THE EFFECT OF ADAPTIVE MICROLEARNING SYSTEM ON ACHIEVEMENT, COGNITIVE LOAD, SELF-REGULATION, AND LEARNING ADAPTABILITY OF IN-SERVICE PERSONNEL

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LIST OF SYMBOLS

a_i	The discrimination, which refers to the test item's ability to distinguish learners' potential characteristics
b_i	The difficulty, which refers to the difficulty of the test item
c_i	The guessing coefficient, which refers to the possibility that a learner can correctly answer the item through random selection without any knowledge of the item
E	The margin of error in calculating sample size
e	The margin of error in calculating the existing level of knowledge
i	The item that the learner has done in the system
n	The required sample size
p	The proportion of the population with the relevant attribute
$P(u_i = 1/\theta)$	The possibility that a learner with existing knowledge level of "θ" can answer item "i" correctly
u_i	the learner's response to item "i"
Z	The critical value corresponding to the confidence level in the standard normal distribution
θ	The existing knowledge level of the learner, the range of values to consider is $[-4.0, +4.0]$ or $[-3.0, +3.0]$

LIST OF ABBREVIATIONS

12-GS	12-Item Grit Scale
3-PL	Three-Parameter Logistic Model
AEHS	Adaptive Educational Hypermedia Systems
AML	Adaptive Microlearning
ANCOVA	Analysis of Covariance
AS	Achievement Scores
ATID	Model for Instructional Design and Development Proposed by Alessi and Trollip
CDMT	Center of Digital Media Technology
CL	Cognitive Load
CLS	Cognitive Load Scale
CLT	Cognitive Load Theory
CML	Conventional Microlearning
CNCRE	China National Computer Rank Examination
DV	Dependent Variables
High-LG	High Level of Learning Grit
IV	Independent Variable
LA	Learning Adaptability
LAIP	Questionnaire on Learning Adaptability of In-service Personnel
Low-LG	Low Level of Learning Grit
MANCOVA	Multivariate Analysis of Covariance
MV	Moderator Variable
RQ	Research Questions
SDG	Sustainable Development Goal
SPSS	Statistical Package for the Social Sciences
SRL	Self-regulation of Learning
WSRLS	Workplace Self-Regulation of Learning Scale

LIST OF APPENDICES

KESAN SISTEM PEMBELAJARAN MIKRO MUDAH SUAI TERHADAP PENCAPAIAN, BEBAN KOGNITIF, KAWALAN KENDIRI, DAN KEBOLEHSESUAIAN PEMBELAJARAN KAKITANGAN DALAM PERKHIDMATAN

ABSTRAK

Kajian ini memberi tumpuan kepada cabaran pembelajaran yang dihadapi oleh pekerja yang sedang berkhidmat, yang sering kali menghadapi kesukaran untuk mencapai hasil pembelajaran yang diinginkan disebabkan oleh masa pembelajaran yang terhad dan terpecah-pecah. Kaedah pembelajaran mikro tradisional kurang berkesan dari segi kedalaman dan kesinambungan pengetahuan, namun ia menuntut keupayaan kognitif, pengawalan kendiri, dan penyesuaian pembelajaran yang tinggi. Bagi menangani cabaran ini, kajian ini membangunkan sistem pembelajaran mikro adaptif (AML) yang disesuaikan dengan keperluan khas golongan pekerja. Tujuan utama kajian ini adalah untuk menilai sama ada sistem AML dapat meningkatkan pencapaian pembelajaran, keupayaan pengawalan kendiri, dan penyesuaian pembelajaran, sambil mengurangkan beban kognitif bagi pekerja yang sedang berkhidmat. Sistem AML ini mempunyai ciri-ciri seperti laluan pembelajaran adaptif, penghantaran kandungan dalam pelbagai format, dan maklum balas masa nyata. Kandungan pembelajaran dibahagikan kepada unit kecil, dengan teks yang dihadkan kepada 50 perkataan dan video terhad kepada 45 saat. Di samping itu, sistem ini menyediakan ujian berdasarkan kemajuan pelajar dan menawarkan penilaian yang disesuaikan dengan pencapaian pembelajaran mereka. Kajian ini menggunakan reka bentuk eksperimen separa untuk membandingkan pencapaian pembelajaran 231 orang pekerja, dengan membandingkan sistem AML (kumpulan eksperimen) dan sistem pembelajaran mikro tradisional (kumpulan kawalan). Sepanjang tujuh minggu kajian, kesan sistem AML terhadap pencapaian pembelajaran, beban kognitif, pengawalan kendiri, dan keupayaan penyesuaian pembelajaran dinilai, dengan ketabahan pembelajaran dijadikan pemboleh ubah moderator. Dapatan kajian menunjukkan bahawa sistem AML secara signifikan meningkatkan pencapaian pembelajaran dan keupayaan penyesuaian pembelajaran, dan mengurangkan beban kognitif berbanding sistem pembelajaran mikro tradisional. Penemuan ini membuktikan bahawa sistem AML adalah penyelesaian inovatif yang sangat sesuai dengan keperluan pendidikan golongan pekerja yang sedang berkhidmat. Hasil kajian ini juga seiring dengan Matlamat Pembangunan Mampan (SDG) 4, yang menekankan pendidikan berkualiti. Kajian ini mencadangkan agar kajian masa depan meneroka pelbagai sampel dan konteks untuk memperhalusi dan mengesahkan keberkesanan sistem AML, serta menyeimbangkan sokongan teknologi dengan keupayaan autonomi pelajar bagi meningkatkan keupayaan pembelajaran berterusan dan daya saing kerjaya pekerja yang sedang berkhidmat.

