A PERSONALISED ADAPTIVE E-LEARNING SYSTEMS BASED ON DEEP LEARNING APPROACHES: A CRITICAL INTERPRETATION OF LEARNING STYLE MODELS

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ABSTRACT

A possible approach for enhancing the efficacy of online learning environments and addressing the challenge of e-learning personalisation is adaptive e-learning. Deep learning-based approaches have gained significant attention in adaptive education systems to impart personalised adaptive education to classify learner types. These approaches utilise an automatic means to recognise dynamic learning styles to enhance the e-learning experience. In this article, the authors present a critical interpretative approach to explore different learning style models, in order to develop a suitable framework that will assist in identifying learning styles. This framework can be instrumental in delivering personalized adaptive learning, primarily grounded in deep learning approaches. The findings indicate that the Felder–Silverman's learning style model is considered the most suitable model for providing adaptivity. It is well-suited for identifying learners' learning styles in e-learning environments, ultimately optimizing the individual learning experience. Future research should focus on empirically evaluating the performance and efficacy of personalised adaptive learning platforms based on deep learning architectures in classifying learners' learning styles.

Keywords: deep learning, e-learning, learning, learning styles, learning style models, personalised adaptive learning

INTRODUCTION

The rapid progress of digital and networking technologies has led to the emergence of e-learning, which leverages technology to transform how knowledge is delivered and accessed (Moubayed et al. 2018). E-learning has unlocked new learning opportunities, providing multiple approaches to individualise and improve the accessibility, flexibility and portability in learning (Zhang et al. 2004). This technology has the potential to improve the quality of education and enhance the overall learning experience (Muniasamy, Ejalani, and Anandhavalli 2014). Because of its capacity to give students flexible, global access to knowledge, e-learning has attracted an enormous amount of attention recently.

Several factors that have shaped the educational landscape can be attributed to the rise in online learning. In order to maintain the sustainability and continuity of educational institutions, universities were forced to fast adapt and offer academic programmes online by the COVID epidemic, which contributed significantly to the adoption of e-learning (Habib and Patel 2020). Online learning and teaching platforms have grown in popularity as a result of this change. Furthermore, the integration of technology related to the fourth industrial revolution (4IR), such as artificial intelligence, has improved e-learning's efficacy and accessibility by fostering personalised and dynamic learning environments (Penprase 2018). Lastly, e-learning supports lifelong learning and skill development by removing barriers related to time, location and cost (Muniasamy et al. 2014).

Despite the aforementioned advantages, e-learning can only support personalisation to a limited extent (Moubayed et al. 2018). The lack of in-person connection in online learning can impede personal engagement, making it challenging to offer personalised support and guidance (Moubayed et al. 2018). Maintaining learners' motivation and engagement while putting in place clear procedures for timely feedback to facilitate individualised learning are essential to addressing this (Gros 2016; Moubayed et al. 2018). Additionally, the substantial diversity among learners presents a significant challenge in personalising e-learning experiences.

The necessity to develop a personalized approach to e-learning has intensified due to the expanding learner populations, aiming to address the heterogenous needs of individual learners (El Mhouti, Erradi, and Nasseh 2018; Moubayed et al. 2018). Learners learn in different ways and their requirements and preferences are unique – certain learners prefer instruction whereas others prefer doing it themselves (Moubayed et al. 2018). Therefore, a personalised adaptive learning (PAL) system based on individual learning styles (LSs) is essential because it caters to diverse ways in which learners absorb and process information (El Aissaoui et al. 2019).

By tailoring educational approaches to individual LS preferences, personalised learning enhances engagement and speeds up the learning process (Moubayed et al. 2018). To this end, deep learning (DL) approaches have gained attention in personalised adaptive (PA) education systems as they dynamically identify LSs to improve the efficiency of learning and enrich the e-learning experience, addressing the challenge of personalising e-learning effectively (Aeiad and Meziane 2019; Bajaj and Sharma 2018; El Aissaoui et al. 2019; Moubayed et al. 2018; Somasundaram, Mohamed Junaid, and Mangadu 2020).

This article discusses research that employs a critical interpretative approach, focusing on the analysis of literature. The research rendered rich data of a theoretical and conceptual nature. The article aims to explore different learning style models (LSMs) that have been used to develop a suitable PAL framework which will support individual LSs based on DL approaches. The most influential LSMs, namely Kolb's Experiential Learning Model, Honey and Mumford (H&M), Myers-Briggs Type Indicator (MBTI) and Felder-Silverman Learning Style Model (FSLSM), and motivation for the preferred LSM to be used in PAL systems are examined. The discussion of each of these LSMs is preceded by a brief conceptualisation of the notion of PAL to support individual LSs.

