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# Optimizing cognitive load and learning adaptability with adaptive microlearning for in-service personnel

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**Adaptive microlearning has emerged as a crucial approach for enhancing the working skills of in-service personnel. This study introduces the design and development of an innovative adaptive microlearning (AML) system and investigates its effectiveness compared to a conventional microlearning (CML) system. The main distinguishing feature of an AML system from a CML system is its adaptive features that tailor the learning experience to individual needs, including personalized content delivery, real-time feedback, and adaptive learning paths. A quasi-experimental study involving 111 in-service personnel ($N_{AML} = 56$, $N_{CML} = 55$) was conducted. ANCOVA results confirmed that the AML system significantly reduced unnecessary cognitive load due to inappropriate instructional design (mean difference of -20.02, $p < 0.05$) and significantly improved learning adaptability (mean difference of 40.72, $p < 0.05$). These findings highlight the potential of adaptive microlearning systems to overcome barriers to effective learning, thereby supporting lifelong learning and professional development in various working contexts.**

Education has long been considered essential for improving human resources in societies and companies worldwide. Among the 17 Sustainable Development Goals (SDGs), SDG 4, which aims to ensure "inclusive and equitable quality education and promote lifelong learning opportunities for all," is vital for achieving other goals[1]. Additionally, both SDG 8 and SDG 9 emphasize improving in-service personnel skills to provide decent work, foster industrial innovation, and support lifelong learning.

Education for in-service personnel is as crucial as general education for overall workforce development. In this study, the term "in-service personnel" refers to individuals formally employed by a company and actively engaged in their professional duties. These individuals are typically adults who have completed their formal education and work in various capacities within their organizations[2]. A report by China's Ministry of Education showed that the in-service personnel education market in China reached 650.5 billion yuan in 2020[3]. The market share is predicted to increase by 12% annually from 2023 to 2025, reaching approximately 900 billion yuan by 2025[4]. Many in-service personnel show a strong interest in enrolling in courses to acquire and update their knowledge and skills, highlighting the demand for continuous education. A LinkedIn study revealed that 94% of employees would stay at a company longer if it invested in their career development[5]. Additionally, 27% cited a lack of learning opportunities as the primary reason for leaving their jobs[6]. This indicates that in-service personnel are passionate about learning, particularly to improve their work-related skills, which underscores the need for effective learning solutions.

However, learning requires regular commitment, and work presents barriers to learning[7]. Due to conflicts between work and learning, in-service personnel seek a learning approach that allows them to use their limited time effectively, making microlearning an attractive option. Microlearning has gained prominence by allowing in-service personnel to acquire knowledge and skills without losing work time[8]. Despite its growth, conventional microlearning systems have significant limitations. Research shows that only 15% of in-service personnel fully utilize the knowledge acquired, and 80% is forgotten after one month[12]. The fragmented availability of learning time often leads to superficial understanding[9,10]. Mere course completion certification can create a false sense of accomplishment without substantial learning[11]. Consequently, the learning outcomes of conventional microlearning systems can be limited and unreliable, highlighting the need for more effective approaches.

To address this gap, this study explores the development and implementation of an adaptive microlearning (AML) system. Unlike conventional microlearning systems, the AML system provides personalized and flexible

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learning experiences by leveraging databases and algorithms to adapt to learners' existing knowledge levels. This approach addresses the limitations of conventional microlearning systems and significantly contributes to the field by extending theoretical and empirical understanding. The significance of this study lies in its potential to enhance learning outcomes and adaptability, supporting lifelong learning, and professional development for in-service personnel.

Additionally, the psychological resources of in-service personnel, particularly cognitive load and learning adaptability, are increasingly considered in conventional microlearning systems[13]. Cognitive load refers to the total mental resources required to perform a task[14]. Cognitive load during microlearning can vary based on content complexity and instructional design[15,16]. Conventional learning systems frequently present overwhelming, disorganized, and incomplete information[17]. Despite modularizing content, the diversity and complexity of large information volumes exacerbate cognitive load[18,19]. A survey found that 22.5% of respondents identified information overload as a common source of stress[20,21]. The vast amount of information in conventional microlearning systems exceeds learners' ability to absorb and digest, making them feel they are regressing[22]. A recent survey found that 65% of in-service personnel reported that information overload has negatively impacted their work performance due to the overwhelming amount of fragmented information[23].

The AML system addresses cognitive overload by using algorithms to assess a learner's existing knowledge level and extract suitable learning content through a database mechanism. By providing tailored learning experiences, the AML system ensures learners receive information appropriate for their current understanding, preventing them from being overwhelmed with content that is either too basic or too advanced. This personalized approach helps manage cognitive load and enhances learning adaptability[24].

Similarly, lack of adaptability to diverse learning environments is another critical challenge for conventional microlearning systems[25]. Learning adaptability refers to learners' ability to actively adjust their learning behavior and strategies in response to the learning environment[26]. Statistics show that many learners, including in-service learners, exhibit low learning adaptability, with 57.4% feeling anxious and 28.4% feeling lonely in the online learning environment[27]. Learning adaptability improves learning efficiency, self-directed learning, and independent learning ability[28,29].

In summary, conventional microlearning systems are continuously updated and strengthened. However, there remains a need for more personalized and effective learning solutions. One approach is the development of "adaptive microlearning," which refers to a learning approach adaptable to in-service personnel. It leverages databases and algorithms to provide a personalized and flexible learning experience tailored to in-service personnel. By addressing the learning challenges faced by in-service personnel, adaptive microlearning systems can contribute to lifelong learning as stated in SDG 4. This article aims to design and develop an adaptive microlearning system specifically for in-service personnel and evaluate its effectiveness based on cognitive load and learning adaptability.

## Theoretical background

### Theoretical framework

Educational theories and instructional technology models collectively form the theoretical framework of the adaptive microlearning (AML) system, as illustrated in Fig. 1. These include Constructivism, Connectivism, the Three-Parameter Logistic (3-PL) model, the Adaptive Educational Hypermedia Systems (AEHS) model, and Cognitive Load Theory (CLT). Each theory offers a unique perspective on learning and instruction, contributing to the development of a robust and effective AML system.

As shown in Fig. 1, constructivism and connectivism provide the foundational principles of instructional delivery from a pedagogical perspective. The 3-PL model offers an algorithmic mechanism for assessing learners' existing knowledge levels and adapting content to individual needs. It works in conjunction with the AEHS model, which links various database elements, to provide a structural framework supporting personalized and adaptive learning pathways. With the aid of CLT, the AML system not only focuses on personalized learning but also ensures that learners' cognitive resources are optimally managed, preventing cognitive overload and enhancing learning efficiency. CLT plays a critical role in regulating the mental effort required from learners, especially in complex or new learning environments, thereby aligning well with adaptive learning principles. Supported by CLT, the AML system ensures that learning materials are presented in a manner that optimizes cognitive resources and prevents overload, further enhancing learning adaptability.

### Constructivism

Constructivism asserts that learning involves actively constructing knowledge rather than merely acquiring it[30]. Constructivism posits that learners are active constructors of knowledge, not passive receivers. Additionally, constructivism advocates for learners to be active participants in the learning environment[31]. The learning environment should be learner-centered, allowing learners to independently control their learning process. Constructivism emphasizes that learners construct their own understanding and knowledge of the world through experiences and reflection[32]. In adaptive microlearning, learners are encouraged to build on their existing knowledge while managing cognitive load. Specifically, adaptive microlearning enables learners to interact with content tailored to their current understanding levels, promoting active learning and critical thinking without overwhelming them with excessive cognitive demands.

According to constructivism, learning should be autonomous and not dictated by "one-size-fits-all" requirements. Therefore, adaptive microlearning, guided by constructivism, shifts from conventional "diffuse irrigation" to "precise drip irrigation," supporting more individualized learning. It supports customized learning, offers different learning paths, and guides learners to complete their learning through exploration and experience[33]. In this process, CLT complements constructivism by ensuring that the learning paths do not impose unnecessary extraneous cognitive load, thereby fostering meaningful engagement and deeper reflection.

