

**Second Language Learning in the Age of Artificial Intelligence:
A Cognitive–AI Literacy–Reading Integration Model (CAR)**

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**Second Language Learning in the Age of Artificial Intelligence:
A Cognitive–AI Literacy–Reading Integration Model (CAR)**

by

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Abstract

This dissertation addresses the urgent need to understand the cognitive and technological factors influencing L2 Chinese reading comprehension challenges among Southeast Asian ethnic minority students (EMs) within the Hong Kong secondary education system. EMs represent a unique linguistic group for investigating L2 literacy development. They face complex academic and orthographic challenges, mainly due to limited exposure to Chinese language and the cross-script interference involved in shifting from their first languages, such as Urdu, Nepali, and Filipino, to logographic Chinese writing system. This unique linguistic profile makes EM learners ideal for examining how cross-linguistic transfer and cognitive factors jointly shape L2 Chinese reading development. Situated at the intersection of cognitive psychology, educational linguistics, and emerging digital literacy, this dissertation, consisting of four empirical studies, explores the intricate relationships among executive function (EF), reading-related linguistic skills, and AI literacy as predictors of L2 Chinese reading comprehension success of EMs in Hong Kong secondary schools. The methodology includes four large-scale cross-sectional studies with students enrolled in senior high schools (Study 1: N=104; Study 2: N=1669; Study 3: N=155; Study 4: N=155). The central theoretical model postulates three primary hypotheses. First, L2 Chinese reading comprehension fundamentally depends on higher-order executive functions, particularly working memory, inhibitory control, and cognitive flexibility, which regulate attention, manage cross-linguistic interference, and support integration of orthographic and semantic information during reading. Second, AI literacy serves as a metacognitive and technological scaffold that enhances reading comprehension by enabling learners to critically interpret, evaluate, and strategically employ AI-assisted feedback and adaptive learning tools. Third, EF is a significant predictor of AI literacy, reflecting that adaptive cognitive control underpins learners' capacity to engage effectively with AI technologies in complex reading

environments. These hypotheses conceptualize L2 Chinese reading comprehension as an outcome of dynamic interactions among cognitive control, language-specific knowledge, and digital literacy.

The research program consists of four empirical studies. Study 1 investigated the relationship between EF and L2 Chinese reading comprehension. An integrated structural model confirmed the relevance of the working memory, inhibitory control, and cognitive flexibility, demonstrating excellent fit ($\chi^2/df = 2.618$, CFI = .965, TLI = .944, RMSEA = .042). The results revealed that working memory ($\beta = 0.18$, $p < .01$) and cognitive flexibility ($\beta = 0.21$, $p < .05$) were significant positive predictors of reading comprehension. Inhibitory control also showed a significant direct effect, but as a negative predictor ($\beta = -0.28$, $p < .05$), indicating that lower cognitive cost (i.e., better inhibition) was associated with higher comprehension. Orthographic knowledge was a strong direct predictor ($\beta = 0.38$, $p < .001$). A key finding was that orthographic knowledge fully mediated the relationship between working memory and reading comprehension, emphasising a crucial indirect pathway through which cognitive resources support reading development.

Study 2 provides the critical theoretical and psychometric foundation for the AI literacy construct in a relevant Chinese educational context. This study validates the multidimensional ABCE framework (Affective, Behavioral, Cognitive, Ethical) and the AI Literacy Questionnaire (AILQ) using a large sample from Shanghai, China. The selection of this population is highly pertinent as Shanghai, like Hong Kong, is a major metropolitan center where AI education is a strategic priority within the national curriculum, ensuring that the validated instrument is contextually appropriate for use in other advanced Chinese educational systems. Through latent profile analysis, the study identifies four distinct AI literacy profiles and reveals grade level as a significant demographic predictor. The robust findings from Study 2 substantiate the AI literacy construct and provide a validated,

culturally relevant measurement tool for investigating its role in the subsequent studies within the Hong Kong context.

Study 3 established AI literacy as a significant and unique predictor of L2 Chinese reading comprehension among EM learners applying AI-powered platform. SEM revealed a significant direct effect of AI literacy on reading comprehension ($\beta = .26, p = .004$).

Furthermore, an indirect pathway was identified, indicating that orthographic knowledge partially mediates this relationship ($\beta = .06, p = .018$). While orthographic knowledge itself was the strongest direct predictor ($\beta = .38, p < .001$), the findings confirm that AI literacy contributes to reading proficiency through both direct and indirect cognitive-linguistic pathways, underscoring its essential role in technology-mediated L2 learning environments.

Study 4 integrated AI literacy into the SEM framework, examining both mediating and moderating mechanisms of reading comprehension. A significant direct effect was established, demonstrating that cognitive flexibility is a strong predictor of AI literacy ($\beta=0.070, p<.001$), suggesting that the mental adaptability component of EF is a cognitive prerequisite for successful engagement with emerging AI-mediated learning environments. In turn, AI literacy was found to be a significant positive predictor of L2 Chinese reading comprehension ($\beta=0.190, p<.05$). Most importantly, the integrated latent variable model provided statistical evidence for a significant indirect effect of cognitive flexibility on reading comprehension that was mediated by AI literacy. This mediational pathway establishes a proposed Cognitive–AI Literacy–Reading Integration Model (CAR), conceptualizing how higher-order cognitive processes interface with digital competence to support L2 reading in AI-enhanced educational contexts. Specifically, CAR posits that EF enables learners to manage cognitive load, adapt strategies, and transfer knowledge across learning modalities, while AI literacy provides the technological means to operationalize these abilities in digital environments.

This dissertation makes four primary contributions. First, it validates the structure of Executive Function and its predictive value for L2 Chinese literacy. Second, it confirms the pivotal role of orthographic knowledge in reading comprehension within a logographic system. Third, and foundationally, it introduces and legitimizes the multidimensional ABCE framework of AI literacy for educational research, by validating its core construct and providing a robust psychometric tool (the AILQ) for its measurement, which enabled the subsequent investigations. Fourth, it establishes AI literacy as a significant mediating mechanism linking the cognitive capacity of cognitive flexibility to L2 reading success, thereby proposing and validating the Cognitive–AI Literacy–Reading Integration Model (CAR). This mediational pathway offers an empirically validated extension of existing L2 reading frameworks into the digital age.

Taken together, the findings provide theoretical innovation. The proposed CAR model reconfigures L2 reading theory by demonstrating that effective reading comprehension necessitates the flexible integration of cognitive skills with digital competence, moving beyond a purely psycholinguistic scope. The results also provide clear practical implications, suggesting the necessity of explicit training modules that foster AI literacy skills to evaluate contrasting outputs and adapt their strategies accordingly. Additionally, the findings guide policy by advocating for AI-mediated reading platforms to be designed to scaffold EF, such as by using prompts to encourage adaptive strategy use or by regulating the working memory load.

Keywords: Cognitive–AI Literacy–Reading Integration Model (CAR), Executive Function, AI Literacy, L2 Chinese Reading Comprehension, Ethnic Minority Students.

Declaration

I declare that this thesis represents my own work. It has not been previously included in a thesis, dissertation, or report submitted to this University or to any other institution for a degree, diploma, or other qualification. I also declare that any use of artificial intelligence tools in the preparation of this thesis was limited to language proofreading.

Signature: _____

Sun Zhengliang

January 2026

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Table of Contents

<i>Abstract</i>	3
<i>Declaration</i>	7
<i>Acknowledgments</i>	8
<i>Chapter 1 Introduction</i>	14
1.1 Background.....	14
1.2 Research Aims	16
1.3 Research Questions	19
1.4 Hypotheses	19
1.5 Operational Definitions.....	20
1.6 Theoretical assumptions	21
1.7 Significance of the study	22
1.8 Organization of dissertation	25
<i>Chapter 2 Literature Review of Executive function</i>	27
2.1 Overview.....	27
2.2 Theories of Executive function.....	28
2.2.1 The structure and components of Executive Function	28
2.2.2 Executive functions and language learning.....	29
2.3 Executive function components and reading comprehension	32
2.3.1 Working memory and reading comprehension	32
2.3.2 Inhibitory control and reading comprehension.....	36
2.3.3 Cognitive flexibility and reading comprehension.....	39
2.3.4 EF contributing to reading comprehension as a unity.....	42
2.4 Conclusion.....	44
<i>Chapter 3 Literature Review of Reading Comprehension</i>	46
3.1 Overview.....	46
3.2 The nature of Reading Comprehension	47
3.3 Theories of Reading.....	48
3.3.1 Construction-Integration model.....	49
3.3.2 Structure Building Framework.....	54
3.3.3 Constructionist theory.....	59
3.3.4 Reading Systems Framework.....	64
3.3.5 Conclusion: Reading comprehension as a cognitive process	67
3.4 Chinese Reading	69
3.4.1 Reading comprehension in Chinese	71
3.4.2 Reading related skills in Chinese	76
3.4.3 Challenge of Chinese reading comprehension for L2 learners	82
3.5 Conclusion.....	86
<i>Chapter 4 Literature Review of Artificial Intelligence and Education</i>	89
4.1 Overview.....	89
4.2 Artificial Intelligence and Education.....	90
4.2.1 The nature of Artificial Intelligence	90

4.2.2 Artificial Intelligence in the Education Context	92
4.2.3 The Role of Artificial Intelligence in Language Learning	94
4.2.4 Summary	96
4.3 Theories of AI literacy	97
4.3.1 What is AI literacy.....	98
4.3.2 AI Literacy Frameworks	99
4.3.3 Integrating AI Literacy into Language Education	102
4.4 Assessment for AI literacy	104
4.5 Conclusion of literature review	107
4.5.1 Executive Function as the Cognitive Engine for Reading Comprehension	107
4.5.2 Reading Comprehension as A Multi-Layered Cognitive Process	108
4.5.3 AI Literacy: Navigating the Future of Language Learning	108
4.5.4 Cognitive Mechanisms of AI Literacy, EF, and Reading Comprehension	109
Chapter 5 Study 1: Exploring the Relationship Between Executive Function and L2 Chinese Reading Comprehension in Hong Kong Learners.....	112
5.1 Introduction	112
5.2 The relation between EF and Chinese reading comprehension.....	113
5.2.1 Working Memory and Reading Process.....	113
5.2.2 Inhibitory Control and Its Role in Resolving Linguistic Interference	114
5.2.3 Cognitive Flexibility and Adaptive Reading Strategies	115
5.2.4 The Present study	116
5.2.5 Research Questions	117
5.3 Method.....	118
5.3.1 Participants	118
5.3.2 Research Instruments	118
5.3.3 Research Procedure.....	121
5.3.4 Data analysis	122
5.4 Results.....	122
5.5 Discussion	126
5.6 Conclusion.....	130
Chapter 6 Study 2: AI Literacy Development in Middle School: Profiles and Demographic Predictors from an ABCE Perspective	132
6.1 Introduction	132
6.2 Literature Review.....	133
6.2.1 The Definition of AI Literacy	133
6.2.2 Factors Contributing to Middle School Students' AI Literacy	136
6.2.3 The Present Study.....	138
6.3 Method.....	139
6.3.1 Participants	139
6.3.2 Data Analysis	140
6.4 Results.....	142
6.5 Discussion	149
6.6 Conclusion.....	156
Chapter 7 Study 3: The Role of AI Literacy in Chinese L2 Reading Comprehension: Evidence from Adolescent Learners in Hong Kong.....	157
7.1 Introduction	157
7.2 Literature Review.....	159

7.2.1 Challenges in L2 Chinese reading.....	159
7.2.2 Artificial intelligence in education and language learning.....	160
7.2.3 Concepts and frameworks of AI literacy.....	161
7.2.4 Theoretical framework of the present study.....	162
7.3 Methodology.....	163
7.3.1 Participants.....	163
7.3.2 Measures.....	164
7.3.3 Procedure.....	166
7.3.4 Data analysis.....	167
7.4 Results.....	167
7.4.1 Preliminary Analyses.....	167
7.4.2 Pearson Analyses.....	168
7.4.3 Hierarchical Regression Analysis.....	169
7.4.4 Path analysis.....	169
7.5 Discussion.....	170
7.5.1 AI literacy and reading comprehension in context.....	171
7.5.2 Orthographic knowledge as a pathway from AI literacy to reading.....	171
7.5.3 Rethinking the role of morphological awareness.....	172
7.5.4 The supportive role of AI literacy in human–AI collaboration.....	174
7.5.5 Implications.....	175
7.6 Conclusion.....	177
<i>Chapter 8 Study 4: Second Language Learning in the Age of Artificial Intelligence: An Integrated Model of Executive Function, AI Literacy and Reading Comprehension.....</i>	<i>179</i>
8.1 Introduction.....	179
8.2 Literature Review.....	181
8.2.1 Challenges of Chinese L2 learning.....	181
8.2.2 L2 learning in AI Era.....	182
8.2.3 The role of EF in L2 learning and AI literacy.....	185
8.2.4 Theoretical framework.....	186
8.3 Methodology.....	189
8.3.1 Research Design.....	189
8.3.2 Participants.....	190
8.3.3 Measures.....	190
8.3.4 Procedure.....	191
8.3.5 Data analysis.....	192
8.4 Results.....	192
8.5 Discussion.....	195
8.6 Implication.....	197
8.7 Conclusion.....	199
<i>Chapter 9 General Discussion.....</i>	<i>201</i>
9.1 Overview.....	201
9.2 Research objectives and research questions.....	201
9.3 Findings.....	202
9.3.1 The structure of executive function.....	202
9.3.2 The Relation between reading skills and L2 reading comprehension.....	204
9.3.3 Relation among executive function, reading skills, and L2 reading comprehension.....	205
9.3.4 The Multidimensional Structure of AI Literacy.....	210
9.3.5 Relation between executive function and AI literacy.....	212
9.3.6 Relation between AI literacy and L2 reading comprehension.....	214

9.4 Limitation.....	216
9.5 Implication	219
9.5.1 Theoretical Implications	219
9.5.2 Pedagogical Implications	221
<i>Chapter 10 Conclusion</i>	<i>224</i>
<i>Reference.....</i>	<i>227</i>

Chapter 1 Introduction

1.1 Background

Second language (L2) acquisition entails more than the mere accumulation of linguistic knowledge (Bulté et al., 2025; Wang & Christiansen, 2024). It constitutes a complex process that engages a diverse array of cognitive and communicative skills. A critical cognitive foundation for successful L2 learning, particularly for languages with complex, logographic writing systems like Chinese, is executive functions (EFs) (Diamond, 2013; Mingjia & Liao, 2025; Miyake et al., 2000). Core EFs, specifically working memory, inhibitory control, and cognitive flexibility, play distinct yet complementary roles. Working memory facilitates the retention and manipulation of unfamiliar orthographic forms while simultaneously integrating semantic information; inhibitory control enables learners to suppress interference from their first language (L1), thereby minimizing cross-linguistic interference (Korko & Williams, 2017); and cognitive flexibility supports the shifting between disparate syntactic structures, character forms, and contextual cues (Lehtonen et al., 2023; Perfetti & Harris, 2013; Rivera et al., 2023). Ultimately, EFs are indispensable not only for lower-level processes like character recognition and vocabulary acquisition but also for higher-order competencies such as inference and reading comprehension, which require the coordination of multiple layers of linguistic and contextual information (Kintsch, 1998).

The foundational role of EFs is further amplified in digital learning environments mediated by artificial intelligence (AI) (Li & Lan, 2022; Zhou & Hou, 2024). Such intelligent systems introduce novel cognitive demands, requiring learners to navigate non-linear learning paths, evaluate automated feedback, and self-regulate their interactions with the technology. These complex activities place a significant premium on higher-order cognitive skills. Consequently, the integration of AI necessitates the parallel development of AI literacy,

which can be defined as the suite of competencies required to effectively understand and critically evaluate AI technologies (Ghosh, 2025). Moreover, this form of literacy is becoming indispensable in the contemporary L2 landscape. For instance, to optimize their learning, students must now engage with platforms that provide personalized character recognition feedback, adaptive reading materials, and real-time grammatical suggestions; doing so effectively requires a fundamental understanding of the underlying AI's capabilities and limitations to interpret its guidance appropriately (Chopra et al., 2024). This synergy suggests a mutually reinforcing relationship between EF and AI literacy, wherein robust EFs facilitate the acquisition of AI literacy, which in turn structures learning in ways that further challenge and refine EFs. This interdependence is integral to successful L2 acquisition and proves particularly critical when mastering cognitively demanding languages such as Chinese (Pergantis et al., 2025).

The intersection of EF and AI literacy represents a significant paradigm shift in language pedagogy, moving from instructor-led models of rote memorization toward dynamic, learner-centered ecosystems mediated by AI (Mammadova et al., 2025). This transformation, however, introduces new challenges, as learners are now required to make autonomous decisions, filter vast amounts of information, and engage independently with feedback systems. Thus, successfully navigating such technologically enhanced environments necessitates both robust executive control and the capacity to critically interpret and interact with AI tools. In the absence of sufficient EF, learners may find it difficult to manage the increased cognitive load imposed by adaptive systems; conversely, without adequate AI literacy, even individuals with strong EF may misinterpret system outputs or develop an overreliance on automated assistance. Therefore, the cultivation of both EF and AI literacy is not merely advantageous but constitutes a dual imperative for contemporary L2 education (Pinski, 2024).

Despite the growing recognition of the individual importance of EF and AI literacy, research examining these constructs within L2 contexts has largely progressed along parallel, non-intersecting trajectories. A critical gap exists in the empirical investigation of their interaction within authentic classroom settings, where learners routinely engage with technologies like intelligent tutoring systems, adaptive testing platforms, and generative AI chatbots. For instance, foundational studies by Kapa and Colombo (2014) demonstrated how EF skills predicted success in acquiring an artificial language, and Gooch et al. (2016) examined reciprocal associations between EF and language development in early learners. More recent scholarship, such as that by Li and Lan (2022), has discussed the broader role of AI-mediated platforms in education, while Pergantis et al. (2025) have highlighted how cognitive regulation supports engagement with AI tools. Yet, it is precisely at the confluence of these domains within technologically mediated learning environments that the dynamic interplay among EF, AI literacy, and L2 achievement assumes its greatest relevance. In these contexts, learners must efficiently allocate cognitive resources to interpret AI-generated feedback, shift flexibly between multiple linguistic representations, and critically evaluate and integrate system-generated suggestions into their developing language proficiency. Elucidating this complex synergy is therefore essential not only for advancing theoretical models but also for providing curriculum designers and language instructors with the empirical foundation needed to equip learners for the linguistically and technologically complex demands of the twenty-first century.

1.2 Research Aims

While the significance of EF and AI literacy is increasingly acknowledged, their interrelationship remains a critical and under-researched area, particularly in the context of L2 acquisition. This dissertation addresses this gap by proposing a four-study sequence that

meticulously investigates how these cognitive and digital competencies interact to shape Chinese L2 reading comprehension in AI-mediated environments. This multi-phase approach facilitates a systematic exploration, moving from establishing the role of the digital skill (AI literacy) to integrating it with the foundational cognitive mechanisms (EF) that underpin both tool use and language processing.

Study 1 lays the cognitive foundation of the dissertation by investigating the relationship between EF and L2 Chinese reading comprehension. Drawing on the tripartite model of EF comprising working memory, inhibitory control, and cognitive flexibility, this study examines how these interrelated cognitive mechanisms contribute to learners' ability to process, interpret, and comprehend Chinese texts. By establishing the predictive relationships among EF components, orthographic knowledge, and reading comprehension, Study 1 provides the essential cognitive baseline for the subsequent investigations.

Study 2 provides the essential conceptual and methodological foundation for the digital dimension of this research. Before the role of AI literacy can be investigated, its construct must be rigorously defined and measured. Therefore, this study adopts and validates the multidimensional ABCE framework (Affective, Behavioral, Cognitive, Ethical) of AI literacy and its corresponding instrument, the AI Literacy Questionnaire (AILQ). By establishing a robust measurement model, this study ensures that the subsequent investigations of AI literacy are built upon a psychometrically sound and theoretically grounded basis.

Study 3 builds upon the findings of the first two studies, constructing a more comprehensive and integrated model. This part of the research integrates three key executive functions including working memory, inhibitory control, and cognitive flexibility to explore how they combine with AI literacy to predict reading comprehension. The core theoretical premise is that learners with stronger executive functions are better equipped to manage the significant cognitive demands of both language processing and the strategic use of AI tools.

Moreover, this study investigates a specific, theoretically grounded mediating pathway that cognitive flexibility, the ability to adapt thinking and switch between different tasks or mental sets, is a prerequisite for the effective adoption and application of AI literacy, which then, in turn, influences reading comprehension outcomes. This pathway suggests a hierarchical relationship where a core cognitive skill enables the strategic use of a digital skill, ultimately leading to improved academic performance.

Study 4 seeks to elucidate the complex interrelationships among EF, AI literacy, and L2 learning, with a particular focus on reading comprehension within AI-mediated learning environments. Grounded in theories from cognitive linguistics and educational technology, this final study models the relational dynamics among executive function, AI literacy, and Chinese reading comprehension performance. It takes into account the unique challenges posed by the Chinese orthographic system and the cognitive demands inherent in the use of AI tools.

Therefore, the present dissertation is guided by the following primary aims:

1. To examine the structural components of executive function, specifically working memory, inhibitory control, and cognitive flexibility, among learners of Chinese as a second language.
2. To identify both the direct and indirect pathways through which executive function and AI literacy contribute to Chinese reading comprehension in L2 learners.
3. To model the relational dynamics among executive function, AI literacy, and Chinese reading comprehension performance in the context of AI-mediated learning, taking into account the unique challenges posed by the Chinese orthographic system and the cognitive demands inherent in the use of AI tools.

1.3 Research Questions

To address the existing literature gaps and test the proposed integrated model, the following research questions were formulated, adhering to the hierarchical and structural relationships often explored in path analysis:

1. What is the structure of executive function (working memory, inhibitory control, cognitive flexibility) among Chinese second language learners?
2. How do second language learners' levels of executive function and AI literacy individually and interactively relate to their Chinese reading comprehension?
3. To what extent does AI literacy mediate the relationship between executive function capacities and Chinese reading development of second language learners in the context of AI-powered language learning tools?

1.4 Hypotheses

This dissertation formulates a series of hypotheses to examine how EF and AI literacy interact to influence Chinese L2 reading comprehension in AI-mediated learning environments.

1. Executive function, comprising working memory, inhibitory control, and cognitive flexibility, will significantly predict Chinese L2 reading comprehension.
2. AI literacy will significantly predict Chinese L2 reading comprehension and partially mediate the relationship between executive function and reading comprehension.
3. Executive function, comprising working memory, inhibitory control, and cognitive flexibility, will significantly predict AI literacy, reflecting that adaptive cognitive skills underpin effective engagement with AI tools in second language reading contexts.

1.5 Operational Definitions

This study investigates the interplay of cognitive skills, AI literacy, and L2 learning. The cognitive dimension involves EF, while the cognitive aspects of AI learning are defined by AI literacy, encompassing conceptual understanding and applied reasoning.

First, *executive function* refers to a set of higher-order cognitive processes crucial for goal-directed behavior, self-regulation, and adaptive problem-solving (Diamond, 2013; Miyake & Friedman, 2012). EFs, in this study, are comprised of three core components:

Working memory is the dynamic cognitive system responsible for the active maintenance and manipulation of information (Baddeley, 2013; Nee & D'Esposito, 2015). This involves the learner's capacity to hold and process linguistic information, such as vocabulary, grammar rules, and sentence structures, during L2 tasks.

Inhibitory control is the ability to suppress dominant responses and resist interference from both internal and external distractions (Diamond, 2013; Munakata et al., 2011). Within L2 learning, this includes managing interference from the learner's first language (L1) and focusing attention on L2-specific rules.

Cognitive flexibility is the capacity to adaptively shift between mental sets, tasks, or responses to changing demands (Ionescu, 2012). For L2 learners, this is essential for switching between linguistic subsystems and adapting to different learning contexts, including those involving AI.

Second, the cognitive dimension of learning about AI involves *AI Literacy*, which is defined as the capacity to critically understand, effectively engage with, and appropriately apply AI-related knowledge, skills, and ethical considerations (Long & Magerko, 2020). This study examines four constructs within AI literacy.

Know and Understand AI. The ability to grasp fundamental AI concepts, including how AI systems function (e.g., machine learning, natural language processing), their strengths, and limitations.

Use and Apply AI. Practical competence in leveraging AI tools for language learning tasks, such as interacting with generative AI (e.g., ChatGPT) for writing feedback or using adaptive platforms for reading comprehension.

Evaluate and Create AI. Higher-order cognitive skills to critically assess AI-generated content (e.g., detecting biases in translations) and creatively design AI-aided solutions (e.g., crafting prompts to elicit culturally appropriate responses).

AI Ethics. Higher-order cognitive skills to critically assess AI-generated content (e.g., detecting biases in translations).

Third, *Second Language (L2) Learning* refers to the process by which individuals acquire proficiency in a language other than their native language. In this study, the focus is on:

L2 reading comprehension refers to the ability to decode, comprehend, and interpret written texts in the L2. It involves a range of skills from basic word recognition to higher-level text comprehension and critical analysis.

1.6 Theoretical assumptions

This study is predicated on several fundamental assumptions concerning the cognitive and technological dimensions of L2 acquisition. First, it is assumed that successful L2 acquisition is fundamentally rooted in cognitive processes, wherein learners actively

construct meaning and develop linguistic proficiency through the coordinated deployment of EFs. Specifically, learners utilize working memory to retain and manipulate linguistic information, employ inhibitory control to mitigate L1 interference, and exercise cognitive flexibility to adapt to the dynamic demands of L2 communication (Diamond, 2013; Miyake & Friedman, 2012).

Second, the integration of AI into L2 learning environments is assumed to introduce qualitatively new cognitive demands. While AI tools offer potential support for learning, they simultaneously require learners to develop novel cognitive strategies for effective engagement. This includes interpreting automated feedback, navigating adaptive learning platforms, and interacting with AI-driven communicative agents.

Third, this study operates under the assumption that AI literacy serves as a pivotal moderating factor in technology-enhanced L2 learning contexts. Learners with higher AI literacy are expected to utilize AI tools more effectively, thereby optimizing their cognitive resources and mitigating the inherent cognitive load of L2 processing. Conversely, learners with limited AI literacy are likely to experience heightened cognitive strain due to difficulties in comprehending and leveraging AI technologies, potentially undermining the intended benefits of AI-mediated instruction.

1.7 Significance of the study

This dissertation makes both theoretical and practical contributions to the field of second language acquisition in the digital age through the formulation and empirical validation of the CAR model. The CAR model conceptualizes L2 Chinese reading as an outcome of dynamic interactions among EF, AI literacy, and linguistic knowledge, thereby

offering a comprehensive framework for understanding literacy development in technologically mediated learning environments.

First, this research provides a critical methodological and conceptual foundation for the study of AI literacy in educational contexts by adopting and validating the multidimensional ABCE framework and its corresponding instrument, the AILQ. By grounding the construct of AI literacy in a robust psychometric model, the study moves beyond vague definitions and provides researchers and educators with a reliable tool to assess this emerging competency. This foundational work is a prerequisite for systematic inquiry into how AI literacy functions across diverse learner populations, including ethnic minority students.

Second, the study positions AI literacy as a novel and empirically validated predictor of Chinese L2 reading comprehension within the CAR framework. While traditional research on reading has emphasized linguistic foundations such as orthographic, morphological, and phonological knowledge, this work demonstrates that the ability to critically engage with AI systems is itself a determinant of reading outcomes in digitally mediated environments. By conceptualizing AI literacy as more than a peripheral digital skill and instead as an essential literacy competency, the study extends current understandings of what constitutes effective reading in contemporary educational contexts.

Third, the dissertation confirms the importance of a multidimensional model of EF in supporting logographic literacy. The validation of working memory, inhibitory control, and cognitive flexibility as distinct but interrelated predictors of Chinese reading underscores the cognitive complexity of learning a logographic script. This finding contributes to the broader literature on EF and bilingualism by showing that higher-order cognitive control processes are not only relevant in alphabetic L2 contexts but are indispensable for navigating the visual, semantic, and structural demands of Chinese characters.

Fourth, the dissertation advances the field by integrating cognitive and digital literacies within a single explanatory framework. Rather than treating EF and AI literacy as parallel domains, the findings demonstrate that these competencies interact dynamically: cognitive flexibility significantly predicts AI literacy, which in turn predicts reading comprehension. This mediating pathway provides a new account of how cognitive processes underpin learners' ability to engage with intelligent systems, offering a theoretically grounded model of reading development in the AI era.

From a pedagogical perspective, the CAR framework underscores the need to embed explicit AI literacy instruction within L2 curricula, ensuring that learners develop not only linguistic knowledge but also the cognitive adaptability and critical evaluation skills required to interact with AI systems effectively. Simultaneously, it suggests that AI-assisted learning platforms should be intentionally designed to scaffold EF by regulating working-memory load, prompting strategic flexibility, and reducing cognitive interference to enhance learning efficiency.

From a theoretical standpoint, the CAR model advances existing models of L2 reading by demonstrating how cognitive and digital competencies converge to produce literacy in the age of artificial intelligence. It challenges the traditional separation between linguistic and technological literacies and reconceptualizes L2 reading as a multifaceted process situated within a cognitive–digital ecosystem. Ultimately, this research highlights that successful second-language acquisition, particularly in logographic systems such as Chinese, is best explained not by isolated variables but by the interactive interplay of cognitive control, digital competence, and linguistic expertise as articulated in the CAR model.

1.8 Organization of dissertation

This dissertation is structured to provide a systematic investigation of the interplay between EF, AI literacy, and Chinese L2 reading comprehension. The research is grounded in the theoretical and empirical literature reviewed in Chapter 2.

Chapter 2 establishes the study's foundation with a comprehensive review of literature on EF and its role in L2 acquisition. Chapter 3 follows with an analysis of reading comprehension, with a specific focus on the cognitive challenges of the Chinese orthographic system. Chapter 4 concludes the literature review by examining the construct of AI literacy and its emerging role in technology-mediated language learning. Collectively, these chapters synthesize existing scholarship and identify the critical gaps this dissertation aims to address the overarching theoretical framework, research questions, and hypotheses.