CONCEPTUALISATION OF PERSONALISED ADAPTIVE LEARNING

PAL is described as a technology-empowered pedagogy that can adapt teaching strategies in real time based on learners' individual characteristics, performance and development (Peng, Ma, and Spector 2019). In support of this, Bajaj and Sharma (2018) and Hmedna, Mezouary, and Baz (2017) mention that PAL systems aim to enhance learning efficiency and performance and alleviate cognitive overload by offering customised learning paths and resources tailored to the unique profile, knowledge and behaviour of each learner. To implement adaptive e-learning services and educational resources that consider individual differences effectively, the ideal educational approach involves analysing learners' individual characteristics and real-time interactions in their learning context, along with expertise in selecting suitable pedagogical approaches to improve the learning process (Almohammadi et al. 2017; Moubayed et al. 2018; Peng et al. 2019). Additionally, personalised e-learning optimises the learning experience by adapting education to the diverse needs and preferences of heterogeneous learner populations, accommodating their varying learning paces, abilities and knowledge levels (Moubayed et al. 2018; Peng et al. 2019). Hence, PA educational systems are constructed with the premise that the learning process varies for each individual learner (Almohammadi et al. 2017).

Acknowledging the individual cognitive preferences and learning processes of each learner, adaptive learning systems can personalise the educational experience to maximise engagement, understanding and information retention (Moubayed et al. 2018). PAL, focuses on accommodating unique LSs, can improve education by acknowledging and accommodating the diverse ways in which learners engage with instructional resources and internalise information (El Aissaoui et al. 2019; Moubayed et al. 2018).

CONCEPTUALISATION OF THE LEARNERS STYLE OF LEARNING

According to El Aissaoui et al. (2019), an LS is a learner's preferred method of perceiving, processing, understanding, and remembering information. Individuals have unique learning preferences that are influenced by various factors, such as personality and environment ; while verbal instructions are preferred by certain learners, experiential learning is preferred by others (Bajaj and Sharma 2018; El Aissaoui et al. 2019; Moubayed et al. 2018).

Studies in psychology have also highlighted individual variations in problem-solving and decision-making among learners, such as those who may struggle if their LS does not align with the teaching approach (Zine, Derouich, and Talbi 2019). El Aissaoui et al. (2019), Graf, Kinshuk, and Liu (2009), Hmedna et al. (2017) and Moubayed et al. (2018) emphasise that to enhance e-learning systems and offer personalised content that maximises learning speed and effectiveness, it is essential to identify learners' LSs, adapt content accordingly and cater to their diverse needs. Therefore, in order to ‘personalise’ e-learning, it is crucial to recognise the diverse learner types, evaluate and identify their LSs to adapt the content and instructional methods to align with their preferred learning approaches (Graf et al. 2009; Hmedna et al. 2017). This approach enhances support for learners in a more effective and efficient manner (Graf et al. 2009; Hmedna et al. 2017).

To identify an LS, established learning model frameworks and theories have been proposed to characterise how individuals prefer to learn and process information (Moubayed et al. 2018). These theories offer various perspectives on categorising individuals based on their unique LS (Bajaj and Sharma 2018). It is worth noting, however, that the empirical evidence supporting the practicality of LSs has faced criticism due to concerns about terminology limitations and a lack of substantial empirical support (Curry 1990; Kulkarni, Banerjee, and Raghunathan 2022). Despite differing categorisations and definitions of LS by researchers, they all emphasise that the LS represents a learner's preferences for acquiring information, placing the learner at the core of their definitions (Soiferman 2019). Notably, despite the limited availability of thorough research findings to definitively support the effectiveness/usefulness of LSs, they remain popular in education, with no conclusive evidence of their ineffectiveness (Zine et al. 2019).

Despite the criticisms, the authors argue that exploring LSMs holds significant value for several reasons:

- These models offer a structured framework for understanding diverse types of learners and evaluating their individual LSs, as each learner has distinct preferences for processing and retaining information (Graf et al. 2009; Hmedna et al. 2017).
- Investigating methods and approaches that support learners' preferred learning styles is crucial. This can lead to improved learning performance by actively engaging and motivating them. Learners thrive when information is presented to them in a manner aligned with their preferences (Hmedna et al. 2017; Karagiannis and Satratzemi 2018; Moubayed et al. 2018; Soiferman 2019; Zine et al. 2019).
- Identifying which model is more adapted to online learning environments is important (Hmedna et al. 2017).
- It is essential to identify individual learner needs to tailor content and learning techniques accordingly, matching teaching styles to a variety of LSs by providing materials and activities aligned with their preferred learning methods, thus, supporting learners more effectively and efficiently (Hmedna et al. 2017). For instance, using videos for visual learners and PDF notes for verbal learners (Graf et al. 2009; Soiferman 2019; Zine et al. 2019). This enables instructors to offer accurate guidance to enhance learning efficiency and support personalised development (Bernard et al. 2015; Xue-Jun et al. 2021). Ultimately, these models offer educators valuable insights into how to adapt their materials and instructional methods to better align with individual learners' learning preferences, resulting in more effective instruction and an enriched overall learning experience.
- LSMs can empower learners to become more self-aware of their LS preferences, enabling them to take control of their learning, leverage their strengths and recognise

their challenges (Bernard, Popescu, and Graf 2022). This awareness allows them to make informed decisions about their study strategies (Bernard et al. 2022).

These compelling reasons inspire a growing interest in research that investigates the integration of LSM and PAL systems to improve e-learning. The next section elaborates on LSMs.