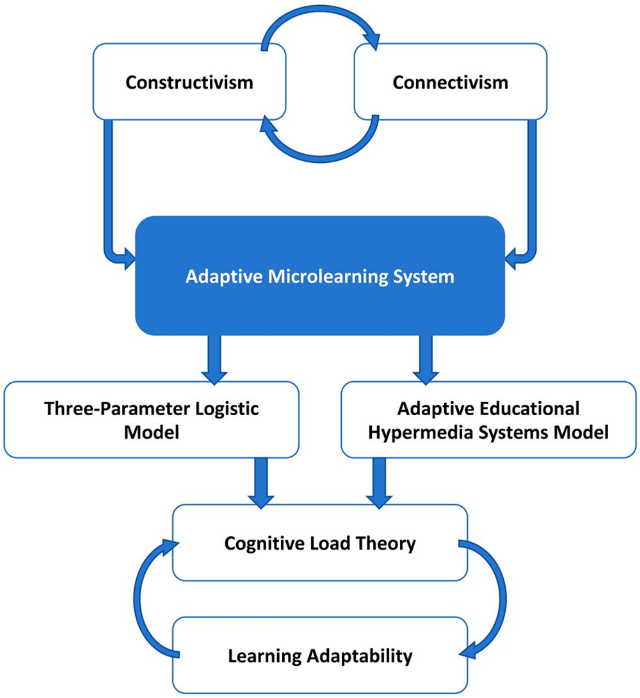


**Figure 1**. Theoretical framework.

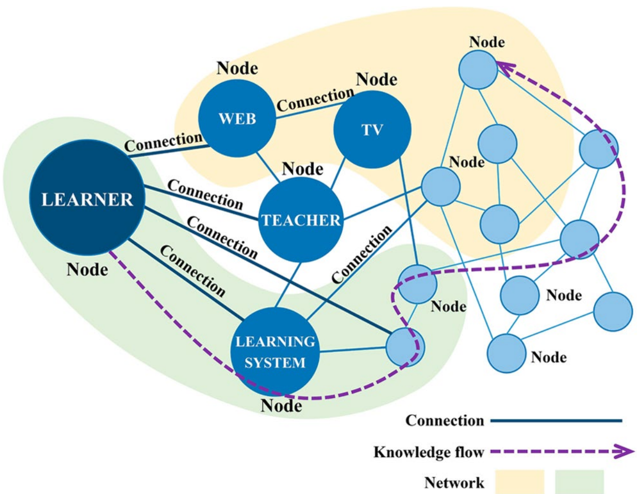


**Figure 2**. Schematic diagram of the learning process of connectivism theory.

*Connectivism*

Connectivism theory posits that learning involves building a connecting knowledge network[34], signifying distributed and expandable knowledge, thus explaining how learning occurs in the digital age. The key elements of connectivism include "nodes," "connections," "networks," and "knowledge flow,"[35,36] as shown in Fig. 2. Connectivism asserts that learning is a dynamic process involving the connection of scattered knowledge nodes to form paths, ultimately creating a knowledge network[37].

According to connectivism, learning occurs through the formation and navigation of networks where knowledge is distributed across connections and learners actively engage in creating and traversing these networks[36]. In conventional microlearning, learning content consists of small, dispersed, and interrelated modules. Adaptive microlearning aims to integrate these loose knowledge units into a personalized learning network for each learner[38]. Learners form meaningful knowledge networks by linking knowledge units scattered across different nodes, facilitating a holistic and integrated learning experience. In the context of cognitive load theory, connectivism can be further enhanced by managing learners' cognitive load as they connect new knowledge nodes to their existing networks. The AML system developed in this study associates and reorganizes learning content into fragmented knowledge units, aligning perfectly with connectivism theory. As learners attempt to integrate new knowledge within the adaptive microlearning system, CLT ensures that expanding these networks does not exceed the learner's cognitive capacity. Using databases and algorithms, learners are recommended knowledge units aligned with their existing knowledge level, helping them clarify their next learning tasks. This ensures a smoother knowledge acquisition process while minimizing cognitive overload, thereby reinforcing both learning adaptability and long-term knowledge retention.

## Cognitive load theory

Cognitivism focuses on the inner mental activities of learners and argues that learning is an information processing process. Cognitive load is the total amount of cognitive resources required by individuals during information processing[14]. Cognitive Load Theory (CLT) serves as a critical component of the AML system. While constructivism and connectivism emphasize active learning and network building, CLT focuses on managing the mental effort involved in these processes. CLT distinguishes among three types of cognitive load: intrinsic, extraneous, and germane.

Intrinsic cognitive load is inherent to the learning content and is related to its complexity and the learner's prior knowledge[39]. It is determined by the interaction between the learning content and the learner's existing knowledge. When the learning content is overly complex and difficult, exceeding the learner's existing knowledge capacity, intrinsic cognitive load increases[40]. In the AML system, intrinsic load is managed by adjusting the content complexity to match the learner's current knowledge level, ensuring that learners are not overwhelmed by overly complex tasks.

Extraneous cognitive load is the unnecessary cognitive load caused by improper instructional design. It primarily arises from the organization and presentation of learning content[24]. These redundant designs consume extra cognitive resources, forcing learners to perform activities unrelated to learning, thereby increasing extraneous cognitive load[41]. Extraneous cognitive load can be reduced by improving how learning content is presented. In adaptive systems like AML, this type of load is minimized by presenting content in a clear, organized manner, thus allowing learners to focus on the core learning material. Reducing extraneous load is crucial to freeing up mental resources for actual learning.

Germane cognitive load refers to the cognitive resources a learner invests in learning, influenced by the learner's motivation and effort[42]. This type of cognitive load is positive. Increasing germane cognitive load effectively promotes learning and can enhance learners' efficiency. By tailoring content complexity and presentation, the AML system optimizes germane load to help learners focus on constructing and internalizing new knowledge.

Cognitive load theory assumes that intrinsic cognitive load is fixed, while extraneous and germane cognitive loads can be managed through better instructional design[43]. Effective instructional design should minimize extraneous cognitive load, manage intrinsic cognitive load, and optimize germane cognitive load. The AML system aims to balance these types of cognitive load by tailoring content complexity and presentation to individual learner needs, ensuring that learners engage meaningfully with the content without feeling overwhelmed.

While constructivism and connectivism guide the overall learning philosophy, CLT serves as the backbone for managing the delivery of learning in practice. Studies show that high levels of extraneous cognitive load can impede learning by overwhelming cognitive resources, while appropriate levels of intrinsic and germane cognitive load can enhance understanding and retention[14]. Given its significant impact on learning outcomes, cognitive load was selected as a variable to evaluate the effectiveness of the AML system. The adaptive nature of the AML system continuously adjusts the learning content to suit learners' cognitive capacity, preventing overload and facilitating deeper learning and better retention.

## Learning adaptability

Learning adaptability refers to a learner's ability to actively self-adjust and respond to changes in the environment to achieve better learning outcomes[26]. In complex learning environments, learners must adjust their mentality and behavior to adapt to changes and respond positively to feedback to persist in learning[44]. Learning adaptability is essential for achieving academic performance and personal development[45], especially in online microlearning environments filled with novelty, variability, and uncertainty.

Learning adaptability can be summarized with two key concepts: "balance" and "flexibility." "Balance" refers to the ability to self-adjust when faced with sudden changes, while "flexibility" refers to the capacity to respond positively to these changes[46]. Learning adaptability allows learners to balance their interactions with the learning environment[47], thereby maintaining positive physiological and psychological states. This balance is crucial for enhancing learners' online learning experiences, helping them remain calm and focused amid the dynamic nature of online microlearning.