THE EFFECT OF ADAPTIVE MICROLEARNING SYSTEM ON ACHIEVEMENT, COGNITIVE LOAD, SELF-REGULATION, AND LEARNING ADAPTABILITY OF IN-SERVICE PERSONNEL

ABSTRACT

This research addresses the significant learning challenges faced by in-service personnel, who often have extremely limited and fragmented time for learning. Conventional microlearning methods frequently fall short in providing the depth and coherence necessary for substantial knowledge acquisition and impose high cognitive load, self-regulation, and learning adaptability demands. To overcome these challenges, this research developed an adaptive microlearning (AML) system tailored to the unique needs of in-service personnel. The purpose of this research was to determine whether the AML system could enhance learning achievement, self-regulation, and learning adaptability while reducing cognitive load for in-service personnel. The AML system includes features such as adaptive learning paths, multi-format content delivery, real-time feedback, and micro-segmentation. Learning content is divided into bite-sized segments, with text content limited to 50 characters and video content limited to 45 seconds. Additionally, the system generates quizzes based on the learner's progress, offering tailored assessments that align with their learning trajectory. A quasi-experimental research involving 231 in-service personnel compared the AML system (experimental group) with a conventional microlearning system (CML, control group). Over seven weeks, this study assessed the impact of the AML system on achievement scores (AS), cognitive load (CL), self-regulation of learning (SRL), and learning adaptability (LA), using learning grit as a moderator variable. The results indicated that the AML system significantly improved AS,

reduced CL, and enhanced LA compared to the CML system, while also supporting SRL through adaptive feedback and content. The findings demonstrate that the AML system offers significant advantages in enhancing learning effectiveness and adaptability for in-service personnel, making it a promising solution for their educational needs. This research underscores the importance of adaptive learning technologies in providing equitable and effective learning opportunities, especially for those with limited and fragmented learning time. These efforts align with Sustainable Development Goals (SDGs) 4 (Quality Education). Future research should explore diverse samples and contexts to further refine and validate the AML system's effectiveness, aiming to balance technological support and learner initiative to enhance continuous learning capabilities and career competitiveness of in-service personnel.

CHAPTER 1

INTRODUCTION

1.1 Introduction

The advent of the Internet and multimedia technology has sparked diverse online learning approaches, including microlearning, mobile learning, e-learning, distance learning, flipped learning, hybrid learning, and other derivations. Among all these learning approaches, microlearning is considered the fastest-growing in the world of education today (Corbeil & Corbeil, 2023). Compared with traditional learning approaches, which often focus on face-to-face classrooms, regurgitating facts, heavy note-taking, lengthy lecture videos, hefty PowerPoint slides, and large reading materials, and often relegate learners to passive recipients of knowledge (Feng et al., 2021), microlearning offers a contrasting approach. It gives learners access to brief units of content, breaking down material into standalone modules or units that typically last 10 to 15 minutes (Taylor & Hung, 2022). Microlearning has gained recognition for its potential to engage in-service personnel in continuous learning without requiring extended time away from their professional duties (Hamilton et al., 2021). It allows learning anytime, anywhere (Andreev, 2023), fostering lifelong learning as stipulated in UNESCO's Sustainable Development Goal 4 (SDG 4) to ensure equitable quality learning opportunities for all. This includes in-service personnel, who are vital human resources contributing to economic growth (United Nations, 2020).

In this research, "in-service personnel" specifically refers to employees with formal, long-term employment contracts who work full-time in structured organizations, as defined in Chinese labor laws. This group contrasts with other categories of working adults, such as freelancers, part-time workers, or temporary employees, who may have more flexible schedules but less stable learning needs. In-service personnel often have fixed working hours, specific job responsibilities, and career advancement requirements that necessitate continuous skill development. These characteristics make their learning demands unique and distinguishable from those of other working adults.

In-service personnel face specific challenges that arise from the demanding nature of their roles. Firstly, in-service personnel experience more intense conflicts between work and learning than other working adults. Work frequently takes precedence for in-service personnel, significantly compressing their available learning time. Their daily learning time accounts for only 2% of their total time (Matthews, 2023a). Secondly, in-service personnel’s learning time is not only limited but also very fragmented. This fragmentation refers to their limited, random, dispersed, and scattered availability of time, making it challenging for them to allocate substantial blocks for learning (Andreev, 2023). Unlike adolescents who receive structured learning in traditional classroom settings, in-service personnel do not have the luxury of dedicating time solely to learning. They typically work under significant pressure, facing time constraints that often leave their time highly fragmented (Horvath, 2024). Additionally, their motivation, learning adaptability, and self-regulation are substantially depleted due to diverse and interrupting learning scenarios, leading to weak learning effects and low participation. Thirdly, there are significant differences in background, education level, skills, interests, and preferences for learning among in-service personnel (Karlsen et al., 2023). The lack of consideration and insufficient customizable feedback for in-service personnel of different backgrounds in current conventional microlearning practices adversely affect the cognitive load required for learning.

The aforementioned problems and challenges signify that conventional microlearning necessitates an additional pedagogical component to meet the unique and targeted needs of in-service personnel. Therefore, this research introduces and evaluates an "adaptive microlearning" approach. This novel pedagogical method incorporates customization and real-time adjustments to support the unique learning scenarios of in-service personnel. A prototype system, named the Adaptive Microlearning (AML) system, was designed and developed to embody this concept.