CONCEPTUALISING LEARNING STYLE MODELS

The domain of LSMs posits that individuals can be effectively classified based on their unique LSs, offering diverse perspectives on how to define and classify these styles (Bajaj and Sharma 2018). Despite their variations, these LSMs share a common objective: to provide valuable insights into individual differences and learning preferences (Soiferman 2019). However, it is crucial to approach the application of these models critically, considering the inherent strengths and limitations associated with each. This section presents a critical interpretative approach, aiming to examine the most influential LSMs within the context of PAL systems. This exploration aims to justify the preference for the most suitable LSM, thereby facilitating the development of a suitable PAL framework that effectively supports individual LSs.

In a recent study conducted by Essa, Celik, and Human-Hendricks (2023), their comprehensive systematic literature review (SLR) sheds light on the diverse range of LSMs employed within PAL systems. Notably, among the array of LSMs, four influential models emerged as prominent in this domain: Kolb's Experiential Learning Model, H&M, the MBTI and the FSLSM. In the subsequent sections, the specifics of each of these LSMs are deeply delved into and their dimensions designed for categorising learners' LSs, the associated questionnaires employed for this purpose and the strengths and limitations thereof are meticulously examined. The prevalence and significance of these LSMs in PAL systems are thoroughly explored. This exploration offers valuable insights into their role in enhancing personalised and adaptive educational experiences through determining LSs.

Kolb’s Experiential Learning Model

Kolb's LSM is grounded in experiential learning theory (ELT), which posits that knowledge emerges from the transformation of experience (Kolb 1984, 38). The ELT model comprises four distinct LSs, each linked to a stage in a four-stage learning cycle (Kolb 1984). According to Kolb and Kolb (2005), experience is central to the learning process, with knowledge emerging from the integration of *grasping* and *transforming* experience. This model is characterised by these two orthogonal dimensions: *grasping*, with poles of concrete experience

(CE) and abstract conceptualisation (AC), and *transforming*, with poles of reflective observation (RO) and active experimentation (AE) (Kolb and Kolb 2005).

The four stages within Kolb's learning cycle are as follows: CE involves facing a new situation or revisiting a similar prior experience; RO entails observing the new experience and reflecting on it based on previous knowledge; AC sees reflections initiating a new understanding or building on existing knowledge; and AE involves putting newly acquired or expanded knowledge into practice. These stages are interconnected, with each one naturally leading to the next. The combinations of these learning cycles result in four LSs: accommodating (CE/AE), diverging (CE/RO), assimilating (AC/RO) and converging (AC/AE). The four stages of the learning cycle and their combinations are summarised in Figure 1. Kolb developed the Learning Style Inventory (LSI), a 12-item forced-choice ranking questionnaire, to identify LSs according to his LSM (Bajaj and Sharma 2018; Feldman, Monteserin, and Amandi 2015; Hmedna et al. 2017; Kolb 1984; Kolb and Kolb 2005; Zine et al. 2019).

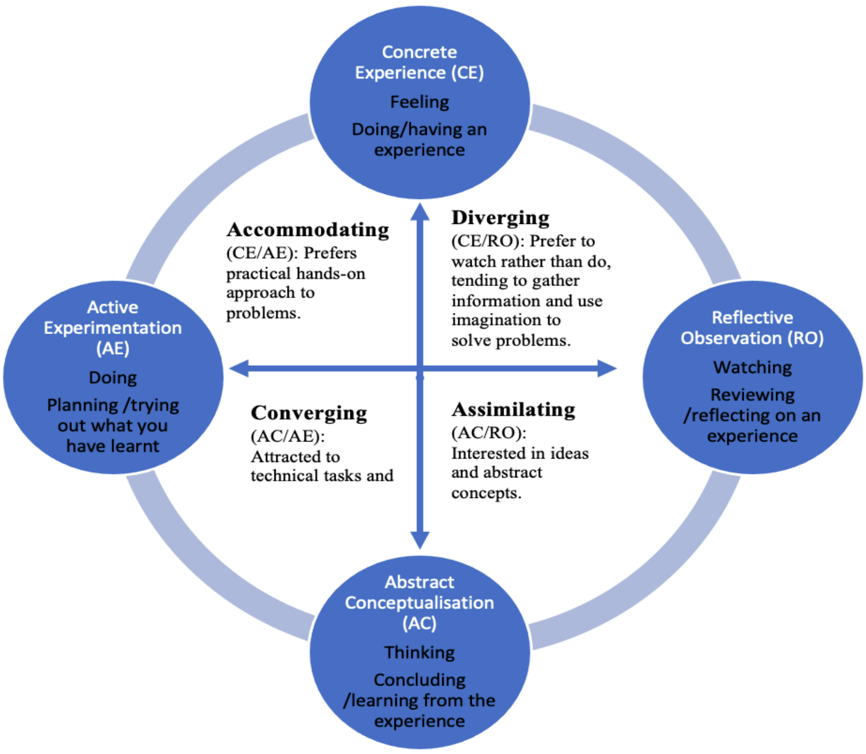

Figure 1: Kolb's LSM (adapted from Hmedna et al. 2017; Moubayed et al. 2018; Zine et al. 2019)

Kolb's ELT is among the earliest LSMs grounded in a clear theoretical framework. The strength of Kolb's LSM is recognising that LSs are not rigid personality traits but instead consistent behavioural patterns. However, it falls short when it comes to precise individual selection, lacking the ability to measure individuals with thorough precision. Additionally, with no concrete literature-based evidence to suggest a significant improvement in academic performance, critics have raised concerns about the psychometric properties of the LSI. The LSI's volatility and unsatisfactory reliability coefficients for its four basic scales further compound these issues (Bergsteiner, Avery, and Neumann 2010; learningstyles, n.d.; Zine et al. 2019).