The AML system is designed to address the unique challenges faced by in-service personnel, particularly the conflict between work and learning and the uncertainty regarding time and place of learning. By incorporating adaptability into the learning design, these systems better support learners in managing their educational pursuits alongside professional responsibilities. The AML system enhances learning adaptability by offering adaptive learning paths and content recommendations that evolve with the learner's progress. This adaptability helps learners better manage their learning processes, making adjustments based on real-time feedback and system suggestions, which is essential for effective lifelong learning and professional development. Additionally, learning adaptability, as a measurement variable, effectively observes and assesses learners' psychological characteristics and abilities to cope with complex and fragmented learning environments.

### Three-parameter logistic model

Item Response Theory (IRT) asserts that a learner's existing knowledge is an invisible psychological trait reflected through test items[48]. IRT is based on two principles. First, in actual tests, learners' test scores are closely related to their potential traits[49], which can be measured in an adaptive microlearning system through quiz sessions. The potential traits in the quiz reflect the learner's existing knowledge level, measured as an unknown value "θ." Additionally, learners' existing knowledge levels can be predicted and modeled based on their quiz responses.

The Three-Parameter Logistic (3-PL) model proposed by Birnbaum is a dichotomous model considering only two possible responses to an item: correct or incorrect. The algorithmic formulation of the 3-PL model is as follows:

$$P\left(u_i = 1/\theta\ \right) = c_i + \frac{(1-c_i)}{1+e^{-1.702a_i(\theta\ - b_i)}}$$

"$P(u_i = 1/\theta)$" indicates the probability that a learner with an existing knowledge level θ can answer item i correctly. "$P(u_i = 0/\theta) = 1 - P(u_i = 1/\theta)$" indicates the probability that a learner with an existing knowledge level θ answers item i incorrectly. "$u_i$" indicates the learner's response to item i. "$u_i = 1$" indicates the learner answered item i correctly. "$u_i = 0$" indicates that learner answered item i incorrectly. "θ" indicates the learner's existing knowledge level, which can be measured by testing. The theoretical value range of the existing knowledge level θ is [-∞, +∞]. However, in practice, the generally considered range is [-4.0, +4.0] or [-3.0, +3.0][50].

"$a_i$" represents discrimination, referring to the test item's ability to distinguish learners' potential characteristics. The higher the item discrimination value, the better it distinguishes learners with different existing knowledge levels.

"$b_i$" indicates difficulty, referring to the test item's difficulty level. The more difficult the item, the less likely the learner is to get it right. Conversely, the less difficult the item, the more likely the learner is to answer it correctly. The value range of the difficulty parameter is the same as the knowledge level range.

"$c_i$" represents the guessing coefficient, referring to the probability that a learner can correctly answer the item through random selection without any knowledge of the item.

The 3-PL model provides a scientifically defensible algorithm for assessing learners' existing knowledge levels. The AML system assumes that parameters (including $a_i$, $b_i$, and $c_i$) are tested and determined in advance and only needs to consider how to select items and calculate the existing knowledge levels of learners. The AML system selects quiz questions for specific knowledge and calculates the learner's existing knowledge level. The application of the 3-PL model helps select appropriate quiz items matching the learner's proficiency, thereby minimizing unnecessary cognitive load and enhancing learning adaptability. By accurately measuring the learner's knowledge state, the AML system can provide targeted content that supports effective learning and reduces the chances of overwhelming the learner with content that is either too difficult or too easy.

### Model of adaptive educational hypermedia systems

The adaptive educational hypermedia systems (AEHS) model proposed by Brusilovsky consists of five core components: a domain model, a learner model, a pedagogical model, an interface module, and an adaptive engine[51]. The database mechanisms of the adaptive microlearning system in this study use the AEHS model as a reference for system design. The reference model uses established standards and norms to guide system development, accurately defining the roles and responsibilities of each system component[52,53]. Figure 3 illustrates the database architecture of the AML system, which is based on a variant of the AEHS model.

- **Domain Model**

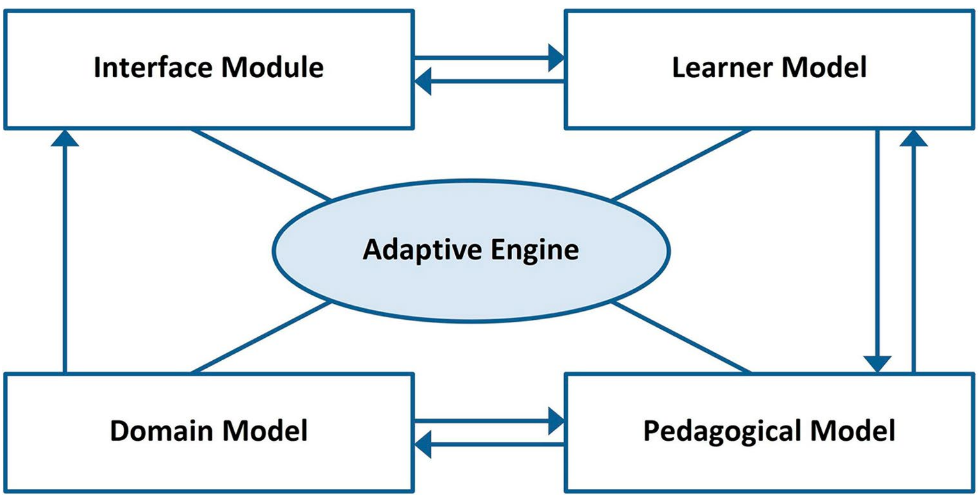


**Figure 3**. Database architecture of the adaptive microlearning system.

The domain model is a database that stores all the learning content in the system[54]. It describes the knowledge nodes involved in the application field and their relationships. The learning content in the domain model is categorized into "courses," "lessons," and "knowledge units." A "knowledge unit" is the smallest component of learning content. Knowledge units are grouped into "lessons," and all lessons together form "courses."

- **Learner Model**

The learner model records the learner's demographic information, interaction data, learning progress and history, and knowledge state and proficiency levels, as shown in Table 1. In the learner model of the AML system in this study, demographic information is static and obtained during the registration, while other information is dynamic and automatically collected by the system during the learning process.

- **Pedagogical Model**

The pedagogical model defines regulations and standards to achieve specific learning goals during the learning process[55,56]. It specifies how to modify and update the learner model and extract learning content from the domain model for different learning sessions based on information recorded in the learner model[57]. The design of the pedagogical model in this adaptive microlearning system is guided by the domain model and the learner model. It makes decisions on updating the learner model, presenting learning content, and providing system feedback[56,58].

- **Interface Module**

The interface module serves as the medium for learners to interact with the learning system[59]. It provides interactive interfaces and presents various sessions and functions based on information from the domain model, learner model, and pedagogical model. Different visual interfaces and presentation content create varied learning experiences for learners[60].

In summary, integrating educational theories and instructional models in the theoretical framework creates a synergistic relationship that enhances the effectiveness of the AML system. Specifically, constructivism and connectivism emphasize the initiative and networked nature of learning, providing guidance on the architecture of the learning environment and the delineation of learning resources. Cognitive load theory is used to manage learners' cognitive resources, ensuring that the learning material is neither too simple nor too complex. This balance is essential for maintaining learner engagement and promoting deep learning. The algorithms in the 3-PL model are implemented in the AML system, allowing it to tailor quiz item difficulty to match the learner's current knowledge level. This adaptability ensures learners are continually challenged at an appropriate level, enhancing both learning effectiveness and learner satisfaction[61]. The AEHS model integrates these elements into a cohesive system, creating a flexible and responsive learning environment. Learning adaptability, a key outcome of this integration, is crucial for learners to navigate and succeed in dynamic and changing environments.