To understand the research on this newly designed system, this chapter first introduces the research background and problem statements faced by in-service personnel, followed by the research objectives, questions, and hypotheses. Additionally, this chapter systematically introduces the primary theoretical basis of the research and explains its significance.

1.2 Background of the Research

Education has long been advocated as an essential pillar for improving human resources in society at large and within specific companies worldwide. The increasing integration of digital technologies has further expanded the scale of education (Runtian, 2020). Various countries around the world have actively adopted online learning approaches as viable alternatives to traditional learning. Among others, the Finnish National Board of Education established "student-centered" online learning platforms to ensure the continuation of effective primary education (Murtonen et al., 2020). Online learning platforms such as Coursera, EdX, FutureLearn, and Moodle are used by major higher education institutions in the United Kingdom to conduct courses for students (Adedoyin & Soykan, 2023). The Korean Ministry of Education implemented a policy requiring free digital textbooks, online learning sites, and educational TV videos for students to study independently at home (Carrillo & Flores, 2020). Increasingly, vast institutions of learning are breaking out of their own “walls” (Park et al., 2016) to adopt online learning tailored for niche groups of learners.

The emergence of microlearning aligns with these needs. Microlearning, rooted in Hermann Ebbinghaus’s forgetting curve, addresses memory retention by presenting information in small, manageable units (Linkedin, 2023). Ebbinghaus’s (1913) findings revealed that memory decays over time but can be improved through repetition and reinforcement, concepts integral to modern microlearning practices. This approach not only caters to learners’ cognitive needs but also matches their fragmented schedules. In this context, “fragmented” refers to the short and irregular intervals of time that in-service personnel have available for learning, often squeezed between work tasks and personal responsibilities (Andreev, 2023). These characteristics make microlearning particularly suitable for in-service personnel, whose learning opportunities are limited and sporadic.

In China, the adoption of microlearning has been supported by a series of national policies that directly and indirectly support the development of microlearning for in-service personnel. For example, China’s “National Medium and Long-term Education Reform and Development Plan (2010-2020)”, promulgated in 2010, elaborated the education informatization plan, emphasizing the need for instructional online learning approaches tailored to different populations, such as in-service personnel (Zhang, 2021). With this policy impetus, the population of in-service personnel with qualifications beyond the tertiary level has doubled in China compared to 2009 (Ministry of Education, 2020). Building on this, the “14th Five-Year Plan”

(2021-2026) for Educational Informatization was proposed to “leverage the advantages of online education, improve the lifelong learning system, and build a learning society” (China Government Network, 2021). This plan promoted the digital economy through initiatives that expanded the deployment of online learning technologies, including cloud computing, big data, learning analytics, and digital content in China’s educational ecosystem (Xue et al., 2022). These policies have laid the groundwork for the widespread adoption of microlearning.

In addition to national policy support, advances in mobile technology have further enabled microlearning in China. As of June 2020, 5G stations in China exceeded 400,000, with 66 million 5G terminals connected across the country (Guo et al., 2022). Relevant networks like the China Educational Research Computer Network and the China Educational Satellite Broadband Transmission Network have provided educational broadcasting services across China (Gu, 2022), laying a foundation for mobile microlearning development. As of March 2020, the number of online learning users in China reached 932 million (Negro, 2022), an increase of 10.1% compared to 2018 (Ren et al., 2023). Additionally, various mobile microlearning systems and certification platforms have been continuously established and standardized in China (Huang & Wu, 2021). Educational and scientific research institutions in over 200 cities are connected to these platforms, making them the most extensive Internet-based academic platform in the world (Chen et al., 2020). Despite the online learning market being valued at 550 billion yuan with over 446 million users in 2021 (Statista Market Forecast, 2024), it continues to grow at a rate of 8% (Zhang & Sivertsen, 2023). China’s paid knowledge content market reached 23.5 billion yuan in 2020 (NetEconomics, 2021). In-service personnel education accounts for 30.2% of the online learning market (Yang, 2022). All this indicates that microlearning for in-service personnel has started to become mainstream in China (Huang & Xiao, 2021).

Despite its advantages, conventional microlearning approaches face limitations when addressing key learning challenges. One of the primary challenges is cognitive load, which refers to the mental resources required to process information (Sweller, 2011). If not carefully managed, cognitive load can hinder learning, especially when content is poorly designed or too complex (Paas et al., 2003). While microlearning reduces cognitive load by delivering small chunks of information, poorly designed content or overly complex material can still overwhelm learners (Khaddage et al., 2015). This makes it essential to develop systems that can dynamically adjust content complexity to suit individual learners' capacities, minimizing unnecessary mental strain.

To address these challenges, adaptive learning systems have emerged as a solution that customizes the learning experience to fit the needs of individual learners. Adaptive learning refers to systems that use algorithms and data to adjust content dynamically based on learners' prior knowledge, learning preferences, and progress (Kerr, 2016). This adaptive approach ensures that learners are presented with information that matches their cognitive capabilities, avoiding overwhelming them with overly complex material while keeping the content sufficiently challenging (Paramythis & Loidl-Reisinger, 2004). Incorporating adaptive elements into microlearning gives rise to adaptive microlearning, which combines the flexibility of microlearning with the personalized features of adaptive systems. Through adaptive microlearning, content is not only delivered in small, manageable units but also personalized to meet the specific needs of each learner (Gherman et al., 2022). This approach helps manage cognitive load by ensuring that content is appropriately challenging and avoids cognitive overload, making learning more efficient.

