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ORIGINAL RESEARCH ARTICLE

Enhancing Online Learning: Designing Adaptive and Personalised E-Learning System Design using VARK and Open-Source Applications

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ABSTRACT
This study investigates the adaptability of e-learning platforms by developing a flexible learning system that evaluates users' learning preferences using VARK (Visual, Auditory, Read/Write, Kinesthetic) questions. The system extracts materials from freely accessible online sources, focusing on usability and diverse criteria. Optimisation with ontology enhances data extraction procedures. Various models are developed to incorporate adaptability and personalisation, notably, the learner's model, which integrates student needs and study domains based on learning style theories. The study significantly enhances adaptive e-learning systems by delivering personalised learning materials efficiently sourced from open-access apps and search engines. Evaluation and feedback mechanisms at the start of each session tailor the learning experience to individual styles, thereby improving learning effectiveness in diverse educational settings.

INTRODUCTION
Online education integrates information and communication technology (ICT) and digital media into the educational process, offering access to higher education for those who face challenges in traditional classroom settings (Liu, 2024). E-learning platforms, which are customisable and personalised, facilitate the dissemination of instructional resources to students (Aeiad & Meziane, 2018). However, existing platforms often lack personalised learning options, providing uniform information and practices to all learners. Personalization in education involves tailoring educational materials to individual students based on their strengths, weaknesses, interests, and learning priorities (Lihua, 2021). This approach aims to adapt education to meet specific learner needs, thereby enhancing educational outcomes (Taylor et al., 2021).

Technological, social, and economic elements constantly transform the global economy, structure, and way of life. These components, in particular, have transformed and will continue to affect organisational learning and teaching. In 2020, Vagale et al. wrote, "The fundamental procedures of workplace training and education have been rethought due to technological advancements, the fast obsolescence of knowledge and training, the necessity of just-in-time training delivery, and the pursuit of cost-effective solutions to address the learning requirements of a globally distributed workforce." Vagale et al. also pointed out that demographic shifts, the demand for more flexible access to lifelong learning, and the skills gap have all influenced the education system.

Tsolis et al. (2010) proposed an open-source software and technology-based adaptive and personalised e-learning system in their study. No e-learning platform ever brought up the promised system, combining educational content and technologies with personalised services and profiles for instructors and students. Both real-time and delayed online education are possible on the suggested platform.

In their study, Diaz et al. (2018) suggested an adaptive e-learning platform and used a sample group of engineering students studying Java object-oriented programming. Positive chi-square values were found in the study. The outcome suggests that students' learning has progressed. The results showed that the standard deviation dispersion rates improved by more than 50%, with 64.93% correct replies.

El-Sabagh (2021) offered an adaptable online learning environment based on the pupils' learning preferences. The project's development strategy was applied to design an adaptive e-learning environment. The capacities, participation, interaction, performance, and emotional components were all measured using the engagement scale. As per the study's findings, there is a statistically significant difference between the experimental and control groups. According to the study's conclusions,

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learning styles are helpful for building instructional tools grounded in learning theories.

In their study, Murtaza et al. (2022) evaluated the benefits and features of a personalised e-learning system compared to a traditional e-learning system. Four primary study issues addressed the requirements and obstacles of creating and implementing a personalised e-learning system. An effective framework for individualised e-learning was proposed, consisting of five modules: Data Module, Adaptive Learning Module, Adaptable Learning Module, Recommender Module, and Content and Assessment Delivery Module. The study findings have proven valuable for academics and researchers attempting to understand the requirements, approaches, and obstacles connected with designing efficient, tailored e-learning systems.

In their study, Chang et al. (2022) enhanced personalised learning services for the Moodle e-learning management system, which synchronises user identification according to the user information database of the third-party user management platform system. Their system exploits user demand to improve learning efficiency by providing e-courses, e-learning resources, and learning modes. The study uses a pre-test and a post-test to compare the benefits of an individualised e-learning platform. The sample population was collected at the University of Technology, Taiwan. The average post-test was higher than the average pre-test.