The academic support and persuasiveness of the AML system are strengthened by integrating theories and models from the theoretical framework, ensuring the AML system is robust and flexible. The AML system responds to the diverse needs of learners in dynamic learning environments and assists in-service personnel in developing the skills necessary for career advancement, thereby sustaining effective lifelong learning.

## Adaptive microlearning system

The adaptive microlearning (AML) system is an enhanced version of the conventional microlearning (CML) system. It is designed and developed to enable in-service personnel to learn anytime and anywhere. It enhances the learning effectiveness and user experience of in-service personnel by reducing the cognitive load and increasing learning adaptability.

The AML system is a mobile application with a user interface offering various functions and supporting components for learning. The core of the AML system is the adaptive engine, which connects various functional components in series. These components include the learner model, domain model, pedagogical model, and interface module. The system architecture of the AML system is shown in Fig. 4.

| Information Type | Specific Content |
|---|---|
| Demographic Information | • Age<br>• Gender<br>• Education Qualification<br>• Job Position<br>• Settings and Preferences |
| Interaction Data | • Login and Logout Information<br>• Content Access Records<br>• Quizzes and Assessments Records |
| Learning Progress and History | • Content Completion<br>• Learning Duration and Frequency<br>• Quizzes Frequency and Accuracy |
| Knowledge State and Proficiency Levels | • Existing Knowledge Level |

**Table 1**. Information stored in learner model.

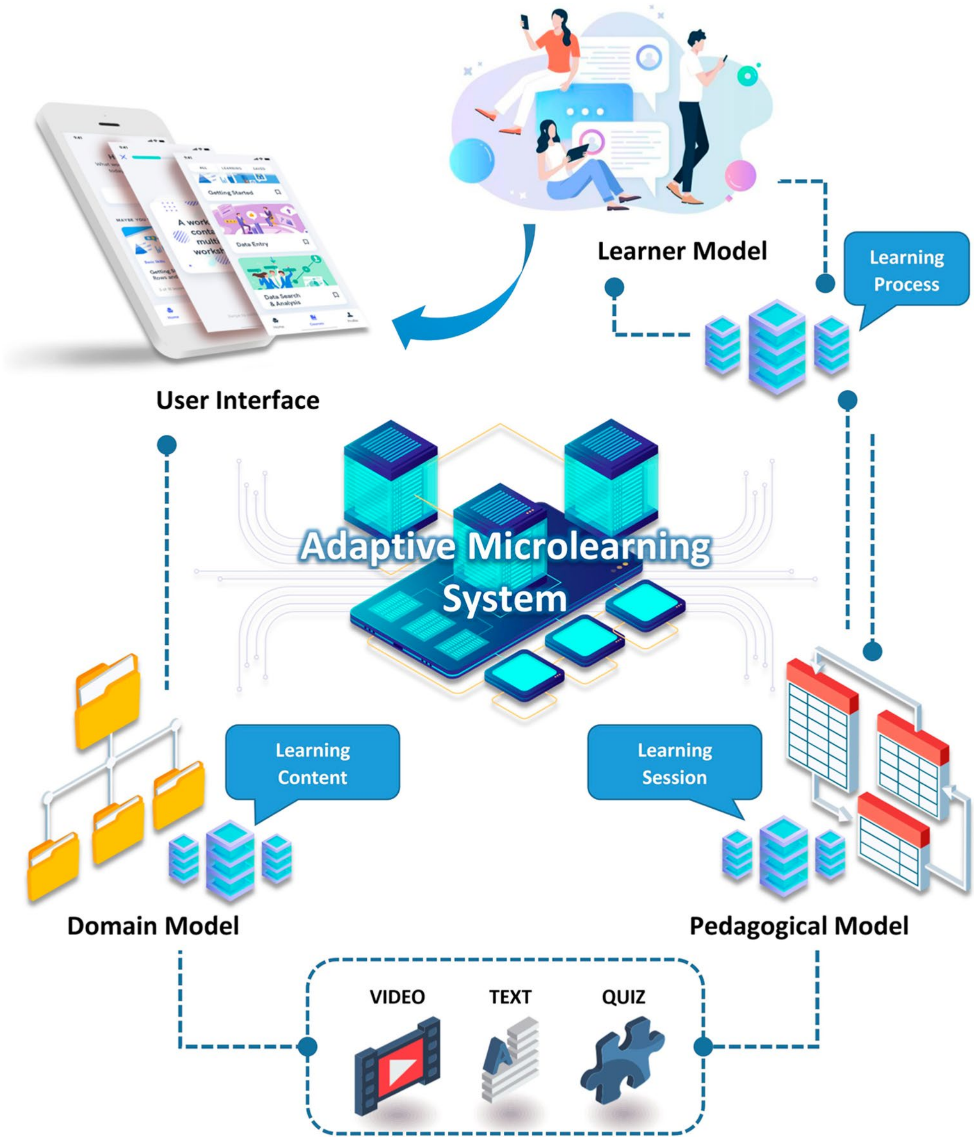


**Figure 4**. The system architecture of the AML system.

The flowchart in Fig. 5 explains the entire process of running the AML system from start to finish, including branches resulting from learners' decisions.

The operation of the AML system starts when the learner logs in. The system automatically runs an "adaptive-driven" session upon login, offering two learning options: the learner decides what to learn, or the system recommends what to learn. If learners choose their content, they can select it directly from the domain model using a search engine mechanism. If unsure, the system automatically recommends suitable content based on the learner's existing knowledge level.

During the learning process, the learner's interaction behavior is continuously recorded in the learner model. Upon completing a learning session, a quiz is unlocked and recommended. The quiz result calculates the learner's existing knowledge level, informing subsequent content recommendations. This iterative process continues until the learner stops learning.

The prototype of the AML system has been outlined, and the differences between the AML and the CML systems are summarized in Table 2.

In contrast to the CML system, the AML system has four main features:

First, the AML system segments the learning content further. Beyond the standard division of courses and lessons, it divides learning content into smaller knowledge units. These units are highly refined and designed for quick browsing. The content length in the AML system is based on survey data and observation. According to the 20th National Reading Survey by the China Network Information Center, most users lose attention after reading more than 50 words or watching videos longer than 50 s[62]. Additionally, in most video applications

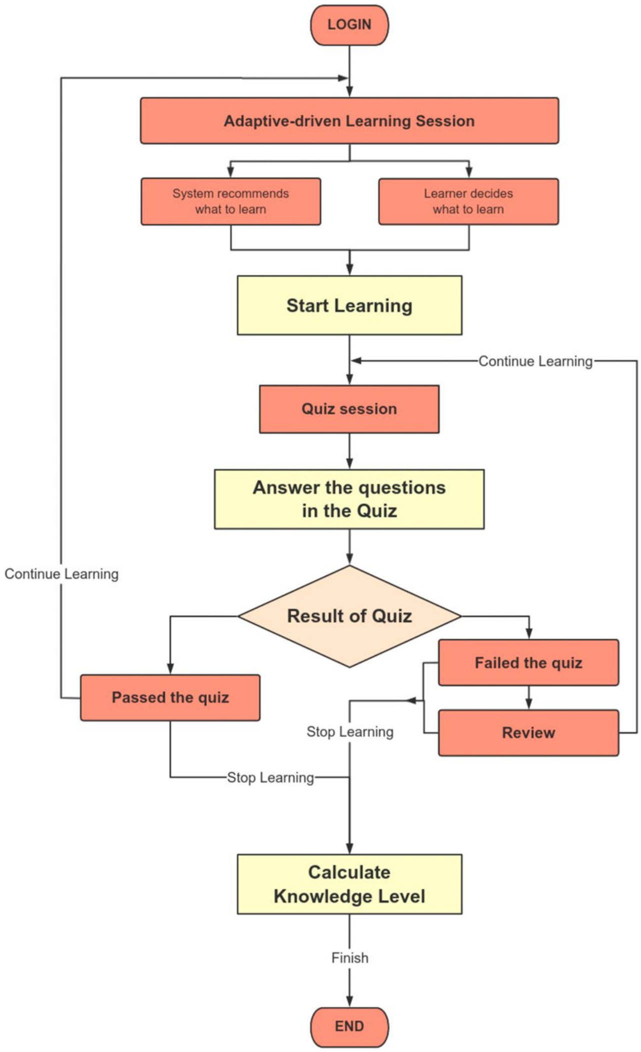


**Figure 5**. The flowchart of the operational sequence in the AML system.

| Aspects of comparison | | AML | CML |
|---|---|---|---|
| Learning content division | Course | YES | YES |
| | Lesson | YES | YES |
| | Knowledge unit | YES | NO |
| Learning display format | Text | YES | YES |
| | Length of Text | < 50 words | 200–500 words |
| | Video | YES | YES |
| | Length of Video | < 45 s | 5–10 min |
| Learning session | Adaptive-driven learning | YES | NO |
| System database | Demographic information | YES | YES |
| | Interaction information | YES | NO |
| | Existing knowledge level | YES | NO |