In addition to concerns about reliability and validity, Kolb's model faces challenges in terms of its theoretical foundation. Kolb's ambiguity regarding whether his model reflects four distinct LSs or four sequential stages in a learning cycle is unclear. LSs typically refer to inherent or acquired personality types, whereas learning stages refer to the sequential steps in a learning cycle. Furthermore, despite the extensive literature on Kolb’s impactful contributions to experiential learning, his graphical model raises concerns related to graphic sufficiency and simplification. Bergsteiner et al. (2010) suggest that Kolb’s model holds potential for further development. This criticism collectively undermines the holistic claims of the model (Bergsteiner et al. 2010; learningstyles, n.d.; Zine et al. 2019).

Honey and Mumford Learning Style Model

The H&M LSM is rooted in Kolb's theory but diverges in that it does not assume the presence of orthogonal dimensions, as is the case with Kolb's LSM (Kolb and Kolb 2005; Honey and Mumford 1992). In contrast, H&M's LSM describes LS as a representation of an individual's preferred approach to learning, encompassing their attitudes and behaviours (Honey and Mumford 1992). The core aim of this model is to encourage learners to attain proficiency in all four stages of the learning cycle – activists (learn by doing), reflectors (observe and reflect), theorists (employ logical and systematic approaches) and pragmatists (emphasise practical application) (Cassidy 2004; Knight 1983; Troussas, Krouska, and Virvou 2021; Zine et al. 2019).

Honey and Mumford's model posits that people learn in a manner similar to how experimental scientists perform research, and that individuals' LSs differ based on the stages of the learning process at which they excel. The characteristics of these four LSs and associated learning activities proposed by Honey and Mumford are summarised in Table 1. To assess an individual's LS, the H&M LS questionnaire was developed, differing from Kolb's LSI in that it consists of 20 items with true/false responses for each LS (Cassidy 2004; Knight 1983; Troussas et al. 2021; Zine et al. 2019).

Table 1: Honey and Mumford LSM (adapted from Troussas et al. 2021; Zine et al. 2019)

Stages/dimensions and LS preferences	Characteristics	Learning activities
Stage 1: Activists (A)	Activists learn by doing; they prefer hands-on experiences and experimentation.	Brainstorming, solving problems, engaging in group discussion, solving puzzles, participating in competitions and role-play among other activities.
Stage 2: Reflectors (R)	Reflectors acquire knowledge by observing and reflecting on outcomes.	Engaging in observational activities, receiving feedback from others, and participating in paired discussions, among other methods.
Stage 3: Theorists (T)	Theorists benefit from comprehending the foundational theory behind activities to enhance their learning.	Utilizing models, statistics, narratives, background information, applying concepts theoretically among other approaches.
Stage 4: Pragmatists (P)	Pragmatists are practical, favouring the application of new concepts to real-world issues.	Conducting experiments, solving problems, analysing case studies, engaging in discussions etc.

The H&M model's notable strength lies in its examination of the attitudes and behaviours that determine learning preferences. Furthermore, it is not a psychometric instrument but rather a checklist about how people learn. Even though this model offers the potential for personal development by helping individuals uncover and support underexploited styles, its application for individual selection based on LSs proves impractical due to a lack of distinctive scale scores that would enable clear categorisation. One of the significant drawbacks of the H&M model is its potential to oversimplify individuals' learning preferences by labelling them as either theorists or pragmatists, disregarding the complexity of human learning; in fact, most people exhibit more than one strong preference. Although it has been widely used in the professional field, researchers have raised concerns about its validity, emphasising the need for more robust evidence to adopt it confidently (Knight 1983; learningstyles n.d.; Zine et al. 2019).

Myers-Briggs Type Indicator

The MBTI and the H&M LSM both attempt to categorise and understand individual differences in learning and cognitive preferences. However, they focus on different aspects of an individual's preferences and tendencies. While the MBTI delves into psychological traits, the H&M model is more focused on preferred approaches to learning. The H&M model categorises learners into four LSs linked to distinct stages of the learning process in contrast to the MBTI model which is aimed at helping to understand an individual's unique personality that divides individuals into distinct personality types based on four dichotomies – attitude, information processing, decision-making and environment. Each dimension is composed of pairs of opposite preferences: attitude (extraversion/introversion), information processing (sensing/intuition), decision-making (thinking/feeling), and environment (judging/perceiving). The four bipolar dimensions can combine to generate 16 personality types. Table 2 provides a clear summary of the four dimensions in the MBTI model, their preferences or scales and the associated learning activity characteristics. To identify LSs based on the MBTI model, three forms of the MBTI instrument have been developed, offering insights into individual cognitive preferences and personality traits (Capraro and Capraro 2002; Cassidy 2004; Girelli and Stake 1993; Knight 1983; Zine et al. 2019).