Chapter 5 presents Study 1, which establishes the role of core EFs in L2 Chinese reading. It details the specific methodology, analytical procedures using SEM, and results. The chapter reports the significant direct effects of working memory and cognitive flexibility, the nuanced negative prediction of inhibitory control, and the critical finding that orthographic knowledge fully mediates the relationship between working memory and reading comprehension.

Chapter 6 presents Study 2, which provides the essential psychometric and conceptual foundation for the AI literacy construct. This chapter summarizes the validation of the ABCE framework and the AI Literacy Questionnaire (AILQ) in a large student population. It details the identification of four distinct AI literacy profiles and the significant demographic predictors of profile membership, thereby establishing a validated model and tool for the subsequent studies.

Building on the cognitive model, Chapter 7 (Study 3) introduces AI literacy as a key variable. It outlines the methodology for testing AI literacy's unique contribution, presenting SEM results that confirm its significant direct effect on reading comprehension and the partial mediation of this relationship through orthographic knowledge. This study establishes AI literacy as an essential component in technology-mediated L2 learning.

Chapter 8 presents the Study 4, which integrates EF and AI literacy into a single comprehensive model. It describes the SEM analysis that tests both mediating and moderating mechanisms. The chapter reports the key findings: that cognitive flexibility is a strong predictor of AI literacy, and that AI literacy mediates the relationship between cognitive flexibility and reading comprehension of L2 Chinese. These results provide the empirical basis for proposing the CAR model.

Chapter 9 provides a synthesized discussion of the findings from all four studies. It interprets the collective results, explaining the intricate relationships between cognitive skills, digital literacy, and linguistic knowledge. The discussion revisits the theoretical framework, explores implications for theory and practice, and elaborates on the significance of the proposed CAR model.

Finally, Chapter 10 concludes the dissertation by summarizing the principal findings, highlighting the study's contributions, acknowledging its limitations, and proposing directions for future research. This chapter also underscores the practical implications of the research for language education, the integration of AI in learning environments, and the development of AI literacy among language learners.

Chapter 2 Literature Review of Executive function

2.1 Overview

A substantial body of research has established the pivotal role of executive functions (EF) in reading comprehension, demonstrating their involvement in cognitive processes ranging from basic word recognition to complex text interpretation (García et al., 2021; Perfetti & Harris, 2013). Intervention studies have further corroborated this relationship, indicating that targeted EF training can lead to significant improvements in reading comprehension outcomes (García-Madruga et al., 2016). However, the extant literature has predominantly concentrated on first language acquisition within alphabetic writing systems, such as English and Spanish, which leaves a critical gap in our understanding of the role of EF in second language acquisition involving logographic systems, such as Chinese. The present chapter seeks to address this gap by systematically reviewing the literature with two primary objectives: (1) to elucidate the cognitive mechanisms by which EF facilitates reading comprehension, and (2) to formulate empirically testable hypotheses regarding the operation of these executive processes in second language reading comprehension, as situated within the theoretical framework guiding this study.

This chapter provides a comprehensive review of EF and its critical role in supporting reading comprehension, with particular emphasis on second language (L2) learners. Section 2.2 examines the theoretical foundations of EF, tracing its conceptual development from early neuropsychological models to contemporary frameworks. This section highlights the three core components of EF, working memory, inhibitory control, and cognitive flexibility, and analyzes their interrelated functions in both cognitive and linguistic tasks. Section 2.3 presents empirical evidence linking each component of EF, as well as the synergistic role of

EF as an integrated system, to reading comprehension. Finally, Section 2.4 concludes by synthesizing the dynamic and multifaceted nature of EF in reading processes.

2.2 Theories of Executive function

EF is a well-established construct in psychological research, traditionally associated with behavioral regulation, problem-solving, planning, and a range of higher-order cognitive processes (Drigas et al., 2019). In recent years, its significance within the domain of language research has garnered increasing scholarly attention. Accordingly, this section begins by introducing the concept of EF and provides a critical review of the relevant literature pertaining to its role in cognitive and linguistic domains.

2.2.1 The structure and components of Executive Function

EF encompasses a suite of higher-order cognitive processes that regulate goal-directed behavior, facilitating planning, sustained attention, and adaptation to dynamic environments (Diamond, 2013). These processes are fundamental to problem-solving, decision-making, and self-regulation across the lifespan. The conceptualization of EF has evolved considerably, from early neuropsychological models such as those proposed by Luria (1966), which emphasized the role of the frontal lobes in orchestrating complex behavior, to contemporary frameworks that delineate distinct yet interrelated subcomponents. However, there is broad consensus in the literature that EF comprises three core components: inhibitory control, working memory, and cognitive flexibility (Miyake et al., 2000). Inhibitory control refers to the ability to suppress automatic or prepotent responses in favor of task-relevant actions, such as resisting distractions during focused activities (Diamond, 2013). Working memory denotes the capacity to temporarily hold and manipulate information, thereby supporting reasoning, comprehension, and planning (Baddeley, 2021). Cognitive flexibility involves the ability to

shift between tasks, strategies, or mental sets, thereby enabling adaptive problem-solving and perspective-taking (Monsell, 2003). Empirical studies employing factor analytic techniques (e.g., Miyake et al., 2000) have demonstrated that while these components are distinguishable, they are also highly interrelated, collectively constituting an integrated cognitive system.

Theoretical models of EF differ in their emphases and conceptualizations. For example, Miyake and Friedman (2012) proposed an integrative framework that posits both a common EF component and specific components such as shifting and updating. In contrast, Diamond (2013) advanced a functionally interactive model, wherein working memory, inhibitory control, and cognitive flexibility collectively contribute to EF-related outcomes. More recently, Cragg and Chevalier (2022) have underscored the developmental trajectories and neural substrates of these components, advocating for a dynamic systems perspective on EF.

Given the centrality of EF to cognitive development and learning, particularly in the context of reading, numerous studies have investigated its role in reading acquisition and comprehension. Consistent with this body of literature, the present study adopts a multidimensional conceptualization of EF, defining it as a cognitive system comprising interrelated elements such as goal setting and planning, behavioral regulation, attentional control, memory management, cognitive flexibility, and self-monitoring. This comprehensive framework informs the theoretical approach to examining the relationship between EF and word reading processes among second language learners.

2.2.2 Executive functions and language learning

EF have been recognized as a fundamental cognitive foundation for language learning and use. For instance, working memory is indispensable for manipulating linguistic information, including vocabulary, grammatical structures, and discourse context, thereby

facilitating the acquisition of new lexical items, the processing of complex sentences, and the integration of information across extended discourse. Inhibitory control plays a critical role in managing interference from the learner's L1 during L2 acquisition. It enables learners to suppress dominant L1 responses, attend to L2-specific rules and patterns, and resolve competition between conflicting linguistic representations; Cognitive flexibility supports the ability to switch between different linguistic systems, adapt to diverse communicative demands, and employ a range of learning strategies. This capacity is particularly salient in L2 learning contexts, where learners must navigate varying accents, grammatical structures, and pragmatic conventions. Collectively, these components of EF underpin the complex cognitive processes required for successful language acquisition and use.

Kapa and Colombo (2014) investigated the bidirectional relationship between EF and language learning, specifically examining whether individuals with stronger EF skills demonstrate greater success in acquiring a novel artificial language. The research comprised two studies: Study 1 involved monolingual adults, while Study 2 focused on monolingual preschool children. Both studies controlled for working memory capacity and native language vocabulary to isolate the effects of EF. The results indicated that, among adults, inhibitory control was a significant predictor of artificial language learning, whereas in children, attentional shifting and monitoring were more predictive of language acquisition outcomes. These findings suggest that EF plays a critical role in the initial stages of language learning, particularly in vocabulary acquisition, thereby supporting the notion that EF skills can facilitate language learning. This has important implications for second language (L2) education and intervention strategies. Furthermore, the results caution against attributing bilingual advantages in EF solely to bilingual experience, as pre-existing differences in EF may also contribute to language learning success.

Gooch et al. (2016) investigated the relationship between EF and language skills during the early school years, utilizing a sample of children with a broad spectrum of language abilities, including those at risk for dyslexia or language impairment. The authors conducted a longitudinal analysis to examine the reciprocal associations between EF and language skills from preschool through the onset of formal schooling. Additionally, the study explored the extent to which these skills predict subsequent attention and behavioral outcomes. The findings revealed a robust concurrent association between language abilities and EF at each assessment point. However, longitudinal analyses indicated that the predictive influence of language skills on later EF (and vice versa) was weak and not statistically significant within this cohort. Importantly, EF skills, but not language skills, were found to be significant predictors of later attention and behavioral ratings. These results suggest that while EF and language skills are closely linked during early development, their longitudinal influence on one another is limited. The findings further underscore the unique contribution of EF to the development of attention and behavioral regulation in early childhood.

Frolli et al. (2022) examined the relationship between EF and foreign language learning in children aged 4 to 5 years, with the aim of elucidating the interaction between these cognitive processes. Participants were divided into three groups according to their level of foreign language proficiency, and their performance on a battery of EF tasks was compared across groups. The findings indicated that children with higher levels of foreign language proficiency demonstrated superior performance on EF tasks. This association suggests that advanced foreign language proficiency is linked to enhanced executive functioning in early childhood. However, the study did not establish a causal relationship between foreign language proficiency and EF. The authors propose that foreign language learning may contribute to the development of EF, or conversely, that stronger EF skills may facilitate foreign language acquisition.

The preceding review highlights the intricate interplay between language and EF, a relationship that is pivotal to multiple facets of learning and development. Notably, research emphasize the concurrent association between language abilities and EF during the early school years, as well as the predictive value of EF for subsequent attention and behavioral outcomes (Frolli et al., 2022; Gooch et al., 2016). Building upon these findings, the following section of this dissertation will examine the individual components of EF including working memory, inhibitory control, and cognitive flexibility and analyze their respective relationships with reading comprehension, a core dimension of academic achievement in language learning.

2.3 Executive function components and reading comprehension

Building on the literature on EF and language learning, this section aims to synthesizes empirical findings that link each EF component, working memory, inhibitory control, and cognitive flexibility, to specific reading processes, and then considers how these components function collectively. While the relationships between individual EF components and reading comprehension are discussed separately for analytical clarity, the present study conceptualizes EF as an integrated construct. In line with Miyake's (2000) framework, EF is treated as comprising both a common underlying factor and component-specific variance. Accordingly, operational measures of EF are derived from psychometric assessments encompassing all three components.

2.3.1 Working memory and reading comprehension

Working memory is a foundational cognitive mechanism for literacy development across diverse linguistic contexts (Bull & Scerif, 2001; García et al., 2021; McCabe et al., 2010; St Clair-Thompson & Gathercole, 2006; Titz & Karbach, 2014). Distinct from simple

short-term memory, which is limited to passive storage, working memory entails the active maintenance and concurrent manipulation of verbal and visuospatial information. These dual functions of storage and processing are critical for a range of literacy-related skills, including word recognition, lexical access, and text production (Daneman & Merikle, 1996). Moreover, working memory is not an isolated system but operates in close interaction with EFs, which facilitate attentional control, updating, and inhibition—regulatory processes that modulate the efficiency of working memory operations. This integrative framework positions working memory as a core component of cognitive architecture essential for supporting the complex demands of literacy acquisition and proficient reading performance.

In the context of reading comprehension, working memory is recognized as a central cognitive mechanism that supports the temporary storage and manipulation of information necessary for meaning construction. Reading is not merely a decoding task but a dynamic process wherein readers generate and maintain phonological and semantic representations of textual content, draw inferences, and integrate incoming information with prior knowledge and contextual cues (Shin et al., 2019). Effective comprehension thus necessitates sufficient working memory capacity to sustain and coordinate these concurrent processes. Empirical evidence suggests that individuals with higher working memory capacity are better able to retain relevant linguistic input while simultaneously engaging in integrative operations, such as updating situational models and resolving referential ambiguities (Carretti et al., 2009). Furthermore, enhanced working memory may reduce the cognitive load associated with lower-level decoding, thereby preserving cognitive resources for higher-order comprehension processes (Mercer, 2005). Consequently, limitations in working memory are likely to constrain the efficiency with which readers construct coherent mental representations of text, underscoring working memory's foundational role in the facilitation of reading comprehension.

Empirical research consistently implicates working memory capacity in a broad range of reading outcomes, most notably reading comprehension (Zhang, 2019). Across studies, working memory shows stronger and more reliable correlations with comprehension than do simple short-term-memory measures, underscoring the importance of controlled attention and information manipulation over passive storage. When working memory is examined in tandem with attentional control, both constructs uniquely predict variance in decoding accuracy and text-level comprehension. The modality of the working-memory task also matters: Arrington et al. (2014) demonstrated that verbal, numerical, and spatial working memory each make separable contributions to children's comprehension, suggesting that multiple domain-specific resources support literacy development. Functionally, working memory supplies the cognitive resources required for essential reading processes such as the rapid retrieval of letter-sound correspondences, the integration of new propositions with the evolving mental model of a text, and the real-time monitoring of coherence. These demands become particularly salient during early adolescence, when readers must manage increasingly complex syntactic structures and discourse relations; evidence from boys aged 11–16 indicates that higher working memory facilitates both the processing and the self-regulation needed to construct meaning from dense expository texts.

Meta-analytic evidence consistently demonstrates that working-memory capacity is a significant contributor to literacy development. Peng et al. (2018), synthesising 148 independent datasets, reported a moderate overall correlation between verbal working memory and composite reading achievement. An earlier quantitative review by Daneman and Merikle (1996) reached a similar conclusion, showing that working memory predicts both listening comprehension and reading comprehension across age groups. More recently, a meta-analysis focused specifically on executive-function correlates of reading comprehension identified working memory as the strongest EF predictor of comprehension ($r \approx .32$) while

also documenting significant links with word decoding and sentence-level listening skills (Follmer & Tise, 2023). Parallel patterns are observed in second-language (L2) contexts: Linck et al. (2014) found that L2 working-memory capacity correlates positively with L2 reading and listening comprehension, even after controlling for overall proficiency. Taken together, these findings position working memory as a central cognitive resource underpinning both first- and second-language literacy.

From a measurement perspective, working memory is typically assessed through tasks that require both the maintenance and manipulation of information, thereby capturing its dual functional components. One widely used measure is the backward digit recall task, such as that included in the Woodcock-Johnson Psychoeducational Battery (WJ-III), which requires individuals to repeat sequences of digits in reverse order (McGrew & Hessler, 1995). This task is considered to more directly engage the executive control processes integral to verbal working memory. Alternative verbal working memory assessments include complex span tasks, such as sentence span tasks, in which participants respond to comprehension questions and subsequently recall the final word of each sentence (Moura et al., 2015). Additional verbal tasks involve the simultaneous storage and manipulation of linguistic items such as letters and words (Swanson et al., 2009). Visual-spatial working memory is commonly assessed through tasks such as the Spatial Span Backward and the Corsi Block-Tapping Test, where participants must reproduce sequences of spatial locations in reverse order. In research settings, a composite working memory score is often derived by averaging performance across multiple subtests, such as forward and backward digit spans, to yield a more robust indicator of individual working memory capacity (Diamond, 2013).

In summary, this section underscores the central role of working memory as a foundational cognitive resource in reading comprehension. Working memory supports both the temporary storage and active processing of linguistic information necessary for

constructing coherent interpretations of text. Its development is closely aligned with the development of reading skills, and deficits in working memory have been consistently associated with reading difficulties. In empirical research, working memory is typically assessed using tasks such as backward digit recall and complex span measures involving sentence processing, which capture both the storage and executive components of this construct.

2.3.2 Inhibitory control and reading comprehension

Inhibitory control is widely recognized as a core component of EF, operating as a foundational process within the broader supervisory attention system (Gastmann & Poarch, 2022). Inhibitory control encompasses abilities such as response inhibition, the suppression of prepotent or automatic responses, and interference control, which involves selectively attending to relevant stimuli while suppressing attention to irrelevant or distracting information (Drijbooms et al., 2015). At its core, inhibitory control is the capacity to resist interference from extraneous information and suppress inappropriate actions. This capacity facilitates the replacement of automatic, impulsive thinking with deliberate, effortful cognitive processing (Arrington et al., 2014).

Inhibitory control plays a pivotal role in various reading processes. At the word level, inhibitory control is essential for suppressing interference from neighboring words that share similar orthographic or phonological features during word recognition (Pan & Lin, 2023). This function is particularly salient in languages such as Chinese, where compound words often contain characters with multiple context-dependent meanings and a high prevalence of homophones. In such contexts, inhibitory control is considered critical for accurate word recognition (Sun, 2019). Additionally, inhibitory control facilitates efficient access to word structures and the identification of morphemic meanings, while also inhibiting the frequent activation of homophonic competitors during reading and writing tasks (Drijbooms et al.,

2015). Moreover, inhibitory control is substantially involved in suppressing inappropriate lexical representations at the word level and irrelevant grammatical structures at the sentence level, thereby enabling the selection of contextually appropriate words and phrase structures. Inhibitory processes are also implicated in the retrieval of correct phoneme-grapheme associations from long-term memory, while simultaneously inhibiting incorrect associations (Blair & Razza, 2007). Collectively, these functions underscore the integral role of inhibitory control in supporting efficient and accurate reading.

More broadly, inhibitory control is posited to facilitate reading performance by enabling the suppression of irrelevant information, thereby supporting sustained attention and focus during reading tasks (Cartwright, 2012). In the context of reading comprehension, inhibitory control allows readers to disregard extraneous or distracting information and concentrate exclusively on content relevant to the comprehension task. For instance, Liao and Zhao (2024) argue that inhibitory control is instrumental in suppressing irrelevant meanings when encountering polysemous words or in selecting the appropriate word among homophones. This capacity to inhibit competing or non-pertinent information is thus critical for effective comprehension and overall reading proficiency.

A growing body of research has examined both the direct and indirect effects of inhibitory control on reading and writing outcomes. For instance, Pan and Lin (2023) found that inhibitory control directly predicted word writing performance among kindergarten children learning Chinese. Additionally, inhibitory control was shown to exert a significant indirect effect on Chinese word reading and writing through its influence on morphological awareness (Chung & McBride-Chang, 2011). However, when working memory and other metalinguistic skills were statistically controlled, the direct predictive effect of inhibitory control on word reading was no longer significant, suggesting that its contribution may be largely shared with morphological awareness and orthographic knowledge. The literature also

presents conflicting findings regarding the extent to which shifting and inhibition skills in pre-kindergarten predict subsequent reading growth or specific literacy skills such as decoding and vocabulary acquisition. Conversely, some studies have reported that inhibitory control makes an independent contribution to foundational literacy skills, such as phonemic awareness and letter knowledge, in kindergarten-aged children (Blair & Razza, 2007). From the perspective of L2 learning, Sun et al. (2024) found that inhibitory control may suppress reading comprehension, potentially due to the characteristics of L2 learners who lack sufficient proficiency in their L1. This finding highlights the complex interplay between EF components and reading outcomes in multilingual contexts.

In the context of reading and language processing research, inhibitory control is typically assessed using a variety of experimental tasks (Ruffini et al., 2024). The Stroop task is among the most frequently employed measures of inhibitory control. In the classic Stroop paradigm, participants are required to name the ink color of a word that is incongruent with the word's semantic content, necessitating the inhibition of the automatic word reading response (Miyake et al., 2000). The Stroop effect, manifested as slower response times in incongruent conditions, is interpreted as an index of inhibitory control. The D-KEFS Color-Word Interference Test is a specific Stroop-based measure designed to assess the ability to inhibit irrelevant information (Delis et al., 2001). Other tasks used to evaluate inhibition include those that require the deliberate suppression of a dominant response, the selective ignoring of specific stimuli, or the ability to switch flexibly between reading sight words and numbers (Altemeier et al., 2008).

In summary, inhibitory control, as a core component of EF, is recognized as essential for a range of reading processes, including the suppression of interfering word-level information, the maintenance of attentional focus, and the inhibition of irrelevant meanings during reading comprehension. Empirical research underscores the association between

inhibitory control and reading difficulties, as well as its direct and indirect contributions to various reading skills. However, the strength and nature of its predictive power appear to vary depending on the specific aspect of reading assessed and the methodological approaches employed. Besides, inhibitory control is most commonly measured using tasks that require the inhibition of automatic responses or the selective ignoring of distracting information, with variations of the Stroop task serving as a primary assessment tool in this domain.

2.3.3 Cognitive flexibility and reading comprehension

Cognitive flexibility, also referred to as set shifting or task switching, is recognized as one of the core components of EF (Ionescu, 2012; Logue & Gould, 2014; Uddin, 2021). This cognitive ability encompasses the capacity to switch flexibly between tasks or mental sets, adapt rapidly to changing situations, rules, or demands, and modify one's perspective or approach in response to novel challenges (Miyake & Friedman, 2012). Cognitive flexibility is believed to emerge during the early preschool years, although its development may lag behind that of other core EF components such as inhibition and working memory. Indeed, cognitive flexibility is thought to be scaffolded by both inhibitory control and working memory (Cordeiro et al., 2020).

Empirical research has demonstrated a robust relationship between cognitive flexibility and reading. While the evidence linking cognitive flexibility to word reading is somewhat limited, existing studies suggest a significant association, and some findings also implicate cognitive flexibility in writing skills (Garon et al., 2008). In the context of complex orthographic writing systems, such as Chinese and Japanese, cognitive flexibility is posited to play a particularly important role (Pan & Lin, 2023; Sun, 2025). Reading and writing in these non-alphabetic systems require the activation and integration of multiple sources of information, including morphological and orthographic cues, and often necessitate the flexible application of different reading strategies. Given the demands of these orthographic

systems, effective word reading may require frequent shifting between strategies. Higher levels of cognitive flexibility have been associated with a reduction in errors when employing reading strategies, thereby facilitating more accurate word reading.

With respect to reading comprehension, cognitive flexibility is posited to enable readers to dynamically shift between multiple components of text processing, including decoding, vocabulary, syntax, discourse, and visual information (Cartwright et al., 2019). A meta-analytic review reported a medium to large correlation between cognitive flexibility and reading comprehension as an outcome variable (Follmer, 2018). However, when a broader composite reading score, encompassing decoding, linguistic skills, and reading comprehension, was utilized, the observed correlation was smaller, though still statistically significant (Cartwright & Palian, 2024). Additionally, cognitive flexibility has been linked to visual receptive language, which pertains to the comprehension of written material (Nathan, 2009). Studies involving Chinese kindergarteners have demonstrated a direct association between cognitive flexibility and word reading within tested models (Pan & Lin, 2023; Ruffini et al., 2024). Notably, cognitive flexibility remained a significant predictor of Chinese word reading even after controlling for other metalinguistic and EF skills, a finding that is consistent with research in alphabetic languages. This suggests that cognitive flexibility may play a universally important role in word reading across diverse orthographic systems by enabling readers to alternate between strategies and flexibly switch among different routes to word recognition.

Despite these findings, cognitive flexibility remains a relatively understudied component of EF in relation to writing skills, although existing evidence suggests it plays a generally important role in writing processes (Drijbooms et al., 2015). The literature presents conflicting results regarding the predictive value of cognitive flexibility for writing outcomes, with some studies failing to identify significant associations between cognitive flexibility and

various writing measures in certain age groups (Altemeier et al., 2008). Furthermore, the extent to which variance in writing skills can be attributed specifically to cognitive flexibility is influenced by the nature of the assessment tasks employed, particularly those that may concurrently engage multiple EF components. This methodological complexity underscores the need for more targeted research to clarify the unique contribution of cognitive flexibility to writing development.

A variety of tasks have been developed to assess cognitive flexibility (Hooper et al., 2022). These tasks typically require participants to adapt their responses in accordance with changing rules or stimuli. The Wisconsin Card Sorting Test (WCST), including specific versions such as the 64-card WCST, is among the most widely used measures, requiring individuals to shift sorting strategies based on feedback related to features such as color or shape (Jodzio & Biechowska, 2010; Nyhus & Barceló, 2009). Rule-switching tasks that manipulate stimulus features similarly assess the ability to flexibly adapt to new demands. Verbal fluency tasks, such as the semantic fluency subtest from the Coimbra Neuropsychological Assessment Battery (BANC), are also employed to evaluate cognitive flexibility. In these tasks, participants are asked to generate as many items as possible within specific categories (e.g., animals, names, foods) within a limited time frame, with higher scores reflecting greater cognitive flexibility (Simões et al., 2016). The rapid automatic switching task, and its various adaptations, further serve as measures of this construct. It is important to note, however, that some commonly used tasks, such as the Delis-Kaplan Executive Function System Trail Making Test (D-KEFS-TMT), may assess the coordination of multiple EF components rather than isolating cognitive flexibility per se. Consequently, findings derived from such tasks should be interpreted with caution, as they may not exclusively reflect cognitive flexibility (Drijbooms et al., 2015).

In summary, cognitive flexibility, together with working memory and inhibitory control, is directly implicated in both lower-order and higher-order cognitive processes, suggesting that enhanced EF skills contribute to improved performance across these domains. In the context of language learning, cognitive flexibility enables learners to interpret text more effectively by facilitating the ability to "read between the lines" and draw inferences from textual evidence. Moreover, cognitive flexibility is conceptualized as the capacity to reengage or reorient attention following the suppression of distractions by inhibitory control, thereby supporting the flexible switching required during complex tasks such as encoding. This dynamic interplay among EF components underscores the integral role of cognitive flexibility in supporting sophisticated language and literacy skills.

2.3.4 EF contributing to reading comprehension as a unity

EF components are not discrete entities but are interrelated processes that operate in concert (Miyake & Friedman, 2012). Some studies have examined EF as a unified construct, rather than isolating the contributions of individual components such as working memory, cognitive flexibility, and inhibitory control (Drijbooms et al., 2015; Hooper et al., 2022). While this holistic approach may obscure the specific effects attributable to each EF component, it reflects an effort to capture the overall influence of executive functioning on cognitive and academic outcomes.

From the perspective of the relationship between cognitive skills and reading, Cartwright et al. (2024) reported a medium to large correlation between cognitive flexibility and reading comprehension when the latter was assessed as a distinct outcome. However, when a broader composite reading score, including decoding, linguistic skills, and reading comprehension, was employed, the correlation with cognitive flexibility was attenuated, though it remained statistically significant. This pattern suggests that while individual EF components such as cognitive flexibility may exhibit strong associations with specific

reading subskills (e.g., reading comprehension), these relationships may appear weaker when reading is measured as a composite construct, likely due to the diverse array of cognitive skills that contribute to overall reading performance. In other words, this finding implies that EF, when considered as an integrated set of skills, may exert a more substantial influence on reading outcomes than any single component in isolation. Moreover, deficits across multiple EF domains have been shown to predict reading difficulties. Specifically, weaknesses in working memory, cognitive flexibility, and inhibitory control have all been found to increase the likelihood of challenges in language comprehension and reading fluency among bilingual adolescents with reading difficulties (Weaver & Kieffer, 2022). This evidence underscores the importance of considering the combined impact of EF components, as their interplay appears to be critical for successful reading development. Thus, conceptualizing EF as an integrated set of cognitive processes is essential for understanding and supporting reading acquisition and proficiency.

Some studies have aggregated variables assessing EF into a single, unified EF construct for data analysis, thereby supporting the conceptualization of EF as a cohesive entity in certain research contexts (Bombonato et al., 2024). Nevertheless, there is an increasing call for research employing comprehensive test batteries that assess multiple EF components and compute an overall EF factor. Such an approach is advocated to provide a more nuanced understanding of the collective contribution of EF skills and to minimize the confounding effects of overlapping constructs (Ruffini et al., 2024).

In summary, the literature suggests that EF, conceptualized as an integrated set of cognitive processes, including monitoring, strategy selection, attentional shifting, and inhibition of irrelevant information, is essential for reading comprehension. While much research has sought to disentangle the specific roles of individual EF components, studies that treat EF as a composite construct or examine the cumulative impact of EF deficits underscore

the importance of EF as a unified system in supporting reading outcomes, particularly reading comprehension. This integrated perspective highlights the necessity of considering both the distinct and collective contributions of EF skills to literacy development.

2.4 Conclusion

This chapter has explored the foundational and multifaceted role of EF in supporting language performance, with a particular emphasis on reading comprehension—a domain that places complex cognitive and linguistic demands on learners. Synthesizing empirical evidence, the three core components of EF, working memory, inhibitory control, and cognitive flexibility, have been shown to contribute both individually and collectively to essential reading processes. Specifically, working memory facilitates the temporary storage and manipulation of phonological and semantic information during reading; Inhibitory control enables the filtering of irrelevant stimuli and the resolution of linguistic interference; and cognitive flexibility allows readers to adaptively shift between decoding strategies, syntactic structures, and contextual cues. These cognitive processes do not operate in isolation but instead form a dynamic, integrated system that underpins effective reading comprehension.

The literature further underscores the value of conceptualizing EF not only as a set of discrete components but also as a unified cognitive construct. This perspective aligns with integrative frameworks proposed by Miyake and Friedman (2012) and has been increasingly adopted in reading-focused research, highlighting the centrality of EF in both academic and real-world literacy contexts. Importantly, this review has emphasized the interaction between decoding and linguistic comprehension processes with EF, offering a neurocognitive foundation for understanding how readers manage multiple simultaneous demands—such as

maintaining coherence, integrating new information, and suppressing irrelevant or conflicting cues.

Building on this EF framework, the next chapter will review prominent reading models and theories that conceptualize the processes involved in reading comprehension. This will include models that elucidate the interplay between cognitive processes and textual understanding. By linking EF to established reading theories, the forthcoming review will clarify how EF can be situated within broader cognitive and linguistic models, thereby providing an integrated lens through which to examine L2 reading development in the digital age.