**Table 2**. Differences between the AML and CML systems.

(e.g., TikTok, YouTube, Likee), short videos under 45 s attract more interest[9]. Therefore, the video and text lengths in the AML system align with market trends.

Second, the AML system's learning content display formats include video and text. Unlike the CML system, the AML system's learning content is designed to be minimal in both formats. For text, in addition to the

traditional “summary text”, a “tip card” format compresses content into a single sentence, catering to learners needing quick knowledge acquisition in limited and fragmented time.
Third, the AML system features an adaptive-driven learning session. Unlike the CML system, which only has system-driven learning session, the adaptive-driven learning session in the AML system enhances the agility and resilience, responds to the diverse learner needs, and increases learning adaptability.
Fourth, the AML system uses three databases: the domain model, learner model, and pedagogical model. The AML system employs a dynamic learner model to record the learner’s interaction data in real time. The existing knowledge level calculated through the pedagogical model informs system recommendations, providing learners with more accurate and suitable content.

The adaptive features of the AML system are highlighted in the comparison with the CML system.

- **Adaptive Content Delivery**

The AML system tracks and records learner performance and progress, dynamically adapting the learning content based on cognitive load theory, including task difficulty and complexity. For example, if a learner excels in a subject, the AML system delivers more advanced and challenging content in subsequent sessions. Conversely, if a learner struggles, the system provides additional exercises or simpler explanations to enhance understanding.

- **Personalized Learning Paths**

The AML system creates personalized learning pathways for each learner by implementing the learner model from the AEHS model. By continuously recording and evaluating performance data, the system adjusts the content sequence and pace of instruction according to learner needs. This personalization ensures learners are neither overwhelmed nor under-challenged.

- **Real-time Feedback and Adaptive Assessment**

The AML system provides real-time feedback on learner interactions during the learning process to help learners understand their achievements and improve their learning strategies. Adaptive assessment is reflected in the quizzes. The algorithmic mechanism provided by the 3-PL model ensures that the assessment accurately reflects the learner’s existing knowledge level, which is used to adjust learning difficulty and content.

- **Interactive and Engaging Content**

The AML system incorporates interactive elements such as searches, navigation, quizzes, and multimedia content to actively engage learners. These elements are customized to different learning styles and preferences, making the learning experience more effective and enjoyable.

During the trial, several modifications and calibrations were made to ensure the effectiveness of the AML system:

- **Initial Calibration**

Before the trial commenced, the AML system underwent an initial calibration phase, testing content and assessments with a small pilot group. Feedback from this group was used to fine-tune the adaptive algorithms, ensuring the AML system responded accurately to different learners’ behaviors and achievement levels.

- **Continuous Adjustments**

The performance of the AML system and learner interactions were monitored throughout the trial. Any issues or anomalies were promptly addressed. For example, if many learners experienced similar difficulties with the same module, the content and difficulty were reviewed and adjusted to better adapt to learners’ requirements.

- **User Feedback Integration**

Feedback from participants was collected throughout the trial through surveys and informal discussions. This feedback was used to make iterative improvements to the AML system, ensuring it consistently aligned with learners’ demands and preferences.

- **Technical Support and Troubleshooting**

A technical support team was on standby to assist participants with any issues encountered while using the AML system. This support included addressing technical glitches, answering user queries, and providing guidance on using the system effectively.

Repeated trials and revisions ensure the AML system is stable and provides a personalized, engaging learning experience through its adaptive features. This has considerable potential for effectively balancing cognitive load and enhancing the learning adaptability of in-service personnel.

## Hypotheses

After presenting the rationale and evidence supporting the advantages of adaptive microlearning (AML) systems, it becomes evident that the AML system can significantly balance cognitive load and improve learning adaptability compared to conventional microlearning (CML) systems. This study aims to empirically test these theoretical expectations. This study initially employed a null hypothesis, assuming no significant differences between the AML and CML systems.

Null Hypothesis (H0): There is no significant difference in cognitive load (CL) or learning adaptability (LA) between in-service personnel using the AML system and those using the CML system.

While the initial null hypothesis provided a foundation for the study, this shift to alternative hypotheses aligns with the exploratory nature of the research, given that the AML system represents a significant update from conventional microlearning approaches. Therefore, the following hypotheses are proposed:

H1: There is a significant difference in cognitive load (CL) between in-service personnel using the AML system and those using the CML system.
H2: There is a significant difference in learning adaptability (LA) between in-service personnel using the AML system and those using the CML system.

Accordingly, the research framework assumes that one independent variable (IV) influences two dependent variables (DVs), as shown in Fig. 6.

## Methods

This study employed a quasi-experimental approach to investigate the effect of an adaptive microlearning system on cognitive load and learning adaptability among in-service personnel. The AML system served as the experimental group, while the conventional microlearning system (CML system), representing typical market-available features, was the control group.

The learning content used in this study was “WPS Office Software Application,” relevant to the work skills of in-service personnel. The learning content for both groups followed the standard syllabus of the “WPS Office Software Application” stipulated by the Chinese Ministry of Education[63]. The only difference was that the experimental group’s system contained adaptive features, including segmentation and presentation of learning content, which were absent in the control group.

The study did not involve clinical trials on animals or humans and it did not violate ethical standards. In accordance with the ethical principles outlined in the Declaration of Helsinki, all participants provided informed consent before participating in the study. The anonymity and confidentiality of participants were guaranteed, and participation was completely voluntary. The experimental protocol for this study was approved by the Centre for Instructional Technology and Multimedia at Universiti Sains Malaysia (USM) and was strictly enforced under its supervision.