In the design and assessment of conventional microlearning systems, cognitive diagnostic models (CDM) are frequently employed. CDM combines Item Response Theory (IRT) with cognitive theories to provide detailed diagnostic information about learners' cognitive strengths and weaknesses (Templin & Henson, 2006). However, it often lacks a robust theoretical foundation to explain why certain items behave in particular ways (Leighton, 2019), making it challenging to directly apply CDM to optimize adaptive learning systems. In contrast, the Three-Parameter Logistic (3-PL) model, a key component of IRT, addresses these issues by offering a more interpretable framework. The 3-PL model evaluates learners' abilities, item difficulty, and the probability of guessing correct answers, allowing for a more personalized and adaptable learning experience (Islam et al., 2021). By introducing 3-PL model, an attempt can be made to address the limitations of CDM. It allows the system to present learners with content that is both appropriately challenging and manageable, ultimately minimizing cognitive load while maintaining engagement.

In addition to managing cognitive load, effective learning for in-service personnel requires addressing three critical psychological factors: learning adaptability, grit, and self-regulation. Learning adaptability reflects the ability of learners to adjust their strategies and behaviors in response to new or changing learning environments (Gocheva et al., 2022). It is particularly important for in-service personnel, who often face unpredictable interruptions during their fragmented learning sessions. Learning grit is a stable psychological state that determines persistence and goal setting in learning tasks (Duckworth et al., 2007a), while self-regulation encompasses active participation, monitoring, and adjustment of learning behaviors (Zimmerman, 1989).

Collectively, these factors enhance learners' ability to navigate the demands of microlearning, while serving as indicators for evaluating the effectiveness of microlearning.

By combining adaptive learning with microlearning and addressing key psychological factors, adaptive microlearning offers a promising solution to the challenges identified in this research. Through the integration of the 3-PL model, adaptive microlearning ensures that learning experiences are personalized, cognitively manageable, and appropriately challenging. This approach not only reduces cognitive load but also fosters the development of critical psychological resources such as self-regulation and learning adaptability. These features make adaptive microlearning particularly well-suited for in-service personnel, enabling them to optimize fragmented learning opportunities while ensuring an efficient, engaging, and personalized learning experience.

1.3 Problem Statement

The main problem faced by in-service personnel in learning is their extreme busyness during work hours, resulting in an immensely fragmented availability of time for learning. On average, they only have 24 minutes per week to dedicate to learning, which constitutes about 2% of their total weekly time (Matthews, 2023a). In addition, the time they can commit to learning is often fragmented, as work commitments such as overtime and business trips (which account for 66% of their working time) further reduce their available learning time (Li, 2019a). Aside from paid work, they are overburdened with unpaid family and social responsibilities, including housework, childcare, medical treatment, and public welfare activities (National Bureau of Statistics of China, 2019). Despite these barriers, many in-service personnel remain motivated to learn and seek opportunities to acquire new knowledge and skills (Li & Shi, 2020). A study found that learning was identified as the top factor contributing to employee happiness at work (Hess, 2019), and 27% of employees reported that lack of learning opportunities was the primary reason for leaving their jobs (Keswin, 2022). However, learning requires regular commitment. Work creates conflicting barriers to learning. Due to these conflicts, enrolling in courses on campus is a formidable challenge for in-service personnel (Eschenbacher & Fleming, 2020). As a result, they are in urgent demand for a customized and innovative approach to learning.

However, the limited availability of learning time is not the only barrier faced by in-service personnel. Another primary challenge faced by in-service personnel is the effectiveness of conventional microlearning. While microlearning is designed to deliver small, digestible chunks of content, the limited, fragmented learning time of in-service personnel presents a risk that learning outcomes of conventional microlearning may be one-sided, superficial, and unreliable (Kassymtayeva, 2020; López, 2020). In many cases, learners may feel they have acquired knowledge after completing a microlearning module, but their understanding may be shallow and short-lived (Zaqoot et al., 2020). Research has shown that up to 80% of knowledge gained through in-service learning is forgotten within a month (Redondo et al., 2021). The lack of time for deeper learning raises questions about whether microlearning, in its traditional form, can truly help in-service personnel develop comprehensive knowledge.

Furthermore, in-service personnel face challenges in self-regulation, which is essential for effective learning. Self-regulation of learning refers to an individual's ability to perceive and control their own learning process, including goal setting, selection, management, and strategies, as well as monitoring and reflecting on the learning process independently (Zimmerman & Schunk, 2011). Given the fragmented nature of their learning time, many in-service personnel struggle with low self-regulation. A survey found that in the process of acquiring knowledge through the Internet, 50% of personnel only read what is on the homepage and headlines, with less than 30% persist in completing all the content (CAPP & Xinhua News Agency, 2023). This lack of sustained engagement is compounded by the interruptions they face from work and daily life, further diminishing their capacity for self-regulated learning. The American Psychological Association reports that only 20% of American in-service personnel consider their daily work to be under control. On average, they are interrupted 4 to 12 times per hour (Ariella, 2022). Data from the edX platform show that videos longer than 9 minutes exhibit a significant drop in attention span. After 2 minutes, learners start skipping parts of the video. Only about 20% of the video is played in its entirety, even though it has been played up to 6 million times (Redondo et al., 2021). The challenge, therefore, is not only to engage in-service personnel with learning content but also to support their ability to manage and sustain their learning in an environment that is prone to distractions.