Chapter 3 Literature Review of Reading Comprehension

3.1 Overview

Reading comprehension is a foundational skill that underpins academic achievement and lifelong learning, functioning as a critical gateway to knowledge acquisition and the development of higher-order thinking skills. As a multifaceted cognitive process, it encompasses not only the decoding of written symbols but also the active construction of meaning through the integration of textual information with prior knowledge and contextual understanding. Within educational contexts, reading comprehension is particularly salient for second language (L2) learners, who must navigate a range of linguistic, cognitive, and cultural challenges in order to achieve proficiency. A thorough understanding of the mechanisms underlying reading processes is thus essential for informing the current study.

This chapter presents a comprehensive review of the literature on reading comprehension, emphasizing its centrality in educational and cognitive development. Section 3.2 begins by examining the nature of reading comprehension, conceptualized as a complex cognitive activity involving the extraction and construction of meaning from written text. Special attention is given to its foundational role in language learning and educational assessment, alongside an overview of the principal theoretical and methodological approaches used to investigate and evaluate it. Section 3.3 explores major cognitive theories of reading, including the Construction-Integration Model, the Structure Building Framework, the Constructionist Theory, and the Reading Systems Framework. Each of these models offers distinct yet complementary perspectives on the ways in which readers process and integrate textual information, highlighting the dynamic interplay between bottom-up and top-down processing during comprehension. Section 3.4 focuses on the specific characteristics of Chinese reading comprehension and the unique cognitive skills it entails. This includes an

analysis of how the structural and orthographic features of Chinese script shape reading strategies and influence cognitive processing. Finally, Section 3.5 synthesizes the preceding discussions, reaffirming the importance of a nuanced understanding of reading comprehension both as a general cognitive phenomenon and within the particular context of Chinese language acquisition.

3.2 The nature of Reading Comprehension

Reading comprehension is a complex cognitive process involving the simultaneous extraction and construction of meaning from written text. It is widely recognized as a fundamental skill, particularly in contemporary, knowledge-driven societies where literacy is essential for personal, academic, and professional development (Clarke et al., 2013; Davis, 1944; Rost, 1989; Woolley, 2011). As a core component of language education, reading comprehension occupies a central position in both assessment and instructional frameworks, and it is examined through a range of theoretical and applied perspectives (Weir & Khalifa, 2008). In light of its significance, considerable scholarly and pedagogical attention has been devoted to defining the construct of reading comprehension and developing effective approaches for its measurement and instruction (Kendeou et al., 2016; Zhu et al., 2020).

Among the various perspectives on reading, the cognitive processing approach has emerged as a particularly influential framework. This approach emphasizes the mental operations readers engage in during comprehension, often in authentic and context-rich scenarios, and represents a departure from earlier models such as the factorial approach, which focused more narrowly on isolated subskills (Mahapatra et al., 2010; Weir & Khalifa, 2008). As such, a comprehensive understanding of reading comprehension is not only critical for academic success but also for enabling individuals to engage meaningfully with the increasingly complex texts that permeate modern life.

3.3 Theories of Reading

A range of theories and models have been developed to account for the complex cognitive processes involved in reading, many of which emphasize the dynamic interaction between bottom-up processing of visual and linguistic input and top-down utilization of prior knowledge and contextual cues (Hung, 2017). While these frameworks differ in how they conceptualize the specifics of this interaction, they generally converge on the view that reading comprehension entails a continuum of understanding. This ranges from surface-level processing, focused on the linguistic and syntactic structure of the text (i.e., surface code and textbase), to deeper levels of comprehension that involve the construction of a situation model, a coherent mental representation integrating the text with background knowledge and inferences. The ultimate goal of reading, therefore, is the successful construction of meaning, achieved through the integration of textual information with cognitive and experiential resources.

Given the multifaceted nature of reading comprehension, this study adopts a theoretically informed approach by drawing on four key cognitive frameworks: the Construction-Integration Model, the Structure Building Framework, the Constructionist Theory, and the Reading Systems Framework. Each of these models offers distinct yet complementary insights into the cognitive mechanisms underlying comprehension. The following subsections provide a rationale for the inclusion of each theory, highlighting their respective contributions to understanding reading comprehension processes within the specific context of this research.

3.3.1 Construction-Integration model

The Construction-Integration (CI) model is a prominent theory of discourse comprehension rooted in cognitive psychology rather than artificial intelligence (Kintsch, 1988; Sadoski, 2018; Wharton & Kintsch, 1991). Recognized as one of the most comprehensive and rigorously articulated models of text comprehension, it is distinguished by its computational implementation, which enables empirical testing of its theoretical assumptions (Barnes et al., 2015; Zhang et al., 2023). Developed as a response to traditional top-down, expectation-driven models of discourse processing, the CI model proposes an alternative framework that foregrounds bottom-up, data-driven mechanisms. Specifically, it posits that the initial stages of comprehension are governed by bottom-up processing, wherein word meanings are activated and combined into propositions and elaborations independently of contextual constraints. This emphasis on the automatic activation and integration of textual information marks a significant departure from earlier models that prioritized anticipatory and schema-based processes.

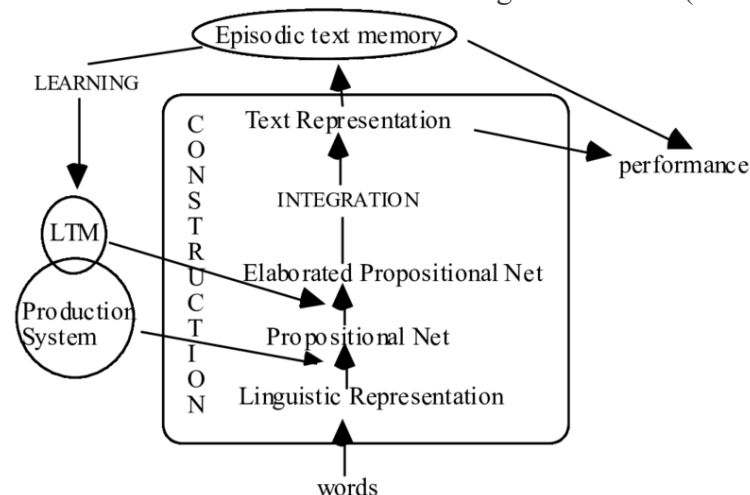
3.3.1.1 The Cognitive Architecture of Construction-Integration model

At the core of the CI model are two fundamental stages: Construction and Integration, as illustrated in Figure 3.1 (Kintsch, 1988; Wharton & Kintsch, 1991). The Construction phase involves the use of what Kintsch refers to as "weak" or "sloppy" rules to generate a broad set of mental representations (Perry et al., 2024). This stage operates primarily through bottom-up processing, in which meanings are activated directly from the linguistic input. These activations result in the formation of propositions and the elaboration of these propositions by retrieving semantically or associatively related concepts from the reader's general knowledge base. The process is best understood as a memory retrieval mechanism, whereby activated lexical and conceptual nodes spread through the reader's mental network, triggering adjacent and contextually relevant knowledge (Fletcher et al., 2012). The outcome

of this phase is an initial, often incoherent, associative network of propositional elements, including both relevant and irrelevant items, with the essential requirement being that the correct, context-appropriate elements are included within the set.

The Integration phase subsequently acts upon this network, refining the loosely structured set of propositions into a coherent mental representation (Yang et al., 2020). During this phase, the model employs connectionist principles such as spreading activation and relaxation processes. Nodes within the associative network are connected by either positive or negative links, reflecting their conceptual compatibility. As activation spreads through the network, a stabilization process occurs: concepts that are well-connected and contextually appropriate maintain high levels of activation, while weakly connected or contextually incongruent nodes are suppressed. This dynamic allows the model to implicitly inhibit implausible interpretations and reinforce those that align with the developing mental model. Importantly, this shift from rule-based processing to a data-driven integration mechanism exemplifies the model's departure from top-down, expectation-based frameworks. In successful comprehension, the process is highly automated and requires minimal conscious oversight. However, if coherence is not achieved, the system re-engages the construction process, generating new propositions and attempting integration anew (Kintsch, 1988).

Figure 3.1 The Structure of the Construction-Integration model (Kintsch, 1988)



The CI model posits that reading comprehension results in the formation of mental representations at multiple levels of cognitive processing (Garnham & Oakhill, 2014). The most frequently discussed levels are the surface code, which encodes the literal wording and syntactic structure of the text; the textbase, which captures the propositional structure derived from the explicit meaning of the text, encompassing basic elements such as "who," "what," "where," and "when"; and the situation model, which represents a deeper level of understanding that integrates the textual content with the reader's prior knowledge, enabling inference generation and elaboration (Heilmann, 2020). Among these, the situation model is particularly emphasized as it reflects the integration of text-based information with existing cognitive schemas, allowing readers to construct a coherent mental representation that extends beyond what is explicitly stated.

The situation model is a central concept in the CI framework, characterized by the dynamic interaction between text-derived propositions and activated background knowledge. It is influenced by mechanisms such as referential overlap, which help maintain coherence across discourse segments. Fundamental assumptions of the CI model include the representation of both text and knowledge as associative networks composed of propositions, and the cyclical nature of processing, whereby comprehension unfolds incrementally in discrete units—typically at the level of sentences or propositions (Goldman & Varma, 2012). The model has been widely employed to simulate a variety of cognitive tasks. Initially, it was applied to discourse comprehension phenomena such as word sense disambiguation and the interpretation of arithmetic word problems, but it has since been extended to domains such as routine computing tasks, illustrating its broad applicability and theoretical robustness.

3.3.1.2 The Strengths, and Limitations of Construction-Integration model

One of the primary strengths of the CI model lies in its capacity to account for situated cognition in a naturalistic and psychologically valid manner (Kintsch, 2018). Designed with

cognitive plausibility as its central aim, the model offers valuable applications beyond theoretical discourse. For instance, it provides a robust framework for the design and evaluation of educational technologies, enabling predictions about how specific digital features may support either surface-level recall (textbase representation) or deeper comprehension (situation model development), depending on whether they foster propositional encoding or promote controlled, constructive inferencing (Butcher, 2024).

In comparison with other prominent models, the CI model shares several theoretical commitments, particularly with the Structure Building Framework (SBF). Both emphasize the incremental construction of mental representations and the interactive nature of cognitive processing. However, the CI model distinguishes itself through its more detailed architecture, particularly in its representation of knowledge at the propositional level (Gernsbacher, 2014; Kintsch & Welsch, 2013). While the CI model assumes that successful comprehension involves largely automatic processing, the SBF accommodates a broader spectrum of cognitive control, allowing for both automatic and consciously mediated operations (Pezzulo & Castelfranchi, 2009). The Landscape Model further complements this discussion by offering computational mechanisms that simulate fluctuations in concept activation. It builds on and integrates assumptions from the CI model and related frameworks by incorporating both automatic processes (e.g., cohort activation) and strategic processes (e.g., coherence-based retrieval) (Schneider & Chein, 2003).

Despite its conceptual richness and broad applicability, the CI model is not without limitations. Notably, it provides only limited explanatory power regarding individual differences in reading comprehension, an area where greater specificity is needed (Goldman et al., 2014; Kintsch & Welsch, 2013; Wharton & Kintsch, 1991). Additionally, the model's architecture remains underdeveloped in areas concerning sensorimotor integration, such as the coordination of perception and action in real-world contexts as well as lacks mechanisms

for capturing cognitive impasses or modeling the effects of learning on long-term memory (Kintsch, 2018). The current instantiation of the model does not support learning in a generalizable manner, and scalability to accommodate large-scale semantic networks remains an open challenge.

Efforts have been made to extend the model by incorporating symbolic, rule-based systems to simulate goal-directed behaviors, but the core model still does not explicitly represent metacognitive processes or the nuanced implementation of reader goals, which are more thoroughly addressed in alternative models such as the Constructionist Theory (Dagar, 2023). Furthermore, the parser responsible for generating propositional representations is not formally embedded within the model, and a more detailed specification of the interaction between the construction and integration phases remains necessary for enhancing its explanatory and predictive power.

3.3.1.3 Summary of Construction-Integration model

The CI model, grounded in cognitive psychology, presents a comprehensive and computationally implementable framework for understanding discourse comprehension. Departing from traditional top-down, expectation-driven approaches, the model prioritizes a bottom-up, data-driven process, wherein meaning is initially derived from linguistic input and subsequently refined into coherent mental representations through integrative mechanisms.

The CI model offers several notable strengths. It effectively accounts for situated cognition, supports applications in educational technology and instructional design, and provides a detailed architectural account of how mental representations are formed at various levels. Its theoretical structure enables the analysis of how different digital features may promote either surface-level comprehension (textbase) or deeper, integrative understanding (situation model), depending on the degree to which they facilitate propositional encoding or constructive inferencing. Additionally, the model has demonstrated utility in simulating a

range of cognitive tasks, including word sense disambiguation and problem-solving.

Nevertheless, the model also has critical limitations. It offers limited insight into individual differences in comprehension, lacks a formally integrated parser for proposition generation, and does not fully incorporate metacognitive processes or the role of reader goals. Moreover, challenges remain regarding its scalability and its capacity to simulate learning processes, which represent essential directions for future research.

In sum, the CI model constitutes a significant contribution to the theoretical understanding of reading comprehension. While it continues to inform cognitive science and pedagogical practice, further refinement is required to enhance its explanatory scope and practical relevance across diverse educational and cognitive contexts.

3.3.2 Structure Building Framework

The Structure Building Framework (SBF), initially proposed by Gernsbacher (1997), is a comprehensive cognitive theory of comprehension designed to be modality-independent. That is, it aims to account for the general cognitive operations involved in comprehension regardless of the modality through which information is delivered, be it textual, auditory, visual, or multimodal (Gernsbacher, 2014; Kendeou et al., 2016). Unlike theories that emphasize modality-specific or low-level perceptual processes, the SBF conceptualizes comprehension as a domain-general process, grounded in the construction of coherent mental representations or cognitive structures.

3.3.2.1 The Cognitive Architecture of Structure Building Framework

At the core of the SBF are three principal processes that govern the construction of mental representations: laying a foundation, mapping, and shifting (Gernsbacher, 2014; Succar, 2009). These processes occur iteratively and cumulatively as comprehenders process incoming information across various units of discourse.

The laying of a foundation is initiated when readers or listeners begin to encode new content, whether at the level of a clause, sentence, paragraph, discourse episode, or when the topic shifts substantially (Wren, 2000). This stage involves the initial allocation of cognitive resources to form a mental structure upon which subsequent information can be integrated. Empirical studies indicate that this process is cognitively demanding; for instance, readers typically exhibit slower processing times at the onset of new discourse segments, suggesting greater cognitive load during foundation building (Gernsbacher, 2014; Bruning et al., 1999). The accessibility of first-mentioned entities in a sentence further supports this theory, as they often serve as anchor points for constructing sentence-level representations.

Following the establishment of a foundation, comprehenders engage in the process of mapping, which involves integrating new, coherent information into the existing mental structure. This process strengthens semantic linkages and enriches the coherence of the representation. Successful mapping is facilitated by various types of informational overlap—syntactic, referential, temporal, spatial, and causal, which enhance the activation of relevant memory nodes and promote integration (Koedinger et al., 2012). Through mapping, the mental structure is incrementally refined and expanded.

When incoming information is not easily integrated, the process of shifting is triggered due to a discontinuity in topic, perspective, or temporal context. Shifting entails the construction of a new mental substructure, effectively initiating a new foundation. This transition requires additional processing effort, as the comprehender must disengage from the previous structure and begin a new one (Gernsbacher, 2014). The ability to shift effectively is essential for maintaining coherence across complex or multi-thematic discourse.

In addition to these core processes, the SBF incorporates two modulatory mechanisms that regulate the activation of memory representations: enhancement and suppression (Gernsbacher, 1995; Gernsbacher, 2013). Enhancement functions to increase the activation of

memory nodes when the represented information is contextually relevant to the developing structure. Conversely, suppression serves to attenuate the activation of memory nodes associated with information that is no longer relevant or contextually appropriate (Frey, 2005; Sanford et al., 2009). Suppression plays a particularly critical role in disambiguation tasks, such as inhibiting irrelevant interpretations of ambiguous lexical items, thereby supporting efficient and accurate comprehension. These processes and mechanisms provide a unified account of how mental representations are constructed and managed during comprehension. The SBF thus offers a versatile and cognitively plausible model for understanding comprehension across modalities and discourse types.

3.3.2.2 The Strengths, and Limitations of Structure Building Framework

A notable feature of the SBF in the context of reading comprehension is its emphasis on accounting for individual differences in comprehension skill. The model posits that skilled and less-skilled readers differ primarily in the efficiency of their suppression mechanisms. Specifically, less-skilled readers often exhibit deficits in suppressing irrelevant or competing information, which can result in the unnecessary construction and maintenance of multiple substructures. Although the SBF does not explicitly frame these differences in terms of strategic comprehension or metacognitive regulation, it nonetheless provides a cognitive account of variation in reader proficiency by highlighting how differences in the regulation of activation influence comprehension outcomes.

From a comparative theoretical standpoint, the SBF shares several conceptual similarities with the CI Model of discourse comprehension. Both models emphasize the incremental and interactive construction of mental representations, and both have been applied to a wide range of discourse types, including narrative and expository texts. Indeed, some scholars have noted that specific mechanisms in the SBF, such as enhancement, bear functional resemblance to the integration processes described in the CI model. In both

frameworks, these mechanisms serve to increase the activation of contextually relevant information following initial activation, thereby facilitating coherent representation building.

Nevertheless, important distinctions exist between the two models. The CI model is characterized by a more propositionally detailed architecture, focusing on how discrete propositions are activated and integrated within a mental representation. In contrast, the SBF offers a more generalized cognitive account, applicable across multiple linguistic units and modalities, including non-verbal forms of discourse (Gernsbacher, 2014). Notably, Gernsbacher argues that the SBF offers a cognitive account of how situation models are constructed, an aspect that is less explicitly addressed in the CI model.

Another critical distinction concerns the degree of automaticity assumed by each model. While the CI model generally conceptualizes comprehension as an automatic, constraint-satisfaction process, the SBF allows for both automatic and controlled processes, suggesting that readers can exert conscious control over structure-building when necessary. Moreover, the SBF's core processes that laying a foundation, mapping, and shifting are considered defining features of the framework and are not paralleled in the CI model's standard architecture. Although some scholars (e.g., McNamara & Magliano, 2009) argue that these processes may be reconcilable with connectionist, constraint-based approaches like CI, the SBF maintains a more explicitly staged and modular architecture.

Despite its broad applicability, the SBF has primarily been validated through studies involving narrative texts and experimentally manipulated short stimuli. This methodological focus raises questions about the model's explanatory power in more complex and informationally dense genres, such as expository texts. For example, Eaton et al. (1999) argue that the relational dimensions emphasized by the SBF, referential, causal, temporal, and spatial coherence, may be insufficient to fully account for the mapping demands posed by

expository discourse, which often requires integration of abstract concepts and hierarchical structures not as readily grounded in concrete situational features.

In sum, while the SBF offers a robust framework for understanding the cognitive underpinnings of discourse processing and individual differences therein, its comparative scope and empirical generalizability may benefit from further extension into diverse textual genres and comprehension contexts.

3.3.2.3 The Summary of Structure Building Framework

The SBF is a domain-general cognitive theory of comprehension that posits understanding as the product of constructing coherent mental representations through fundamental cognitive operations (Gernsbacher, 1997). The framework delineates three core processes: laying a foundation, mapping, and shifting, which together facilitate the incremental and dynamic construction of meaning. These processes are modulated by two central mechanisms: enhancement, which increases the activation of relevant memory nodes, and suppression, which inhibits irrelevant or competing information. These regulatory mechanisms are critical for maintaining coherence and resolving ambiguities during reading, thus supporting sustained comprehension.

A significant strength of the SBF lies in its capacity to account for individual differences in comprehension performance, particularly through variation in suppression efficiency (Bråten et al., 2014). The model's flexibility enables its application across a variety of input modalities and linguistic units, making it broadly applicable beyond traditional text comprehension. Although the SBF shares key features with the CI model, notably the emphasis on mental representation and incremental meaning construction, it diverges by explicitly conceptualizing foundation laying, mapping, and shifting as distinct, sequential processes (Wharton & Kintsch, 1991). Moreover, while the CI model tends to frame comprehension as an automatic constraint-satisfaction process, the SBF accommodates both

automatic and controlled processing, offering a more nuanced account of cognitive regulation during reading.

Despite these strengths, the SBF has limitations. Empirically, it is predominantly grounded in research using short, narrative texts, which may constrain its generalizability to more complex and abstract discourse, such as expository texts. Furthermore, while the SBF identifies several coherence dimensions of referential, causal, temporal, and spatial, these may not fully capture the demands of mapping and integration in information-dense or conceptually abstract materials.

In conclusion, the Structure Building Framework offers a versatile and cognitively grounded model of comprehension, particularly valuable for elucidating individual variability and its relevance across diverse modalities. However, further theoretical refinement and empirical extension are needed to enhance its explanatory power in contexts involving expository and disciplinary literacy.

3.3.3 Constructionist theory

The Constructionist theory of comprehension emphasizes the various factors that constrain the inferential processes underpinning reading comprehension (Graesser et al., 1994). This theoretical framework emerged in response to ongoing debates regarding the nature and frequency of inferences generated by readers. Specifically, it contrasts with perspectives suggesting that readers either pursue global coherence only when local coherence fails, or that they routinely generate all possible inferences during reading (Fallon, 1987; Long et al., 2013). A central tenet distinguishing the Constructionist theory is the "search after meaning" assumption, which asserts that readers adopt explicit or implicit reading goals that motivate them to actively construct meaning from the text (Long & Lea, 2005). This section will review the Constructionist model in order to elucidate reading comprehension as a complex cognitive process.

3.3.3.1 The Assumptions of Constructionist theory

The "search after meaning" principle within the Constructionist theory is characterized by three foundational assumptions: the goal assumption, the coherence assumption, and the explanation assumption.

First, the goal assumption posits that readers engage in the construction of a coherent mental representation of the text as a primary objective of reading (Caccamise et al., 2008; Graesser, 2007). Reading is conceptualized as an inherently goal-directed activity, wherein readers are presumed to possess explicit or implicit objectives that motivate their cognitive efforts and guide their attention to specific content in pursuit of comprehension. These reading goals, in turn, influence the cognitive processes activated during reading (Yussof, 2012).

Second, the coherence assumption asserts that deep comprehension is achieved when readers construct situation models that integrate both local and global coherence (Caccamise et al., 2008). According to this assumption, readers are intrinsically motivated to attain coherence at multiple levels and actively strive to build a unified mental representation of the text. This process involves bridging incoming information with preceding textual content as well as with relevant prior world knowledge (van den Broek & Kendeou, 2017). The generation of text-connecting inferences, which integrate propositions through pragmatic and inferential reasoning, is essential for achieving coherence. Furthermore, readers engage in comprehension monitoring to ensure consistency between their evolving mental representation and both the text and their background knowledge. Notably, the Constructionist model maintains that readers attempt to connect both proximal and distal information within the text, even when local coherence is already established, thereby distinguishing it from minimalist models of inference generation (Coiro & Dobler, 2007).

Third, the explanation assumption posits that individuals possess an inherent drive to seek explanations for events they encounter (Nassaji, 2007; Wodak, 2011). The construction of explanations is fundamental to meaning-making and serves as a critical mechanism for achieving coherence in comprehension. This explanatory drive prompts readers to generate inferences, particularly those that elucidate causal antecedents, agent goals, and causal relationships within the text (Gregor & Benbasat, 1999). The Constructionist theory contends that readers routinely evaluate their capacity to generate such explanations based on their available knowledge. This motivation underlies the generation of inferences that account for why events occur, including the actions and intentions of characters. Furthermore, prediction is conceptualized as both a coherence- and explanation-oriented strategy, consistent with the Constructionist framework, as it encourages readers to integrate information and maintain global coherence across the text.

Collectively, these three assumptions including the goal, coherence, and explanation assumptions constitute the core of the Constructionist theory and account for why readers generate inferences during reading. They are regarded as signature principles that distinguish this model from alternative theories of comprehension (Potter, 1996). The Constructionist theory offers specific predictions regarding the types of inferences readers routinely generate and the contextual conditions that facilitate their generation. While the theory shares certain foundational assumptions with other models, such as those concerning memory stores, levels of representation, world knowledge, activation, and automaticity, its defining characteristics are these three guiding principles that direct the active search for meaning during reading.

3.3.3.2 The Strengths, and Limitations of Constructionist theory

The Constructionist theory offers a comprehensive theoretical framework for investigating the processes underlying reading comprehension and for informing the implementation of instructional strategies, such as prompting readers to generate explanations

and inferences. By delineating the processes presumed to operate in optimal reading scenarios, the model also implicitly identifies potential sources of comprehension deficits that may arise when its core assumptions are not met.

When contrasted with Kintsch's CI model, a salient distinction emerges in their respective emphases on process control. While the CI model acknowledges the role of automatic memory retrieval during the construction phase, the Constructionist theory places greater emphasis on top-down, controlled, and effortful processes that are guided by the reader's goals (Kintsch, 2018). The Constructionist theory seeks to explain the underlying motivations for inference generation, namely the drives for goal attainment, coherence, and explanation, a focus that is less pronounced in the CI model. Although both models ultimately aim for the construction of an integrated mental representation, such as a situation model, the CI model posits a more passive, associative mechanism for initial activation, whereas the Constructionist theory conceptualizes the reader as highly motivated and strategically engaged in an active search for meaning.

In comparison to the Structure Building Framework (SBF), the Constructionist theory is specifically tailored to reading comprehension, whereas the SBF constitutes a more general cognitive model applicable across various modalities (Barbehön, 2020). The SBF primarily describes the cognitive mechanisms involved in comprehension, while the Constructionist theory is concerned with elucidating the reasons underlying inference generation. The Constructionist theory places a stronger emphasis on controlled and effortful processing, whereas the SBF allows for both controlled and automatic processes (Gernsbacher, 2014).

Overall, the Constructionist theory is distinguished by its emphasis on the active, goal-directed role of the reader and its explicit predictions regarding the generation of inferences (Graesser & Zwaan, 2012). It provides a detailed account of the motivations which is rooted in goals, coherence, and explanation needs that drive readers to generate various types of

inferences. The theory characterizes reading as a strategic, goal-oriented process undertaken by a highly motivated reader. Alongside the CI model and the SBF, the Constructionist theory addresses the qualitative and structural aspects of comprehension products, and it is among the few models to explicitly incorporate extratextual dimensions.

Nevertheless, the Constructionist theory is not without limitations. Although it specifies production rules for inference generation, these rules have yet to be formally implemented in computational models. The notion of an active search for meaning, particularly as operationalized through its production rules, has been critiqued by some scholars as lacking psychological plausibility. Furthermore, the theory provides limited guidance regarding how comprehension processes may vary depending on the extent to which readers adhere to its core assumptions. It also does not elaborate on how comprehension is affected by text difficulty or specific textual characteristics. While the theory underscores the importance of effortful processing, it does not offer a comprehensive account of individual differences in comprehension skill.

3.3.3.3 The Summary of Structure Building Framework

The Constructionist theory conceptualizes readers as active constructors of meaning, motivated by specific goals and a fundamental need for coherence and explanation. This framework offers valuable insights into the motivational and inferential dimensions of reading comprehension. Developed in response to competing perspectives regarding the timing and rationale behind inference generation, the theory posits that such processes are neither automatic nor arbitrary, but are instead guided by the reader's intentional efforts to achieve understanding. While the Constructionist theory has been influential in framing reading as an active, meaning-oriented endeavor, it is not without limitations. Notably, it lacks formal computational implementation and provides limited consideration of how text difficulty or individual differences among readers may impact comprehension. Nonetheless,

the theory's emphasis on strategic comprehension processes establishes a foundation for further exploration of how these cognitive mechanisms operate in the context of complex texts.

3.3.4 Reading Systems Framework

The Reading Systems Framework is not conceived as a singular, narrowly defined theory of reading, but rather as a broad, integrative framework that encompasses the multifaceted components of the reading process (Perfetti & Stafura, 2014). This framework is designed to provide a comprehensive perspective on reading within the context of a language-cognitive architecture, spanning processes from initial visual perception to higher-level comprehension. It emphasizes the dynamic application of various knowledge sources during reading, highlighting that these processes can be both constrained and interactive.

Within this framework, the cognitive system is understood to involve interconnected pathways between perceptual mechanisms and long-term memory, all of which operate under conditions of limited processing resources. The Reading Systems Framework functions as a scaffold for the development of more specific theories, enabling the examination of particular language systems, such as complex orthographic writing systems. Consequently, the framework facilitates the generation of hypotheses regarding comprehension difficulties, positing that observable weaknesses in one or more components of the system can serve as indicators of reading problems, especially in lower-level processes such as decoding (Kendeou et al., 2016; Stafura & Perfetti, 2017).

Moreover, the framework accommodates hypotheses concerning the emergence of individual differences in reading skill and the development of both reading expertise and weaknesses. It is also applicable to the investigation of local comprehension processes, such as the integration of individual words into coherent text segments. In sum, the Reading Systems Framework provides a versatile and comprehensive foundation for exploring the

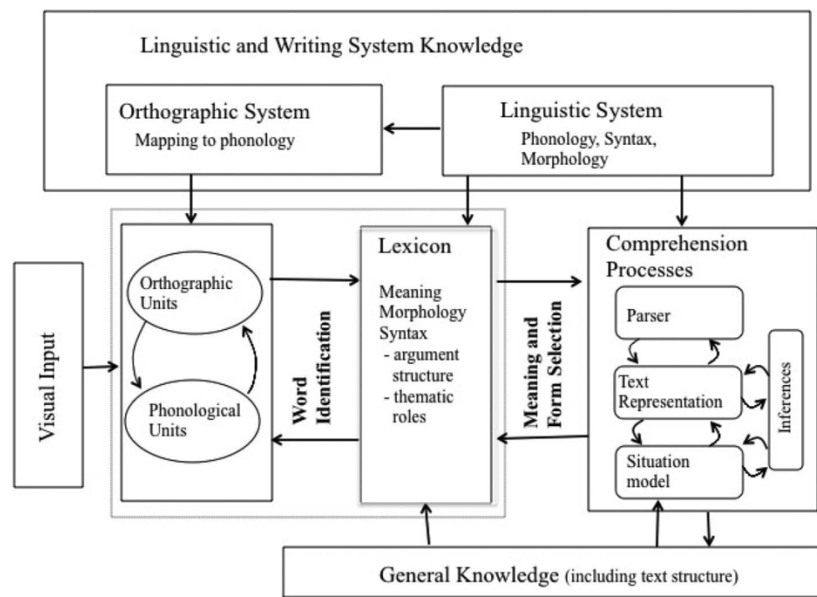
cognitive architecture underlying reading and for identifying the sources of variability in reading comprehension.