## Population

The target population of this study was in-service personnel aged 35 to 40 years from two companies with similar scales and business scopes in Dongying City, Shandong Province, China. The age group of 35 to 40 years was selected because, firstly, this group faces the most urgent learning problems. According to the 2023 Survey Report on In-service Personnel’s Learning Intention of China, Fig. 7 shows that among in-service personnel with a strong willingness to learn, those with over 10 years of working experience accounted for 38%, and their age distribution was 35 to 40 years[64]. Secondly, in-service personnel aged 35 to 40 usually have mature work experience and career backgrounds, which, according to experiential learning theory, profoundly impacts

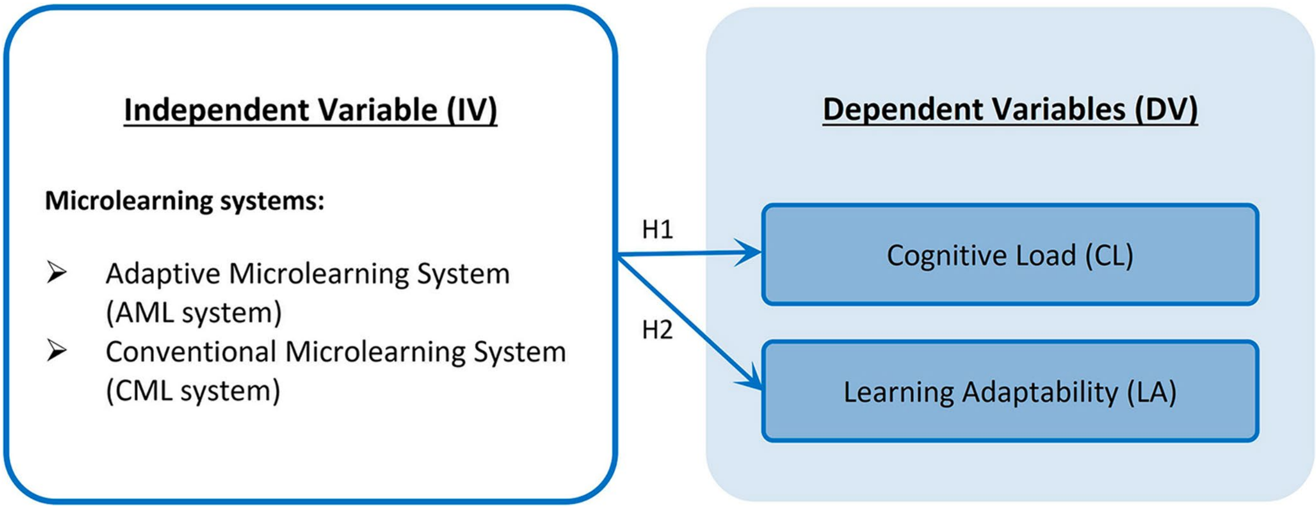


**Figure 6**. Research framework of the study.

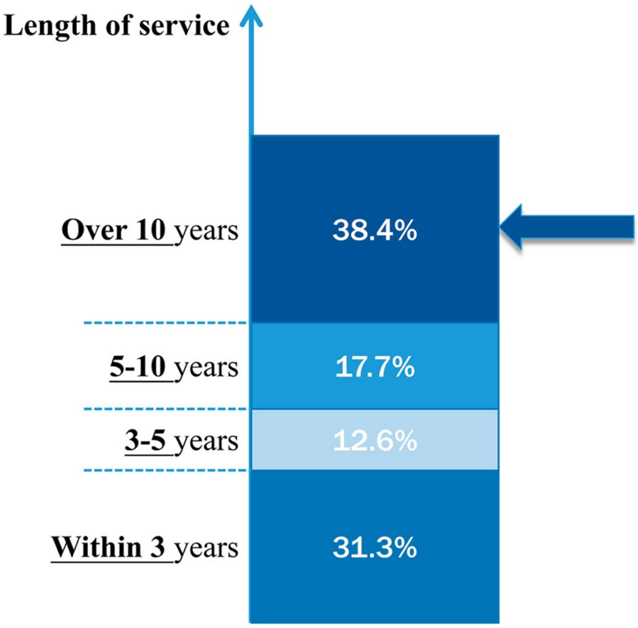


**Figure 7.** Survey report on in-service personnel's learning intention of China (in terms of years of work experience).

| Demographic Variable | | Experimental Group (AML) | Control Group (CML) |
|---|---|---|---|
| Age Range (35–40) | | 60 | 60 |
| Gender | Male | 32 | 31 |
| | Female | 28 | 29 |
| Education Level | Associate's Degree | 11 | 8 |
| | Bachelor's Degree | 45 | 48 |
| | Master's Degree | 4 | 4 |
| Job Position | Administrative | 20 | 22 |
| | Technical | 26 | 23 |
| | Managerial | 14 | 15 |
| Total | | 60 | 60 |

**Table 3.** Demographic information of respondents.

learning effectiveness[65]. Thirdly, working adults aged 35 to 40 typically fall into the establishment period (25–44 years old) of their careers[66]. They face pronounced work-learning balance challenges[67], making the need for adaptive microlearning more noticeable. Lastly, in-service personnel aged 35 to 40 who graduated years ago particularly need to upgrade their WPS Office-related skills through microlearning. When they were in school, WPS Office courses were not widely available, and they primarily learned and used Microsoft Office products[68]. Therefore, selecting this age range ensured they would respond positively to the learning content.

A total of 120 participants were recruited. This study employed cluster sampling. In cluster sampling, each company was regarded as a single unit. One company was randomly selected as the experimental group, with all in-service personnel using the AML system, while the other company was selected as the control group, with all in-service personnel using the CML system. Respondents, unaware of the experiment details, were group-assigned to different microlearning systems. Demographic information about the respondents, including gender, education level, and job position, is detailed in Table 3 to provide context for the learning effect analysis.

## Measurement instruments

Three instruments were used to measure the variables in this experiment. A pretest was developed based on the learning content to measure the prior knowledge of the in-service personnel. Cognitive load was measured using the Questionnaire on Cognitive Load (QCL). The Questionnaire on Learning Adaptability (QLA) was used to measure learners' learning adaptability. Both the QCL and QLA were modified and adapted from existing questionnaires to fit the linguistic habits and cultural characteristics of the target population. The QCL was adapted from Leppink's Cognitive Load Scale[69], while the QLA was adapted from the Learning Adaptation Questionnaire for Adult Higher Education Online Learning developed by Junfen and Chuner[70].

| Item | Cronbach's α if Item Deleted |
|---|---|
| CL1 | 0.783 |
| CL2 | 0.804 |
| CL3 | 0.809 |
| CL4 | 0.807 |
| CL5 | 0.799 |
| CL6 | 0.784 |
| CL7 | 0.795 |
| CL8 | 0.809 |
| CL9 | 0.813 |
| CL10 | 0.803 |

**Table 4**. The items Cronbach's α of QCL.

| Item | Cronbach's α if Item Deleted | Item | Cronbach's α if Item Deleted |
|---|---|---|---|
| LA1 | 0.896 | LA23 | 0.897 |
| LA2 | 0.897 | LA24 | 0.893 |
| LA3 | 0.893 | LA25 | 0.896 |
| LA4 | 0.900 | LA26 | 0.894 |
| LA5 | 0.897 | LA27 | 0.896 |
| LA6 | 0.898 | LA28 | 0.894 |
| LA7 | 0.896 | LA29 | 0.893 |
| LA8 | 0.897 | LA30 | 0.893 |
| LA9 | 0.894 | LA31 | 0.900 |
| LA10 | 0.894 | LA32 | 0.897 |
| LA11 | 0.897 | LA33 | 0.898 |
| LA12 | 0.895 | LA34 | 0.891 |
| LA13 | 0.894 | LA35 | 0.901 |
| LA14 | 0.892 | LA36 | 0.895 |
| LA15 | 0.898 | LA37 | 0.896 |
| LA16 | 0.898 | LA38 | 0.894 |
| LA17 | 0.899 | LA39 | 0.899 |
| LA18 | 0.892 | LA40 | 0.897 |
| LA19 | 0.895 | LA41 | 0.893 |
| LA20 | 0.896 | LA42 | 0.897 |
| LA21 | 0.895 | LA43 | 0.893 |
| LA22 | 0.891 | LA44 | 0.897 |

**Table 5**. The items Cronbach's α of QLA.

| Instrument | Items | Cronbach's α |
|---|---|---|
| QCL | 10 | 0.817 |
| QLA | 44 | 0.898 |

**Table 6**. The overall Cronbach's α of QCL and QLA.

The reliability of the items in the questionnaire was further determined by conducting an item deletion analysis to examine changes in Cronbach's α values after the deletion of specific items[71], with results presented in Tables 4 and 5.