In their study, Ristić et al. (2023) constructed an adaptive learning management system model and integrated it into Moodle. During the system evaluation, 228 people were employed. The usefulness of an adaptive e-learning system was explored in the study. The experiment indicates that learning differs greatly. An adaptive online learning platform's efficacy. Nonetheless, the study's findings validated its hypothesis and illustrated how adopting an e-learning system may boost students' educational prospects.

Online learners' diverse backgrounds and interests pose challenges to the traditional 'one-size-fits-all' educational model, which assumes uniform delivery of course materials (Amin et al., 2023). To address these challenges and enhance the utilisation of traditional e-learning resources, there is a need for adaptive and personalised systems. Such systems leverage freely available online educational materials to create and deliver content tailored to individual learners. This approach can benefit self-learners, resource-constrained universities, and anyone seeking specialised knowledge in various fields.

The primary objective of this research is to develop an intelligent system for designing, testing, and evaluating online courses using current open-source software. This system aims to empower users to create personalised learning content based on globally recognised courses and resources, circumventing the inefficiencies of traditional search engines in finding suitable learning materials.

Furthermore, this study addresses three critical challenges: firstly, identifying learner needs such as learning styles and subject interests; secondly, defining knowledge domains using ontologies to access relevant learning materials; and thirdly, aligning curriculum goals with curated content from credible websites to facilitate effective learning. Additionally, the adaptive and personalised nature of the system allows for continuous updates and adjustments based on user interactions over time.

MATERIALS AND METHODS

Research Methodology

This study uses quantitative and qualitative approaches to obtain all the relevant information for this analysis based on the research objectives. When both quantitative and qualitative research methods are used, it just means that data has been gathered and analysed using a mix of research methods to get a full picture of the study problems that might not be possible with just one method (Sabeima et al., 2022). This methodological choice allows for a thorough exploration of both the quantitative aspects (performance metrics, usage patterns) and qualitative aspects (user experiences, perceptions) of the e-learning system and ensures that the research objectives are addressed comprehensively, providing robust insights into the design, implementation, and effectiveness of the personalised e-learning system under study (Sayed et al., 2022). By integrating quantitative and qualitative methods, the study offers practical recommendations for optimising e-learning experiences based on empirical data and user perspectives.

Research Process

Research is studied in different definitions by numerous writers; the importance of the research process is supplied by Saunders et al. (2009), as it indicates that research provides a platform on which the research approach can be built. However, research onions might go with almost different research techniques. The research onion highlights the layers and discusses the functions carried out in every stage of the layers. The layers include the research philosophy, strategies, techniques, research choice, processes, data collection, and time zone, as depicted in Figure 1 below.

Research Philosophy

Research philosophy is a system of assumptions and beliefs about knowledge development (Saunders et al., 2016). The study's methodology and approaches were selected based on these assumptions. It also helps the researcher analyse and recognise the most relevant approaches to be applied in the entire research process by encouraging the researchers to be more creative in adjusting the required research approach. Research philosophy is separated into three: interpretivism, positivism, and pragmatics, as depicted in Figure 2 below.

Research philosophy comprises three essential assumptions about interpreting the world (Saunders et al., 2016). They include;

- Ontology: assumptions about the nature of reality.
- Axiology: techniques and nature of how academics evaluate their research.
- Epistemology: assumptions that create accurate knowledge.

Table 1 below outlines these philosophical concepts of positivism and interpretivism.