Table 2: MBTI learning styles (adapted from Capraro and Capraro 2002; Zine et al. 2019)

Dimension	Preferences/scales	Learning activities characteristics
EI – Attitude	Extraversion (E)	General attitude oriented outward to other persons and objects (E)
	Introversion (I)	Internally oriented attitude (I)
SN – Information processing	Sensing (S)	Preference for relying on observable facts detected through the senses (S)
	Intuition (N)	Insight-based intuition preference (N)
TF – Decision-making	Thinking (T)	Logical thinking and decision processes (T)
	Feeling (F)	Subjective, interpersonal feeling-based approach (F)
JP – Environment	Judgement (J)	Prefers prompt decisions, planning and organising activities (J)
	Perception (P)	Prefers flexibility and spontaneity (P)

The MBTI has certain strengths, such as its widespread use and its ability to provide a comprehensive view of an individual's personality, including their learning preferences, by utilising four bipolar scales that result in 16 personality types. However, it has been dismissed by LS researchers as the model places more emphasis on personality traits than on cognitive processes and behaviours specifically related to learning, making it less specific for educational purposes. Furthermore, the construct validity of the MBTI has been a subject of debate, with questions raised about the instrument's forced-choice format and the assumption that all individuals can be neatly classified into distinct personality catergories. Another critique involves the varied emphasis placed on gender weighting, which complicates direct comparisons between males and females, particularly on the 'thinking-feeling' scale. Additionally, the research evidence supporting the MBTI as an effective tool for evaluating LSs and providing pedagogical support is still inconclusive, as some critical examinations of its validity have been superficial and neglectful. Moreover, the connections between elements and scales are extremely complex and prone to misinterpretation. Lastly, the practical implementation of MBTI in pedagogy remains ambiguous as it is unclear which elements are relevant for educational purposes. These critiques highlight the need for further research and refinement of the MBTI's role in education (Capraro and Capraro 2002; Girelli and Stake 1993; learningstyles, n.d.; Vacha-Haase and Thompson 1999; Zine et al. 2019).

Felder-Silverman Learning Style Model

The FSLSM is a distinctive approach to LS assessment that sets itself apart from other models such as Kolb's or H&Ms due to its multidimensional nature; whereas the other LSMs emphasise broad LS categories. Developed by Richard Felder and Linda Silverman in 1988, the FSLSM was specifically designed for engineering education. This model catergorises learners based on their positions on various scales, allowing educators to assess how learners perceive and process information in a more detailed manner. FSLSM characterises each learner across four dimensions, each representing a stage in the information reception and processing process: perception, input, processing and understanding (Felder and Silverman 2002; Litzinger et al. 2007).

In each dimension, there exists two contrasting preferences for LS with each learner having a predominant preference in each dimension. For example, in the information processing dimension, learners can either prefer to actively engage with information through hands-on involvement or reflectively process it through introspection. In the information perception dimension, learners may favour perceiving or taking in information through sensory channels, such as sensing or intuitive preferences. In the dimension of information reception, learners might lean towards information being presented visually or verbally. Finally, in the dimension of information understanding, learners may lean towards progressing in their understanding either sequentially, step-by-step, or holistically, in a global manner. The FSLSM provides a comprehensive view of individual LSs, making it a valuable tool in the field of education (Felder and Silverman 2002; Litzinger et al. 2007).

Moreover, these LS preferences also extend to the types of learning objects (LOs) that are more effective for each category. For example, active learners may prefer an LO involving practical problem-solving, while reflective learners may find examples and exercises more appealing. Sensing learners tend to thrive with an LO based on sensory experiences and concrete materials, while intuitive learners may prefer an abstract LO and mathematical models. Visual learners gravitate towards LO-like videos and images, whereas verbal learners are more inclined towards textual representations, whether written or spoken. Sequential learners prefer an LO structured as step-by-step exercises, while global learners may find outlines and overviews more suitable. This detailed understanding of LS preferences helps educators tailor their instructional materials to better match individual learners' needs. Table 3 provides a detailed explanation of each of the FSLSM dimensions and the corresponding LS and LO preferences (Felder and Silverman 2002; Litzinger et al. 2007).

Table 3: Dimension of teaching and learning style (based on Felder and Silverman, 2002)

Dimension	Information processing: The manner in which perceived information is converted into knowledge.	
Learning Style (A/R)	Active	Reflective
Description	Active learners prefer to learn and comprehend information by actively engaging with and applying it in the external world through experimentation.	Reflective learners prefer to learn by thinking things through and working individually. Therefore, this category of learners leans towards introspective examination and individual manipulation of information.
Learning Objects	• Practical problem-solving • Forum access and posts	• Examples and exercises • Read post
Dimension	Information perception: The type of information the learner prefers to perceive.	
Learning Style (S/I)	Sensory (External)	Intuitive (Internal)
Description	Learners with a sensing learning style prefer to use their sensory experiences to learn facts and concrete learning material.	Intuitive learners favour learning abstract material such as theories and their underlying meanings, with general principles and discovering relationships.
Learning Objects	• Examples and exercises • Practical problem-solving	• Abstract learning object • Mathematical models
Dimension	Information reception: The manner in which learners prefer to receive external information.	
Learning Style (V/V)	Visual	Verbal