Item deletion analyses showed that reliability remained stable when any items were deleted. This consistency suggests that both the QCL and the QLA are reliable measurement instruments. Their overall Cronbach's α values are shown in Table 6. Data analysis showed that the Cronbach's α for both the QCL and QLA was greater than 0.8, indicating high and acceptable reliability[72].

Questionnaire content validity was achieved by adapting well-established scales and modifying them to fit the cultural and linguistic context of the target population. The instrument was pilot tested with 30 in-service personnel to ensure it accurately measured the intended constructs. Feedback from the pilot test was used to further refine the instrument.

### Procedure

The experiment duration was seven weeks in total. The first week was an introduction, followed by six weeks of training. Pre-assessment and post-assessment were conducted at the end of the first and seventh weeks, respectively. The research procedure flowchart is shown in Fig. 8.

During the introduction week, respondents were briefed on the study process and how to use the assigned microlearning system, including its various functions and course-taking steps. The microlearning system assigned to the respondents was the only system they used throughout the experiment to enhance internal validity. At the end of the introduction week, respondents completed the pretest, ensuring between-group homogeneity by assessing prior knowledge.

The second week marked the beginning of the learning phase. The entire learning process was conducted online over six weeks, ending in the seventh week. This study aimed to explore the effectiveness of an augmented microlearning system in meeting the learning aspirations of in-service personnel. Therefore, the respondents were not subjected to standardized definitions or behavioral constraints during the learning period. They were encouraged to learn freely in a natural setting.

Post-assessment, including the QCL and QLA, were administered at the end of the seventh week. The experiment concluded after all data collection was completed.

### Data analysis methods

To address internal validity threats inherent in the quasi-experimental design, corresponding strategies were implemented. Specifically, respondents' prior knowledge level, measured by the pre-test, was considered as a covariate in the analyses[73]. Therefore, ANCOVA (Analysis of Covariance) was employed to examine the differences between the AML and CML groups. This approach allows for controlling initial differences in prior knowledge levels and provides a more accurate assessment of the AML system's effectiveness.

All collected data were statistically analyzed using SPSS (Statistical Product for Service Solutions) version 26. The significance level (p-value) for this study was set at 0.05. The hypothesis was not rejected if the p-value was less than 0.05 ($p < 0.05$) and rejected if it was greater than 0.05 ($p > 0.05$).

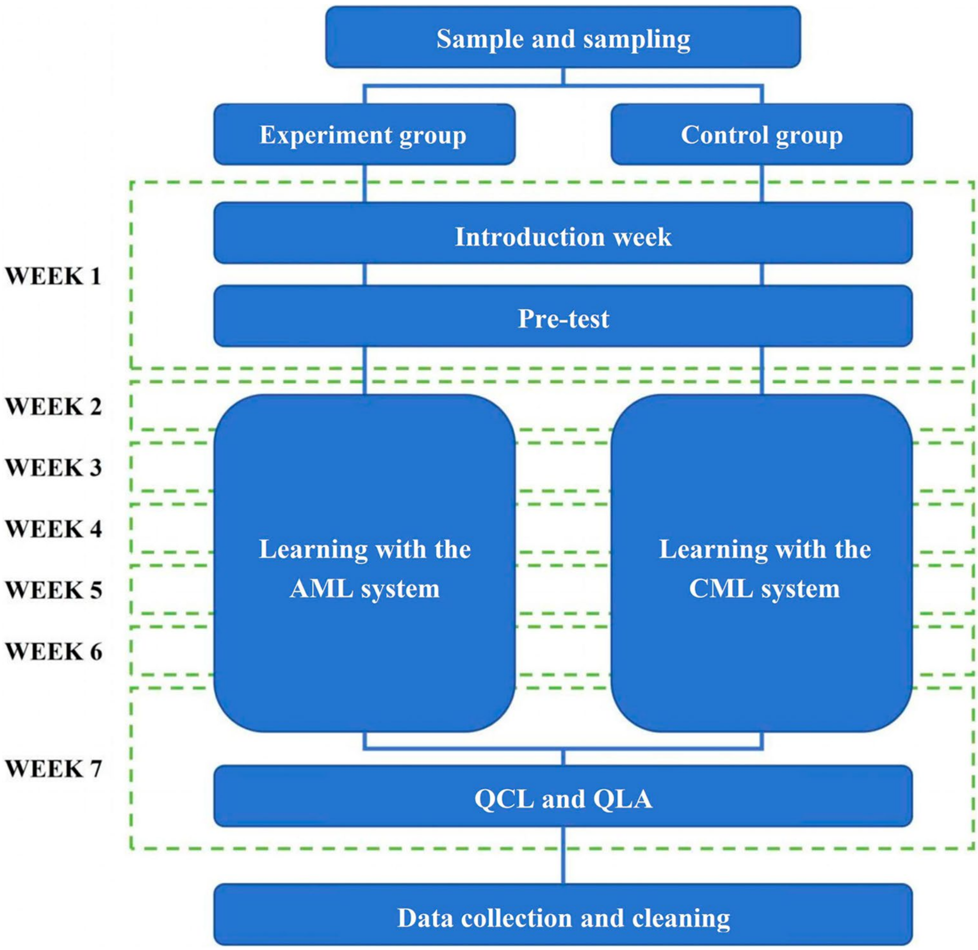


**Figure 8**. The research procedure.

| Group | N | Cognitive Load | | Learning Adaptability | |
|---|---|---|---|---|---|
| | | Mean | Std. Deviation | Mean | Std. Deviation |
| AML | 56 | 24.43 | 4.921 | 188.43 | 11.143 |
| CML | 55 | 44.45 | 6.301 | 147.71 | 14.285 |

**Table 7**. Descriptive statistics.

| | Group | N | Mean | Std. Deviation | t | df | Sig. (2-tailed) |
|---|---|---|---|---|---|---|---|
| Pre-test | AML | 56 | 4.88 | 1.080 | −1.010 | 109 | 0.315 |
| | CML | 55 | 5.07 | 0.979 | | | |

**Table 8**. Homogeneity analysis of pretest.

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Group | 570.997 | 1 | 570.997 | 18.103 | 0.000 |
| Pre-test | 97.625 | 1 | 97.625 | 3.095 | 0.081 |

**Table 9**. ANCOVA results for cognitive load (CL).

# Results

## Descriptive statistics

The 120 respondents in this study were selected through cluster sampling. However, due to absence during the experimental period (attendance below 70% or voluntarily withdraw), nine respondents were excluded. Ultimately, 111 respondents were included in the data collection.

Table 7 presents the descriptive statistics for the experimental (AML) and control (CML) groups, including means and standard deviations for cognitive load (CL) and learning adaptability (LA).

## Homogeneity analysis

To ensure the experimental and control groups were comparable at the start of the study, a homogeneity analysis of prior knowledge levels (Pre-test) was conducted. The results of the analysis, shown in Table 8, indicate that there were no significant differences between the experimental and control groups ($p = 0.315$), suggesting that any differences observed in CL and LA can be attributed to the intervention rather than pre-existing differences.

The dependent variables (CL and LA) were tested for homogeneity by Levene's test to ensure no significant prior differences between the experimental and control groups.

The results of Levene's test indicate that the homogeneity of variances assumption is not violated for either CL ($p = 0.063$) or LA ($p = 0.094$), which suggests that variances in CL and LA are equal across groups ($p > 0.05$).

## Results of cognitive load

ANCOVA was conducted to compare cognitive load between the AML and CML groups while controlling for pre-test, as shown in Table 9.

The results of ANCOVA revealed a significant difference in CL between the AML and CML groups when controlling for pre-test [$F(1, 107) = 18.103$, $p < 0.05$]. The AML group demonstrated lower cognitive load ($M = 24.43$, $SD = 4.921$) compared to the CML group ($M = 44.45$, $SD = 6.301$). The pre-test scores did not significantly contribute to the model [$F(1, 107) = 3.095$, $p = 0.081$], indicating that prior knowledge levels were effectively controlled.