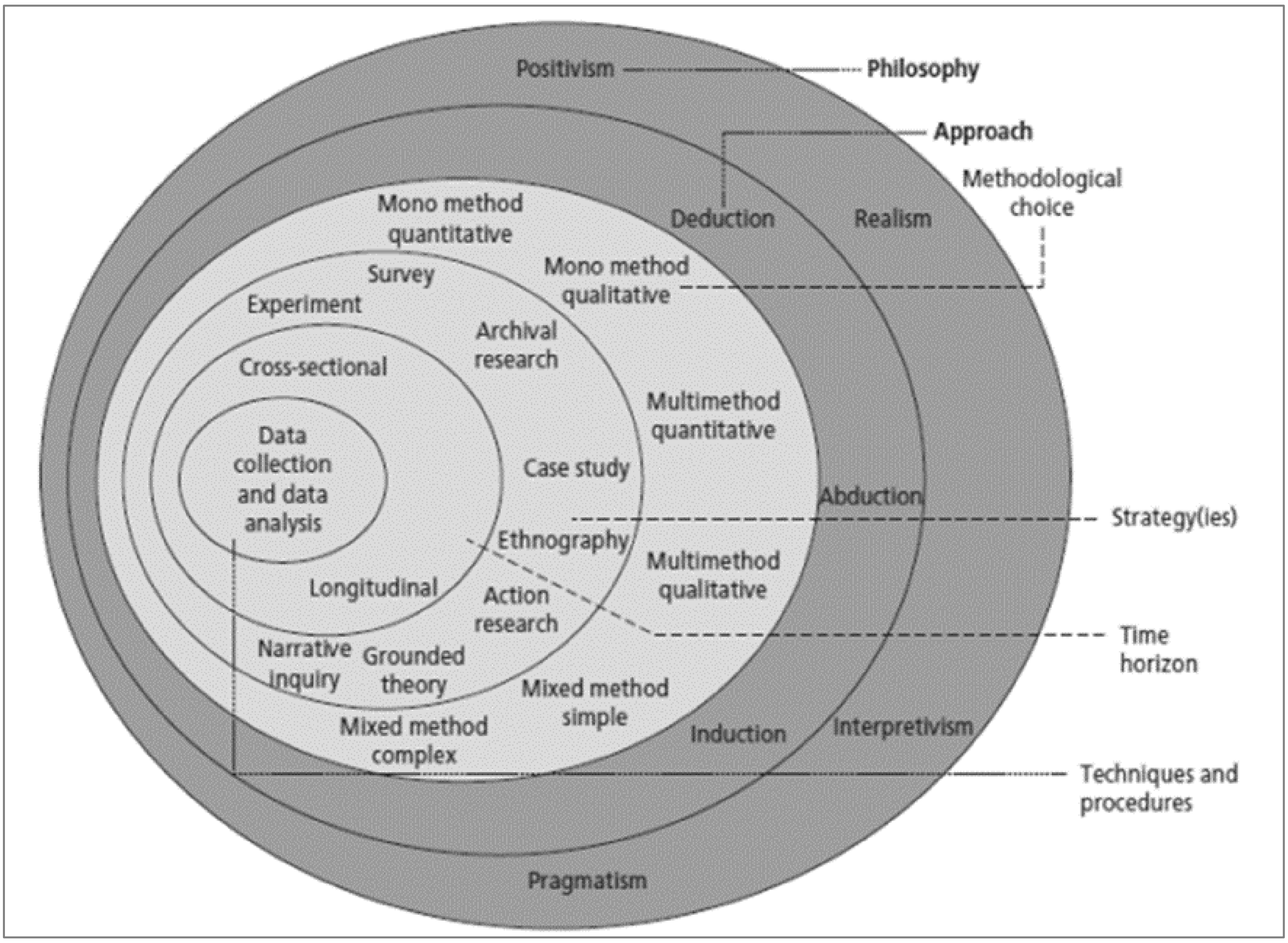

Figure 1: Research Onion (Dudovskiy 2019)