Information overload is another pressing issue. Although conventional microlearning has modularized and segmented its learning contents into smaller units, the information can be still overwhelming (Li & Chan, 2022). For in-service personnel, this excess information increases cognitive load and negatively affects learning effectiveness (Sweller, 2010). Globally, online users spend about 144 minutes a day on social media. An American checks their mobile phone 96 times a day, or roughly every ten minutes (US Bureau of Labor Statistics, 2022). When learners are bombarded with too much content at once, it becomes difficult to process and retain the material (Duckworth et al., 2021a; Xu & Gutsche, 2021). In a survey in Germany, 22.5% of respondents cited information overload as one of the most common sources of their stress (Arnold et al., 2023; Meyer et al., 2021). This issue is especially critical for older in-service personnel, who may experience diminished cognitive capacity as they age (Naughton, 2023). In conventional microlearning, the sheer volume of information, combined with the frequent switching between modules, creates unnecessary cognitive strain, making it harder for learners to integrate and retain the knowledge.

Finally, in-service personnel face a lack of adaptability to the diverse learning scenarios (Romero et al., 2020). Low learning adaptability efficiently induces various negative emotional responses to learning tasks, such as loneliness, anxiety, and laziness (Gan, 2020). Statistics show that many learners, including in-service learners, have a low degree of learning adaptability. 57.4% of online learners felt anxious and 28.4% felt lonely while learning online. A significant finding is that 56.6% of learners acknowledged having weak learning adaptability. This highlights the importance of enhancing the learning adaptability of in-service personnel within the microlearning context (IIMedia Report, 2020).

In-service personnel face significant challenges, including limited learning time, cognitive overload, and low self-regulation, as well as the need for higher learning adaptability. These challenges hinder the effectiveness of conventional microlearning. Hug (2005) defines microlearning as a holistic approach and emphasizes that microlearning can be personalized, modular, and flexible. While microlearning provides small, digestible content in short, focused episodes, it often fails to meet the deeper, personalized needs of learners, especially in terms of adaptability to diverse learning contexts. To address these limitations, recent advancements have integrated technology into microlearning, enhancing its adaptability and responsiveness to the needs of learners. Kovachev (2011) explored how technological advancements, such as mobile apps and adaptive learning platforms, can improve microlearning's effectiveness by providing more personalized, real-time learning experiences. Building on this, Sankaranarayanan et al. (2023) further expanded this understanding, showing through their bibliometric analysis how microlearning is evolving in diverse contexts, especially with the inclusion of new technologies that cater to varied learner needs and environments.

In light of these developments, adaptive microlearning emerges as a more fitting solution. By incorporating technological advancements, adaptive microlearning tailors content to the in-service personnel's learning pace, prior knowledge, and preferences, overcoming the constraints imposed by time limitations. This personalization helps improve learning outcomes by ensuring that content is more relevant and engaging, addressing the fragmented learning time and diverse needs of in-service personnel. As a result, adaptive microlearning not only fosters sustained engagement but also enhances the effectiveness of learning by better matching the learner's needs.

The importance of this research lies in its potential to revolutionize how learning is delivered, not only for in-service personnel but also for a broader range of learners. As education shifts toward more personalized, flexible models, adaptive microlearning could serve as a model for future learning systems that are scalable, engaging, and responsive to diverse learner needs across various sectors. This research will evaluate whether adaptive microlearning can effectively improve learning performance, reduce cognitive load, increase self-regulation, and enhance adaptability, ultimately contributing to a more efficient and accessible learning environment.

1.4 Objectives of the Research

The main objective of this research is to design, develop, and evaluate an innovate adaptive microlearning system (AML system) as a potential solution to the learning problems faced by in-service personnel. The specific research objectives are as follows:

(i) To investigate the effects of the Adaptive Microlearning (AML) system on in-service personnel's learning achievement scores compared to the Conventional Microlearning (CML) system.

(ii) To investigate the effects of the AML system on in-service personnel's cognitive load compared to the CML system.

(iii) To investigate the effects the AML system on in-service personnel's self-regulation of learning compared to the CML system.

(iv) To investigate the effects of the AML system on in-service personnel's learning adaptability compared to the CML system.

(v) To investigate the effects of using the AML system on in-service personnel's learning achievement scores, cognitive load, self-regulation of learning, and learning adaptability among in-service personnel with different levels of learning grit compared to the CML system.

(vi) To investigate the interaction effects of using the AML and CML systems on in-service personnel's learning achievement scores, cognitive load, self-regulation of learning, and learning adaptability among in-service personnel with different levels of learning grit.

1.5 Research Questions (RQ)

The research will specifically answer the following Research Questions (RQ):

RQ1. Is there any significant difference in learning achievement scores (AS) among in-service personnel using the adaptive microlearning (AML) system compared to the conventional microlearning (CML) system?

RQ2. Is there any significant difference in cognitive load (CL) among in-service personnel using the AML system compared to the CML system?

RQ3. Is there any significant difference in self-regulation of learning (SRL) among in-service personnel using the AML system compared to the CML system?

RQ4. Is there any significant difference in learning adaptability (LA) among in-service personnel using the AML system compared to the CML system?

RQ5. Is there any significant difference in the four dependent variables (AS, CL, SRL, LA) among in-service personnel with different levels (high or low) of learning grit who use the AML system compared to the CML system?

