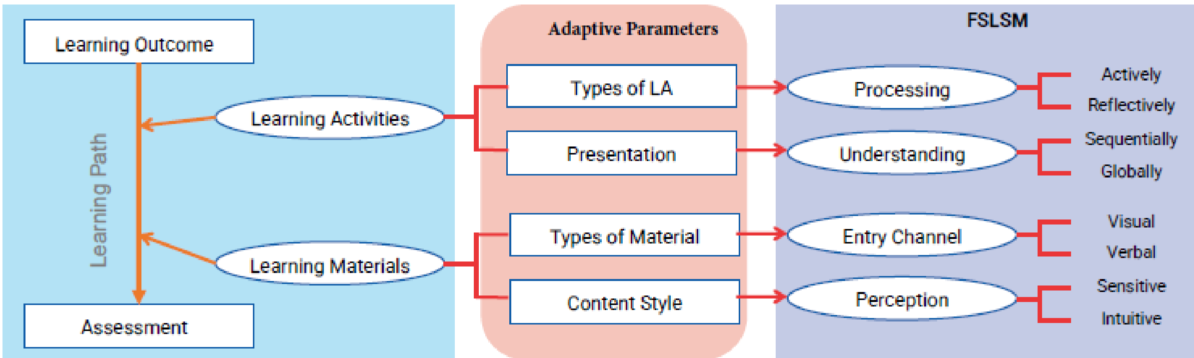

Figure 3. The Proposed Integrated Instructional Approach for Adaptive Content Design

The approach enables personalization that is pedagogically sound and technically feasible. Furthermore, it sets the stage for incorporating adaptive logic into LMS systems, where machine learning-driven decision-making processes can continuously inform content adaptation using learner profiles and performance data.

Implementation prospects of the approach within adaptive learning systems

This section outlines the practical implementation of the proposed integrated theoretical approach within LMS to create dynamic adaptive learning environments. Leveraging learner analytics and machine learning, the approach aims to personalise e-content delivery based on individual learner profiles. This adaptive approach can be seamlessly integrated into Learning Management System platforms such as Moodle. Figure 4 illustrates the flow diagram for the implementation process:

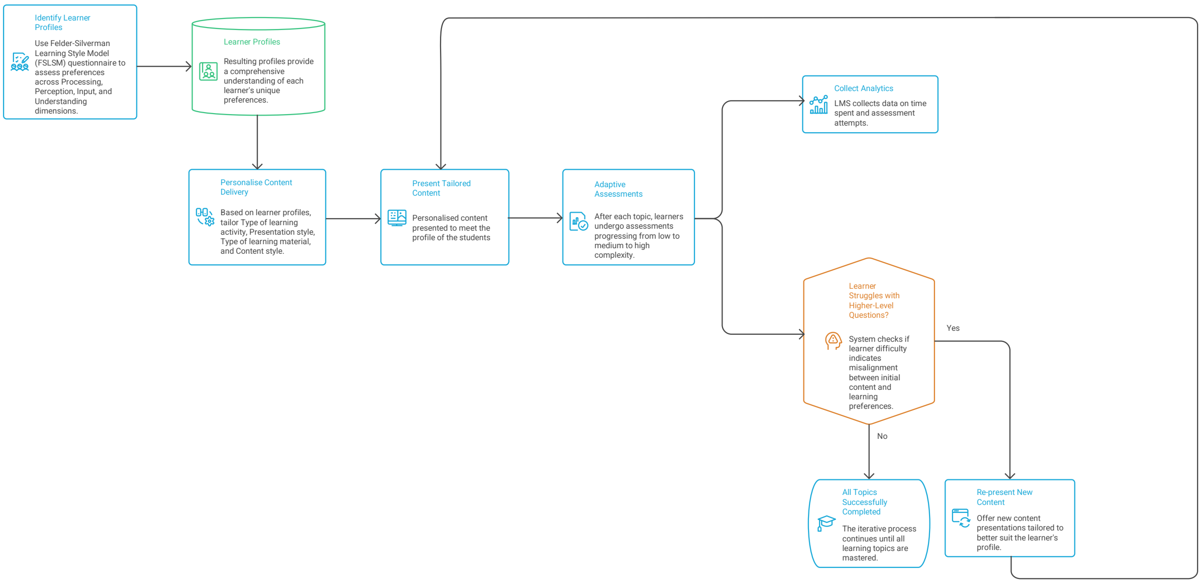

Figure 4. The Flow Diagram for the Implementation Process of the Adaptive Learning System

The initial step involves identifying learner profiles using the Felder-Silverman Learning Style Model (FSLSM) questionnaire. This questionnaire assesses preferences across the four core dimensions: Processing (Active/Reflective), Perception (Sensing/Intuitive), Input (Visual/Verbal), and Understanding (Sequential/Global). The resulting profiles provide a comprehensive understanding of each learner's unique preferences, which serve as the foundation for personalised content delivery-based Type of learning activity, Presentation style of the activity, Type of learning material, Content style of the material.

Once learner profiles are established, the LMS presents content tailored to these preferences. For example, visual learners might receive diagrams and video content, while verbal learners might be provided with textual narratives and audio explanations. This personalised approach ensures that learners engage with materials that align with their preferred learning preferences.

Following the completion of each learning topic, learners undergo adaptive assessments designed to progress in complexity from low to medium to high levels. These assessments are dynamically adjusted based on the learner's demonstrated knowledge level, ensuring that feedback is timely, relevant, and constructive.