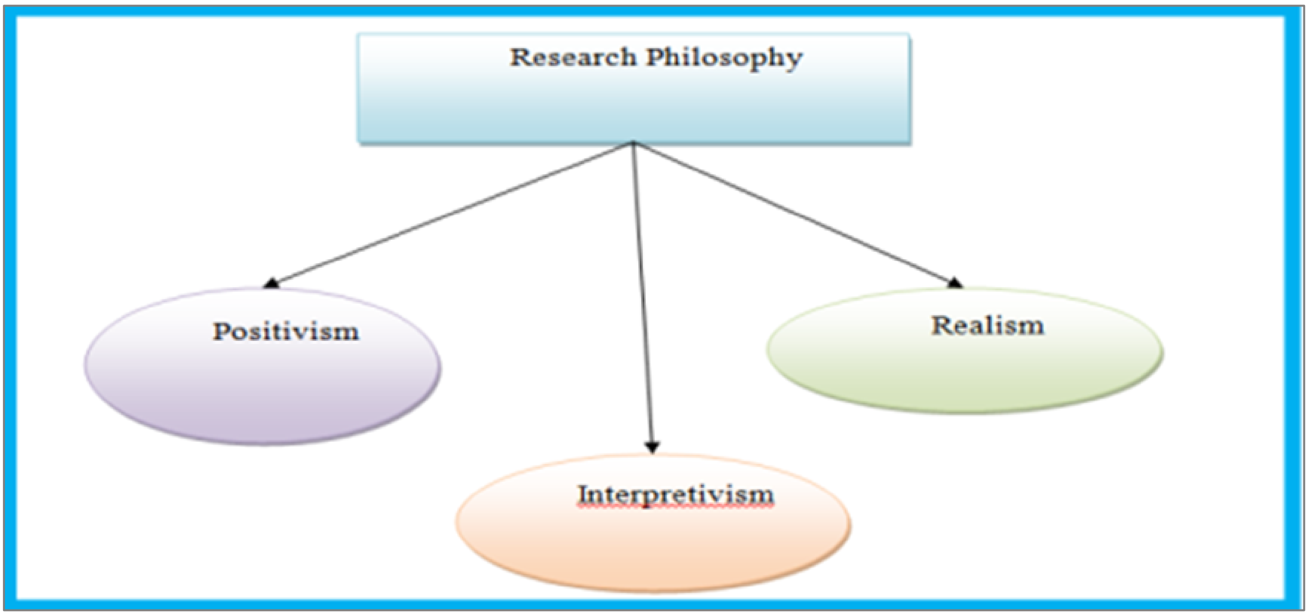

Figure 2: Research Philosophy

Table 1: Philosophical Views of Positivism and Interpretivism Assumptions

Philosophical Assumptions	Positivism	Interpretivism
Ontology	Social reality is the objective of the researcher	Social reality is subjective to the researcher.
Axiology	The researcher maintains an objective posture. The findings are valuable and unbiased.	The researcher maintains a subjective posture. The findings are prejudiced and not that valuable.
Epistemology	Objective evidence supplies the knowledge.	Subjective evidence arises from participants.
Methods of Assumptions	Larger Samples, Quantitative Analysis, Deductive Research Approach	Smaller Samples, Qualitative Analysis, Inductive Research Approach

Research Approach

The research approach aims to provide a researcher with a platform to guide selecting the most appropriate research methods and planning and defining data collection and analysis procedures based on the study objectives (Saunders et al., 2016). The research approach is inductive and deductive, as shown in Figure 2 above.

Research Strategy

The research strategy adopted for this research is the survey strategy, which satisfies the research objectives by allowing the researcher to examine the quantitative and qualitative data using inferential statistics and descriptions (Saunders et al., 2016). The questionnaire is the survey strategy to be employed, as it is extensively used in collecting standardised information from a large population in a very accommodating way of establishing comparisons (Maiia Marienko et al., 2020).

A questionnaire was designed and delivered to learners to gather information or data about their learning preferences. Moreover, the questionnaire is based on the VARK learning style, which comprises questions about learners' preferences in verbal, aural, read/write, and kinesthetic learning modes. The questionnaire is based on the research technique (deductive), philosophy, and methodological way of acquiring data.

Data Collection Techniques

Data collection is a significant and critical component of research outcomes, as it supports the research's claim with strong evidence to make the theoretical model more applicable (Xian & Meng-Lewis, 2018). Data collection approaches are classified into primary and secondary tactics used to gain data for this research.

Primary Data

Primary data is a collection of original data that has yet to be analysed, reviewed, or summarised by other researchers' work (Zikmund et al., 2010). Researchers gather a range of data according to their needs (Xian & Meng-Lewis, 2018). The main techniques by which primary data can be obtained include focus groups, interviews, and questionnaires (Xian & Meng-Lewis, 2018). The questionnaire was used in this study to collect primary data.

Questionnaire

According to Rishard et al. (2022), questionnaires are the most effective strategy, accessible to respondents, and cost-efficient compared to interviews. The Bristol Online Survey (BOS)/JISC Online Survey is used to administer the questionnaire for this survey.