RQ6. Is there any interaction effect between the microlearning systems (AML and CML systems) and the learning grit on the four dependent variables (AS, CL, SRL, and LA)?

1.6 Research Hypotheses

This research aims to develop an adaptive microlearning system potentially suitable for in-service personnel to learn during available fragmented time. Since there is no existing similar research for reference, it is assumed that the research does not affect learners.

This research contains six main hypotheses. Hypotheses 5 and 6 each contain 4 branch hypotheses.

$H_0$1: There is no significant difference in achievement scores (AS) between in-service personnel using the AML system and the CML system. (RQ1)

$H_0$2: There is no significant difference in cognitive load (CL) between in-service personnel using the AML system and the CML system. (RQ2)

$H_0$3: There is no significant difference in self-regulation of learning (SRL) between in-service personnel using the AML system and the CML system. (RQ3)

$H_0$4: There is no significant difference in learning adaptability (LA) between in-service personnel using the AML system and the CML system. (RQ4)

$H_0$5: There is no significant difference in AS, CL, SRL, and LA among in-service personnel with different levels of learning grit using the AML and CML systems. (RQ5)

$H_0$5.1: There is no significant difference in the AS among in-service personnel with different levels of learning grit using the AML and CML systems. (RQ5)

$H_0$5.2: There is no significant difference in the CL among in-service personnel with different levels of learning grit using the AML and CML systems. (RQ5)

$H_0$5.3: There is no significant difference in the SRL among in-service personnel with different levels of learning grit in the different groups using the AML and CML systems. (RQ5)

$H_0$5.4: There is no significant difference in the LA among in-service personnel with different levels of learning grit using the AML and CML systems. (RQ5)

$H_0$6: There is no interaction effect between the microlearning systems (AML and CML systems) and different levels of learning grit on AS, CL, SRL, and LA. (RQ6)

$H_0$6.1: There is no interaction effect between the microlearning systems (AML and CML) and learning grit (high and low levels) on the AS. (RQ6)

$H_0$6.2: There is no interaction effect between the microlearning systems (AML and CML) and learning grit (high and low levels) on the CL. (RQ6)

$H_0$6.3: There is no interaction effect between the microlearning systems (AML and CML) and learning grit (high and low levels) on the SRL. (RQ6)

$H_0$6.4: There is no interaction effect between the microlearning systems (AML and CML) and learning grit (high and low levels) on the LA. (RQ6)

1.7 Conceptual Framework

A 2x2 quasi-experimental factorial design was employed to measure the effect of the adaptive microlearning system on the learning of in-service personnel. The conceptual framework assumed one independent variable (IV) impacting four dependent variables (DVs), which were the four indicators of learning effects in the context of the research, as summarized in Figure 1.1.

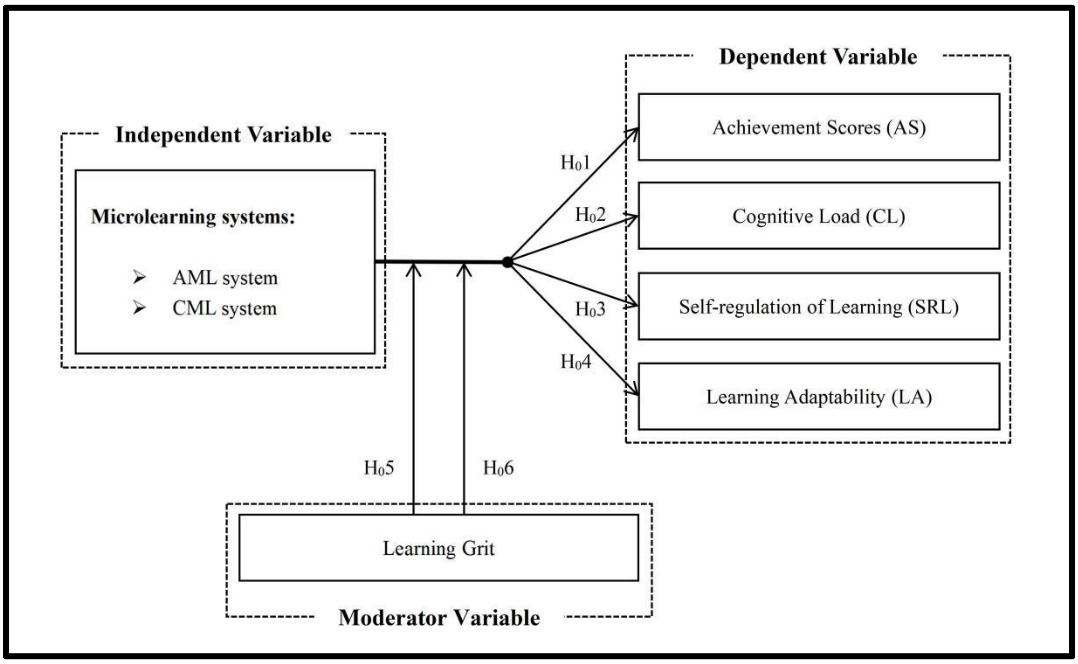

Figure 1.1 Conceptual Framework of the Research

The independent variable (IV) was the microlearning systems, consisting of the adaptive microlearning (AML) system and the conventional microlearning (CML) system. The dependent variables (DVs) were achievement scores (AS), cognitive load (CL), self-regulation of learning (SRL), and learning adaptability (LA).