The system collects analytics on various metrics, such as the time spent on learning activities and the manner in which learners attempt assessments. If a learner struggles to complete higher-level questions, the system assumes that the initial content presentation did not align well with their learning preferences. Consequently, new content presentations are offered, tailored to better suit the learner's profile. This iterative process continues until all topics are successfully completed.

Machine learning algorithms play a crucial role in this adaptive approach. By analysing learner analytics, these algorithms continuously refine content delivery to match the learner's evolving needs. For instance, extended time spent on certain content types may indicate difficulty in grasping the material, prompting the system to adjust the content presentation accordingly.

By embedding this adaptive logic within Learning Management System platforms, educators can create personalised learning experiences that are both pedagogically sound and technically feasible, ultimately enhancing learner engagement and achievement.

Educational Implications of the approach and further study

The proposed approach for adaptive multimedia e-content design and development is unique in its comprehensive approach to addressing research gaps and integrating instructional design principles. Unlike traditional adaptive learning systems that often focus solely on learner analytics and machine learning, this approach systematically incorporates the Felder-Silverman Learning Style Model (FSLSM) and backward design principles. This integration ensures that content delivery is not only personalised but also pedagogically sound, aligning instructional activities and resources with well-defined learning objectives.

One of the key innovations of this approach is its emphasis on creating multi-dimensional learner profiles based on FSLSM dimensions. This allows for a more nuanced understanding of individual learning preferences, which informs the design and delivery of adaptive content. By mapping these profiles to backward design elements, the proposed approach operationalises adaptive e-content development in a way that has not been extensively explored in previous research. This methodical mapping ensures that learning activities and resources are tailored to meet diverse learner needs, enhancing engagement and effectiveness.

A significant educational implication of this approach lies in its emphasis on multimedia-driven adaptive content design. The integration of FSLSM—particularly the visual/verbal input dimension—naturally necessitates the use of multimodal learning materials, including videos, infographics, simulations, and interactive elements, alongside textual resources. In this context, personalization is not limited to sequencing or recommendation, but extends to how content is represented and experienced by learners. This perspective is strongly supported by the Cognitive Theory of Multimedia Learning (CTML), which posits that learners process information through dual channels (visual and verbal), and that learning is enhanced when instructional materials are designed to optimise cognitive processing across these channels (Mayer, 2021). Accordingly, the proposed content design approach positions multimedia not as a supplementary feature, but as a core pedagogical mechanism that enables deeper understanding, improved retention, and more meaningful engagement. By aligning adaptive content with both learner preferences (FSLSM) and cognitive principles (CTML), the approach provides a theoretically grounded basis for designing effective personalised learning experiences.

Furthermore, the use of adaptive assessments and real-time learner analytics in the proposed approach addresses a critical gap in existing adaptive learning systems. By continuously monitoring learner performance and adjusting content presentation accordingly, the system ensures that learners receive the most effective instructional strategies. This iterative process of content adaptation, driven by machine learning algorithms, supports a personalised learning journey that evolves with the learner's progress. While not explicitly stated, this approach aligns with the Sustainable Development Goals by promoting inclusive and equitable quality education and reducing educational inequalities.

Future research should focus on testing this approach in the development of content and validating it through expert reviews. Implementing the approach in real educational scenarios will be crucial to measure its effectiveness. This involves creating adaptive e-content based on the approach, deploying it within LMS platforms like Moodle, and collecting data on learner engagement, performance, and satisfaction. Expert validation can be achieved through methods such as the Fuzzy Delphi method, ensuring the approach's constructs are robust and applicable in diverse educational settings. Additionally, measuring the effectiveness of the adaptive learning environment will require comprehensive usability evaluations and impact assessments, focusing on metrics such as learner progress, knowledge retention, and overall academic achievement. These steps will help refine the approach and demonstrate its potential to transform personalised learning environments.

Conclusion

This study presents a novel integrated theoretical approach for designing and developing adaptive e-content to support personalised learning environments. By combining the Felder-Silverman Learning Style Model (FSLSM), backward design principles, and adaptive techniques, the proposed approach offers a dynamic approach to e-content creation. This method ensures that learning management systems can leverage machine learning algorithms to personalise learning objects effectively. The approach’s unique integration of detailed learner profiling, adaptive assessments, and real-time learner analytics addresses critical gaps in existing adaptive learning systems, providing a more nuanced and effective educational experience.

The educational implications of this approach are significant, promoting inclusivity and addressing diverse learner needs. By tailoring instructional activities and resources to individual learning preferences, the approach enhances engagement, motivation, and academic achievement. Furthermore, the iterative process of content adaptation ensures that learners receive the most effective instructional strategies, supporting a personalised learning journey that evolves with their progress. This approach aligns with the Sustainable Development Goals by fostering inclusive and equitable quality education and reducing educational inequalities, ultimately contributing to a more inclusive and just society.

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Acknowledgment

We would like to express our sincere gratitude to Dr. Fawaz for his expert guidance and invaluable insights throughout the development of this research. We also extend our heartfelt thanks to Ms. Fathimath Nasiha for her meticulous proofreading and constructive feedback, which have greatly enhanced the clarity and coherence of this paper.

Funding Information

There is no funding associated with the research or writing of this article.

AI and LLM Disclosure (Limited Use)

Limited use of generative AI/LLMs supported language clarity and formatting. All AI-assisted content was critically reviewed, edited for originality, and validated by the authors, who assume full responsibility for the submission.

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