Description	The visual learner remembers, understands and assimilates information more effectively when it is presented visually.	Verbal learners favour learning through textual representations, whether in written or spoken form.
Learning Objects	• Recorded videos • Images – graphics diagrams	• Textual explanation – documents • Audio
Dimension	Information understanding: The way learners progress towards understanding.	
Learning Style (S/G)	Sequential	Global
Description	Sequential learners typically progress through a course following logically, step-by-step, in a linear manner.	Global learners favour learning in large leaps understanding the larger picture first by skipping to more complex material. This category of learners are holistic learners.
Learning Objects	• Step-by-step exercises • Linear access for learning concepts	• Outline • Overviews

Felder and Solomon created the Index of Learning Styles (ILS), a 44-item online questionnaire designed to identify individuals' learning style preferences grounded in the FSLSM. The ILS assesses a learner's personal preference on a scale with values ranging from +11 to -11 for each dimension, covering sensing-intuitive, visual-verbal, active-reflective and sequential-global preferences. Learners respond to 11 questions for each dimension by selecting one of two alernatives representing opposite poles of the LS scale. This structured questionnaire helps individuals identify their LS profiles (Felder and Silverman 2002; Litzinger et al. 2007).

The FSLSM has gained significant recognition in the field of LSMs and has been widely used by educators across various disciplines (Zine et al. 2019). Zine et al. (2019) highlight that based on the literature, FSLSM has emerged as the most preferred LSM in learning theories. It has been effectively utilised in numerous prior studies, particularly in the individualized adaptation of learning materials (Zine et al. 2019). Similarly, previous reviews by Özyurt and Özyurt (2015) and Truong (2016) also indicate that FSLSM is the model of choice. A recent SLR by Essa et al. (2023), which examined the frequency of machine learning algorithms used for LS identification between 2015 and 2022, reveals that the FSLSM was the most frequently employed model in 37 out of 48 studies. Moreover, FSLSM is one of the frequently employed LSMs in technology-enhanced learning and (Graf 2006; Kuljis and Liu 2005; Zine et al. 2019). It is regarded as among the most suitable models for adaptive systems, as it provides a comprehensive description of four distinct dimensions of LS (Graf 2006; Kuljis and Liu 2005; Zine et al. 2019).

One of the distinguishing features of FSLSM is its consideration of LSs as tendencies rather than rigid categories, recognising that learners may exhibit different preferences on different occasions (Brusilovsky 1999; learningstyles, n.d.; Zine et al. 2019). The FSLSM evaluates the learners' LSs on a scale across four dimensions resulting in the identification of 16 distinct LSs (Bernard et al. 2015). Moreover, these descriptions outline the variety of LO that can be in-cooperated in each LS preference (detailed in Table 3), aiding in the design of instruction and assessment sequences tailored to LSs (El Aissaoui et al. 2019). Additionally, the ILS instrument has proven to be effectively used in numerous studies for instruction and design by enabling the control of the number of dimensions and offering easily interpretable and implementable results (Felder and Silverman 2002; Graf 2006; Kuljis and Liu 2005; Litzinger et al. 2007; Zine et al. 2019).

While the FSLSM has shown success in several areas, particularly in providing adaptivity and enhancing instruction and assessment in e-learning environments, it may not be as effective in predicting academic performance (Zine et al. 2019). Nevertheless, studies have indicated acceptable convergent and discriminant validity, along with limited reliability and satisfactory consistency (learningstyles, n.d.; Zine et al. 2019).

Considering the aforementioned benefits, the FSLSM appears to be the most appropriate model for providing adaptivity, accurate instruction and assessment design by identifying the learners' LSs in e-learning environments. Consequently, due to several advantages of this model, the authors have selected the FSLSM as their preferred model to provide PAL.

Personalised adaptive learning to identify learning styles

The effectiveness of PA educational systems relies on the methodology used to categorise and gather information about the learners' LSs based on their needs and characteristics (Bajaj and Sharma 2018). Additionally, the effectiveness depends on the way the information is processed to create an adaptive and intelligent learning environment, as noted by Bajaj and Sharma (2018). Conventional approaches for identifying learner LSs entails completing an LSM questionnaire, however, this solution has significant limitations (El Aissaoui et al. 2019). First, completing LSM questionnaires is a time-intensive process (El Aissaoui et al. 2019). Second, the results obtained from these questionnaires may not accurately reflect learners' true LSs because they may lack self-awareness of their preferences, leading to uninformed answers (El Aissaoui et al. 2019). Third, LSs are dynamic and can evolve throughout the learning process, in contrast to the static nature of results obtained from LSM questionnaires (El Aissaoui et al. 2019).

To overcome these limitations, PA education systems have turned to machine learning (ML) approaches for the automatic detection of LSs, as advocated by Bajaj and Sharma (2018) and Hmedna et al. (2017). The automatic detection of LSs, which classify learners based on their preferred learning methods, offers several advantages. This method is not only more efficient than questionnaire-based approaches but is also dynamic and adaptable to changes in learners' behaviours, as highlighted by El Aissaoui et al. (2019).