## Results of learning adaptability

ANCOVA was conducted to compare learning adaptability between the AML and CML groups while controlling for pre-test, as shown in Table 10.

The ANCOVA results indicated a significant difference in LA between the AML and CML groups [$F(1, 107) = 15.462$, $p < 0.05$]. The AML group ($M = 188.43$, $SD = 11.143$) had significantly greater learning adaptability than the CML group ($M = 147.71$, $SD = 14.285$). The pre-test scores did not significantly impact the model [$F(1, 107) = 1.055$, $p = 0.307$].

# Discussion

## Cognitive load implications

The results of this study indicate that the adaptive microlearning (AML) system demonstrates significant effectiveness in controlling cognitive load compared to the conventional microlearning (CML) system. Cognitive load theory suggests that reducing unnecessary cognitive load improves learning outcomes[41]. The adaptive features of the AML system, especially personalized content delivery and flexible learning paths, contribute to more effective management of learners' cognitive resources. Additionally, AML systems can provide tailored

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Group | 2541.263 | 1 | 2541.263 | 15.462 | 0.000 |
| Pre-test | 173.347 | 1 | 173.347 | 1.055 | 0.307 |

**Table 10**. ANOVA results for learning adaptability (LA).

learning experiences based on learners' existing knowledge levels. Findings from Smith et al. (2018) suggest that adaptive instructional technology improves learner engagement and knowledge retention by aligning learning activities with individual needs[74]. The AML system continuously adjusts learning strategies and content difficulty according to learners' progress to ensure they are neither overwhelmed nor under-challenged, maintaining optimal cognitive load and promoting effective learning. It is inferred that the adaptive feature of the AML system is the primary factor contributing to these results.

### Learning adaptability implications

Significant effects on learning adaptability were found in the experimental group using the AML system compared to the control group, highlighting the potential of the AML system to promote flexible learning strategies. The adaptive features of the AML system, applying segmented learning content, enabled learners to adapt more effectively to new information and tasks. This is particularly advantageous for in-service personnel who need to continuously update their skills in a dynamic work context.

Compared to the CML system, the AML system presents learning content in easy-to-manage knowledge units. Such small, independent, and incoherent knowledge units can be quickly transformed and connected in changeable learning scenarios to form a knowledge network that matches the learner's demands[38], reflecting the principle of Connectivism. Additionally, according to the Constructivism perspective, where learners actively construct new knowledge based on prior knowledge, the AML system assists learners in selecting learning materials and adjusting subsequent content according to their progress and needs through real-time feedback. This iterative process facilitates learners in accumulating knowledge progressively, thus deepening their construction and understanding of knowledge[32,33].

Research by Wenxiu (2015) corroborates that adaptive systems can significantly improve learning performance by providing personalized feedback and adjusting learning paths based on individual performance[75]. The results of the present study are consistent with these findings, both emphasizing the benefits of adaptive features in complex educational environments.

### Limitations

Despite the promising findings, it is important to recognize some limitations. First, the quasi-experimental design, while practical, poses a potential threat to internal validity. Future research could use randomized controlled trials to strengthen causal inferences. Second, the study was conducted in a specific population (35-40-year-old in-service personnel), which may limit the generalizability of the findings to other age groups or professional contexts. In future studies, the inclusion of a more diverse sample would improve the external validity of the findings.

Another limitation is the use of multiple theoretical frameworks (such as constructivism, connectivism, and cognitive load theory) to support the study. While these frameworks were chosen to provide a comprehensive view of learning and instructional design, it may have introduced complexity into the study's theoretical foundation. Future research may benefit from focusing on a single theoretical framework, particularly when measuring specific outcomes like cognitive load, to provide a more streamlined and focused analysis.

Additionally, the measures of cognitive load and learning adaptability relied on self-reports, which may introduce response bias. Future studies should consider incorporating objective measures alongside self-reports to allow for a more comprehensive assessment of systemic effects.

Finally, although the AML system showed significant benefits in balancing cognitive load and improving learning adaptability, the long-term impact of these improvements remains uncertain. Longitudinal studies are needed to examine whether the observed benefits persist over time and translate into improved job performance and continued learning in professional settings.

## Conclusion

This study provides compelling evidence for the effectiveness of an adaptive microlearning (AML) system in balancing cognitive load and improving learning adaptability for in-service personnel. The ANCOVA results revealed significant differences between the AML and conventional microlearning (CML) groups, supporting both hypotheses proposed in the study.

Compared to those using the CML system, in-service personnel using the AML system reported significantly lower cognitive load [$F(1, 107) = 18.103$, $p < 0.05$]. These findings can be attributed to the adaptive nature of the AML system, which tailors learning content to learners' specific needs, minimizing information overload and enhancing cognitive processing. Similarly, the ANCOVA results showed a significant difference in learning adaptability between the AML and CML groups [$F(1, 107) = 15.462$, $p < 0.05$], suggesting that the AML system significantly enhances the ability of in-service personnel to adapt their learning strategies and behaviors to the learning environment. The personalized and flexible approach of the AML system likely contributed to this improvement, allowing learners to better manage their learning processes and effectively adjust to new information.

These findings align with the Sustainable Development Goals (SDGs), particularly SDG 4, which emphasizes inclusive and equitable quality education and lifelong learning opportunities for all. By effectively managing cognitive load and improving learning adaptability, the AML system addresses key barriers to effective learning for in-service personnel, enabling them to acquire and apply new knowledge and skills more efficiently. This not only enhances job performance and satisfaction but also contributes to broader goals of economic growth and innovation (SDG 8 and SDG 9).

The AML system incorporates core principles of constructivism and connectivism, offering a personalized, flexible, and networked learning experience. Constructivism suggests that learners build new knowledge upon the foundation of previous learning, facilitated by the AML system through its personalized content and adaptive feedback. Connectivism, focusing on learning through diverse connections, is evident in the system's ability to adapt content based on ongoing assessments and interactions.

In conclusion, the AML system offers a promising solution to the limitations of conventional microlearning for in-service personnel. Its adaptive features significantly balance cognitive load and enhance learning adaptability, supporting lifelong learning and professional development in various organizational contexts. By incorporating the adaptive microlearning system as an alternative to conventional microlearning systems in corporate training programs, it will more effectively contribute to the continuous professional development of in-service personnel. Policymakers are expected to support the development and deployment of sustainable innovations of adaptive technologies in instruction to enhance the job skills and productivity of in-service personnel. Continuous evaluation of the effectiveness of adaptive microlearning systems is recommended to ensure they are responsive to the changing needs of learners.

Future research should continue to explore the long-term impacts of adaptive microlearning and investigate additional factors to further optimize learning outcomes for in-service personnel, ensuring high-quality, accessible education for all learners. By addressing these limitations, future research can build on this study's findings to further understand the potential and challenges of adaptive microlearning systems in diverse educational and professional contexts.

## Data availability

Data sets generated during the current study are available from the corresponding author on reasonable request.

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## Author contributions
All authors carried out the research and contributed to design and development of the system. The contribution of author B.Z. to this article is mainly in the research design and experimental execution. The contribution of author K.T.C. to this article is mainly in the theoretical derivation and discussion sections. Author N.A.M.M. played an important role in the editing and reviewing stage of the article. All authors reviewed the manuscript of the article.

## Declarations

## Ethics declarations
The study did not involve clinical trials on animals or humans and it did not violate ethical standards. In accordance with the ethical principles outlined in the Declaration of Helsinki, all participants provided informed consent before participating in the study. The anonymity and confidentiality of participants were guaranteed, and participation was completely voluntary. The experimental protocol for this study was approved by the Centre for Instructional Technology and Multimedia at Universiti Sains Malaysia (USM) and was strictly enforced under its supervision.

## Competing interests
The authors declare no competing interests.

## Additional information
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