The questionnaire was designed based on the VARK learning style questionnaire and the literature review (Xian & Meng-Lewis, 2018). The VARK learning approach is applied in this study, as indicated by Saunders et al. (2015), where the quality of the research data depends on the valid questions used by the researchers.

Secondary Data

These are the data gathered by prior researchers for various purposes (Xian & Meng-Lewis, 2018). This means that the secondary data can be summarised, published, or re-analysed based on the objectives of other researchers. For this project, secondary data is used to examine:

- Adaptability in e-learning systems
- Using open-source software to create an adaptable system framework
- Benefits of using e-learning technologies for adaptation
- Theories of learning, the learning model, and the adaptation model process
- Learners' or students' learning style
- How adaptable systems will assist in applying VARK for learning reasons

RESULTS

Research Presentation and Analysis

Data Presentation and Analysis

Data analysis is the act or process of gathering, investigating, analysing, and comparing the obtained data (Saunders et al., 2016). Qualitative and quantitative data analysis were used in this study, with the qualitative data shown descriptively and the quantitative data presented thematically. As a result, the statistical mechanism (BOS-Jisc Online Survey) was used to apply the research VARK questionnaire, which contains 101 respondents. In this research, the responses from the users are used for quantitative data analysis of the VARK learning style in adaptable and personalised system design using open-source apps.

Learning Profile Responses

The respondent's e-learning profile is the first phase of the questionnaire, which focuses on finding the features of the respondent's preferences during learning. This phase analysis reveals how learners wish to study, hours spent on computers, preferred methods of acquiring learning materials to know whether students previously utilised e-learning, and the learners' requirement to construct the learning support system. The following are the questionnaire data presentations and analyses based on the questions in the respondents' learning profiles.

Figure 3 below indicates that 38 (37.6%) of the respondents always choose to use computer displays to study, 23 (22.8%) prefer computer monitors, and 35 (34.7%) and 5 (5%) are neutral and do not prefer computer monitors to study, respectively. Generally, most learners choose computer monitors to learn.

Figure 4 below shows that 20 (19.8%) of the respondents spent less than two hours on a computer, 36 (35.6%) spent three to four hours on a computer, 18 (17.8%) spent four to six hours on a computer, and 27 (26.7%) spent more than six hours on a computer. The majority of the learners spent three to four hours on a computer.

Figure 5 below shows that 28 (27.7%) of the respondents prefer the electronic way, 2 (2%) prefer the traditional technique, and 71 (70.3%) prefer both the conventional and electronic means of accessing learning materials. Most learners enjoy both traditional and technological means of accessing learning materials.

Figure 6 below shows that 23 (22.8%) of the respondents once used the e-learning system, and 53 (51.5%) commonly use the e-learning system in their day-to-day activities. It also reveals that 14 (13.9) and 12 (11.9) always utilise e-learning, and some have yet to use e-learning. Based on the survey responses, learners frequently use the e-learning system.

Figure 7 below reveals that 40 (39.6) of the respondents strongly agreed with the need for a learning support system, 46 (45.5) agreed to the essential requirement for a learning support system, and 12 (11%) and 3 (3%) were neutral and disagreed with the demand for a learning support system. The majority of respondents agreed that a learning support system was necessary to allow users to learn better.