CONCEPTUALISATION OF DEEP LEARNING AS A MACHINE LEARNING APPROACH

DL is a subset of ML that utilises artificial neural networks to model and solve complex tasks (Moubayed et al. 2018; Muniasamy and Alasiry 2020). It is characterised by the use of multiple layers of interconnected neurons or component parts to automatically extract hierarchical features from data (Almohammadi et al. 2017). These deep neural networks are designed to emulate the human brain's capability to learn and identify patterns from extensive amounts of information (Muniasamy and Alasiry 2020). DL provides intuitive algorithms that capable of predicting potential outcomes using user data. This enables the computer to display behaviours learned through experience in contrast to human interactions (Muniasamy and Alasiry 2020). Notably, as new data is continuously fed into the DL model, its level of intuitiveness progressively improves, making it a dynamic and adaptive tool, as highlighted by Muniasamy and Alasiry (2020). Moreover, as ML algorithms enable computers to learn from data, systems possess an increased capability to adapt to new inputs and make predictions or decisions based on patterns and examples present in the data (Moubayed et al. 2018). Due to their ability to adapt, ML algorithms have gained considerable attention, leading to their utilization in various applications to personalise and adapt e-learning experience (Aeiad and Meziane 2019; Bajaj and Sharma 2018; El Aissaoui et al. 2019; Somasundaram et al. 2020).

DL methodologies are pivotal in the domain of e-learning, offering autonomous solutions that span various aspects of the learning process. These methodologies begin with the initial stages of data extraction and assessment from learning management systems (LMSs). Subsequently, they employ predictive analytics based on historical performance and individualised learning goals, thereby enhancing the personalisation of e-learning experiences. DL further contributes to e-learning by optimising the allocation of personalised online resources to individual learners. By identifying gaps in a learner's knowledge and matching them with resources tailored to their unique learning goals, DL ensures that learners have access to the right materials at the right time. This resource allocation not only enhances the learning experience but also empowers learners to progress towards their goals effectively (Muniasamy and Alasiry 2020).

One of the key advantages of DL in e-learning is its capacity to refine the classification of content elements. In the digital learning landscape, learners often require content to be delivered in multiple formats and accessible across various platforms. DL's ability to optimise content classification ensures that learners receive materials in formats that align with their preferences and needs, fostering a more engaging and effective learning experience. Ultimately, the integration of smart DL environments into e-learning holds the promise of motivating learners to actively engage with the educational platform. By offering personalised content and resources, DL encourages a more engaging and rewarding learning experience. This, in turn, contributes to improved learning outcomes and performance for online learners (Muniasamy and Alasiry 2020).

DISCUSSION AND IMPLICATIONS

In this work, the authors present a critical interpretative approach exploring different LS models to develop a PAL framework that supports the individual LSs summarised in Table 4 which shows the key dimensions, associated questionnaires, strengths and weaknesses of each of the LSMs discussed previously.

Table 4: Summary of LSMs (adapted from Zine et al. 2019, 527)

LSM	Key Dimensions	Associated Questionnaire	Strengths	Weakness
Kolb	• Grasping: Concrete Experience (CE) vs Abstract Conceptualisation (AC) • Transforming: Reflective Observation (RO) vs Active Experimentation (AE)	Kolb's Learning Style Inventory (LSI)	• Flexible and consistent LSs • Reliable instrument • Suitable for individualising instruction	• Inappropriate for individual selection • Inadequate understanding of a learning cycle • Doubtful psychometric properties • Disputed reliability • Controversial construct validity • Low predictive validity

LSM	Key Dimensions	Associated Questionnaire	Strengths	Weakness
				• Lack of theoretically basis for pedagogical impact • Graphical model
H & M	• Activist: learn by doing • Reflectors: observe and reflect • Theorists: logical and systematic approaches • Pragmatists: emphasise practical application	Honey and Mumford Learning Style Questionnaire	• Specific to learning • Beneficial for individuals to strengthen an under-used style • Instrument translated into numerous languages	• Individuals labelling • Ineffective for assessment/selection • Highly criticised model design • Moderate internal consistency • Speculative validity • Lack of empirical evidence regarding pedagogical impact
MBTI	• Attitude: Extroversion (E) vs Introversion (I) • Information Processing: Sensing (S) vs Intuition (N) • Decision-making: Thinking (T) vs Feeling (F) • Environment: Judging (J) vs Perceiving (P)	Myer-Briggs Type Indicator (MBTI) Assessment	• Offers a overview of the entire personality • Demonstrates high-reliability coefficients • Acknowledged face validity	• Not tailored to learning • Complex relationships between elements and scales • Limited stability of the LS • Questionable construct validity • Lack of evidence for positive outcomes regarding the pedagogical impact • Weights applied to gender
FSLSM	• Information processing: active vs reflective • Information perception: sensing vs intuitive • Information reception: visual vs verbal • Information understanding: sequential vs global	Felder-Silverman Index of Learning Styles (ILS)	• Learning specific • Flexible and consistence LSs • Detailed description of a learner’s LS • Extensively used • Acceptable convergent and discriminant validity • Limited reliability	• Low predictive validity

LSM	Key Dimensions	Associated Questionnaire	Strengths	Weakness
			• Suitable for individualised instruction • Questionnaire easy to interpret and implement	

The authors chose the FSLSM as the most suitable model for providing adaptivity for several compelling reasons. The FSLSM offers a detailed characterisation of LSs by assessing preferences across four distinct dimensions and using scales to measure the strength of these preferences, distinguishing them from other models (Bernard et al. 2015). It considers LSs as tendencies rather than fixed types, providing a more flexible and accurate representation (Brusilovsky 1999). Additionally, the FSLSM specifies the types of LOs suitable for each LS preference, aiding in determining learner sequences (El Aissaoui et al.,2019). In technology-enhanced learning, the FSLSM is widely utilised and considered one of the leading models for adaptive systems due to its comprehensive depiction of four distinct dimensions of LSs (Graf 2006; Kuljis and Liu 2005; Zine et al. 2019). Furthermore, the ILS associated with the FSLSM has been effectively applied in various studies, offering control over the number of dimensions and ease of interpretation and implementation (Zine et al. 2019).