The achievement score serves as an indicator of how well learners can apply the skills and knowledge acquired during the adaptive microlearning sessions. In this research, AS refers to the measure of learners' mastery over the WPS Office Software Application, which was the primary content of the learning modules provided to the respondents. It was specifically selected because it directly reflects the intended outcomes of the microlearning modules, focusing on practical proficiency in using the software.

It was predicted that a moderator variable (MV), namely learning grit, would have an impact on the DVs. Learning grit plays a crucial role in influencing a learner's persistence, focus, and ability to overcome challenges during learning (Duckworth et al., 2007a). It is treated as a MV because it is hypothesized to influence how learners engage with the microlearning content and, in turn, affect the DVs. Specifically, learning grit is expected to moderate the relationship between the IV (microlearning systems) and the DVs (AS, CL, SRL, and LA). It is not treated as a direct DV because its role is to influence the learners' responses to the learning experience, thereby shaping their overall learning outcomes.

In-service personnel were selected as the respondents in the research. The findings about the effects of AML on learners' AS, CL, SRL, and LA were significant for designing and developing a quality microlearning system that could accommodate the unique learning situations of in-service personnel learners.

This research focuses on the effect of the adaptive microlearning system on in-service personnel learning the WPS Office Software Application. This research is experimental in nature, and it is important to acknowledge that the generalizability of the findings may be limited to the specific context of in-service personnel learning WPS Office Software. The research provides valuable insights into the effectiveness of adaptive microlearning in addressing the unique learning needs of this group while also recognizing the need for future research to explore its broader applicability in other educational and professional contexts.

1.8 Theoretical Framework

Four theories were adopted in this research: Constructivism Theory (Fosnot, 2013; Fosnot & Perry, 1996), Connectivism Theory (Siemens, 2005, 2007), Cognitive Load Theory (Sweller, 2011), and Mayer's Segmented Principles (Mayer, 2014a, 2017). Together, these theories form the theoretical foundation for the adaptive microlearning (AML) system, which addresses the unique needs of in-service personnel. Figure 1.2 illustrates how these theories integrate into a unified framework, with learning theories guiding the strategies for knowledge acquisition and instructional theories shaping the design of effective and efficient learning experiences.

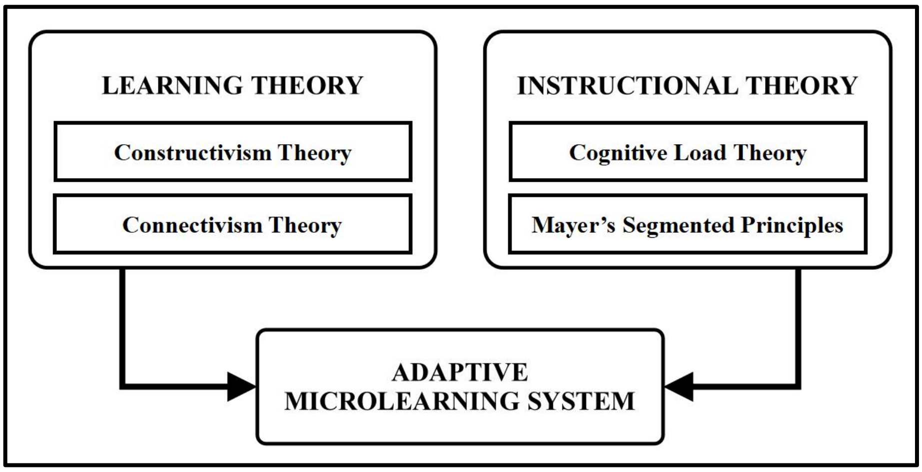

Figure 1.2 Theoretical Framework for the Research

Figure 1.2 illustrates the theoretical framework, providing a visual representation of how these theories interconnect to guide the development and implementation of the AML system. The framework is structured into two complementary parts: learning theories, which include constructivism and connectivism, and instructional theories, which encompass cognitive load theory and Mayer's segmented principles. These components collectively contribute to the concept of adaptive microlearning by addressing both the strategies for knowledge acquisition and the principles of effective instructional design, ensuring the AML system is tailored to meet the unique needs of in-service personnel. Learning theories guide the strategies that engage learners and promote knowledge acquisition, while instructional theories ensure that these strategies are effectively implemented through well-structured content design. For instance, the interactive and participatory nature of constructivism is supported by instructional techniques derived from cognitive load theory, ensuring that the complexity of the content does not overwhelm learners.

Similarly, the flexibility and adaptability emphasized in connectivism are operationalized through Mayer's segmented principles, allowing learners to navigate content in a way that aligns with their unique cognitive capacities and learning contexts.

Constructivism theory asserts that learners construct knowledge through active participation and experiential interaction (Fosnot, 2013). Based on this theory, the AML system was designed to guide in-service personnel to be active learners who participate and interact with the environment to construct knowledge. Connectivism theory posits that learning is realized through network connectivity and information flow, emphasizing the connection of information and knowledge in the digital age (Siemens, 2005). In the AML system, connectivism helps utilize networks and technologies to provide diverse learning resources and information flows, enabling learners to flexibly acquire and apply knowledge.

Cognitive load theory was applied to ensure the AML system manages the cognitive load level of in-service personnel. Based on cognitive load theory, the AML system was designed with appropriate learning tasks and content segmentation to reduce learners' cognitive load and enhance learning efficiency. Mayer's Segmented Principles of multimedia posit that appropriate division and staged presentation of complex information increase learners' attention while minimizing their cognitive load (Mayer, 2014b). Mayer's segmentation principle advocates breaking down learning content into smaller units or parts so that learners can better understand and memorize it. In the AML system, the application of the segmented principle broke down complex information into small, easy-to-digest segments, improving learners' absorption and comprehension.