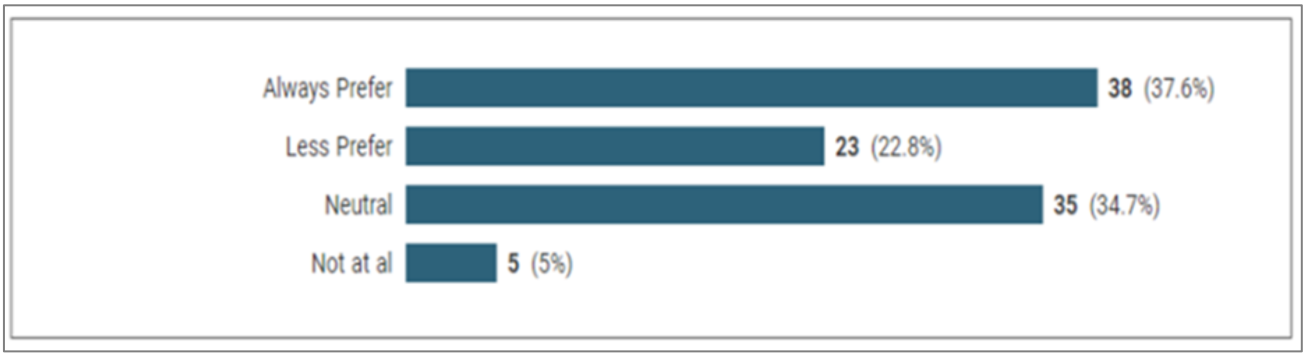

Figure 3: Question 1 - Respondents' Learning Profile

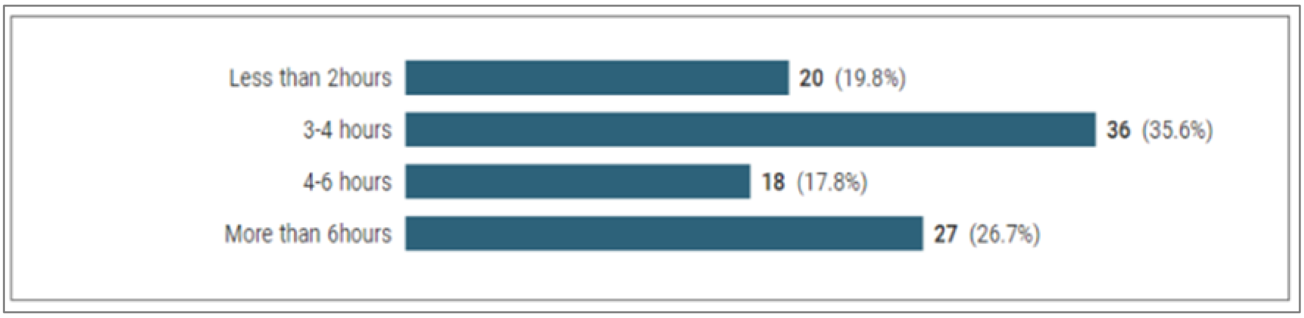

Figure 4: Question 2 - Respondents' Learning Profile

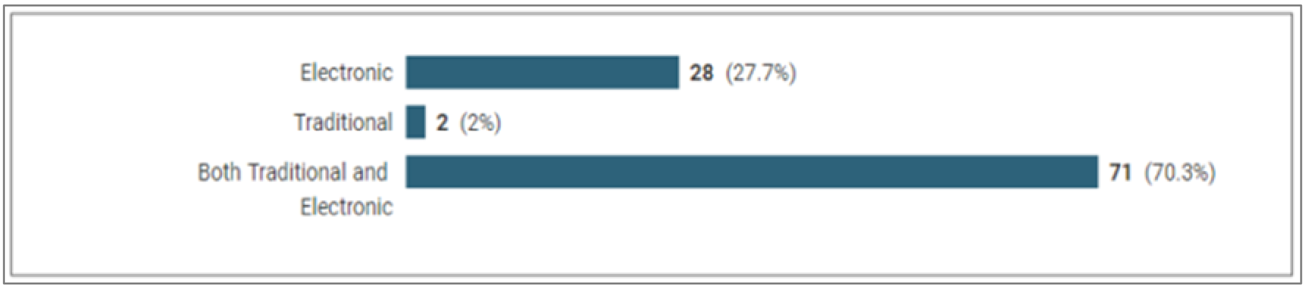

Figure 5: Question 3 - Respondents' Learning Profile

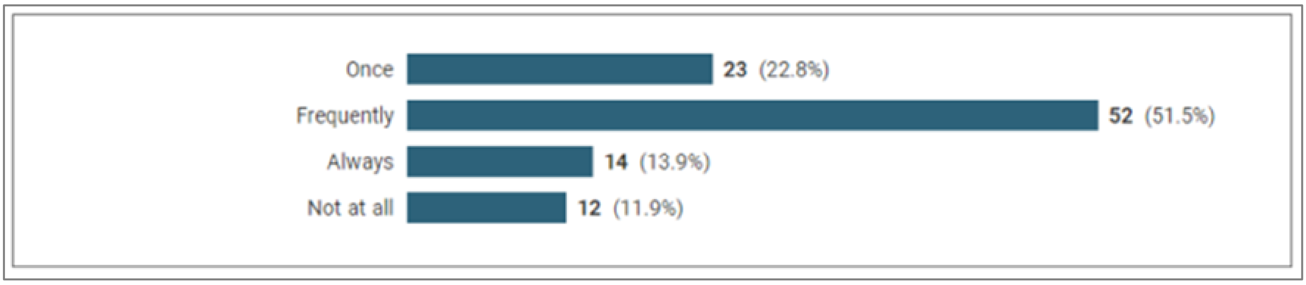

Figure 6: Question 4 - Respondents' Learning Profile

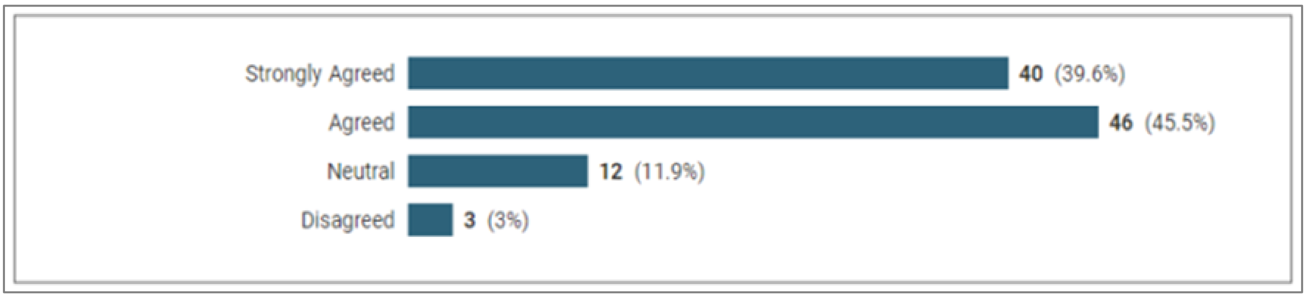

Figure 7: Question 5 - Respondents' Learning Profile

VARK Learning Style Responses

The VARK learning style responses reveal the most consistent findings about varied learning preferences (Gligorea et al., 2023). VARK is essential because learners realise, they are instinctively fit to practice. Learning preferences differ from strengths (Acuna et al., 2021). The cumulative scores for each VARK question reveal how the respondents prefer to learn. For improved understanding, learners with the multi-dimensional model set of the VARK learning style need to analyse facts in different modalities. The following questionnaire responses are based on the VARK questionnaire used in this research to examine learners' preferences in e-learning.

DISCUSSION AND EVALUATION OF THE VARK QUESTIONNAIRE

Soler Costa et al. (2021) research various widely employed learning styles and the ways they are employed in adaptive e-learning. Suitable learning styles were analysed using the Taylor et al. (2021) criteria to establish the proper learning approach for the e-learning domain. Evaluation criteria for flexible learning styles were defined in terms of descriptiveness, measurability, and time effectiveness (Taylor et al., 2021). Based on the preceding criteria, the most relevant learning methods were supplied to the learner in this study to enhance personalisation and flexibility.

Measurability: In order to evaluate if a personalised and flexible learning environment is best suited to a student's requirements, it is vital to assess whether the learning style model is measurable (Taylor et al., 2021). There is an adequate and topical questionnaire for the type of learning employed and assessed in this study.

Time Effectiveness: The length of time it would take the student to complete the questionnaire and how well the questions connected to the intended personalization were used to assess the learning styles. Utilizing the most time-efficient method produces high results for this class, whereas using the least time-efficient technique yields poor results (Acuna et al., 2021). The learning style evaluation was determined by the learner's perceived requirement to complete the survey, and the relevance of the questions to the desired degree of customisation were the factors influencing the learning style assessment.

Descriptiveness: In this part, we'll review the system's learner categories and the technique for modifying a student's unique learning category. The Felder-Silverman tools identify individuals depending on their preferred learning style, which might be sequential or global, sensory or intuitive, active or introspective, or visual or verbal.