3.3.4.1 The structure of Reading Systems Framework

The structure of the Reading Systems Framework, as proposed by Perfetti and Stafura (2014), emphasizes the integration of multiple knowledge sources and fundamental cognitive processes involved in reading (see Figure 3.2). The framework delineates three primary classes of knowledge sources essential for reading: linguistic knowledge, orthographic knowledge, and general knowledge, which encompasses both world knowledge and familiarity with various text structures. The cognitive processes articulated within the framework include decoding, word identification, meaning retrieval, constituent building, inferencing, and comprehension monitoring. These processes may operate in a constrained manner, for instance, decoding relies predominantly on orthographic and phonological knowledge, or in an interactive fashion, such as when inferencing draws upon general knowledge and propositional meaning. All of these processes are situated within a cognitive system characterized by interconnected pathways between perceptual mechanisms and long-term memory, and are subject to the limitations imposed by finite processing resources.

A distinctive feature of the Reading Systems Framework is its focus on the lexicon (Wade-Woolley et al., 2022). The lexicon is conceptualized as a central nexus linking the word identification system to the comprehension system. It serves as the output of the word identification process and as the input to higher-level comprehension processes, including those operating at the sentence, text, and situation model levels. This centrality highlights the pivotal role of lexical access in bridging lower-level and higher-level reading processes within the overall architecture of reading comprehension.

Figure 3.2 Reading Systems Framework (Perfetti & Stafura, 2014)



3.3.4.2 The Strengths, and Limitations of Reading Systems Framework

The Reading Systems Framework offers a comprehensive perspective on reading by encompassing processes that range from low-level perceptual mechanisms to high-level comprehension. By explicitly incorporating word-level processes alongside the higher-level processes that are typically the focus of comprehension research, the framework seeks to provide a more holistic account of the reading process (Brossette et al., 2022; Hiebert et al., 2022). This integrative approach is particularly advantageous for addressing the inherent complexity of reading, as it allows for the formulation of adaptable claims that can inform the development of more specific models. Furthermore, the framework explicitly considers individual differences in comprehension skill, thereby offering a structural basis for hypothesizing the origins of reading difficulties. Of particular significance is its emphasis on the lexicon, which serves as a critical interface between word identification and comprehension systems.

The Reading Systems Framework also incorporates constructs such as the situation model, aligning its word comprehension component with the construction and integration phases of the CI model, which characterizes comprehension as an outcome of interactive top-

down and bottom-up processes. Additionally, the framework shares with the SBF a focus on coherence and individual differences in reading. In contrast to the Constructionist theory, which primarily emphasizes the attainment of deep understanding and the construction of integrated mental representations, the Reading Systems Framework integrates both low-level word recognition processes and higher-level text comprehension. This integration yields a more comprehensive understanding of the reading process as a whole (Levesque et al., 2021).

3.3.4.3 The Summary of Reading Systems Framework

A comprehensive understanding of reading comprehension is facilitated by frameworks and models that elucidate the multifaceted nature of this cognitive process. The Reading Systems Framework offers a broad, integrative perspective on the reading system as a whole, with particular emphasis on the pivotal role of the lexicon in bridging word identification and higher-level comprehension processes.

In comparison to other models, the Reading Systems Framework provides a thorough overview of the components and processes involved in reading, spanning from low-level decoding to advanced comprehension. Its comprehensive scope makes it especially well-suited for guiding research that addresses multiple levels of the reading process, thereby supporting investigations into both the foundational and complex aspects of reading comprehension.

3.3.5 Conclusion: Reading comprehension as a cognitive process

Reading comprehension is conceptualized as a complex cognitive process in which readers simultaneously extract and construct meaning from written text, integrating these elements into a coherent mental representation. This process entails the interplay of "bottom-up" visual information derived from the text and "top-down" world knowledge that the reader brings to the task. To account for the intricacies of reading comprehension, researchers have advanced a range of theories and models. In this dissertation, four prominent frameworks

including the CI model, the SBF, the Constructionist Theory, and the Reading Systems Framework are synthesized to establish a comprehensive theoretical foundation for understanding reading comprehension as a dynamic cognitive activity.

The CI model provides a foundational account of how readers form mental representations of text through iterative cognitive cycles. It posits that readers initially construct a network of activated concepts and propositions, drawing from both the text and their long-term memory. Building on this, the SBF elucidates the cognitive mechanisms of enhancement and suppression that operate during reading comprehension, highlighting how skilled comprehenders efficiently suppress irrelevant information, whereas less-skilled readers may maintain multiple, extraneous substructures.

The Constructionist Theory further extends this perspective by emphasizing the active, goal-directed role of the reader in the pursuit of meaning, which necessitates the generation of inferences. This theoretical stance is particularly salient for understanding strategic reading behaviors and for informing interventions aimed at enhancing comprehension. In relation to language-specific features, the Reading Systems Framework underscores the centrality of the lexicon, conceptualizing word comprehension as a process of word-to-text integration, wherein activated word meanings are modulated by contextual cues and the reader's evolving situation model. Additionally, this framework provides a scaffold for generating hypotheses regarding the origins of comprehension difficulties, enabling the identification of weaknesses within specific knowledge processes.

By integrating these models, the theoretical framework of the present study characterizes reading comprehension as a dynamic, multifaceted cognitive activity shaped by the characteristics of the text, the reader's cognitive capacities and strategies, and the complex interactions between lower-level processing and higher-level meaning construction.

More detail, this comprehensive theoretical framework for reading comprehension integrates the contributions of following approaches:

- (1) Representation Building: Reading involves constructing and maintaining multi-level mental representations, from explicit text details to a deeper understanding integrated with prior knowledge, to build a situation model for comprehension.
- (2) Dynamic Processing: Reading requires construction through dynamic cycles for activating information from text and knowledge sources and integrating it into coherent structures.
- (3) Cognitive Mechanisms: Reading involves cognitive processes (foundation, mapping, shifting) and mechanisms (enhancement, suppression) responsible for building and managing mental. The efficiency of these mechanisms impacts comprehension skill.
- (4) Resource Allocation: Reading operates within a cognitive system supported by general resources including working memory.
- (5) Active and Goal-Directed Engagement: Readers actively engage in reading as a goal-directed process with cognitive flexibility and inhibitory control to generate inferences and build deep understanding.
- (6) Word-Level Integration: Lower-level processes, especially word identification and the rich knowledge associated with the lexicon, are fundamental inputs to comprehension, forming a crucial bridge between decoding and higher-level meaning construction through word-to-text. Weaknesses at this level or in the interaction between word and text processing can impair comprehension.

3.4 Chinese Reading

Building upon the theoretical framework of reading comprehension outlined in Section 3.3, it is imperative to consider how cognitive principles and reading models interact with the

distinctive characteristics of complex orthographic writing systems, such as Chinese (Tan et al., 2001; Wu et al., 2012). Chinese represents a unique case in reading research due to its logographic script, in which characters function as the smallest lexical units. Each character comprises intricate visual forms, consisting of multiple strokes organized into radicals that convey semantic or phonological information (Chen, 1996; Feldman & Siok, 1999; Wang et al., 2014). Unlike alphabetic systems, Chinese lacks explicit inter-word spacing, and characters, as visual units, frequently appear within compound words.

The structural features of the Chinese writing system suggest that lower-level visual and orthographic processing which emphasized in models such as the CI model and the SBF must begin with the accurate identification and segmentation of characters and radicals prior to the engagement of higher-level comprehension processes. Consequently, foundational reading processes in Chinese are more visually and spatially demanding than those in alphabetic systems. Furthermore, given that Chinese lexical representations encompass both orthographic form and morphemic structure, lexical processing assumes a particularly central role, as highlighted in the Reading Systems Framework.

Additionally, when comparing Chinese reading across first-language readers and second-language learners, it becomes evident that the cognitive processes described by these models must be interpreted in light of cross-linguistic factors. These include the demands of orthographic learning, the transfer of reading strategies across writing systems, and the ways in which instructional practices can scaffold comprehension within a system that operates under constraints distinct from those of alphabetic scripts.

The following section provides a detailed review of research on reading comprehension in Chinese, as well as related reading skills, from both first-language and second-language perspectives. Drawing on the aforementioned theoretical foundations, this section will

examine how Chinese readers process text at the character, word, sentence, and discourse levels, and how cognitive and linguistic variables influence their comprehension outcomes.

3.4.1 Reading comprehension in Chinese

The nature of the writing script significantly influences how reading comprehension is acquired and processed. Chinese is a logographic writing system that characters represent both meaning and pronunciation (Chen, 1996; Shu, 2003). However, unlike alphabetic scripts, Chinese characters provide less explicit information about phonology, and their construction follows rules based on graphic units rather than phonemes, partly due to the prevalence of homophones. Furthermore, regarding polysemous words and homonyms, Chinese lacks an inflectional system which can introduce ambiguity in sentence structure and the assignment of thematic roles, highlighting the need for strong vocabulary depth (McCaughren, 2009).

The reading comprehension of Chinese could be seen as a multi-layered process including lower-level processing of character, lexical level of word recognition, and higher level of text integration and meaning construction (Li & Pollatsek, 2020; Liao, 2015; Shu, 2018; Zhou, 2023). The reading process begins when the reader visually encounters written Chinese characters. Readers engage in orthographic processing, analysing the visual form of the characters, which involves recognising strokes and radicals to extract the surface structure of words for subsequent steps (Lin & Zhang, 2023; Luo et al., 2011). Simultaneously, phonological access occurs, where the pronunciation and tone associated with the character is retrieved (Han & Bi, 2009). While Chinese characters have a less transparent orthography-to-phonology mapping than alphabetic systems, phonological processing is still involved and is related to reading skill, particularly for beginners of Chinese readers. On the other hand, morphological analysis may also begin at this level, as many Chinese characters represent morphemes, and readers start breaking down characters

and potential multi-character words into their meaningful constituent units (Xie et al., 2019; Zhou, 2022).

At the lexical level of word recognition, readers need to identify word boundaries and recognising words, which is challenging in unspaced text (Leong et al., 2008; Li et al., 2012). Word reading, or decoding, which is the ability to recognize characters and words, is emphasised by theories of reading comprehension as having a crucial role. The ability to read words has consistently shown a strong association with reading comprehension in Chinese and is considered a fundamental skill for decoding Chinese texts. While early cross-sectional studies sometimes showed inconsistent unique contributions of decoding, longitudinal studies have provided stronger evidence for its developmental role (Padeliadu & Antoniou, 2014; Yan et al., 2021). However, it is important to point out the meaning of many two-character words (compound words) is often holistically bound, distinguishing word reading from single character reading and implying that analytical processing of individual characters may not be sufficient. Moreover, given features of the Chinese language such as homonyms and polysemous words, vocabulary breadth (number of words known) and depth knowledge (understanding of word meanings and usage) is particularly necessary to for the lexical level process (Zhao et al., 2025). Vocabulary knowledge in Chinese has been conceptualized as encompassing in-depth semantic knowledge and knowledge of word usage, which has been suggested as a unique predictor of reading comprehension in some analyses, highlighting its importance and strong overlap with Chinese word reading (Cai & Liao, 2024; Fan, 2015). The word recognition process also involves the construction of local and global coherence in Chinese text, which is important given the language's topic-prominent nature (Wang, 2019; Yang et al., 2017).

At the final stage as text integration and meaning construction, readers need to integrate recognised characters and words into larger meaningful units such as phrases and sentences

(Liu et al., 2024; Zhang et al., 2012). Cognitive factors such as verbal working memory, reading fluency, and syntactic skills are consistently found to be important (Pan & Lin, 2023; Yeung, 2022). Working memory and the ability to read pseudowords were particularly salient in distinguishing good from poor readers in studies involving Hong Kong children, with verbal memory underscored as especially important for modeling reading comprehension (Leong et al., 2008). Longitudinal studies have further confirmed the developmental importance of cognitive skills in Chinese children's reading comprehension (Zhao et al., 2021). Working memory has also been shown to mediate the relationship between rapid automatized naming and Chinese reading comprehension. Moreover, as readers engage in inference and integration, drawing upon the literal meaning of words and sentences, as well as their background knowledge, vocabulary depth, and understanding of morphemes, to interpret meaning, make connections, and build a model of the text's content (Paris, 2018). Besides, metacognitive strategies, such as monitoring comprehension and employing strategies like looking up unknown words or guessing from context, help readers navigate difficulties and ensure understanding (Cromley, 2023).

While the fundamental cognitive mechanism of Chinese reading comprehension is assumed to be universal across languages, the specific features of a language system can influence which skills and processes are particularly important or challenging (Perfetti et al., 1992; Perfetti et al., 2005). Research examining Chinese reading comprehension from kindergarten children to adults has shown that EF significantly predicts both L1 and L2 comprehension. (Hung, 2021; Pan & Lin, 2023; Sun, 2021; Zou et al., 2022). Because Chinese writing system contains few inflectional cues, multiple interpretations can remain active while one reads, requiring working-memory capacity and successful comprehension depends on efficiently suppressing those that prove irrelevant. Such process of reading comprehension make higher-order cognitive skills of EF especially critical for Chinese

(Gao et al., 2023; Liu et al., 2024; Weng et al., 2016). Developmental evidence further suggests that a single EF factor supports comprehension in early childhood. Moreover, distinct EF components become increasingly differentiated and exert more specialized influences on reading success as readers mature.

The ability of working memory to manipulate text information while processing text appears critical for building a coherent understanding, especially when dealing with more complex passages or those requiring deeper inferencing (Deng, 2025; Huang et al., 2022). For Chinese native speakers, working memory has been shown to play an important role in reading comprehension as early as primary grades 3 children (Gao et al., 2023). Some studies further suggest it may be even more crucial than word recognition in explaining individual differences in reading comprehension (Weng et al., 2016). In the context of adult second language learners of Chinese, individual differences in working memory capacity contribute to the learning of characters (Kim, 2020). Specifically, working memory has been found not only be helpful in learning Chinese characters but also the complex reading comprehension process.

Cognitive flexibility has been also analysis in different research explain that readers must shift quickly among mental representations and infer implicit subjects or discourse relations when overt syntactic markers are sparse (Cartwright, 2009; Gao et al., 2008). Studies have investigated the contribution of cognitive flexibility to Chinese reading comprehension and have found a significant direct effect of L1 and L2 learners (Hung & Loh, 2021; Xiu & Chu, 2023). For instance, research with Chinese beginning readers measured cognitive flexibility in Grade 1 and found it significantly explained variance in reading comprehension at Grade 3 (Xu et al., 2024). Similarly, a study with third-grade primary school children found that cognitive flexibility was a significant predictor of reading comprehension, uniquely accounting for variance beyond age and metalinguistic measures

including morphosyntactic skill and discourse awareness (Zhao et al., 2022). Beyond its direct influence, cognitive flexibility also appears to exert indirect effects on reading comprehension, mediated by other skills. In Chinese beginning readers, its relationship with reading comprehension was partially mediated through language-specific abilities such as morphological awareness and Chinese word reading (Xu et al., 2024). Hierarchical relationships were also found, where cognitive flexibility influenced foundational literacy skills like phonological awareness, which in turn impacted reading comprehension.

While inhibition control is acknowledged as a core EF component potentially related to reading difficulties and the ability to suppress irrelevant information relevant in Chinese reading (like homophone meanings), the role of inhibition control in Chinese reading comprehension is still understudied compared to working memory and cognitive flexibility (Kim, 2023; Sun, 2021). Studies on children illustrates that children with low reading comprehension performance show deficiencies in inhibition (Locascio et al., 2010). This suggests a direct link between inhibition deficits and difficulties in reading comprehension, even when basic word recognition is intact. When discussing possible explanations for the direct effect of inhibitory control on reading comprehension, Liu and Liu (2020) proposes that it might be mediated through enhanced linguistic skills, explicitly listing updating and inhibition as relevant components. This suggests a potential pathway where inhibition skills could support the reading comprehension by suppressing distractions, such as the meanings of homophones and homographs.

To sum, the multi-layered of reading Chinese suggest that proficiency across various linguistic levels including orthography, phonology, and morphology as well as cognitive skills of EF. The interplay between lower-level skills of character recognition and higher-level skills of syntax is crucial for successful comprehension. In the next section, reading

related skills in Chinese reviewed above will be detailed analysis their role in Chinese reading comprehension.

3.4.2 Reading related skills in Chinese

As previously discussed, reading Chinese is a complex and multifaceted process that necessitates the integration of both linguistic and cognitive skills. Effective comprehension of written Chinese requires learners not only to recognize individual characters but also to accurately segment continuous text into meaningful word units, a particularly demanding task given the absence of explicit word boundaries in the script. This process relies on a range of metalinguistic abilities, including morphological awareness, orthographic knowledge, and phonological awareness (Deacon & Kirby, 2004; Li et al., 2017; Tong et al., 2009; Xie et al., 2019). As outlined in Section 3.4.1, cognitive skills play a crucial role in reading comprehension, often by supporting the development and application of these metalinguistic components.

Accordingly, a comprehensive examination of these foundational skills is essential for a nuanced understanding of reading comprehension in Chinese. The following sections provide an in-depth review of the ways in which phonological awareness, orthographic knowledge, and morphological awareness, both individually and collectively, contribute to reading comprehension within the context of Chinese literacy acquisition.

3.4.2.1 Orthographic knowledge

Orthographic knowledge refers to the memory for visual and spelling patterns that facilitate the identification of individual words or word components (Apel et al., 2019; Burt, 2006; Ehri, 2014; Geva & Willows, 1994). It encompasses a range of cognitive abilities, including sensitivity to the correspondence between the sound structure of spoken language and its written representation, the application of sound-symbol rules, and an understanding of

the spelling conventions associated with irregular or low-frequency words (Leong et al., 2011; Loh et al., 2018; O'Connor & Jenkins, 1995).

In the context of Chinese, orthographic knowledge involves an awareness of the internal structure of characters, particularly the functional roles and positional regularities of phonetic and semantic radicals (Chan et al., 2023; Loh et al., 2024; Tong et al., 2009). Given the morphosyllabic and visually dense nature of Chinese script, this form of knowledge includes sensitivity to the spatial configuration, legal radical combinations, and overall visual integrity of characters—features that distinguish it significantly from alphabetic systems.

The relationship between orthographic knowledge and reading comprehension in Chinese has been well-documented (Liao et al., 2022; Siok & Fletcher, 2001; Wong, 2020). Empirical findings indicate that orthographic processing makes a unique contribution to reading outcomes even after controlling for phonological awareness (Lin et al., 2019; Liu & Liu, 2000; Zhang et al., 2022). Among L2 Chinese learners, orthographic knowledge has been shown to significantly predict performance in word reading, word dictation, and reading comprehension (Loh et al., 2018), suggesting its essential role in supporting both basic literacy and higher-order comprehension skills.

Importantly, orthographic awareness functions not only as a direct predictor but also as a mediating mechanism in the reading process. It has been found to mediate the relationship between writing ability and reading comprehension, indicating that the act of character writing contributes to reading development by enhancing orthographic representations (Packard et al., 2006). From a cognitive processing perspective, fluent access to visual word forms which is supported by well-developed orthographic knowledge is crucial for efficient reading, especially in a writing system that lacks explicit word boundaries (Braze & Gong, 2017). This fluency facilitates faster word recognition and enables smoother integration with lexical and semantic knowledge, ultimately improving comprehension of connected text.

When comparing orthographic knowledge with other linguistic subskills, findings are mixed. Some studies report that orthographic and phonological awareness exhibit similar effect sizes in predicting reading comprehension (Cheung et al., 2001; Li et al., 2012). However, evidence also suggests that orthographic skill may hold greater predictive power than phonological awareness, particularly for L2 learners who cannot rely on phoneme-grapheme correspondence strategies commonly used in alphabetic scripts (Loh et al., 2018).

In summary, orthographic knowledge plays a vital role in Chinese reading comprehension due to the visual-structural complexity and morphosyllabic nature of the script. It underpins word recognition, mediates the influence of writing on reading, and enhances access to lexical representations. Given its multifaceted contribution, orthographic knowledge represents a foundational component of literacy development in Chinese, especially for L2 learners.

3.4.2.2 Morphological awareness

Morphological awareness is a fundamental metalinguistic and cognitive skill, defined as the ability to reflect upon and manipulate morphemes and to apply word formation rules in language (Chan, 2013; Duncan, 2018; Ku & Anderson, 2003; Kuo & Anderson, 2006; McCutchen & Stull, 2015). Morphemes, the smallest units of meaning in a language, are conceptualized as abstract mental categories, while their concrete realizations in speech or writing are referred to as morphs (Nida, 1948; Taft & Zhu, 1995). This skill is particularly salient in Chinese reading due to the morphosyllabic nature of the writing system, wherein each character typically corresponds to a morpheme that also represents a syllable (Hung, 2012).

One of the defining characteristics of the Chinese lexicon is its strong reliance on compounding. The majority of modern Chinese words are disyllabic compounds, and the meanings of many of these words can be inferred from their constituent morphemes (Arcodia,

2007; Perfetti et al., 2005; Yip, 2000). Consequently, morphological awareness facilitates the comprehension of novel or unfamiliar words through morphemic analysis. For example, a learner who understands the meaning of a morpheme within a compound can often deduce the meaning of the entire word, thereby enhancing vocabulary acquisition and reading comprehension.

Empirical studies have consistently identified a significant relationship between morphological awareness and Chinese reading comprehension (Tong & McBride, 2017; Xie et al., 2019; Zhou, 2022). Tong et al. (2009) demonstrated that morphological awareness predicts reading comprehension both concurrently and longitudinally. However, this relationship is not uniformly observed across all studies. For example, Xie et al. (2019) reported that morphological awareness contributed significantly to reading comprehension only in later primary school years (Grades 5–6), and only after controlling for word reading and vocabulary knowledge.

In addition to its direct influence, morphological awareness also exerts indirect effects through mediating roles in the reading process (Liu & Liu, 2000). It has been found to mediate the relationship between Chinese character writing and reading comprehension, suggesting that writing proficiency enhances reading comprehension by strengthening morphological processing (Cheng et al., 2016). Moreover, morphological awareness significantly predicts word reading (Lin et al., 2019; Tong et al., 2016), and its mediating role remains robust even when speeded word reading is included in statistical models (Liu & Liu, 2020). This indicates that morphological awareness supports reading comprehension beyond its association with lexical access and fluency, likely through its contribution to deeper semantic processing and vocabulary development.

Comparative analyses further reinforce the importance of morphological awareness in Chinese literacy development. A meta-analysis by Dong et al. (2020) found that

morphological awareness had the strongest correlation with reading comprehension among Chinese learners, surpassing both phonological awareness and orthographic skills, which were moderately correlated. This pattern holds across both L1 and L2 learners, underscoring the uniquely prominent role of morphological processing in navigating the Chinese script.

In summary, morphological awareness plays a pivotal and multifaceted role in Chinese reading comprehension. Its contributions are both direct and indirect, supporting the interpretation of compound words, mediating the relationship between writing and reading, and predicting reading proficiency more reliably than other linguistic subskills. Although its influence may vary developmentally and contextually, morphological awareness remains a key target for literacy research and instruction in the Chinese context.

3.4.2.3 Phonological awareness

Phonological awareness, defined as the conscious sensitivity to the sound structure of spoken language, is widely recognized as a foundational component of reading acquisition across diverse writing systems (Anthony & Francis, 2005; Cheung et al., 2001; Gillon, 2017; Venkatagiri & Levis, 2007; Yopp & Yopp, 2009). This metalinguistic skill encompasses the ability to manipulate phonological units such as syllables, onset–rime segments, and phonemes (Haigh et al., 2011; Nancollis et al., 2005; Seymour et al., 1999). In the context of Chinese reading, however, the role of phonological awareness manifests in distinctive ways due to the language’s morphosyllabic structure and logographic script (Ho & Bryant, 1997; Huang & Hanley, 1995; McBride-Chang et al., 2012; Siok & Fletcher, 2001; Song et al., 2016).

Empirical studies suggest that syllable- and onset–rime-level awareness are more relevant to reading acquisition in Chinese than phonemic awareness, which plays a more dominant role in alphabetic languages (Newman et al., 2011; Zhao, 2017). This is attributable

to the fact that Chinese characters map onto morpheme-syllables rather than phonemes, reducing the functional utility of fine-grained phonemic segmentation.

The association between phonological awareness and Chinese reading comprehension has yielded mixed findings (McBride-Chang et al., 2004; Siok & Fletcher, 2001; Song et al., 2016). While some studies report a positive correlation between phonological awareness and reading performance, the magnitude of this relationship tends to be modest and often diminishes when other variables, such as morphological awareness, vocabulary knowledge, and rapid automatized naming, are statistically controlled (McBride-Chang & Ho, 2000; Pan et al., 2016). This reduced predictive power may be due in part to the high incidence of homophones in Chinese, which undermines the reliability of phonological cues for character identification compared to orthographic and morphological information. Nevertheless, phonological awareness has been found to uniquely predict performance on tasks such as word dictation, underscoring its specific, though limited, role in Chinese literacy (Kalindi & Chung, 2018).

Moreover, the development of orthographic knowledge in Chinese is closely linked to phonological awareness. Some studies suggest that phonological processing contributes to the acquisition of orthographic representations, even within a logographic system (Dong et al., 2020). However, unlike alphabetic languages, where the phonological route is central in connecting print to meaning, Chinese readers often rely on alternative pathways, such as the direct mapping of semantic radicals to meaning, a process described as orthography-semantic awareness (Liu, 2018).

In sum, although phonological awareness is universally acknowledged as a critical early reading skill, its unique contribution to reading comprehension in Chinese, particularly among more advanced readers, appears less robust than that of morphological awareness or

orthographic knowledge. Its role is nonetheless important during the initial stages of literacy development, especially in tasks requiring phonological decoding or orthographic learning.

3.4.3 Challenge of Chinese reading comprehension for L2 learners

As outlined in the preceding sections, multiple factors associated with the structural and functional complexity of the Chinese writing system significantly influence reading comprehension among Chinese L2 learners. These challenges extend beyond the linguistic level to encompass core cognitive processes that are instrumental in the decoding and interpretation of written text (Leong et al., 2019; Shu et al., 2024; Yang et al., 2023). The cognitive demands placed on learners are shaped not only by the unique features of Chinese as a morphosyllabic and logographic language but also by the learners' L1 background and stage of cognitive development.

In particular, cognitive mechanisms such as working memory, cognitive flexibility, and inhibitory control are central to managing the high visual density of Chinese characters, navigating the lack of phonological transparency, and segmenting unspaced text into meaningful lexical units. These EF skills enable learners to reconcile bottom-up decoding with top-down comprehension strategies, especially when faced with unfamiliar or visually similar characters. Furthermore, the influence of L1 reading strategies which is often optimized for alphabetic systems can interfere with the development of effective processing routines for Chinese unless deliberately suppressed or restructured.

Thus, a comprehensive understanding of Chinese L2 reading comprehension must account for the dynamic interaction between linguistic competence and domain-general cognitive skills. These interactions are further modulated by individual differences in L1 proficiency, literacy background, and metacognitive awareness. Investigating how these cognitive and linguistic dimensions intersect provides critical insight into the variability of reading outcomes among L2 learners of Chinese, and underscores the need for instructional

approaches that explicitly integrate cognitive strategy training alongside character learning and morphological instruction.

3.4.3.1 Linguistic features of Chinese writing system

The linguistic characteristics of the Chinese writing system present considerable challenges for L2 learners, particularly in the domain of reading comprehension (Bassetti, 2025; Wang & Yang, 2008). These challenges are closely tied to the substantial linguistic distance between Chinese and the alphabetic systems familiar to many L2 learners, as discussed in Section 3.4. Regardless of learners' L1 backgrounds, acquiring the repertoire of Chinese characters necessary for proficient reading has consistently been identified as one of the most demanding aspects of Chinese language acquisition.

A primary source of difficulty lies in the absence of a systematic and transparent relationship between orthography and phonology (Branner, 2011). Unlike alphabetic scripts, where grapheme-phoneme correspondence facilitates decoding, Chinese characters often lack predictable phonological cues. Although some characters contain phonetic radicals that ostensibly indicate pronunciation, these elements are frequently unreliable or only partially informative. As a result, L2 learners cannot rely on phonological decoding strategies in the way that readers of alphabetic languages typically do (Li & Woore, 2023). Instead, successful reading comprehension in Chinese requires robust orthographic processing and direct visual recognition of character forms. In this context, orthographic knowledge becomes more critical than phonological awareness for effective decoding.

Beyond the level of individual characters, morphological complexity further compounds the challenge. While a subset of characters can function independently as single-morpheme words, the majority of modern Chinese vocabulary consists of compound words formed through the combination of two or more characters (Arcodia, 2007). One particularly distinctive feature of written Chinese is the absence of inter-word spacing, which necessitates

that learners segment continuous character strings into meaningful lexical units. This segmentation process places significant cognitive demands on L2 readers, who must flexibly engage both bottom-up decoding of characters and words, and top-down inferencing based on prior linguistic and contextual knowledge (Kong, 2006; Lin et al., 2024).

Moreover, the high degree of homophony and synonymy in Chinese which is substantially greater than in many alphabetic languages requires learners to develop strong morphological awareness to infer meanings from character combinations (Liu et al., 2013). While some compound words are semantically transparent, others are opaque, and thus meaning cannot always be derived from constituent parts. The density of visually similar characters and the prevalence of polysemy and context-sensitive meanings further complicate character recognition and word identification. These features place a premium on EFs such as inhibitory control, which must be engaged to suppress irrelevant or misleading interpretations based on prior knowledge (Sun, 2021).