The AML system was designed to provide personalized and effective learning experiences by integrating guidance from learning and pedagogical theories. The AML system adaptively adjusted learning content and strategies based on learner needs and status to optimize learning outcomes. The AML system utilized the aforementioned theories to design and deliver learning modules that met the needs of in-service personnel and enhanced learning through personalized adjustments and content segmentation. By comparing the differences in learning achievement, cognitive load, self-regulation of learning, and learning adaptability between the AML system and the conventional microlearning system, the effectiveness of the AML system was verified to provide a better learning solution for in-service personnel.

1.9 Significance of the Research

This research provides a potential solution to the learning problems faced by in-service personnel. In-service personnel are not conventional adult students in the traditional sense. They have tight schedules that limit their learning opportunities. They face numerous challenges in learning due to their limited and fragmented time. Despite their limited and fragmented time, they still need to learn for career advancement, salary increases, or directives from their superiors. The success of the research could help by suggesting an alternative way of learning: using a microlearning system that accommodates their fragmented time.

If this research demonstrates positive results, it will provide evidence for the suitability of adaptive microlearning systems for in-service personnel's learning. Such evidence will provide insight into how theoretical frameworks can be applied to develop appropriate microlearning systems for in-service personnel and offer a perspective on the acceptance of such learning systems by in-service personnel.

This research is also of theoretical significance by integrating related theories to design adaptive microlearning, potentially expanding the body of knowledge in microlearning and other online learning approaches for future research. Furthermore, this research encourages future researchers to generalize the learning characteristics of in-service personnel to other categories of learners. For example, this research addresses the learning grit of in-service personnel, which is rarely explored in other studies.

This research provides a practical application for in-service personnel. It designed and developed an adaptive microlearning system for in-service personnel to learn the "WPS Office Software Application" released by the China National Computer Rank Examination. This means the research has practical value for anyone preparing for the formal examination on WPS software. The AML system divided the learning content into fragmented units to align with the in-service personnel's situation, where their time is fragmented and limited. The successful use of the AML system showcases an innovative instructional system for learning highly technical courses, such as the "WPS Office Software Application."

Lastly, the overall findings from this research serve as an empirical reference for companies, enterprises, managers, policymakers, and commercial institutions to determine whether to adopt the adaptive microlearning system in their existing learning settings for in-service personnel. It provides valuable information on how the AML system could serve as an alternative to conventional microlearning systems.

1.10 Operational Definitions

The following terms used in this research are operationally defined as follows:

Online Learning: Online learning refers to learning activities conducted using mobile devices in a network environment (Anderson, 2008). In this research, it involves learning using a smartphone where learners interactively and freely choose the learning content of the “WPS Office Software Application” based on their available learning time and personal needs (Carliner, 2004; Rudestam & Schoenholtz-Read, 2009).

In-Service Personnel: Broadly, in-service personnel refers to individuals who are actively employed and receive remuneration for their work in organizations, including private enterprises, public institutions, and government organizations (Brooks & Ran, 2003). This definition typically encompasses those fulfilling job responsibilities under formal employment contracts or agreements, as defined by Labor Laws of China (Chen & Francesco, 2000). In the context of this research, in-service personnel refers specifically to employees working in cultural media companies in Dongying City, China. The research focuses on a targeted group of active staff aged 35 to 40, who are formally employed and currently engaged in their professional roles. Non-active employees, such as those on medical, maternity, or personal leave, are excluded from the sample. This specific definition reflects the scope and scale of the research, which aims to address the learning needs and challenges of in-service personnel within a clearly defined professional and demographic context.

Fragmented time: Fragmented time refers to the short, irregular intervals of time dispersed throughout a day, often caused by competing responsibilities, such as work deadlines, family obligations, and personal tasks (Matthews, 2023b). This fragmented nature of time poses challenges for completing sustained and uninterrupted activities, impacting productivity and focus in both personal and professional contexts.

Fragmented learning time: Fragmented learning time is a subset of fragmented time, specifically referring to the short, irregular intervals available for learning activities. These intervals are often squeezed between professional and personal responsibilities, making it difficult for learners to engage in structured or prolonged learning sessions (Zhao et al., 2022; Andreev, 2023). In the context of this research, fragmented learning time is a significant barrier to achieving deep, consistent learning outcomes for in-service personnel, necessitating adaptive learning strategies like microlearning.

Microlearning: Microlearning is an online learning system that leverages Internet technology to enable learners to rapidly acquire knowledge and skills through short blocks or units of learning content (Corbeil & Corbeil, 2023). Usually, each small block is called a “module” (Cole, 2017). In this research, microlearning refers to learning acquired from small blocks of content (10-15 minutes) spread across a few modules.

Adaptive learning: Adaptive learning refers to a personalized learning approach that uses technology, algorithms, and data to dynamically adjust learning content, pace, and difficulty according to the individual needs, abilities, and progress of learners (Tseng et al., 2008; Khosravi et al., 2020). The core principle of adaptive learning is to provide tailored educational experiences by continuously analyzing learner behaviors and feedback, ensuring that the content aligns with their current knowledge levels and learning goals. This approach is particularly effective in addressing fragmented learning time and varied learner preferences, as it allows