Validity

This study assessed the VARK learning style assessment's dimensionality. The VARK evaluates four perceptual preferences: visual (V), aural (A), read/write (R), and kinesthetic (K). VARK questions may be referred to as testlets because respondents can pick a large number of things within a single question. The correlations between items within testlets are a form of technique effect. To evaluate the VARK's dimensionality, four multitrait-multimethod confirmatory factor analysis models were investigated. For the VARK scores, the correlated trait-correlated method model showed the greatest match. The calculated reliability coefficients were satisfactory. The research revealed preliminary evidence for the validity of the VARK scores. Potential difficulties with item wording and the scale's scoring mechanism were identified, and concerns about using the VARK in research were addressed.

Reliability

This research also reveals that Cronbach's alpha underestimates the dependability of VARK scores because it presupposes that all items are parallel measurements of the construct, which is not the case with VARK. As a result, they computed dependability using confirmatory factor analysis. The VARK subscale scores showed reliability estimates of .85, .82, .84, and .77, respectively, which is regarded as satisfactory considering that the VARK is not used for high-stakes choices.

Table 2: Evaluation of the Vark Questionnaire

	Learning Style Preference Responses by %			
Questions	**V**	**A**	**R**	**K**
Q1	25.7%	49.5%	7.9%	16.8%
Q2	29.7%	18.8%	9.9%	41.6%
Q3	30.7%	10.9%	16.8%	41.6%
Q4	39.6%	11.9%	18.8%	29.7%
Q5	11.9%	51.5%	16.8%	19.8%
Q6	5%	73.3%	9.9%	11.9%
Q7	18.8%	9.9%	9.9%	61.4%
Q8	14.9%	29.7%	19.8%	35.6%
Q9	15.8%	47.5%	29.7%	6.9%
Q10	10.9%	34.7%	31.7%	22.8%
Q11	38.6%	26.7%	22.8%	11.9%
Q12	14.9%	28.7%	28.7%	27.7%
Q13	60.4%	27.7%	7.9%	4%
Q14	16.8%	13.9%	26.7%	42.6%
Q15	53.5%	6.9%	16.8%	22.8%
Q16	16.8%	26.7%	34.7%	21.8%
Sum of Percentage/Number of Questions= Overall Style%	404 / 16 = 25.25%	468.3 / 16 = 29.26%	308.8 / 16 = 19.25%	418.9 / 16 = 26.125%
Total	25.25% + 29.26% + 19.25% + 26.125% = 99.885 ~ 100%			

CONCLUSION

In conclusion, this research has focused on developing an adjustable and customisable e-learning system using open-source software, informed by theories of learning and adaptability in educational technology. The study explored various approaches and methodologies to design a system that caters to learners' diverse preferences and needs, particularly through utilizing the VARK model for assessing learning styles—visual, auditory, read/write, and kinesthetic. The findings underscored the importance of adaptability in learning systems, highlighting the effectiveness of tailoring educational content and delivery methods based on learners' feedback and preferences. By integrating open-source tools and methodologies, the developed system not only enhances accessibility to educational resources but also promotes personalised learning experiences across different domains. Future research in this area could build upon these foundations in several key directions:

Enhanced Personalization Techniques: Further refine and expand the personalization capabilities of e-learning systems, integrating advanced algorithms and AI to dynamically adapt content delivery based on real-time learner interactions and performance data.

Integration of Emerging Technologies: Investigate the integration of emerging technologies such as virtual reality (VR), augmented reality (AR), and artificial intelligence (AI) in e-learning systems to create immersive and interactive learning environments tailored to individual learning styles.

Longitudinal Studies and Impact Assessment: Conduct longitudinal studies to assess the long-term impact and effectiveness of personalised e-learning systems on learning outcomes, retention rates, and learner satisfaction.

Ethical and Legal Considerations: Further explore the ethical and legal implications of personalised e-learning systems, particularly concerning data privacy, accessibility, and equitable access to educational opportunities.

Cross-cultural Adaptation: Investigate how personalised e-learning systems can be adapted and culturally customised to meet the needs of diverse global learners, considering cultural differences in learning preferences and educational practices.

By addressing these avenues for future research, the field can continue to advance towards more effective, inclusive, and ethical e-learning solutions that empower learners worldwide.

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Conflict of interests

The authors declare no conflict of interest.

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