In sum, the linguistic features of the Chinese writing system including opaque orthography, morphological composition, absence of word boundaries, and high visual and semantic density create a cognitively demanding reading environment. For L2 learners, developing Chinese reading proficiency requires sustained engagement with orthographic and morphological knowledge, coupled with the deployment of executive control processes to navigate ambiguity and optimize comprehension.

3.4.3.2 Linguistic Distance and Transfer

The linguistic distance between Chinese and the alphabetic writing systems that characterize many learners' L1 learning presents a significant barrier for L2 readers of Chinese (Wang et al., 2003). As previously discussed, this distance stems from both structural and functional differences, including script type, phonological transparency, and morphological composition. Due to this disparity, cross-linguistic transfer exerts a powerful

influence on reading development. Learners often attempt to apply L1-based strategies to L2 Chinese reading. However, while effective in alphabetic contexts, such strategies are frequently ill-suited for the logographic nature of Chinese. For instance, speakers of English, a language with relatively transparent grapheme-phoneme mappings, tend to encounter greater difficulty when learning to read Chinese than they do when learning other alphabetic languages such as German or Spanish, where decoding processes align more closely with familiar L1 patterns (Cheng, 2011; Cordella et al., 2015; Li & Post, 2014).

As a result, Chinese L2 learners must develop novel decoding strategies that are absent from their L1 repertoire, while simultaneously suppressing interference from ineffective transfer. The ability to inhibit L1-based interference is critical, particularly during the transitional phases of proficiency development, and is modulated by the relative balance between learners' L1 and L2 competencies. At the same time, domain-specific skills such as Chinese character writing proficiency (CCWP) contribute positively to reading performance, serving as a compensatory mechanism for negative transfer. However, the beneficial effects of CCWP are attenuated as linguistic distance increases, highlighting the complexity of cross-linguistic influence (Liang & Cai, 2025).

L1 background further shapes decoding strategies and metacognitive behaviors. Learners from the Chinese Cultural Sphere (CCS) including native speakers of Japanese, Korean, or Vietnamese often display an initial advantage due to prior exposure to Chinese characters or similar orthographic conventions. However, this early benefit tends to diminish at more advanced levels of proficiency, where deeper semantic and syntactic integration becomes necessary (Duff & Doherty, 2018; Xu & Long, 2021). In contrast, non-CCS learners, faced with more pronounced linguistic and cultural distance, often compensate through deliberate metacognitive monitoring and strategic processing. Regardless of L1 background, however, the orthographic complexity of Chinese requires all learners to sustain

character- and word-level decoding strategies over extended periods, even as they gradually develop automaticity in word recognition (Chang et al., 2014; Guo & Huang, 2020).

3.4.3.3 Summary

Chinese reading comprehension poses a uniquely complex challenge for L2 learners due to the visually intricate nature of its logographic script and the opaque correspondence between orthographic form and phonological representation—features that diverge markedly from the alphabetic systems familiar to many learners' L1 learning. As such, successful comprehension in Chinese requires the integration of multiple linguistic competencies, particularly orthographic awareness and morphological knowledge. The cognitive demands on Chinese L2 readers are further heightened by the necessity to inhibit misleading prior knowledge, distinguish visually similar characters, and employ flexible processing strategies that alternate between character-level decoding and higher-order semantic integration. EF including working memory, cognitive flexibility, and inhibitory control are therefore critical in supporting reading comprehension. These cognitive mechanisms enable learners to suppress ineffective L1-based strategies and adapt to the unique demands of Chinese script processing. Consequently, the development of Chinese reading proficiency in L2 learners is contingent not only on linguistic competence but also on the sustained engagement of EF over an extended period of language acquisition.

3.5 Conclusion

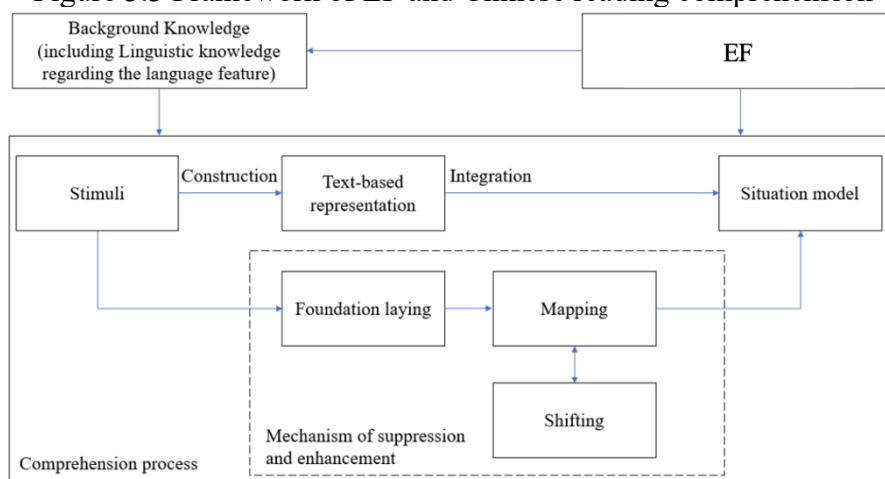
This chapter has systematically reviewed the cognitive and linguistic dimensions of reading comprehension, with particular attention to the unique challenges posed by the Chinese writing system. Drawing upon four major theoretical models of the CI Model, the SBF, Constructionist Theory, and the Reading Systems Framework, the chapter developed a multi-layered understanding of the reading process. These models collectively illuminate how

readers process Chinese texts, ranging from character-level decoding informed by language-specific knowledge to discourse-level comprehension supported by executive and inferential skills. The CI Model emphasizes the cyclical construction and integration of meaning; the SBF highlights enhancement and suppression mechanisms that distinguish skilled from less-skilled readers; Constructionist Theory focuses on goal-directed inference making; and the Reading Systems Framework stresses the lexicon's central role in bridging word recognition with higher-order comprehension processes.

Building on this theoretical foundation, the chapter examined the cognitive demands of reading Chinese. It analyzed how visual complexity, radical structure, and the absence of explicit word boundaries heighten the difficulty of lower-level processing. Empirical findings were reviewed concerning phonological, orthographic, and morphological awareness, as well as EF skills that contribute to comprehension performance in Chinese reading. These findings culminate in the framework presented in Figure 3.3, which conceptualizes the dynamic interaction between EF and reading comprehension in Chinese. Successful reading comprehension is understood to depend on the interplay between foundational decoding abilities and higher-order cognitive regulation.

As this chapter concludes, attention turns to the influence of emerging technologies on literacy. The next chapter will investigate the evolving role of artificial intelligence (AI) in language learning, with a particular focus on AI literacy which is defined as the competence to interact meaningfully and critically with AI systems in educational contexts. The cognitive challenges specific to Chinese reading offer a compelling lens through which to consider how AI can scaffold language-specific processing demands. By linking the cognitive foundations of reading comprehension established here with contemporary discourse on AI integration, the subsequent chapter will explore how AI literacy may reshape multilingual comprehension and redefine the role of EF in the digital age.

Figure 3.3 Framework of EF and Chinese reading comprehension



Chapter 4 Literature Review of Artificial Intelligence and Education

4.1 Overview

Artificial Intelligence (AI) is playing an increasingly prominent role in education, particularly in the domain of language learning, where it is emerging as a transformative force that is reshaping the ways in which knowledge is accessed, processed, and assessed.

This chapter presents a comprehensive literature review on AI in educational contexts, with particular emphasis on the role of AI literacy in language learning. Section 4.2 explores the integration of AI in education, with a focus on its pedagogical applications in language acquisition. Section 4.3 introduces the concept of AI literacy as a critical competency in the digital age, emphasizing that it encompasses not only technical proficiency but also a nuanced understanding of AI's capabilities, limitations, and ethical implications. Various AI literacy frameworks, such as the AI Curriculum Framework and AI4K12, are reviewed to elucidate the cognitive domains of AI literacy and their relevance to language education. Section 4.4 examines current approaches to assessing AI literacy, highlighting existing tools and methods used to evaluate learners' competencies. Finally, Section 4.5 synthesizes the reviewed literature to propose the theoretical framework guiding the current study. It conceptualizes the interrelationship among executive function (EF), reading comprehension, and AI literacy, positing that robust EF skills are foundational for engaging with complex textual content—whether traditionally authored or AI-generated. The chapter concludes by asserting that AI-supported language learning requires elevated levels of critical thinking and metacognitive awareness, both of which are deeply grounded in EF. The synergistic development of these three domains is presented as essential for learners to succeed in an increasingly AI-mediated educational landscape.

4.2 Artificial Intelligence and Education

AI has rapidly emerged as a transformative agent in education, fundamentally reshaping the modalities through which knowledge is accessed, delivered, and assessed (Lytras et al., 2024). Within the domain of language learning, AI assumes an increasingly central role, embedded within a spectrum of tools including automated translation, speech recognition systems, adaptive learning platforms, and AI-driven writing assistants. These technologies afford learners immediate, personalized feedback and support, while enabling scalable, data-informed instructional approaches tailored to individual learner profiles. Furthermore, AI facilitates innovative forms of learner engagement by enabling interaction with virtual tutors, conversational agents, and immersive digital environments, thereby fostering communicative competence and intercultural awareness. As AI integration in educational contexts intensifies, particularly within language acquisition, it is imperative to critically examine both its affordances and constraints. This necessitates a nuanced understanding of how AI enhances linguistic input, promotes metacognitive development, and supports learner autonomy, alongside a conscientious appraisal of challenges pertaining to algorithmic bias, equitable access, and ethical considerations. The ensuing sections undertake a detailed exploration of these dynamics, conceptualizing AI not merely as a technological instrument, but as a cognitive collaborator within the evolving landscape of language education.

4.2.1 The nature of Artificial Intelligence

AI can be broadly defined as a technological paradigm that emulates human intelligence to assist individuals in performing cognitive tasks, particularly those related to learning and problem-solving, by leveraging rule-based systems and contextual information (Beetz, 2007; Jarrahi, 2018; Konar, 2018; Korteling et al., 2021; Shabbir & Anwer, 2018). At its core, AI encompasses computational systems and toolsets engineered to execute functions

traditionally requiring human intelligence (Heer, 2019; Karray & De, 2004). Historically, AI research has evolved from addressing specific problem-solving challenges toward automating broader human cognitive and behavioral processes (Fügener et al., 2022; Raisch & Fomina, 2025). Contemporary definitions emphasize AI as machine-based systems capable of generating predictions, recommendations, or decisions grounded in human-defined objectives (Estevez Almenzar et al., 2022). A defining characteristic of AI is its adaptive capacity, achieved through the processing of extensive datasets without explicit, step-by-step programming.

The objectives of AI development are generally conceptualized along two complementary dimensions. The first, a technological aim, seeks to design computer systems that perform practically useful tasks (He et al., 2019; Lu et al., 2018). The second, a scientific aim, involves employing AI models to enhance our understanding of human cognition and other manifestations of intelligent behavior (Xu et al., 2021). These dual aims converge to enable AI's particular strengths in identifying patterns within large datasets and making informed decisions in structured environments.

Notwithstanding its capabilities, the nature and application of AI raise significant ethical concerns (Owe & Baum, 2021; Safdar et al., 2020; Sun & Ye, 2023). Issues such as fairness, algorithmic bias, misinformation, ethical decision-making, and inclusivity warrant critical attention (Emma, 2024; Li et al., 2024; Mensah, 2023). Research highlights that processes such as datafication often embed biases introduced through human choices during dataset curation and training (Hintz, 2024). Consequently, ethical AI design is imperative, advocating for the development of systems that responsibly reflect human values and intelligence (Díaz-Rodríguez et al., 2023). In educational contexts, ethical AI usage entails upholding academic integrity and addressing concerns related to plagiarism, authorship, ownership, transparency, and disclosure (Mulenga & Shilongo, 2024).

In summary, AI can be understood as computational systems engineered to emulate human intelligence in support of learning. The interplay between its technological utility and scientific inquiry has propelled AI from early problem-solving algorithms to sophisticated, data-driven applications capable of autonomous pattern recognition and decision-making in well-defined domains. Nonetheless, the profound capabilities of AI necessitate rigorous ethical scrutiny. Recognizing both AI's functional potential and its attendant ethical responsibilities is essential. With this foundational understanding of AI's nature established, the subsequent section examines the intersection of AI technologies with educational practice, with particular attention to their application in language learning.

4.2.2 Artificial Intelligence in the Education Context

AI is increasingly instrumental in supporting and transforming various facets of education (Pedro et al., 2019; Zootzky & Pfeiffer, 2024). The integration of AI within educational environments, commonly termed Artificial Intelligence in Education (AIED), has evolved since the 1980s, leveraging advanced AI technologies and applications to enhance teaching, learning, and administrative processes (Chen et al., 2020; Chen et al., 2022; Huang et al., 2021; Khosravi et al., 2022). AIED systems simulate aspects of human intelligence to perform inferences, make judgments, and generate predictions, thereby offering personalized guidance, support, and feedback tailored to individual learner needs. These systems are employed not only to augment instructional delivery and facilitate student engagement but also to automate routine administrative functions.

Key AI technologies applied within educational settings include automated assessment tools, adaptive learning platforms, humanoid robots, and web-based chatbots, frequently underpinned by machine learning and natural language processing (NLP) techniques to optimize personalized learning experiences (Alqahtani et al., 2023; Frank, 2024). Given AI's

multifaceted impact on education, it is essential to critically examine how these technologies enhance learning, particularly through cognitive dimensions.

From a cognitive development perspective, AI systems are capable of constructing individualized learning pathways that emphasize learner engagement, depth of comprehension, and the cultivation of higher-order thinking skills across diverse academic domains, such as academic writing and reading comprehension (Diwan et al., 2023; Tapalova & Zhiyenbayeva, 2022). Instructional AI tools that integrate voice recognition, natural language processing, multimedia, and gamified storytelling facilitate richer textual engagement and promote critical reasoning. Moreover, AI assumes functions traditionally performed by educators, including the evaluation of student assignments and provision of real-time formative feedback (Chen et al., 2020; Qazi et al., 2024; Tulli, 2022). These AI-enabled systems not only reduce the time educators spend on grading through automatic scoring but also support the analysis of student work, enabling timely pedagogical interventions (Messer et al., 2024).

Despite the cognitive and operational benefits highlighted in the literature, practical challenges remain. Issues such as equitable access to AI technologies and the adequacy of teacher training continue to impede widespread and effective adoption. Educators must acquire the expertise to interpret AI-generated outputs critically and to detect AI-produced content to ensure the integrity of assessment practices (Pan et al., 2024). Thus, the effective integration of AI in education requires comprehensive implementation frameworks, ongoing professional development, and a sustained commitment to transparency and equity. These measures are essential to position AI as an empowering adjunct rather than an opaque or replacement agent in educational processes (Enemosah, 2025).

In summary, AI offers considerable potential to enhance cognitive outcomes during learning, but its successful and ethical application demands careful deliberation. Building on

this broad overview of AI in educational contexts, the subsequent section will focus more specifically on AI-supported reading comprehension, with particular emphasis on second-language learning environments.

4.2.3 The Role of Artificial Intelligence in Language Learning

The integration of AI into educational settings, particularly language learning, has garnered increasing scholarly attention due to its potential to enhance instructional practices and enrich the language acquisition process. AI technologies support core language skills of listening, speaking, reading, and writing thereby transforming traditional pedagogical approaches. As a multidisciplinary field encompassing machine learning, neural networks, and NLP, AI simulates human cognitive functions such as learning, reasoning, and problem-solving. This capability underpins the development of AI language models, which are designed to process linguistic input and generate human-like responses, thereby enabling personalized and responsive language instruction.

The theoretical foundation for applying AI in language learning can be traced back to early models such as Quillian's Teachable Language Comprehender (TLC) (1969), which sought to emulate human language understanding through input-driven learning. Subsequently, Computer-Assisted Language Learning (CALL) established an early paradigm for integrating technology into language pedagogy (Garrett, 2019), primarily through structural drills and rule-based feedback mechanisms. While relatively rudimentary, these early systems anticipated the potential of AI by providing semi-adaptive responses to learner input. Building on this foundation, Intelligent Computer-Assisted Language Learning (ICALL) incorporates AI and NLP techniques to create more interactive and communicative learning environments, addressing the complexities of authentic language use and fostering learners' strategic and communicative competence beyond static grammar exercises (Amaral & Meurers, 2011).

Contemporary AI-driven language learning technologies encompass Intelligent Tutoring Systems (ITS), NLP-based applications, and Mobile-Assisted Language Learning (MALL) platforms (Kannan & Munday, 2018). ITS adapt instructional content dynamically to meet individual learner needs, while NLP-based tools have revolutionized feedback mechanisms in pronunciation, grammar, and real-time language use. These systems leverage modern AI's ability to process vast linguistic datasets, advancing second language acquisition through cognitive processes including learning, reasoning, and self-correction (Polyakov, 2019). Specifically, learning involves data collection and algorithm development to transform raw data into actionable insights; reasoning pertains to selecting suitable algorithms to generate accurate outcomes; and self-correction refers to iterative refinement of these algorithms to enhance performance over time.

From a practical standpoint, recent advances in large language models and generative AI, exemplified by tools such as ChatGPT and Bing Chat, have inaugurated a new paradigm in language learning (Dao, 2023; Guerra et al., 2025; Obaidoon & Wei, 2024). These innovations afford extensive opportunities for informal digital language learning (IDLE) and support autonomous second language development beyond formal classrooms (Soyoof, 2023). For instance, Liu et al. (2024) employed an explanatory sequential mixed-methods design to investigate how Chinese learners of English as a Foreign Language (EFL) utilize generative AI tools for out-of-class language practice. Their findings indicate that the natural language processing capabilities of such AI enable learners to produce linguistically accurate and contextually appropriate texts, while also recognizing language varieties, cultural nuances, and discourse genres. AI chatbots facilitate interactive dialogue and provide instant feedback, empowering learners to engage in personalized, creative language use and meaning-making processes. Grounded in the Technology Acceptance Model (TAM), the study identified perceived usefulness as the primary determinant of learners' adoption of

generative AI. This perception is fostered through experiential engagement, wherein students appreciate the tools' intelligent conversational abilities, personalized tutoring features, and resource recommendations. Moreover, cost-free and accessible platforms enhance their appeal. Although initial limitations, such as single-modal interaction and occasional biased outputs, may challenge users, learners often develop metacognitive strategies, including prompt engineering and critical evaluation, to optimize tool efficacy.

Beyond direct learner interaction, AI facilitates immersive and adaptive learning experiences (Rane et al., 2023). AI-driven simulations allow learners to practice language in realistic, context-rich scenarios, promoting negotiation of meaning and authentic second language acquisition (Dai & Ke, 2022). Advances in speech synthesis and voice recognition further promise increasingly naturalistic and human-like AI interactions, bridging gaps between theoretical knowledge and practical application (Chandra et al., 2022). The incorporation of AI into web-based platforms and social networks expands opportunities for collaborative learning and authentic communication, including AI chatbots offering personalized learner support. Furthermore, AI's capacity to analyze extensive learner data enables educators to identify challenging language features, monitor learner progress, and predict areas prone to forgetting, thereby facilitating tailored and effective pedagogical interventions (Zhuang et al., 2017). In sum, AI's ability to provide comprehensible input and facilitate comprehensible output underscores its growing significance in language education, advancing more personalized and effective learning paradigms.

4.2.4 Summary

The integration of artificial intelligence into language learning holds substantial promise for enhancing instructional methodologies and improving learner outcomes. Empirical research substantiates the efficacy of AI-driven tools in promoting L2 reading comprehension by increasing learner motivation, managing cognitive load, and delivering

adaptive learning approaches tailored to individual developmental levels. With the progression of CALL to ICALL, these technologies offer increasingly personalized support, thereby strengthening language acquisition processes.

However, the effective implementation of AI in language education necessitates that both learners and educators develop a sophisticated understanding of the functioning of AI systems. This underscores the critical role of AI literacy. As AI becomes deeply embedded within language learning environments, fostering AI literacy among educators and learners is imperative—not only to optimize the pedagogical advantages of AI but also to promote its responsible and equitable application. The subsequent section provides an in-depth examination of AI literacy, addressing its definitions, fundamental dimensions, and its vital role in equipping learners to engage with AI-enhanced educational contexts with confidence, critical discernment, and ethical awareness.

4.3 Theories of AI literacy

Despite the widespread integration of artificial intelligence into user-facing technologies and its pervasive presence in various aspects of daily life, from educational tools to virtual assistants, public understanding of AI remains limited (Brauner et al., 2023). This knowledge gap presents significant challenges, particularly within educational contexts where AI functions not only as a learning aid but also as a mediating agent that influences how learners acquire and process knowledge.

For both educators and learners, cultivating a comprehensive understanding of AI literacy is imperative as a foundational competency in the digital era. AI literacy encompasses a spectrum of skills necessary for the effective use of AI tools across diverse contexts. Given AI's expanding role in instructional design, assessment practices, and student

support services, the development of AI literacy is crucial for fostering learner success from a cognitive perspective (Hooda et al., 2022).

The following section therefore introduces the concept of AI literacy through a critical review of its definitions, core dimensions, and the theoretical frameworks that inform its development and practical application in educational settings.

4.3.1 What is AI literacy

AI literacy is an emergent and evolving construct that has yet to be definitively conceptualized (Chiu et al., 2024; Ng et al., 2021). The term was initially introduced by Burgsteiner et al. (2016) and Kandlhofer et al. (2016), who framed AI literacy as the competencies required to understand fundamental knowledge and concepts related to artificial intelligence. Expanding on this foundation, Long and Magerko (2020) articulated AI literacy as a multidimensional set of competencies encompassing critical evaluation of AI technologies, effective communication and collaboration with AI systems, and proficient use of AI tools across digital environments, including domestic and professional contexts. Furthermore, Ng et al. (2021) positioned AI literacy as an essential component of twenty-first-century digital literacy, applicable to a broad audience beyond computer scientists, and relevant to both workplace and everyday settings.

Focusing specifically on non-technical populations, particularly within K–12 education, more recent scholarship (Chiu et al., 2024) conceptualizes AI literacy as an individual's ability to clearly articulate how AI technologies function and affect society, alongside the capacity to employ AI tools ethically and responsibly, and to communicate and collaborate effectively with AI in diverse contexts. This definition foregrounds AI literacy as a fundamental skill set that extends beyond mere technological or computational proficiency to include critical, reflective, ethical, and social dimensions.

Accordingly, this section will undertake a detailed examination of theoretical frameworks underpinning AI literacy, aiming to elucidate the conceptual interrelations among AI literacy, language education, and cognitive processes.

4.3.2 AI Literacy Frameworks

Numerous AI literacy frameworks have been developed across various educational levels, reflecting diverse conceptualizations of what it means to be literate in an AI-driven world. These frameworks frequently build upon and adapt preexisting literacies, such as digital literacy, data literacy, and computational thinking.

One of the earliest frameworks, the AI Curriculum Framework by Kandlhofer et al. (2016), was grounded in the theory of computation and derived from foundational concepts presented in an undergraduate textbook. This framework posits the relevance of AI literacy across the full educational spectrum, from kindergarten through university, defining it as the capacity to comprehend fundamental techniques and concepts underlying AI. It identifies seven core elements: automata, intelligent agents, graphs and data structures, sorting algorithms, problem-solving via search strategies, classical planning, and machine learning.

To provide a more comprehensive and age-appropriate framework for K–12 education, Touretzky et al. (2019) introduced AI4K12, which outlines national guidelines for AI literacy education. This framework is organized around five essential "big ideas" intended as foundational knowledge for all K–12 students: Perception (computers perceive the world through sensors), Representation and Reasoning (agents maintain and utilize internal models of the world), Learning (computers learn from data), Natural Interaction (intelligent agents require diverse knowledge to interact naturally with humans), and Societal Impact (AI influences society both positively and negatively). The AI4K12 framework aligns AI literacy with computational thinking by integrating AI-related processes such as testing and evaluation within broader computational concepts (Touretzky et al., 2023).

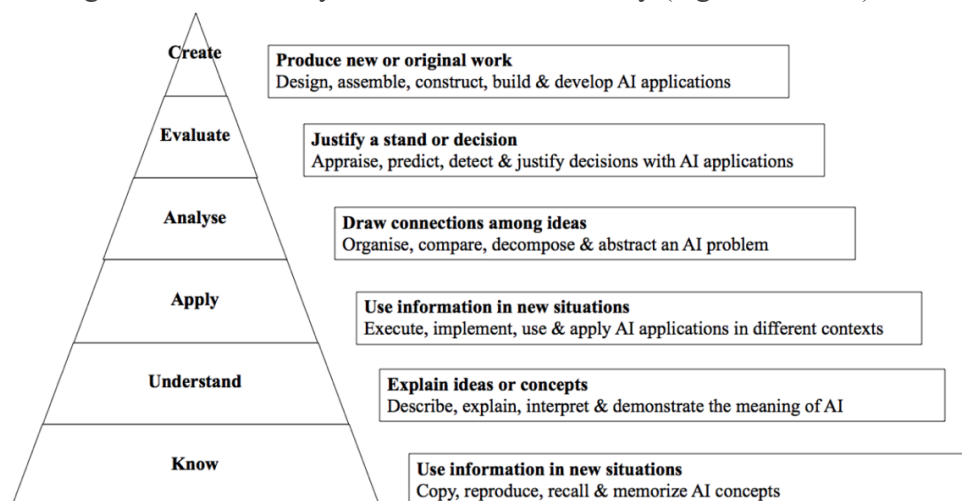
From a competency perspective, Long and Magerko (2020) developed the AI Literacy Framework through an extensive interdisciplinary literature review, including a scoping study of 150 publications. Targeted at both students and the general public, this framework identifies seventeen specific AI literacy competencies, ranging from recognizing AI technologies to analyzing distinctions between human, animal, and machine intelligence. It further articulates fifteen design considerations for AI literacy education, including explainability, embodied interaction, data contextualization, transparency, and progressive disclosure. Significantly, the framework emphasizes interdisciplinarity, encouraging learners to engage with multiple perspectives on intelligence and recognize AI's manifestations across cognitive systems, robotics, and machine learning.

Building upon these foundational models, Ng et al. (2021) applied Bloom's taxonomy to categorize AI literacy into four cognitive domains: Know and Understand AI, Use and Apply AI, Evaluate and Create AI, and AI Ethics. The first domain, Know and Understand AI, entails acquiring fundamental concepts, skills, and attitudes regarding AI's basic functions and underlying technologies, emphasizing confidence and readiness without necessitating prior technical expertise. Use and Apply AI involves practical engagement with AI tools across diverse scenarios, including everyday contexts and professional environments. Evaluate and Create AI encompasses higher-order cognitive skills, such as critical evaluation, appraisal, prediction, and the design of AI-driven solutions, corresponding to Bloom's higher levels of analysis, evaluation, and creation. The AI Ethics domain addresses human-centered concerns related to fairness, accountability, transparency, safety, privacy, and social responsibility.

Extending their earlier work, Ng et al. (2024) introduced the Affective, Behavioural, Cognitive, and Ethical (ABCE) Framework tailored to secondary education. This model adds affective and behavioral dimensions to offer a more holistic understanding of AI literacy. The

affective dimension focuses on students’ attitudes and socio-emotional competencies, recognizing the importance of emotional engagement and openness toward AI technologies. The behavioural dimension emphasizes active participation through collaborative inquiry and problem-solving, deemed essential for meaningful AI interaction. The cognitive dimension retains the progressive learning stages identified in prior models, while the ethical dimension encompasses critical considerations including safety, privacy, transparency, and awareness of AI’s societal impacts. Collectively, these four interconnected domains constitute an integrated framework that fosters a comprehensive, responsible, and developmentally appropriate approach to AI education.

Figure 4.1 AI literacy and Bloom’s Taxonomy (Ng et al., 2024)



More recently, Chiu et al. (2025) proposed a conceptual framework specifically designed to address AI literacy within K–12 education, responding to the growing imperative for a forward-looking and ethically grounded approach to integrating technology in school settings. Within this model, AI literacy is defined as the capacity to articulate clearly how AI technologies function and how they affect individuals and communities, underscoring the ethical responsibility inherent in employing AI to facilitate knowledge construction. This framework marks a paradigmatic shift from traditional constructionist perspectives, which prioritize learning through making and experimentation, toward a post-humanistic orientation

that acknowledges the intricate interdependencies between human learners and AI systems within the educational process. A central tenet of this model is the notion of “AI thinking,” which encourages learners to critically reflect on and comprehend the ways in which AI technologies influence knowledge formation, societal dynamics, and human interactions.

In summary, this section illustrates the evolving landscape of AI literacy frameworks. Although no universally accepted definition of AI literacy currently exists, there is broad consensus that it encompasses four principal cognitive domains, informed by Bloom’s taxonomy, constructionism, computer science, and computational thinking. These domains include: (1) knowing and understanding AI, which involves developing foundational knowledge and awareness of AI technologies; (2) using and applying AI, which pertains to the practical engagement with AI tools and concepts across diverse contexts; (3) evaluating and creating AI, which entails higher-order cognitive skills such as critical analysis, prediction, and the design of AI applications; and (4) understanding ethical issues related to AI, including concerns surrounding data bias, privacy, and societal implications. While technical competencies such as programming are occasionally incorporated, they are generally not considered essential components of AI literacy in educational contexts targeting broad learner populations. Despite the proliferation of conceptual frameworks, a significant gap remains in the development of models tailored explicitly to specific learning domains, indicating a promising direction for future research and theoretical refinement.

4.3.3 Integrating AI Literacy into Language Education

As artificial intelligence becomes increasingly embedded within language learning environments, the integration of AI literacy into language education has emerged as a critical imperative (Godwin-Jones, 2013; Pokrivčáková, 2019; Schmidt & Strasser, 2022). AI literacy transcends mere operational knowledge of AI tools, encompassing a comprehensive understanding of their capabilities, limitations, and ethical ramifications. Traditionally,

language learners have been positioned as passive end users of educational technologies; however, the advent of adaptive systems and generative language models has fundamentally altered this dynamic (Evurulobi et al., 2024). Learners now engage with AI tools that simulate human-like communication, offer real-time feedback, and autonomously generate content. Consequently, effective navigation of this evolving landscape necessitates that learners transition from passive consumers to critical users of AI, cultivating not only technical awareness but also a sophisticated understanding of AI language processing mechanisms.