DL is particularly well-suited for PAL systems to identify LSs for several reasons. First, DL models, excel at processing large and diverse datasets – essential when dealing with the multitude of variables associated with LS identification (Moubayed et al. 2018; Muniasamy and Alasiry 2020). Second, the hierarchical and non-linear nature of DL models allows them to capture complex relationships within data, which can be crucial for understanding the diverse range of individual LSs (Moubayed et al. 2018; Muniasamy and Alasiry 2020). Third, DL can adapt and evolve, enabling PAL systems to continually refine their understanding of each learner's learning preferences as they engage with the platform (El Aissaoui et al. 2019; Muniasamy and Alasiry 2020). Fourth, the ability to work with unstructured data, such as learner interactions and behaviour in online learning environments, makes DL a powerful tool for modelling the dynamic nature of LSs (Anantharaman, Mubarak, and Shobana 2019; El Aissaoui et al. 2019; Moubayed et al. 2018). Finally, DL's capacity to handle multimodal data, combining information from various sources such as text, images and user interactions, allows for a comprehensive assessment of LSs (Muniasamy and Alasiry 2020). As a result, DL serves as a promising approach for automating the identification of LSs within PAL systems, ultimately enhancing the effectiveness of educational experiences for individual learners.

The findings of a SLR conducted by Essa et al. (2023), reported a paucity of studies documenting the adoption, comparison and evaluation of the performance of advanced classification models, such as DL algorithms, in classifying LSs to offer higher adaptability. Therefore, based on the aforementioned discussion, to impart PA education, a DL methodology is proposed. This approach aims to understand the connections between e-learners' actions in e-learning settings and their respective LSs according to the FSLSM. These LSs can then be mapped to learning techniques to deliver personalised education to enhance individual learning experience.

The importance of these systems is due to their ability to aid educators in reconsidering and refining the learning design of courses, thereby offering an improved learning experience. Moreover, LS information can be used by instructors to provide more accurate guidance to their learners. Additionally, these systems can assist in enhancing the customisation, engagement and effectiveness of educational content based on individual LSs, ultimately leading to improved learning outcomes for learners with diverse LS preferences. Thus, this will act as a supportive tool and will not take away from the necessary engagement between the lecturer and the learner. The authors contend that by accurately identifying LSs, adaptive learning systems can use LS information to offer more precise personalisation, optimising individual learning and enhancing the overall learner experience. Consequently, learners stand to benefit from enhancements in performance, satisfaction, engagement and time efficiency (Bernard et al. 2015; Hmedna et al. 2017; Moubayed et al. 2018; Pappas and Giannakos 2021; Zine et al. 2019).

CONCLUSION

The convergence of the COVID pandemic, technology advancements such as 4IR technologies, accessibility, flexibility, cost-effectiveness and changing learner needs have contributed to the increase in the online education paradigm. Adaptative e-learning provides a promising solution to address the challenge of personalising e-learning by enhancing learners' learning processes based on various factors, including their LSs. Acknowledging the individual cognitive preferences and learning processes of each learner, adaptive learning systems can personalise the educational experience to maximise engagement, understanding and information retention. Hence, to 'personalise' e-learning effectively, it is essential to comprehend the various types of learners. This involves evaluating and classify their LSs to adapt the content and learning techniques based on their preferred LS, ultimately providing more effective and efficient support.In this article, the authors presented a critical interpretative approach exploring different LSMs to develop a suitable framework that will assist in identifying LSs to provide PAL based on DL approaches. The findings indicate that the FSLSM is the most suitable model for providing adaptivity to identify learners' LSs in e-learning environments to optimise individual learning. DL-based approaches have gained significant attention in adaptive education systems to impart PA education to classify learner types. These approaches utilise an automatic means to recognise dynamic LSs, thus enhancing the e-learning experience. To support continuous progress, personalised learning necessitates research covering the spectrum of PAL based on DL. This involves the automated and dynamic identification of LSs to create an adaptive and intelligent learning context.

FUTURE RECOMMENDATIONS

The literature reviewed has highlighted the importance of investigating a PA system within an e-learning environment that *classifies* participants' based on their LS and dynamically *adapts* content and techniques according to their individual LSs for an enhanced learning experience. The literature has reported a paucity of documentation on the performance of advanced classification models such as DL algorithms to determine LSs in a South African context. It is therefore recommended to conduct further research to empirically evaluate the efficacy and performance of the PA learning platform based on DL architectures in classifying learners' LSs. Furthermore, here is a need for research comparing DL architectures integrated with FSLSM to adapt and personalise learning approaches for individual learners. Additionally, evaluating the performance and accuracy of these strategies in classifying learners' LSs is of equal importance. Such investigations can enhance adaptability and recommendation capabilities.

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