Several core dimensions of AI literacy are particularly salient within language learning contexts. Firstly, the domain of ‘knowing and understanding AI’ is essential, as learners must grasp foundational techniques and principles underlying AI-driven language technologies (Schmidt & Strasser, 2022). This includes discerning the varied applications of AI in educational settings and appreciating the relevance of AI and computational literacy for future career prospects in an increasingly globalized workforce. Secondly, ‘using and applying AI’ pertains to learners’ ability to effectively employ AI-enabled tools for language tasks such as reading comprehension and engaging with adaptive, personalized learning platforms. Competency in this area constitutes a vital component of digital literacy and enhances learners’ capacity to benefit from AI-supported pedagogies (Pokrivčáková, 2019). Thirdly, the ability to critically evaluate and create AI-mediated content is imperative. Learners must be equipped to scrutinize the accuracy of machine-generated translations and critically assess the appropriateness of AI feedback (Lee, 2023). This critical engagement exemplifies higher-order cognitive skills that enrich both digital and linguistic competences.

Beyond learner competencies, educators require comprehensive training to effectively facilitate AI literacy development. Educational institutions must ensure equitable access to reliable AI technologies, implement clear ethical guidelines, and incorporate dedicated

curricular space for critical discourse on emerging technologies. Furthermore, assessment practices must evolve to valorize learners' capacity to thoughtfully interpret and interact with AI tools, moving beyond mere production of AI-generated outputs (Cope et al., 2021).

Finally, learners must develop an acute awareness of the socio-technical issues inherent in AI systems, including algorithmic bias and data privacy concerns (Ramnani, 2024). These considerations are particularly pertinent for second-language learners, as many AI tools are trained on datasets reflecting dominant cultural norms and native-speaker varieties, potentially marginalizing non-standard dialects and perpetuating cultural assumptions (Godwin-Jones, 2024; Hall & Cunningham, 2020). Cultivating critical awareness of these biases enables learners to more judiciously evaluate AI-generated content and recognize embedded socio-cultural perspectives.

In summary, the integration of AI literacy within language education equips learners with a synergistic blend of analytical, ethical, and cognitive competencies. As AI technologies become increasingly entrenched in language learning contexts, the ability to critically engage with these tools assumes equal importance alongside traditional linguistic and cognitive skills. Supporting second-language acquisition in the AI era thus demands a triadic competency framework: linguistic proficiency to engage meaningfully with content; executive cognitive functions to process and comprehend complex language; and AI literacy to effectively navigate, critically assess, and ethically interact with AI systems. Collectively, these competencies constitute the foundation for learner success within an increasingly AI-mediated educational landscape.

4.4 Assessment for AI literacy

According to the framework of AI literacy, researchers have predominantly employed quantitative methodologies to assess this multifaceted construct, with self-report

questionnaires emerging as the most prevalent instruments (Lintner, 2024). These questionnaires commonly utilize Likert-scale formats to gauge individuals' perceived knowledge, confidence, attitudes, and experiences related to AI. Their standardized scoring systems render them particularly practical for large-scale educational applications. However, despite their widespread use, many existing AI literacy questionnaires require further psychometric refinement, including cross-cultural validation and the evaluation of measurement error (Biagini et al., 2024). Moreover, comprehensive content validation remains limited, constraining the generalizability of these instruments across diverse demographic groups.

A notable example is the Scale for the Assessment of Non-Experts' AI Literacy (SNAIL) developed by Laupichler et al. (2023), which was constructed via a Delphi expert consensus method. SNAIL assesses non-expert critical engagement with AI across three dimensions: technical understanding, critical appraisal, and practical application. While this scale demonstrates robust structural validity and internal consistency in both Turkish and German versions, potential floor effects have been identified, which may reduce sensitivity in detecting lower proficiency levels.

Another prominent instrument is the Meta AI Literacy Scale (MAILS), currently regarded as the most comprehensive AI literacy measure available (Carolus et al., 2023). Based on Ng et al.'s (2022) conceptual framework, MAILS encompasses 18 items distributed across four domains: "Use & Apply AI," "Know & Understand AI," "Detect AI," and "AI Ethics". The scale exhibits strong structural validity, internal consistency, and construct validity, supporting its utility in diverse research contexts.

Focusing on adolescent populations in secondary education, Ng et al. (2024) developed the AI Literacy Questionnaire (AILQ), grounded in the ABCE learning framework. The AILQ captures AI literacy through four interrelated dimensions: affective learning (attitudes),

behavioral learning (actions), cognitive learning (knowledge), and ethical learning (values). Empirical testing indicates moderate content validity alongside high structural validity and internal consistency, suggesting the instrument's appropriateness for secondary school students.

In early childhood education, despite cognitive and linguistic limitations, self-report measures have also been employed to investigate children's perceptions of AI (Lim, 2023). For instance, the AI Perception Questionnaire explores constructs such as perceived intelligence, truthfulness, and comprehension of AI agents, while the Perception of Robots Questionnaire assesses children's attribution of rule-following, intelligence, and anthropomorphic or toy-like qualities to robots (Su & Yang, 2024). Although these instruments are designed with developmental considerations in mind, their psychometric properties remain under ongoing evaluation.

In sum, although significant advancements have been made in the development of AI literacy assessments, particularly via self-report questionnaires, notable gaps persist. Most instruments exhibit strong internal consistency and structural validity; however, comprehensive content validation and cross-cultural generalizability are often lacking. A critical limitation is the predominant focus on perceived competence rather than actual, demonstrated AI-related skills, which may hinder the instruments' capacity to fully capture the depth of cognitive engagement essential for authentic learning contexts. This limitation is especially pertinent in language education, where learners are expected not only to utilize AI tools but also to critically appraise their outputs in task-specific scenarios, such as reading comprehension and writing. As AI literacy becomes increasingly integral to education, there is a pressing need to refine assessment tools to better represent the competencies required for meaningful, context-specific interaction with AI technologies. Such refinement should

include the development of instruments tailored to particular learner populations and aligned with the AI-supported learning activities relevant to those learners' educational experiences.

4.5 Conclusion of literature review

The preceding chapters have meticulously explored the foundational roles of EF and Reading Comprehension, and the burgeoning influence of AI in education. This concluding section synthesizes these three critical domains, illustrating their intricate interdependencies and emphasizing their collective importance for effective learning in the digital age, particularly within the context of second language acquisition.

4.5.1 Executive Function as the Cognitive Engine for Reading Comprehension

Chapter 2 delineated EF as a fundamental constellation of cognitive processes, comprising working memory, inhibitory control, and cognitive flexibility, that are indispensable for goal-directed behavior and the execution of complex cognitive tasks. These components operate not in isolation but as an integrated system exerting significant influence on reading comprehension. Working memory facilitates the temporary storage and manipulation of linguistic information, enabling readers to construct coherent mental representations of text and integrate incoming information with existing knowledge schemas. Inhibitory control is critical for suppressing irrelevant stimuli and resolving linguistic interference, a capability that is particularly salient in languages characterized by high homophony and structural ambiguity, such as Chinese. Cognitive flexibility supports the adaptive modulation of reading strategies, the parsing of diverse syntactic constructions, and the generation of inferences based on contextual information that correspond with the strategic inferencing processes highlighted in the Constructionist theory of reading. Empirical evidence consistently affirms that enhanced EF capabilities are positively correlated with

superior reading comprehension outcomes, both when considered as discrete cognitive faculties and as a cohesive, integrated construct.

4.5.2 Reading Comprehension as A Multi-Layered Cognitive Process

Chapter 3 examined reading comprehension as a multifaceted and cognitively demanding process involving the concurrent extraction and construction of meaning from text. Drawing upon theoretical frameworks such as the CI model, the SBF, the Constructionist Theory, and the Reading Systems Framework, the chapter elucidated how readers develop hierarchical mental representations ranging from surface-level decoding to sophisticated situation models.

The distinctive features of the Chinese writing system including its logographic script, morphosyllabic structure, and absence of inflectional morphology posing unique cognitive challenges that intensify the demands placed on readers' processing capacities. Specifically, proficient Chinese reading necessitates efficient orthographic processing, well-developed morphological awareness, and the capacity to infer implicit grammatical elements such as subjects. The dynamic interaction between foundational lower-level skills (e.g., character recognition) and advanced higher-level cognitive processes (e.g., syntactic parsing and inference generation) is essential for successful comprehension.

Within this complex interplay, EF components, particularly working memory and cognitive flexibility, play a pivotal role in managing the simultaneous processing of multiple linguistic cues and enabling adaptive cognitive shifts necessary for accurate and coherent comprehension of Chinese texts.

4.5.3 AI Literacy: Navigating the Future of Language Learning

Chapter 4 conceptualizes AI literacy as an essential competency in the context of an increasingly AI-driven global landscape. AI literacy is defined not merely as technical

proficiency but as a multifaceted capacity encompassing an understanding of how AI technologies operate, their broader societal implications, and the ethical considerations involved in their use. Prominent frameworks, such as the ABCE model, delineate AI literacy across cognitive, behavioral, affective, and ethical dimensions, highlighting its complexity and scope.

Within the domain of language learning, AI-enabled tools—including adaptive learning systems and generative AI chatbots, presenting unprecedented opportunities to enhance personalized feedback, facilitate immersive practice, and provide access to a broad range of linguistic input. Nevertheless, to harness these advantages effectively, learners must cultivate critical AI literacy. This entails a nuanced comprehension of the capabilities and inherent limitations of AI, the ability to critically evaluate the reliability and potential biases embedded in AI-generated content, and the strategic application of metacognitive approaches (such as prompt engineering) to optimize interactions with AI platforms.

Moreover, ethical considerations are integral to the construct of AI literacy. Issues surrounding data privacy, algorithmic bias, and responsible authorship must be foregrounded to ensure that AI functions as a transparent and empowering tool rather than an opaque or potentially harmful influence. Cultivating such ethical awareness is vital for fostering learners' capacity to engage with AI technologies in a manner that is both informed and socially responsible.

4.5.4 Cognitive Mechanisms of AI Literacy, EF, and Reading Comprehension

Drawing on the preceding literature review, Figure 4.2 presents the theoretical framework guiding this study on EF, reading comprehension, and AI literacy. This study proposes an integrated cognitive-linguistic-technological model in which EF, reading-related skills (orthographic knowledge and morphological awareness), and AI literacy interact dynamically to influence L2 Chinese reading comprehension. Rather than conceptualizing

these components as discrete constructs, the framework highlights their interconnectedness and reciprocal influence.

At the core of this framework is the proposition that EF, particularly working memory, inhibitory control, and cognitive flexibility, provides the foundational cognitive resources necessary for the development of both linguistic skills and AI literacy. Working memory supports the retention and manipulation of complex linguistic input as well as the interpretation of AI-generated output. Inhibitory control enables learners to filter out irrelevant, misleading, or distracting information, a capacity that becomes especially important when engaging with AI applications that may generate unreliable or biased content. Cognitive flexibility facilitates learners' ability to switch between multiple representational formats, adapt to evolving digital interfaces, and integrate AI-generated insights with pre-existing knowledge structures.

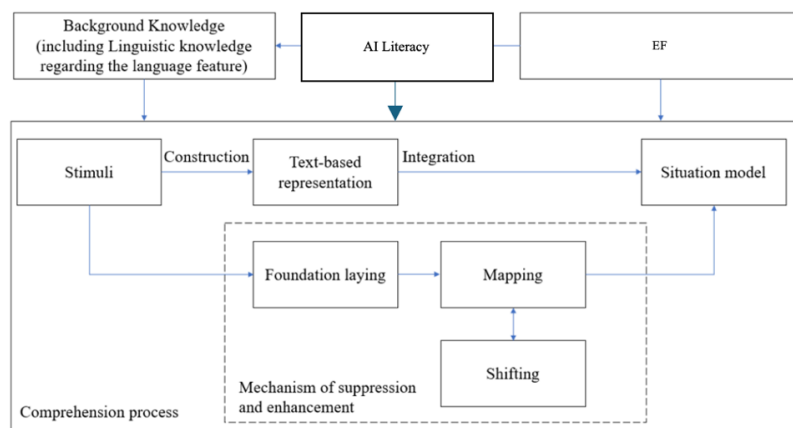
Within this model, AI literacy is defined as a multidimensional construct encompassing the ability to access, interpret, and critically evaluate AI-generated content in digital reading contexts. It is hypothesized to exert a direct influence on reading comprehension by enhancing learners' capacity to interact with, personalize, and interrogate AI-mediated textual environments. In addition to this direct effect, the model proposes indirect pathways: for instance, cognitive flexibility may support the development of AI literacy, which in turn contributes to improved reading comprehension outcomes.

The integration of AI into educational contexts also necessitates a re-examination of traditional approaches to reading instruction and assessment. Although AI tools can personalize learning and scaffold comprehension through adaptive feedback, they simultaneously demand elevated levels of metacognitive awareness and critical thinking, capacities grounded in EF. Learners must not only comprehend the literal content of a text but also develop an understanding of how AI processes language, identify potential

algorithmic biases, and critically evaluate the reliability and ethical implications of AI-generated information.

In conclusion, the synergistic development of EF, reading skills, and AI literacy is essential for fostering deep and critical reading comprehension, particularly in linguistically complex domains such as Chinese. As AI technologies become more embedded in education, AI literacy emerges not as an ancillary skill, but as a vital extension of traditional literacy. This integrated framework aims to empower learners to navigate complex information ecosystems, engage meaningfully with technological innovation, and thrive as informed, adaptable, and ethically responsible individuals in the 21st century.

Figure 4.2 Theoretical Framework of the current study



Chapter 5 Study 1: Exploring the Relationship Between Executive Function and L2 Chinese Reading Comprehension in Hong Kong Learners

5.1 Introduction

Reading comprehension is a complex cognitive process that requires the integration of linguistic knowledge and cognitive skills (Perfetti & Stafura, 2014). For second language (L2) learners, this process is further complicated by the need to navigate unfamiliar orthographic, syntactic, and semantic structures. In the case of Chinese, a logographic language with unclear character-sound relationships, reading comprehension imposes unique cognitive demands on learners (Wang & Yang, 2008; Pan & Lin, 2023). Executive function (EF), a set of higher-order cognitive processes that regulate goal-directed behavior, has been increasingly recognized as a critical factor in reading comprehension across languages (Diamond, 2013; Miyake & Friedman, 2012). However, the specific role of EF in L2 Chinese reading comprehension, particularly among learners in Hong Kong with alphabetic first language background, remains underexplored.

Hong Kong provides a compelling context for this investigation due to its bilingual education system, where students often learn Chinese (Cantonese or Mandarin) alongside English. Given the cognitive challenges posed by Chinese orthography, such as character recognition, morphological parsing, and contextual inference, EF may play an even more pivotal role in L2 Chinese reading than in alphabetic languages (Shu, 2003; Liu et al., 2024). Understanding how EF supports L2 Chinese reading comprehension can inform targeted instructional strategies to enhance literacy development in this population.

This study examines the relationship between EF and L2 Chinese reading comprehension among Hong Kong learners, focusing on three core EF components: working

memory, inhibitory control, and cognitive flexibility. Drawing on empirical evidence on Chinese literacy development, this study investigates how these EF components individually and collectively contribute to reading success. The findings will shed light on the cognitive mechanisms underlying L2 Chinese reading and offer practical insights for educators working with learners in similar linguistic and educational contexts.

5.2 The relation between EF and Chinese reading comprehension

EF encompasses a set of cognitive processes that enable individuals to plan, focus attention, regulate interference, and flexibly adapt to task demands (Diamond, 2013). Research has identified three core EF components, working memory, inhibitory control, and cognitive flexibility, that are particularly relevant to reading comprehension (Miyake & Friedman, 2012). These components operate both independently and interactively to support text processing, inference generation, and meaning integration (Cartwright & Palian, 2024).

5.2.1 Working Memory and Reading Process

Working memory is identified as one of the most crucial foundational cognitive skills contributing to literacy development across various languages (Bull & Scerif, 2001; García et al., 2021; Titz & Karbach, 2014). Unlike simple short-term memory, working memory encompasses both the capacity for temporary storage and the ability to hold words, phrases, and propositions in mind while integrating them with prior knowledge to construct coherent mental representations (Baddeley, 2021). It involves the simultaneous maintenance and manipulation of verbal and visuospatial information, skills that are considered essential for processes like word recognition and production (Daneman & Merikle, 1996). In Chinese, where characters often carry multiple meanings and require contextual disambiguation, working memory is essential for resolving ambiguities and sustaining comprehension across

sentences (Gao et al., 2023). Empirical studies have shown that working memory capacity strongly predicts reading performance in both L1 and L2 Chinese learners (Linck et al., 2014; Weng et al., 2016).

In context of Chinese reading, where characters often carry multiple meanings and require contextual disambiguation, working memory is essential for resolving ambiguities and sustaining comprehension across sentences (Gao et al., 2023). The ability of working memory to manipulate text information while processing text appears critical for building a coherent understanding, especially when dealing with more complex passages or those requiring deeper inferencing (Deng, 2025). For Chinese native speakers, working memory has been shown to play an important role in reading comprehension as early as primary grades, and some studies suggest it may be even more crucial than word recognition in explaining individual differences in reading comprehension (Weng et al., 2016). In the context of adult second language learners of Chinese, individual differences in working memory capacity contribute to the learning of characters and the complex reading comprehension process (Kim, 2020).

5.2.2 Inhibitory Control and Its Role in Resolving Linguistic Interference

Inhibitory Control is recognised as a core component of EF as it functions as a low-level EF process that contributes to a supervisory attention system (Gastmann & Poarch, 2022). Inhibitory Control encompasses abilities such as inhibiting prepotent responses and selectively attending to stimuli while suppressing attention to others (Drijbooms et al., 2015). Fundamentally, inhibitory Control is the capacity to resist interference from distracting information or automatic responses and to suppress inappropriate responses, enabling the replacement of automatic thinking with effortful thinking (Arrington et al., 2014).

Inhibitory Control plays a significant role in various reading processes. At the word level, it can be crucial for suppressing distractions from neighbouring words that share

similar orthographic or phonological characteristics during word recognition (Pan & Lin, 2023). In languages like Chinese, which feature compound words with characters having multiple context-dependent meanings and numerous homophones, inhibitory Control is considered critical for word recognition (Sun, 2019). On the other hand, it is thought to assist in efficiently accessing word structures and detecting morpheme meanings, and in inhibiting the frequent activation of homophone competitors during reading or writing (Drijbooms et al., 2015). Inhibitory Control may be substantially involved in suppressing inappropriate lexical representations at the word level and grammatical structures at the sentence level, as well as selecting a relevant set of words and phrase structures. Inhibition processes are also implicated in retrieving correct phoneme-grapheme associations from long-term memory while inhibiting incorrect ones (Blair & Razza, 2007).

5.2.3 Cognitive Flexibility and Adaptive Reading Strategies

Cognitive flexibility is known as set shifting or task shifting as one of the core components of EF (Logue & Gould, 2014; Uddin, 2021). This cognitive skill involves the ability to switch flexibly between tasks or mental sets. It is the capacity to adapt quickly and flexibly to changing situations, rules, tasks, and mental sets, and to change one's perspective or approach to a problem while flexibly adjusting to new challenges (Miyake & Friedman, 2012). Cognitive flexibility is thought to emerge during the early preschool period and might develop later than the other core EF components like inhibition and working memory. It is considered to be built upon inhibition and working memory (Cordeiro et al., 2020).

Specifically regarding reading comprehension in Chinese, where word boundaries are unmarked and sentence structures often rely on pragmatic cues, cognitive flexibility helps learners dynamically adjust their processing approaches (Xu et al., 2024). Studies have investigated the contribution of cognitive flexibility to Chinese reading comprehension and have found a significant direct effect of L1 and L2 learners (Liao et al., 2022). For instance,

research with Chinese beginning readers measured cognitive flexibility in Grade 1 and found it significantly explained variance in reading comprehension at Grade 3 (Xu et al., 2024). Similarly, a study with third-grade primary school children found that cognitive flexibility was a significant predictor of reading comprehension, uniquely accounting for variance beyond age and metalinguistic measures (Zhao et al., 2022). Beyond its direct influence, cognitive flexibility also appears to exert indirect effects on reading comprehension, mediated by other skills (Xu et al., 2024). From the perspective of second language learning, however, only limited studies found that cognitive flexibility contributes to both word reading and higher-level comprehension, particularly in inferential and integrative tasks (Hung & Loh, 2021).

5.2.4 The Present study

Despite growing evidence on significant relations between EF and reading, several significant gaps remain, particularly concerning L2 Chinese learners in specific educational contexts. Firstly, while studies have explored EF and reading in various populations, there is a notable scarcity of research specifically focusing on L2 Chinese learners in Hong Kong. Hong Kong presents a unique bilingual educational context where students are often exposed to both English and Chinese from an early age. This bilingual environment may influence the development and interplay of EF and reading skills in ways that are not fully captured by studies conducted in monolingual L2 contexts. Understanding these specific dynamics is crucial for tailoring effective pedagogical approaches.

Secondly, much of the existing research tends to examine individual EF components in isolation when relating them to reading comprehension. While this approach provides valuable insights into the unique contributions of each component, it often overlooks the integrated and synergistic nature of EFs. EFs are not typically deployed in isolation during complex cognitive tasks like reading; rather, they operate as a coordinated system. A

comprehensive understanding requires investigating how these components collectively contribute to reading comprehension, and whether their combined effects reveal pathways that are not evident when examined separately.

Thirdly, previous studies often focus on the direct relationships between EF and reading comprehension, sometimes neglecting the potential indirect pathways through which EF might influence reading. For instance, EF could enhance other cognitive or linguistic skills that, in turn, contribute to reading comprehension. Exploring such mediating roles can provide a more nuanced and complete picture of the underlying mechanisms.

This study directly addresses these critical gaps by building an integrated structural model that examines how working memory, inhibitory control, and cognitive flexibility , alongside related linguistic skills (such as orthographic knowledge and morphological awareness), collectively predict L2 Chinese reading comprehension in Form 4 South-east Asian students in Hong Kong. By adopting a comprehensive L2 perspective within this specific bilingual context, this research aims to:

1. Identify the direct and indirect pathways linking individual EF components and reading-related linguistic skills to L2 Chinese reading comprehension.
2. Model the relational dynamics among EF, linguistic components, and L2 Chinese reading comprehension, offering novel insights into the cognitive underpinnings of reading development in an L2 setting.

5.2.5 Research Questions

Building on the identified research gaps, the present study aims to advance understanding of how EFs and linguistic skills jointly contribute to Chinese L2 reading comprehension within Hong Kong's bilingual educational context. Specifically, it seeks to model both the direct and indirect pathways through which these cognitive and linguistic factors operate. Accordingly, the study addresses the following research questions:

1. How do the core components of EF (working memory, inhibitory control, and cognitive flexibility) directly and indirectly contribute to Chinese L2 reading comprehension among Form 4 Southeast Asian students in Hong Kong?

2. How do EF components and reading-related linguistic skills (orthographic knowledge and morphological awareness) interact within an integrated structural model to explain the cognitive and linguistic pathways underlying L2 Chinese reading comprehension?

5.3 Method

5.3.1 Participants

A total of 104 Form 4 Chinese L2 students (45 girls and 59 boys) participated in the study. They were Southeast Asian ethnic minority (EM) students recruited from four secondary schools in Hong Kong. All participants primarily used their first languages, such as Urdu, Hindi, Tagalog, Nepali, or English, in daily communication with parents and peers, with Chinese primarily used in academic settings. From a linguistic perspectives, the students' native languages are alphabetic, differing significantly from Chinese. It is essential to point out that EM students lack a supportive Chinese language environment at home. As a result, EM students often struggle to keep pace with their Chinese-speaking peers, and this achievement gap tends to widen without sufficient instructional and community support.

5.3.2 Research Instruments

The instruments were divided into two main types: literacy measures including Chinese reading comprehension and reading related skills as well as EFs including inhibitory control, working memory, and cognitive flexibility. Except for the EF tests, all materials and instruments were presented in the Chinese language.

5.3.2.1 Chinese Reading Comprehension

Chinese reading comprehension was assessed using selected reading tests from the Hong Kong Territory-wide System Assessment (TSA) Chinese reading comprehension test for Form 3 students. In this thesis, reading comprehension is defined as the ability to decode, comprehend, and interpret written texts in Chinese as an L2. TSA reading tasks require readers to construct meaning from connected text under time constraints, integrating word-level decoding with sentence- and discourse-level comprehension. Accordingly, TSA-based performance is treated here as a curriculum-aligned operationalization of L2 reading comprehension for Hong Kong secondary learners, with the limitation that it primarily reflects proficiency within the local curriculum and test format rather than all aspects of broader reading proficiency (Law, 2014). The test comprised two articles, with students instructed to answer all questions including multiple choice, short answer, true or false, and open-ended questions based on the content of each text. Scoring was based on the official marking scheme provided by the Hong Kong Examinations and Assessment Authority. A total score for the entire test is 20. Students were given approximately 30 minutes to complete the assessment. To support score reliability, internal consistency was estimated in the study sample, and inter-rater agreement was checked on a subset of constructed-response items using double scoring (reliability = 0.76).

5.3.2.2 Reading related skills

Two Chinese literacy skills closely related to Chinese text processing were measured: orthographic knowledge and morphological awareness. Both tasks were administered in Chinese and scored for accuracy. Orthographic knowledge was measured by Orthographic Choice in Context (Leong et al., 2011; reliability = 0.82). This task assesses knowledge of legal character forms and sensitivity to orthographic and radical-level constraints in context. Each of the 20 items presented a sentence with one target position and two visually similar character options: one orthographically and semantically appropriate for the sentence, and

one foil that was visually similar but inappropriate in meaning or character legality for the context. (Example: “早上（陽光/洋光/羊光/楊光）照進教室。” correct answer is 陽光)

Morphological knowledge was assessed by the Morpheme Recognition Task that evaluated students’ understanding of morphological relationships between morphemes that form compound words (Ku & Anderson, 2003; reliability = 0.91). This task assesses awareness of morphemic meaning in Chinese compound words, specifically the ability to identify when the same character contributes the same meaning across words versus when it carries a different meaning. Each of the 20 items presented a target two-character word with a target character underlined and asked students to identify the second character’s meaning is derived from the first one.. (Example: 老鼠（是 / 否） correct answer is 否).

5.3.2.3 Executive function

In this study, the three principal components of EF were evaluated. All EF tasks were administered on desktop computers to standardize timing and enable automated capture of responses. Specifically, the Color–Word Interference Test indexed inhibitory control (Delis-Kaplan Executive Function System [D-KEFS]; reliability = 0.80). Inhibitory control was indexed by the additional response time (RT) cost of naming font color when word meaning conflicted with font color. Stimuli were Chinese color words presented in colored font. Block 1 comprised 24 trials requiring participants to identify the font color of a neutral stimulus. Block 2 comprised 24 incongruent color-word trials intermixed with 6 congruent trials. Each stimulus remained on screen for up to 3500 ms, with a 1200 ms inter-stimulus interval. For each participant, the mean RT was computed for correct trials in the baseline condition and in the incongruent condition. Higher values of inhibitory-control index indicate greater susceptibility to interference.

Cognitive flexibility was assessed through the D-KEFS Sorting test (Delis-Kaplan Executive Function System [D-KEFS]; reliability = 0.80). Participants were required to sort

six cards into two groups of three cards according to changing rules. Participants were asked to produce as many different valid sorts as possible by switching between rules (e.g., color, shape, size, or semantic categories of printed words). Across card sets, up to eight distinct sorting rules were available. The observed cognitive-flexibility score was the number of confirmed correct sorts produced (range 0–8), following D-KEFS scoring principles.

Working memory was assessed using the Digit Span task (Waters & Caplan, 2003; reliability = 0.81). Working memory was assessed using a backward digit span task, emphasizing both temporary storage and manipulation. On each trial, a sequence of digits (1–9) was presented one at a time at a fixed pace. After the final digit, participants recalled the sequence in reverse order. Sequence length increased gradually, with two trials per length, and discontinuation after two consecutive failures at the same length. Each trial was scored as correct only if the entire sequence was recalled in the correct reverse order. The observed working-memory score was the total number of correctly recalled trials across all administered sequences. If a response was blank, the trial was scored as incorrect.

5.3.3 Research Procedure

The assessments were primarily conducted in the IT rooms of the sampled schools. Each participant was provided with a desktop computer. Despite prior parental consent, students retained the autonomy to decline participation in the study before the assessment commenced. All students were required to complete all measures. Additionally, participants' demographic information, including age, gender, and the duration of their Chinese language study, was collected. During the assessment, the primary researcher and a class teacher were present in the classroom to facilitate the tests. Visual aids accompanied instructions provided before each task. No interference or assistance from teachers or researchers was permitted once the tests had begun.

5.3.4 Data analysis

In addition to descriptive and correlational analyses conducted to reveal the relationships among Chinese reading comprehension, EF components, and related skills, hierarchical regression analysis was employed as a preliminary analysis to identify the main predictors contributing to Chinese reading. To examine the multivariate relationships of all predictors to the dependent variable, structural equation modeling (SEM) was performed.

5.4 Results

Descriptive statistics were computed for all study variables to examine data distributions and evaluate the assumptions for parametric analyses. As shown in Table 5.1, reading comprehension and orthographic knowledge showed moderate variability. Morphological awareness displayed larger dispersion, reflecting substantial individual differences among L2 Chinese learners. Executive-function task scores showed approximately symmetric distributions.

Table 5.1 Means and standard deviations for all variables

Measures	Mean	SD	Skewness	Kurtosis
Reading comprehension	14.75	4.27	-.62	-.20
Orthographic knowledge	13.37	4.64	-.39	-.75
Morphological awareness	10.02	8.33	-.08	-.61
The Color–Word Interference Test	233.70	48.62	.21	1.28
Sorting test	5.20	3.78	.06	1.03
Digit Span task	4.63	4.51	.02	1.24

N = 104

Table 5.2 summarizes Pearson correlations among reading comprehension, linguistic skills, and executive-function task scores. Reading comprehension demonstrated significant positive correlations with orthographic knowledge ($r = .370, p < .001$), working memory ($r = .451, p < .001$), and cognitive flexibility ($r = .327, p < .05$). A significant negative correlation emerged between reading comprehension and inhibitory control ($r = -.239, p < .05$).

Orthographic knowledge showed positive associations with morphological awareness ($r = .193, p < .01$) and working memory ($r = .211, p < .01$). Morphological awareness was not significantly correlated with any cognitive measures. Among the cognitive variables, inhibitory control was negatively correlated with cognitive flexibility ($r = -.254, p < .01$). Cognitive flexibility showed associations with working memory ($r = .214, p < .05$).

Table 5.2. Matrix of correlation coefficients among EF, reading comprehension, and reading related skills of L2 Chinese learners in Hong Kong.

	1	2	3	4	5	6
1. Reading comprehension	-	.193*	.370***	.451***	-.239*	.327*
2. Morphological awareness		-	.193**	.184	.255	.176
3. Orthographic knowledge			-	.211**	.361	.141
4. Working memory				-	.214*	-.254**
5. Inhibitory control					-	
6. Cognitive flexibility						-

Note. * $p < .05$ ** $p < .01$, *** $p < .001$. Correlations were correlation coefficients among L2 Chinese learners in Hong Kong ($n = 104$).

A hierarchical regression was conducted to examine whether executive-function (EF) task measures predicted reading comprehension and whether linguistic skills explained additional variance beyond EF (Table 5.3). In Step 1, working memory, cognitive flexibility, and inhibitory control were entered as predictors of reading comprehension. This model was statistically significant, $F(3, 101) = 21.30, p < .001$, indicating that EF measures jointly explained variance in L2 Chinese reading comprehension. Step 1 accounted for 29% of the variance in reading comprehension ($R^2 = .29$). Working memory emerged as the strongest positive predictor ($\beta = .375, t = 5.36, p < .001$), and cognitive flexibility also showed a significant positive effect ($\beta = .274, t = 3.89, p < .001$). Inhibitory control was a smaller but statistically significant predictor ($\beta = -.171, t = -2.44, p = .017$).

In Step 2, orthographic knowledge and morphological awareness were entered in addition to the EF predictors from Step 1. The full model remained statistically significant.

Orthographic knowledge was a significant positive predictor of reading comprehension ($\beta = .220$, $t = 2.73$, $p < .01$), whereas morphological awareness did not contribute unique variance ($\beta = .070$, $t = 1.33$, $p = .185$). The addition of the two linguistic variables yielded a modest but statistically significant increase in explained variance beyond Step 1 ($\Delta R^2 = .04$), $F\text{-change}(2, 98) = 3.20$, $p < .05$.

Table 5.3 Hierarchical multiple regression analysis of EF and reading related skills predicting L2 Chinese reading comprehension

Predictor	B	SE B	β
Step 1			
Working memory	.45	.084	.375***
Cognitive flexibility	.32	.082	.274***
Inhibitory control	-.18	.070	-.171*
Step 2			
orthographic knowledge	.25	.075	.210*
morphological awareness	.08	.060	.070

Note. * $p < .05$, ** $p < .01$, *** $p < .001$. Correlations were correlation coefficients among L2 Chinese learners in Hong Kong ($n = 104$).

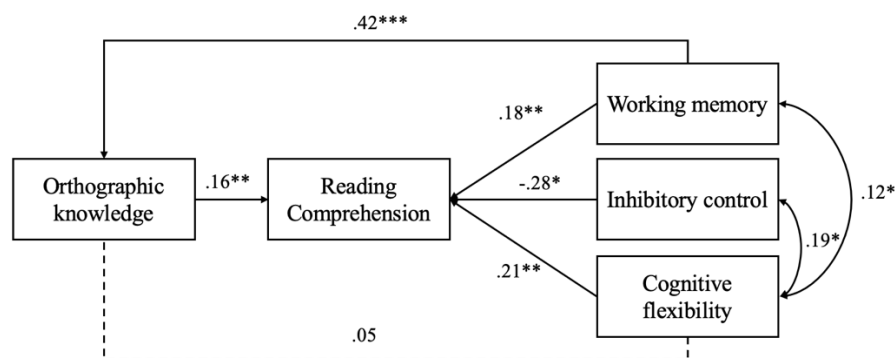
To evaluate direct and indirect pathways simultaneously, an observed-variable path model was estimated in AMOS 29 (Figure 5.1). Because each construct was operationalized using a single observed task score, the model should be interpreted as a path model among observed measures rather than a latent-variable SEM with an explicit measurement model; therefore, measurement error was not modeled via latent factors. Missing-data patterns were examined, and the path model was estimated using full-information maximum likelihood (FIML), which uses all available information under a Missing at Random (MAR) assumption. Thus, cases were not excluded solely due to partial missingness on model variables. Indirect effects were evaluated using nonparametric bootstrap inference (5,000 resamples) with 95% bias-corrected confidence intervals (two-sided). Overall, the model demonstrated acceptable fit ($\chi^2/df = 2.62$, SRMR = 0.048, RMSEA = 0.042, TLI = 0.944, CFI = 0.965).

Working memory significantly predicted orthographic knowledge ($\beta = 0.42$, $p < .001$), supporting the hypothesis that working memory facilitates the retention and manipulation of

visual–orthographic patterns (e.g., character strokes and radicals). Orthographic knowledge partially mediated the association between working memory and reading comprehension: the indirect effect was significant ($\beta = 0.16$, $p = .002$), and the direct path from working memory to reading comprehension also remained significant ($\beta = 0.18$, $p = .008$).

Inhibitory control and cognitive flexibility exerted direct effects on reading comprehension ($\beta = -0.28$ and $\beta = 0.21$, respectively). If higher Color–Word Interference scores indicate poorer inhibitory control, the negative coefficient indicates that better inhibitory control (lower interference) is associated with higher reading comprehension. Cognitive flexibility showed a positive association with reading comprehension, consistent with the role of switching between decoding and meaning integration during text processing. However, neither inhibitory control ($\beta = -0.08$, $p = .352$) nor cognitive flexibility ($\beta = 0.05$, $p = .482$) significantly predicted orthographic knowledge, suggesting that these two executive components may contribute primarily to online comprehension processes rather than to orthographic knowledge in this sample.

Figure 5.1. SEM path diagram among L2 Chinese learners in Hong Kong



Note. * $p < .05$, ** $p < .01$, *** $p < .001$. The solid line represented significant path using 90% confidence interval on bootstrap analysis with 5000 bootstrapped sample. The dash line represented insignificant among L2 Chinese learners in Hong Kong ($n = 104$).

5.5 Discussion

The present study examined how EF components relate to Chinese L2 reading comprehension among Southeast Asian ethnic minority secondary students in Hong Kong whose first languages are alphabetic. By considering working memory, cognitive flexibility, and inhibitory control alongside orthographic knowledge and morphological awareness, the study aimed to clarify which cognitive–linguistic resources are most strongly associated with comprehension in a logographic writing system. Overall, the findings indicate that EF is meaningfully related to L2 Chinese reading comprehension, but that EF components appear to operate through partially distinct pathways: working memory is linked to comprehension both directly and indirectly via orthographic knowledge, whereas cognitive flexibility and inhibitory control primarily show direct associations with comprehension rather than with orthographic knowledge. These patterns refine current accounts of EF–reading relations by highlighting the potential importance of orthographic processing demands in Chinese for learners with alphabetic L1 backgrounds.

Across both hierarchical regression and the path model, working memory emerged as the most robust positive predictor of reading comprehension. This finding aligns with extensive evidence that working memory supports reading by maintaining and integrating information across words, sentences, and discourse, especially when comprehension requires updating interpretations and sustaining representations over time (Carpenter & Just, 2013). In Chinese reading, these demands may be amplified because character recognition often requires fine-grained visual–orthographic processing and rapid integration with lexical–semantic information. Consistent with this explanation, working memory was positively associated with orthographic knowledge and significantly predicted orthographic knowledge in the path model, suggesting that students with stronger working memory may be better able to encode, retain, and manipulate orthographic representations that support fluent reading

(Chang et al., 2019). Importantly, the direct path from working memory to comprehension remained significant even after accounting for orthographic knowledge, indicating that working memory likely contributes to comprehension through additional mechanisms beyond orthographic learning.

Similarly, cognitive flexibility was found to be a significant positive predictor of L2 Chinese reading comprehension. This aligns with previous research demonstrating the contribution of cognitive flexibility to Chinese reading comprehension in both L1 and L2 learners (Xu et al., 2024). In the unique context of Chinese, where word boundaries are unmarked and sentence structures often rely on pragmatic cues, cognitive flexibility is crucial for learners to dynamically adjust their processing approaches. This includes the ability to switch flexibly between character-level and discourse-level processing, a skill that is particularly valuable for navigating the script's visual complexity and lack of clear word boundaries. The SEM analysis showed a direct effect of cognitive flexibility on reading comprehension, suggesting its role in supporting efficient switching between lower-level decoding and higher-level meaning construction, especially when reconciling multiple possible readings or integrating contextual information rapidly.

Inhibitory control is traditionally viewed as beneficial for suppressing distractions during reading, its association with reading comprehension in the current study reflect the unique demands of Chinese, where readers must often activate multiple meanings for homophones or polysemous characters. The SEM analysis indicated that stronger inhibitory control, as represented by a lower cognitive cost on the Color-Word Interference Test, was associated with better reading comprehension, suggesting inhibitory control support the access to potentially relevant semantic cues or competing character interpretations, thereby potentially increasing cognitive resources needed for text integration. This result supports the assumption that inhibitory control universally supports reading comprehension across

languages and underscores the importance of considering language-specific orthographic and semantic features when examining the role of EF in reading (Han et al., 2025).

More importantly, this study shed light on the role of orthographic knowledge. Orthographic knowledge emerged as a significant predictor of reading comprehension in the hierarchical multiple regression analysis (Li et al., 2012). Furthermore, the SEM analysis revealed that orthographic knowledge significantly mediated the relationship between working memory and reading comprehension, with a significant indirect effect. This finding highlights that working memory's significant contribution to reading comprehension, at least in part, occurs through its facilitation of orthographic knowledge acquisition. It emphasizes the foundational and central role of orthographic knowledge in Chinese literacy development, particularly for L2 learners with alphabetic first language backgrounds. Interestingly, neither inhibitory control nor cognitive flexibility emerged as significant predictors of orthographic knowledge in the SEM analysis. This suggests that, unlike working memory, these two EF components may not directly facilitate the learning of the visual-orthographic patterns that constitute Chinese characters. Instead, their benefits to reading comprehension appear to operate at the level of text comprehension rather than at the stage of orthographic acquisition. Morphological awareness, while often considered important for Chinese reading, did not significantly predict reading comprehension in this study, nor was it significantly correlated with any of the cognitive measures. This could be due to the specific age group or proficiency level of the learners, or the nature of the morphological awareness task used.

These findings have pedagogical implications for L2 Chinese instruction in Hong Kong and similar bilingual contexts; however, they should be interpreted with appropriate caution. Although working memory, cognitive flexibility, and inhibitory control were associated with reading comprehension, the present evidence is correlational and does not establish that these executive functions can be directly trained in ways that yield durable and transferable gains to

L2 Chinese reading outcomes. Indeed, the literature on executive-function training has raised ongoing questions regarding the magnitude, durability, and far-transfer of training effects beyond tasks that closely resemble the training activities. Accordingly, rather than framing executive function as a direct and standalone instructional target, a more defensible implication is that instruction can be designed to scaffold executive demands during reading and to embed executive-control supports within literacy activities.

From this perspective, classroom practices may focus on reducing working-memory load and supporting integration processes during reading. For example, structured annotation, guided summarization, note-taking templates, and reciprocal teaching routines can externalize interim representations and encourage students to maintain and update key ideas across sentences and paragraphs. Similarly, to support cognitive flexibility within authentic reading, teachers can incorporate activities that require students to compare alternative interpretations of ambiguous characters or phrases, practice switching between character-level decoding and discourse-level integration, and apply different reading strategies across genres and text structures. With respect to inhibitory control, instructional tasks can emphasize selective attention to context-relevant cues, for instance, exercises that contrast visually or semantically confusable characters, require students to justify why one interpretation is more context-appropriate, or prompt students to inhibit a dominant but incorrect meaning in favor of a text-consistent interpretation. Importantly, these approaches are best understood as strategy scaffolds and task designs that leverage executive processes during reading, rather than as evidence that executive functions themselves can be reliably improved through brief training with broad transfer.

At the same time, the findings more directly support a second pedagogical priority: strengthening orthographic knowledge, which emerged as a significant predictor of reading comprehension and partially mediated the association between working memory and

comprehension. For learners from alphabetic L1 backgrounds, explicit instruction in character structure (e.g., radicals, stroke patterns, and positional regularities) may be particularly valuable (Chan & Nunes, 2001). Techniques such as character decomposition, radical-based grouping, and systematic comparison of visually similar characters may help learners develop stable orthographic representations that support both character recognition and comprehension. Given the observed mediation pattern, orthographic instruction may also help learners make more efficient use of limited working-memory resources during reading by reducing the cognitive cost of character identification.

Despite these contributions, the present study has limitations that constrain interpretation. The cross-sectional design prevents causal conclusions regarding whether executive-function components or orthographic knowledge drive subsequent gains in reading comprehension or whether reciprocal pathways operate over time. Future research should employ longitudinal designs and, where feasible, intervention studies that compare strategy-based instructional supports and orthographic training to test whether changes in orthographic knowledge and executive-function-related processes lead to improvements in L2 Chinese reading. Further, because each EF component was measured using a single task score, future studies should strengthen measurement to better capture executive-function variance and reduce attenuation due to measurement error. Expanding samples across proficiency levels, grade groups, and L1 backgrounds will also clarify the generalizability of the observed pathways.

5.6 Conclusion

This study provides compelling evidence for the central role of EF in L2 Chinese reading comprehension. By integrating targeted cognitive training and orthographic instruction into L2 Chinese curricula, educators can better support Hong Kong's L2 learners

in mastering the complexities of Chinese reading. Continued research in this area, particularly with longitudinal and diverse-sample designs, will further refine pedagogical approaches and address the evolving challenges of learning complex orthographies.

Chapter 6 Study 2: AI Literacy Development in Middle School: Profiles and Demographic Predictors from an ABCE Perspective

6.1 Introduction

As artificial intelligence (AI) technologies become increasingly pervasive in modern society, the capacity to understand, interact with, and critically evaluate these systems has emerged as a crucial competency (Pedro et al., 2019). From algorithm-driven platforms that influence personal choices to AI-powered tools that shape educational, economic, and political landscapes, AI is no longer confined to the realm of specialists. Instead, it plays a formative role in shaping the everyday experiences of individuals, including young learners (Ivanashko et al., 2024). In this context, the concept of AI literacy has gained significant traction in educational discourse, with growing calls to equip students with the knowledge, skills, and ethical awareness necessary to navigate an AI-mediated world (Nemorin et al., 2023).

Middle school students, in particular, represent a critical demographic for early and meaningful engagement with AI concepts (Zhang et al., 2024). Positioned at a transitional stage of cognitive and emotional development, they are beginning to form the intellectual and social foundations that will influence their long-term academic and career trajectories. As future citizens and creators of AI technologies, they must be prepared not only to understand how AI works but also to reflect on its broader implications for society (Lee et al., 2021). Yet, despite increased attention to AI education, existing definitions and assessment tools often fail to capture the full spectrum of competencies required for responsible and holistic AI engagement at this age level.

This study addresses this gap by adopting a comprehensive framework, the ABCE model, that reconceptualizes AI literacy across four interrelated domains: Affective,

Behavioural, Cognitive, and Ethical learning (Ng et al., 2023). Moving beyond narrow technical definitions, this approach emphasizes the importance of motivation, self-efficacy, behavioural engagement, and moral reasoning in shaping how young learners understand and apply AI concepts. In doing so, it responds to calls for interdisciplinary and developmentally appropriate models that reflect the complex realities of AI in contemporary life (Baum, 2021).

Finally, this study contributes to the field by validating the AI Literacy Questionnaire (AILQ) (Ng et al., 2023), an assessment instrument designed specifically for middle school students based on the ABCE framework. The AILQ is intended to support both empirical research and practical educational initiatives by offering a reliable and context-sensitive tool for measuring AI literacy in diverse learning environments. Through its dual focus on theory-building and instrument development, this study seeks to inform curriculum design, teacher training, and policy development aimed at fostering inclusive and future-ready AI education.

6.2 Literature Review

6.2.1 The Definition of AI Literacy

AI literacy has rapidly emerged as a foundational construct in contemporary education, encompassing the knowledge, skills, attitudes, and dispositions necessary for individuals to engage meaningfully with AI technologies (Oosthuizen, 2024). As AI systems become increasingly embedded in daily life, educational contexts, and the global workforce, AI literacy extends the conceptual foundations laid by digital and computational literacy to address the unique challenges posed by intelligent and adaptive systems.

A seminal contribution to the formalization of the concept was made by Long and Magerko (2020), who defined AI literacy as the ability to "understand, use, and evaluate AI

as a human-centered sociotechnical system". This definition underscores that AI literacy transcends mere technical proficiency, requiring a critical awareness of the broader social, ethical, and cultural implications of AI. As such, AI literacy equips individuals to interpret, question, and respond to the multifaceted impact of AI on society (Kumar & Sangwan, 2024).

In response to the escalating relevance of AI, a number of conceptual models have been proposed to delineate the constituent dimensions of AI literacy. Ng et al. (2021), for instance, introduced a framework that emphasizes technical understanding, data literacy, and ethical awareness. Similarly, Lee et al. (2021) highlighted the importance of human-AI interaction, machine learning principles, and societal impact. These models reflect the inherently interdisciplinary nature of the field, aiming to integrate cognitive and practical competencies with social and ethical considerations. Building upon these foundational frameworks, the present study adopts the ABCE model, which conceptualizes AI literacy across four interrelated domains: Affective, Behavioural, Cognitive, and Ethical learning (Ng et al., 2024). This model extends the traditional ABC framework by explicitly incorporating ethical considerations, thereby offering a more comprehensive understanding of how individuals interact with AI in both technical and sociotechnical contexts.

Within the ABCE framework, affective learning pertains to learners' emotional responses and attitudes toward AI. This includes factors such as intrinsic motivation and self-efficacy in understanding and using AI systems, all of which significantly influence learners' engagement and preparedness for AI education. Behavioural learning refers to observable actions that indicate engagement with AI technologies, such as commitment to AI learning, collaboration on AI-related tasks, and the intention to apply AI knowledge in future contexts. Cognitive learning encompasses the understanding and application of AI concepts, aligning with Bloom's Taxonomy to span from foundational knowledge to higher-order thinking skills such as analysis, evaluation, and creation. Ethical learning, a distinguishing feature of the

ABCE model, highlights the necessity of human-centered and responsible engagement with AI. This domain includes awareness of key principles such as fairness, accountability, transparency, and safety, alongside the capacity to critically engage with issues such as algorithmic bias, data privacy, social equity, inclusivity, and digital rights.

In educational contexts, particularly at the middle school level, AI literacy must be regarded as both an intellectual and civic imperative (Kaletski-Maisel & Jowallah, 2025). Students are not merely consumers of AI-driven tools but future citizens and decision-makers who will be directly impacted by and contribute to the trajectory of AI development. Accordingly, AI education at this developmental stage should aim to cultivate the capacity to pose critical questions, analyze data ethically and effectively, and participate meaningfully in discussions concerning the responsible use of AI (Zawacki-Richter et al., 2025).

Moreover, it is essential to recognize that AI literacy is both context-sensitive and developmentally contingent. The competencies expected of a university-level computer science student differ significantly from those appropriate for a young learner. Consequently, a scaffolded, interdisciplinary instructional approach is necessary—one that integrates AI concepts across subjects such as science, social studies, language arts, and digital citizenship (Chiu et al., 2024). This approach ensures that AI literacy is cultivated not only as a technical skill set but also as a holistic capacity essential for ethical and informed participation in an AI-driven world.

To support empirical research and educational evaluation in this area, the AI Literacy Questionnaire (AILQ) has been developed as a multidimensional instrument to measure middle school students' AI literacy in alignment with the ABCE framework (Ng et al., 2023). The AILQ operationalizes AI literacy across affective, behavioural, cognitive, and ethical domains, enabling a comprehensive assessment of learners' dispositions, actions, knowledge, and values related to AI. It captures not only students' understanding of AI concepts and their

ability to apply them, but also their emotional engagement, future orientation toward AI-related careers, and awareness of ethical concerns such as fairness, bias, and social responsibility. By integrating these diverse dimensions, the AILQ offers a robust tool for measuring AI literacy developmentally and contextually, particularly in middle school settings where students are forming foundational attitudes and competencies that will shape their long-term relationship with AI.

6.2.2 Factors Contributing to Middle School Students' AI Literacy

The development of AI literacy among middle school students is shaped by a range of demographic and contextual variables. Among these, gender and grade level have emerged as particularly salient factors, influencing how students access, engage with, and make sense of AI-related content (Celik, 2023).

Gender has long been recognized as a significant determinant of engagement in STEM education, and similar patterns are evident in the domain of AI literacy (Regan & DeWitt, 2014). Male and female students often enter AI learning environments with differing social experiences, self-perceptions, and levels of confidence. Research suggests that female students, despite performing comparably to their male peers, frequently report lower self-efficacy in technology-related tasks (Huffman et al., 2013). These perceptions, shaped by sociocultural norms and gendered expectations regarding who belongs in technical domains, may influence behavioral engagement in AI education. For example, girls may be less inclined to take initiative in coding exercises, express interest in AI-related careers, or assume leadership roles in collaborative projects (Gursch, 2022). Importantly, such differences are not rooted in cognitive capacity but rather in socially constructed beliefs about competence and belonging. The conditions under which these gender differences emerge are critical. Inclusive pedagogical strategies, such as the integration of diverse role models, emphasis on collaborative and inquiry-based learning, and use of socially relevant AI applications, have

been shown to mitigate gender-based disengagement (Careemdeen, 2023). When female students perceive AI as meaningful, socially impactful, and aligned with their interests, they are more likely to participate actively and persist in learning. Conversely, the absence of such intentional support can contribute to disparities in AI literacy development, reinforcing existing gender gaps in digital competence and constraining future opportunities in AI-related fields (Shah, 2024).

In addition to gender, grade level also plays a significant role in shaping students' readiness for and engagement with AI education (Dai et al., 2020). As students progress through middle school, they differ in cognitive maturity, academic exposure, and metacognitive awareness, all of which influence how they interact with AI concepts and tools. Older students, typically in higher grades, tend to demonstrate greater autonomy in exploring AI technologies, deeper conceptual understanding of algorithmic systems, and an increased capacity for abstract reasoning, including ethical considerations surrounding AI decision-making and data bias (Hidayat-ur-Rehman, 2024). These developmental differences underscore the importance of aligning instructional content with students' cognitive stages. For instance, younger learners may benefit from hands-on, visually oriented tools that introduce machine learning through playful experimentation—such as image recognition or simple rule-based classifiers. In contrast, older students are better positioned to engage with real-world datasets, critically analyze algorithmic outputs, and draw interdisciplinary connections across subjects like mathematics, social studies, and language arts. Empirical observations support these patterns, with students in upper grade levels generally exhibiting more sophisticated conceptions of AI, including an appreciation of its probabilistic nature, ethical implications, and societal applications. Younger students, by comparison, often view AI in more functional or instrumental terms, focusing on its visible outputs rather than its underlying logic or social context (Jiang et al., 2022).

6.2.3 The Present Study

Despite increasing global recognition of the importance of AI education, a critical gap persists in both conceptual frameworks and empirically validated assessment tools tailored to the developmental needs of middle and secondary school students. Much of the existing research on AI literacy has focused narrowly on technical knowledge and cognitive skills, often to the exclusion of the affective, behavioural, and ethical dimensions that are essential for fostering responsible and sustained engagement with AI (George et al., 2025; Ng et al., 2024). Moreover, the majority of available instruments emphasize either procedural proficiency or ethical awareness, without accounting for the socio-emotional and motivational factors that significantly shape learning trajectories, particularly in adolescence.

The present study seeks to address this gap by adopting the ABCE framework, which conceptualizes AI literacy as a multi-dimensional construct encompassing Affective, Behavioural, Cognitive, and Ethical domains. In contrast to traditional models that prioritize technical competencies, the ABCE framework offers a holistic perspective that reflects the lived experiences of students as they interact with AI technologies. It acknowledges that students' engagement with AI is influenced not only by their conceptual understanding but also by their emotional responses, motivational orientations, practical actions, and ethical awareness. This comprehensive model is especially pertinent for middle school learners, whose developmental stage is characterized by evolving identities, increasing autonomy, and heightened sensitivity to social and moral issues.

Building on this framework, the study introduces the AI Literacy Questionnaire (AILQ), a novel instrument designed to assess AI literacy among adolescents in a developmentally appropriate and psychometrically robust manner. The AILQ is explicitly aligned with the ABCE model and has been developed to capture the diverse competencies required for meaningful participation in an AI-mediated society. Its construction prioritizes

internal consistency, structural validity, and convergent validity, thereby ensuring its reliability for use in both educational research and practical implementation.

In addition to addressing theoretical and measurement gaps, this study examines how AI literacy varies across key demographic, particularly gender and grade level, which have been shown to influence students' engagement with STEM-related domains. By integrating these variables, the study contributes to a more nuanced understanding of how middle school students develop AI literacy and how instructional practices can be tailored to support equitable and developmentally appropriate learning experiences. The findings aim to inform curriculum design, teacher professional development, and education policy in order to better prepare young learners for ethical and informed participation in an AI-driven world.

6.3 Method

6.3.1 Participants

This study recruited a total of 1,669 students from one senior middle school in Shanghai, China. The school has piloted a curriculum on AI literacy, which covers understanding AI-related concepts, using AI applications, and AI ethics. Instruction is delivered through a combination of lectures and hands-on activities. The curriculum places particular emphasis on ethical aspects of AI, including dedicated modules on AI fairness, privacy, and responsible use, which are integrated into classroom activities and project-based learning. This sampling strategy was designed to capture a broad and representative cohort of students engaged in AI-related educational initiatives within the school. All students enrolled in the relevant programs were invited to participate. Descriptive statistics indicate that the sample comprised 908 female students (54.4%) and 761 male students (45.6%). In terms of academic level, 591 students were in Year 10, 531 in Year 11, and 547 in Year 12.

Participants completed the translated Chinese version of the AILQ during regular school hours. The original English instrument was first translated into Chinese by a trained research assistant fluent in both languages. To ensure semantic and conceptual equivalence, the Chinese version was then independently back-translated into English by another bilingual researcher unfamiliar with the original questionnaire. Discrepancies between the back-translated and original versions were reviewed and resolved through discussion among the research team until 90% consensus was reached. The administration of the questionnaire took approximately 15 minutes and was conducted under standardized conditions. Participation was voluntary and anonymous, with informed consent obtained in accordance with institutional ethical guidelines. Only non-identifiable demographic information, specifically, gender and grade level, was collected in conjunction with students' responses to the AI literacy scale.

6.3.2 Data Analysis

Data analysis was conducted using a multi-step approach, systematically moving from validating the measurement model to identifying latent profiles of AI literacy, and concluding with an examination of demographic predictors.

Initially, Measurement Model Validation was performed through Confirmatory Factor Analysis (CFA). It was conducted using Mplus 8.8, with robust maximum likelihood estimation (MLR) to account for potential non-normality of the questionnaire data. Missing data were handled using Full Information Maximum Likelihood (FIML), which leverages all available data under the assumption that values were missing at random (MAR). This approach has been widely recommended in latent variable modeling for reducing bias compared to listwise or pairwise deletion (Enders, 2010). Global model fit was evaluated using multiple indices, including the Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean

Square Residual (SRMR), with recommended thresholds of CFI and TLI ≥ 0.95 , RMSEA ≤ 0.06 , and SRMR ≤ 0.08 (Hu & Bentler, 1999). Convergent validity and reliability were assessed using Composite Reliability (CR) and Average Variance Extracted (AVE), with recommended thresholds of CR > 0.70 and AVE > 0.50 (Fornell & Larcker, 1981).

Following model validation, Latent Profile Analysis (LPA) was employed to identify distinct subgroups of students based on their varying levels of AI literacy. A range of models, from one to six latent profiles (C=1 to C=6), were tested to determine the optimal solution. The fit of each model was evaluated using a suite of standard indices, including the Log-Likelihood (LL), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Sample-size Adjusted BIC (aBIC). Model classification quality was further assessed using Entropy, average posterior probabilities, and classification error rates. The statistical significance of model improvement over solutions with fewer classes was examined using the Lo-Mendell-Rubin Likelihood Ratio Test (LMR(p)) and the Bootstrap Likelihood Ratio Test (BLRT(p)). The selection of the optimal number of profiles was based on a careful consideration of the relative values of these fit indices, prioritizing statistical significance and theoretical interpretability.

Finally, the study proceeded to analyze the Demographic Predictors of AI Literacy Profiles. This involved two main components. First, the association between Demographics and Profiles was investigated using Chi-square (χ^2) tests of independence. These tests explored the relationship between key demographic variables, specifically gender and grade level, and the established AI literacy profiles. Second, to examine the effects of gender and grade level on latent profile membership, we employed the three-step (R3STEP) procedure in Mplus (Asparouhov & Muthén, 2014). This approach accounts for classification uncertainty by incorporating measurement error from the latent profile model into the regression analyses, thereby providing more robust estimates compared to models based on hard class

assignments. Logistic regressions were conducted with “Poor AI Literacy” specified as the reference category, and odds ratios (ORs), predicted probabilities, and 95% confidence intervals were reported.

6.4 Results

The foundational aspect of the research involved establishing the psychometric soundness of the constructs. For the first-order constructs, as detailed in Table 6.1, all subscales demonstrated robust reliability and convergent validity. Intrinsic Motivation (IM) exhibited strong properties with an AVE of 0.737 and CR of 0.917. Similarly, Self-efficacy (SE) showed exceptional strength (AVE=0.835, CR=0.968), as did Behavioral Commitment (BC) with an AVE of 0.778 and CR of 0.946. Collaboration (CL) also reported high validity and reliability (AVE=0.838, CR=0.939). The "Know and Understand" (KU) and "Apply, Evaluate, and Create" (EC) subscales consistently met the criteria for good psychometric properties (KU: AVE=0.735, CR=0.892; EC: AVE=0.740, CR=0.895). Finally, AI Ethics (AE) emerged with particularly strong indicators (AVE=0.803, CR=0.970). Moving to the second-order constructs in Table 6.2, these also exhibited excellent reliability and validity. Affective Learning, comprising IM and SE, had an AVE of 0.812 and CR of 0.896. Behavioral Learning, including CL and EC, showed an AVE of 0.850 and CR of 0.919. Cognitive Learning, encompassing KU and EC, demonstrated exceptionally high values with an AVE of 0.954 and CR of 0.976. One standardized second-order factor loading slightly exceeded 1.0 (KU → Cognitive = 1.007), likely due to high correlations among indicators, which is considered acceptable given the overall strong model fit ($\chi^2 = 70,491.98$, $df = 496$, $p < .001$, $p < .001$, CFI = 0.97, TLI = 0.965, RMSEA = 0.041, SRMR = 0.035), and high CR (>0.90) and AVE (>0.70).

Table 6.1 Standardized Factor Loadings, Average Variance Extracted (AVE), and Composite Reliability (CR) for First-Order Constructs

Subscales	Factor loadings	AVE	CR
Intrinsic Motivation (IM)			
IM1	0.696	0.737	0.917
IM2	0.910		
IM3	0.897		
IM4	0.912		
Self-efficacy (SE)			
SE1	0.933	0.835	0.968
SE2	0.933		
SE3	0.932		
SE4	0.938		
SE5	0.827		
SE6	0.915		
Behavioral commitment (BC)			
BC1	0.751	0.778	0.946
BC2	0.860		
BC3	0.919		
BC4	0.945		
BC5	0.922		
Collaboration (CL)			
CL1	0.935	0.838	0.939
CL2	0.929		
CL3	0.881		
Know and understand (KU)			
KU1	0.874	0.735	0.892
KU2	0.797		
KU3	0.897		
Apply, evaluate, and create (EC)			
EC1	0.807	0.740	0.895
EC2	0.856		
EC3	0.915		
AI ethics (AE)			
AE1	0.825	0.803	0.970
AE2	0.908		
AE3	0.879		
AE4	0.901		
AE5	0.930		
AE6	0.935		
AE7	0.915		
AE8	0.871		

Table 6.2 Standardized Factor Loadings, Average Variance Extracted (AVE), and Composite Reliability (CR) for Second-Order Constructs

Second-order factor	Subscale	Factor loadings	AVE	CR
Affective learning	IM	0.863	0.812	0.896
	SE	0.938		
Behavioral Learning	CL	0.922	0.850	0.919
	EC	0.922		
Cognitive learning	KU	1.007	0.954	0.976
	EC	0.945		

Prior to conducting latent profile and subgroup analyses, measurement invariance of the second-order CFA model was tested across gender and grade. Configural, metric, and scalar invariance were evaluated using changes in CFI and RMSEA, following recommended thresholds ($\Delta\text{CFI} \leq 0.01$, $\Delta\text{RMSEA} \leq 0.015$; Cheung & Rensvold, 2002). As shown in Table 3, the configural model demonstrated a good baseline fit ($\chi^2 = 70,491.98$, $df = 496$). The metric model ($\chi^2 = 70,550.00$, $df = 504$) and scalar model ($\chi^2 = 70,610.25$, $df = 512$) both showed minimal changes in fit ($\Delta\text{CFI} = 0.002$, $\Delta\text{RMSEA} = 0.001$ for metric; $\Delta\text{CFI} = 0.002$, $\Delta\text{RMSEA} = 0.001$ for scalar), well below the recommended thresholds ($\Delta\text{CFI} \leq 0.01$, $\Delta\text{RMSEA} \leq 0.015$; Cheung & Rensvold, 2002). These results indicate full scalar invariance across both gender and grade, supporting valid comparisons of latent means and regression relationships across groups.

Descriptive analyses were conducted for all four AI literacy dimensions— affective, behavioral, cognitive, and ethics—to provide context for the latent profiles (Table 6.3). Overall, students scored relatively high across all dimensions. Means ranged from 4.0 to 4.6 ($SD = 0.4\text{--}0.6$), with the highest average observed in the AI ethics dimension ($M = 4.6$, $SD = 0.4$). Skewness values ranged from -0.4 to -0.85 , suggesting slight negative skew particularly for AI ethics. Notably, 18% of students achieved the maximum score in AI ethics, indicating a potential ceiling effect, whereas ceiling percentages for the other dimensions were lower (8–12%).

Table 6.3. Descriptive Statistics for AI Literacy Dimensions (N = 1,669).

Dimension	Mean	SD	Skewness	% at max
Affective	4.2	0.5	-0.60	10%
Behavioral	4.0	0.6	-0.40	8%
Cognitive	4.1	0.5	-0.50	12%
Ethics	4.6	0.4	-0.85	18%

Building on these descriptive patterns, latent profile analysis was conducted to identify distinct subgroups of students based on their scores across all four AI literacy dimensions. As shown in Table 6.4, the model fit indices (AIC, BIC, and aBIC) consistently decreased as the number of latent classes increased, with the most substantial improvement observed up to the four-class solution (C=4). Beyond four classes, the rate of improvement diminished. Entropy values for all models exceeded the recommended threshold of 0.80 (Lubke & Muthén, 2007), with the four-class model achieving the highest entropy (0.951). While entropy remained high for the five- and six-class models (0.945 and 0.944, respectively), the increase was negligible. In addition to entropy, posterior classification diagnostics indicated strong reliability of class membership. The average posterior probabilities (AvePP) were consistently high across the four profiles (Poor = 0.92; Moderate = 0.90; Good = 0.93; Excellent = 0.95), exceeding the recommended threshold of 0.70 for acceptable classification quality and indicating excellent classification (>0.90) (Muthén & Muthén, 2000; Nylund et al., 2007). Correspondingly, the classification error rates were low, ranging from 0.05 to 0.10, further supporting the accuracy of class assignments (Nylund et al., 2007). These values suggest that the vast majority of students were classified with high certainty, supporting the stability of the latent profiles. Furthermore, both the Lo–Mendell–Rubin (LMR) test and the Bootstrap Likelihood Ratio Test (BLRT) indicated that the four-class model significantly improved upon the three-class model (LMR(p)=0.005; BLRT(p)=0.006). However, for models with five or more classes, at least one class comprised fewer than 5% of the sample (e.g., 2% in C=5; 2% and 4% in C=6), reducing interpretability and practical utility. Balancing statistical fit, parsimony, and class interpretability, the four-class solution (C=4)

was selected as optimal. The class probabilities for this model were 0.039 (Poor), 0.237 (Moderate), 0.318 (Good), and 0.405 (Excellent), providing a meaningful distribution of AI literacy profiles.

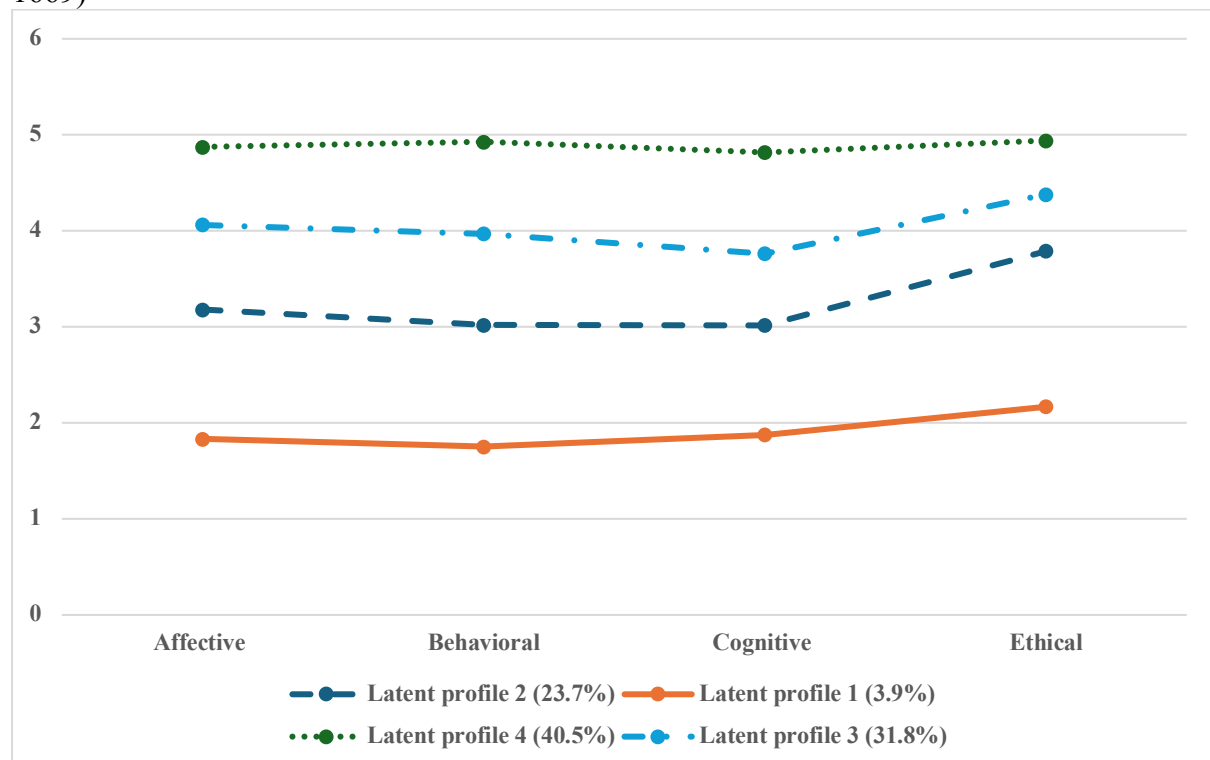
Table 6.4. Model fit indices for different profile solutions of students' AI literacy (N = 1669).

M	LL	AIC	BIC	aBIC	Entropy	LMR (p)	BLRT (p)	Class probabilities
C=1	-8652.715	17321.430	17364.790	17339.375	---	---	---	---
C=2	-6918.761	13863.522	13933.982	13892.683	0.874	0.000	0.000	0.37, 0.63
C=3	-6082.926	12201.852	12299.412	12242.228	0.916	0.001	0.001	0.22,0.36,0.42
C=4	-5442.508	10931.017	11055.676	10982.608	0.951	0.005	0.006	0.039,0.237,0.318,0.405
C=5	-5201.212	10458.424	10610.183	10521.231	0.945	0.028	0.030	0.021,0.142,0.092,0.412,0.332
C=6	-4961.194	9988.388	10167.247	10062.411	0.944	0.004	0.005	0.024,0.043,0.134,0.113,0.253,0.432

Figure 1 illustrates the mean scores of four latent profiles across the affective, behavioral, cognitive, and ethical dimensions of AI literacy. These profiles, derived through Latent Profile Analysis, are labeled as Poor AI Literacy (Profile 1), Moderate AI Literacy (Profile 2), Good AI Literacy (Profile 3), and Excellent AI Literacy (Profile 4), representing 3.9%, 23.7%, 40.5%, and 31.8% of the sample, respectively. Latent Profile 1, representing a small proportion of students, demonstrated a low scores, around 2 on average, across all dimensions. This group appears to have a marginal level of AI literacy, suggesting limited exposure or engagement with AI-related learning experiences. Latent Profile 2, exhibited consistently low scores across all four domains, with means slightly above 3. This indicates limited affective engagement, weak behavioral commitment, and minimal cognitive understanding and ethical awareness related to AI. Latent Profile 3 remained in the high 4 range on average, suggesting a similarly robust, though slightly less elevated, AI literacy profile. Meanwhile, Latent Profile 4, the largest group in the sample, achieved mean scores near 5 across all domains. This pattern reflects a well-rounded and high level of AI literacy, indicating strong intrinsic motivation, active engagement, cognitive competence, and ethical awareness. Notably, the ethical and affective dimensions were particularly strong in this group, possibly reflecting greater socio-emotional sensitivity to AI-related issues. The clear separation among the profiles confirms the presence of distinct patterns of AI literacy among

students. The high concentration of students in the Good and Excellent profiles (over 70% combined) suggests a generally strong AI literacy level within the sample. However, the presence of the Poor AI Literacy group, even though it comprises a small proportion of the sample, together with the Moderate profile, underscores the importance of implementing differentiated instructional strategies to support learners at varying levels of proficiency. The relatively higher scores in the ethical domain across all profiles may indicate either a particular curricular emphasis or a greater student sensitivity to AI-related ethical considerations.

Figure 6.1. Students' AI literacy means according to the latent profile membership (N = 1669)



Further investigation explored the demographic variables predicting students' AI literacy profiles (Table 6.5). A statistically significant association was found between gender and AI literacy profiles ($\chi^2=12.5$, $p<.001$). Grade level also demonstrated a significant association with AI literacy profiles ($\chi^2=18.0$, $p=0.005$). These patterns suggest that both

gender and grade level serve as meaningful predictors of AI literacy attainment among secondary school students, though their influence varies across proficiency levels.

Table 6.5. Demographic variables predicting students' AI literacy profiles

Variables	Students' AI literacy profiles				χ^2	p
	Poor AI literacy (n = 65)	Moderate AI literacy (n = 396)	Good AI literacy (n = 532)	Excellent AI literacy (n = 676)		
Gender					12.5	<.001
Male	31(47.5%)	210(53.0%)	233(42.0%)	349(51.6%)		
Female	34(52.5%)	186(47.0%)	309(58.0%)	327(48.4%)		
Grade level					18.0	0.005
10	28(43.4%)	145(36.6%)	162(30.4%)	313(46.3%)		
11	20(30.5%)	160(40.3%)	159(29.9%)	213(31.5%)		
12	17(26.0%)	91(23.1%)	211(39.7%)	150(22.2%)		

Finally, multiple logistic regression analyses using the three-step R3STEP procedure in Mplus, with “Poor AI Literacy” as the reference class (Table 6.6), identified demographic predictors of AI literacy profile membership. Gender and grade level were significant predictors for some profiles, particularly the “Excellent AI literacy” group. Being male increased the odds of belonging to the “Excellent AI literacy” profile by approximately 78% ($B = 0.58$, $SE = 0.12$, $Wald = 23.36$, $p < .001$, $OR = 1.78$, 95% CI: 1.40–2.25). Year 10 students had higher odds of being in the “Excellent” profile compared to Year 12 students ($B = 0.65$, $SE = 0.13$, $Wald = 25.00$, $p < .001$, $OR = 1.91$, 95% CI: 1.47–2.47), as did Year 11 students ($B = 0.40$, $SE = 0.09$, $Wald = 19.75$, $p < .001$, $OR = 1.49$, 95% CI: 1.25–1.78). While gender and grade level did not significantly predict membership in the “Moderate” or “Good” AI literacy profiles, these findings underscore the importance of demographic factors in distinguishing the highest-achieving students.

Table 6.6. Results of Multinomial Logistic Regression Using the Three-Step (R3STEP) Procedure With “Poor AI Literacy” as the Reference Class

Latent profile	B	SE	Wald	p	OR	95%CI OR	Predicted probability (95% CI)
Moderate AI literacy							
[gender=male]	0.51	0.21	5.90	0.06	1.67	1.10-2.54	0.63 (0.52-0.72)
[Grade=10]	1.05	0.60	3.06	0.12	2.89	0.88-9.30	0.74 (0.47-0.90)
[Grade=11]	0.72	0.25	8.29	0.004	2.06	1.39-3.06	0.62 (0.52-0.72)
Good AI literacy							
[gender=male]	0.48	0.25	3.69	0.06	1.62	1.04-2.53	0.62 (0.51-0.72)
[Grade =10]	1.16	0.58	4.00	0.07	3.19	1.04-9.79	0.76 (0.51-0.91)
[Grade =11]	0.63	0.34	3.44	0.06	1.88	1.03-3.44	0.65 (0.51-0.77)
Excellent AI literacy							
[gender=male]	0.58	0.12	23.36	<.001	1.78	1.40-2.25	0.64 (0.58-0.69)
[Grade =10]	0.65	0.13	25.00	<.001	1.91	1.47-2.47	0.66 (0.59-0.71)
[Grade =11]	0.40	0.09	19.75	<.001	1.49	1.25-1.78	0.42 (0.56-0.64)

Note. Predicted probabilities and 95% confidence intervals were calculated based on logistic regression with “Poor AI Literacy” as reference group.

6.5 Discussion

This study aimed to examine the psychometric properties of AI literacy constructs and to identify how gender and grade level influence students’ AI literacy profiles. The findings contribute to both the theoretical and practical understanding of AI literacy by offering empirical validation of a multi-dimensional measurement model and illuminating how student characteristics correspond to different proficiency level.

The robust psychometric performance of the AILQ provides strong empirical support for the ABCE framework, affirming its utility as a comprehensive and theoretically grounded model for assessing AI literacy in adolescence. High levels of convergent and composite reliability across the affective, behavioral, cognitive, and ethical underscore the framework's conceptual soundness. In particular, the ethical domain exhibited exceptional construct validity, reinforcing recent calls to embed human-centered values and ethical reasoning within AI curricula (Long & Magerko, 2020; Ng et al., 2023). This result is significant given the increasing global emphasis on responsible AI use and the need to prepare students not only to operate AI systems but to critically evaluate their societal impact. Furthermore, the affective and behavioral components, often underrepresented in traditional STEM assessments, demonstrated high reliability, indicating that students' motivation, confidence, and applied practices are integral to their overall literacy.

Through latent profile analysis, the study identified four distinct student profiles of Poor, Moderate, Good, and Excellent representing a spectrum of AI literacy competencies. These profiles provide a more granular understanding of student differences than unidimensional assessments allow. Notably, 72.3% of students belonged to the Good or Excellent profiles, suggesting that students in the selected middle school are capable of developing advanced AI competencies when provided with appropriate guidance. This finding supports the argument that AI education is not inherently too complex for younger learners but can be successfully integrated into early secondary education (Macar et al., 2023). However, the Poor and Moderate profiles together account for 27.7% of learners, underscoring the persistence of significant disparities in foundational knowledge. These students may require additional scaffolding and individualized support to fully engage with AI content, echoing broader concerns about digital inequality in access to emerging technologies.

Demographic analyses yielded important insights into the predictors of AI literacy profile membership. Logistic regression results indicated that male students had significantly higher odds of being in the Excellent AI literacy profile compared to the Poor profile. This pattern may reflect greater variability in engagement, self-efficacy, or interest among male students, leading to more polarized outcomes. This finding aligns with prior studies reporting gender differences in digital literacy and computational skills (Peng & Yum 2022; West et al., 2019). While such differences are more commonly observed in less economically developed contexts, the current study was conducted in Shanghai, China—a region that, despite being in a developing country, has relatively high educational and economic resources. The presence of gender differences in such a resource-rich setting suggests that factors beyond material access, such as entrenched cultural norms and expectations, may play a role.

Sociocultural factors, including gendered stereotypes about technology, societal expectations regarding appropriate academic pursuits, and classroom dynamics may shape students' confidence and willingness to engage with AI-related tasks. Prior research has shown that female students often internalize societal narratives that portray computing and AI as male-dominated fields, which can contribute to reduced self-efficacy even when objective performance is comparable to that of their male peers (Eisenhart & Allen, 2020). Furthermore, as this study assesses students' self-perceptions of AI competence, such internalized beliefs may lead female students to systematically underestimate their abilities, creating a self-reinforcing cycle of lower engagement and weaker skill development. These dynamics highlight the complex interplay between gender, cultural context, and self-perception in shaping AI literacy, underscoring the need for further investigation into how educational practices and interventions might reduce disparities.

Academic year was also a significant predictor of AI literacy profiles. Students in Year 10 and Year 11 were more likely to achieve Excellent literacy compared to their Year 12 peers. Interestingly, Year 10 students represented the largest proportion of the Excellent group, suggesting that early secondary education may serve as a particularly critical period for cultivating high AI literacy. In contrast, Year 12 students were most prevalent in the Good profile but underrepresented in the Excellent profile. This pattern is consistent with prior studies indicating that younger students often display greater openness and curiosity toward emerging technologies, while older students may experience competing academic priorities that constrain engagement (Chiu & Fung, 2022; Dawadi, 2020). In particular, the transition to high-stakes examinations and university preparation in the final year of secondary schooling has been shown to narrow curricular focus, reduce opportunities for exploratory learning, and suppress motivation to pursue novel or interdisciplinary subjects (Amrein & Berliner, 2002; Dawadi, 2020). Such dynamics may partially explain why Year 12 students, despite greater academic maturity, demonstrated lower odds of belonging to the highest literacy profile.

At the same time, these findings challenge assumptions that technological competence naturally accumulates with age or grade level (Autio, 2011). Instead, they suggest a nonlinear developmental trajectory in which early exposure and sustained support are crucial for fostering advanced AI literacy. This aligns with evidence from digital and computational literacy research, which shows that interventions introduced earlier in secondary schooling often yield more lasting gains than those delivered in later stages (Voogt & Roblin, 2012). The underrepresentation of Year 12 students in the Excellent profile highlights a structural issue: the tension between national examination systems and the cultivation of 21st-century competencies. Unless AI education is deliberately integrated into senior curricula and aligned with assessment frameworks, students may disengage at precisely the stage when deeper conceptual understanding could be consolidated.

The practical implications of this research are significant for AI curriculum design and instructional planning. The ABCE framework provides a structured lens through which educators can design learning experiences that holistically develop students' affective dispositions (e.g., curiosity, confidence), behavioral practices (e.g., experimentation, collaboration), cognitive competencies (e.g., AI concepts, data reasoning), and ethical awareness. Such an approach enables a richer and more meaningful engagement with AI than narrow technical instruction alone.

The profile-based findings underscore the necessity for differentiated instruction strategies that cater to students' varying levels of AI literacy. For students in the Poor and Moderate profiles, who exhibit lower affective and behavioral engagement, foundational modules emphasizing hands-on exploration are crucial. Project-based learning, where students collaboratively engage in AI-related tasks, can demystify complex concepts and foster a deeper understanding (Barron et al., 2014). Such approaches not only enhance cognitive competencies but also build confidence and intrinsic motivation through iterative feedback loops. Conversely, students in the Good and Excellent profiles can be challenged with advanced design thinking tasks or ethical simulations to deepen their understanding and application of AI concepts.

In addition to differentiated instruction, the findings highlight the importance of equity-focused initiatives to ensure all learners have the opportunity to succeed. Culturally responsive teaching (CRT) integrates students' cultural backgrounds, experiences, and perspectives into learning activities, helping them connect AI concepts to meaningful real-world contexts (Gay, 2018). Examples include using datasets and case studies reflecting diverse populations to explore algorithmic bias, or engaging students in projects addressing local community challenges, thereby strengthening both cognitive and ethical AI literacy. Gender-inclusive teaching can complement CRT by ensuring equitable participation and

representation in AI learning (Vizcarra-Garcia, J., 2021). This can involve structured group work that encourages contributions from all students, highlighting diverse AI role models, and designing curriculum tasks free from gendered assumptions. Such practices foster affective outcomes, behavioral skills, and cognitive competencies, helping students of all genders succeed in AI literacy. By combining differentiated instruction, CRT, and gender-inclusive practices, educators can create learning environments that address the diverse needs of students across AI literacy profiles.

Despite the valuable insights offered by this study, several limitations point to important directions for future research. While the sample size is relatively large, it is drawn from a single school, which may limit the generalizability of the findings to other educational contexts or regions. Factors specific to this school such as curriculum design and teacher expertise may have influenced students' engagement and AI literacy outcomes. Future research could strengthen external validity by employing multi-site or multi-level designs, including schools from different regions, educational systems, or demographic contexts. Such approaches would help determine whether the observed patterns in AI literacy profiles and predictors hold across broader populations. The cross-sectional design also limits the ability to draw causal inferences regarding the development of AI literacy over time. Longitudinal studies are therefore warranted to examine how students' literacy profiles evolve and to identify the specific educational experiences, pedagogical approaches, or contextual factors that facilitate progression across literacy levels. Moreover, a key limitation of this study is that only gender and grade level were included as demographic predictors. Other potentially important factors such as socioeconomic status, parental education, prior exposure to digital or AI technologies, and variations in curriculum were not considered. Future research should incorporate these variables to provide a more comprehensive understanding of the factors influencing AI literacy and to identify potential equity gaps. For example, including measures

of students' home technology environment, prior AI learning experiences, and school-level curriculum differences could help to clarify how these contextual factors shape students' engagement and proficiency in AI. In addition, the current study's reliance on quantitative methods, while appropriate for large-scale profiling, may obscure nuanced aspects of students' AI learning experiences. Qualitative research including interviews, focus groups, and classroom observations could complement these findings by capturing students' motivations, challenges, and contextual realities in greater depth. Such approaches may be especially valuable for unpacking the gender-related complexities observed in this study, offering insights into how identity, self-efficacy, and sociocultural influences shape students' engagement with AI (Roza, 2025).

While the AILQ demonstrated strong psychometric properties within the current sample, its applicability should be tested across diverse cultural and educational contexts to assess its generalizability. Future studies should also investigate the instructional strategies and curricular designs that most effectively promote the development of AI literacy across the four ABCE dimensions. Particular attention should be paid to how these pedagogical interventions operate across different student groups, including those underrepresented in AI education. Finally, to strengthen the ecological validity of the ABCE framework, future research should explore whether distinct AI literacy profiles correspond to meaningful real-world outcomes such as ethical reasoning in AI dilemmas, competent use of AI tools in problem-solving tasks, or informed participation in civic discourse on AI-related issues. Establishing such links would further validate the framework's relevance and provide actionable insights for educators and policymakers committed to fostering AI readiness among young learners.

6.6 Conclusion

This study demonstrates that AI literacy is a multifaceted and unevenly distributed construct among middle school students. By validating the ABCE framework and identifying key demographic predictors of AI literacy profiles, it provides a foundation for evidence-based, inclusive AI education. As AI becomes increasingly central to all sectors of society, equipping young learners with the skills, dispositions, and ethical understanding to navigate this landscape is not only an educational goal but a societal imperative. The findings call on researchers, educators, and policymakers alike to ensure that AI literacy is accessible, equitable, and developmentally appropriate for all students.

Chapter 7 Study 3: The Role of AI Literacy in Chinese L2

Reading Comprehension: Evidence from Adolescent Learners in Hong Kong

7.1 Introduction

The growing integration of Artificial Intelligence (AI) into education has transformed how learners acquire, process, and engage with language (Lytras et al., 2024). In second language (L2) learning contexts, AI-driven platforms, ranging from intelligent tutoring systems and adaptive reading environments to character-recognition and translation tools, have become central to instructional practice (Aggarwal, 2023; Chiu, 2021; Eswaran et al., 2025; Hussain et al., 2024). These technologies can analyze learner performance in real time to scaffold complex language processes such as vocabulary development and reading comprehension (Jegede, 2024; Shafiee Rad, 2025). In Hong Kong, AI-supported Chinese learning platforms are increasingly adopted across secondary schools, allowing L2 learners, particularly those from South or Southeast Asian backgrounds, to strengthen character recognition and reading comprehension through digital flashcards, handwriting recognition, and adaptive reading exercises (Cheng & Wang, 2023; Niu et al., 2022). These tools not only supplement classroom instruction but also provide learners with individualized, multimodal exposure to Chinese texts.

However, effective use of AI tools for language learning depends critically on learners' AI literacy to understand, evaluate, and strategically interact with AI technologies (Long & Magerko, 2020; Ng et al., 2024). While AI can provide rich linguistic input and feedback, learners must possess the cognitive and metacognitive skills to interpret AI-generated suggestions and apply automated feedback to improve linguistic performance. Without sufficient AI literacy, the pedagogical potential of such technologies may remain unrealized

or even lead to misconceptions. Thus, AI literacy functions as a crucial mediating factor between technological affordances and learning outcomes, shaping how students perceive, process, and internalize digital input (Chiu et al., 2024; Long & Magerko, 2020).

In the context of Chinese L2 learning, this relationship is especially important due to the visual and morphological complexity of the language. Chinese reading comprehension requires strong orthographic knowledge, the ability to recognize and differentiate characters based on radical structure and stroke configuration, as well as morphological awareness, which supports understanding of compound words and semantic composition (Shen, 2018; Perfetti et al., 2013; Tong, X., & McBride-Chang, 2010). Recent studies indicate that AI-assisted tools can enhance these subskills through multimodal visual feedback, pattern recognition algorithms, and context-based learning (Chen & Gong, 2025). These benefits presuppose learners' ability to interact with AI systems effectively, an ability underpinned by AI literacy. For example, a student with higher AI literacy may better interpret an AI-based character correction suggestion, refine a reading prompt for contextual understanding, or evaluate an AI translation output critically to strengthen comprehension.

Yet, the interrelationship between AI literacy and these specific facets of Chinese L2 reading comprehension remains largely uncharted, representing both a theoretical and empirical void. To address this gap, the present study proposes and tests an integrated framework linking AI literacy with L2 Chinese reading comprehension. The study focuses on examining how AI literacy may influence learners' comprehension performance and their engagement with AI-based learning tools that support reading-related processes. Specifically, the study addresses the following research questions:

- (1) How does learners' level of AI literacy relate to their L2 Chinese reading comprehension performance?

- (2) In what ways does AI literacy shape learners' use of AI-powered language learning tools to enhance their Chinese reading comprehension?

7.2 Literature Review

7.2.1 Challenges in L2 Chinese reading

Chinese presents a uniquely complex challenge for L2 learners due to the visual–orthographic nature of the writing system. Unlike alphabetic languages, learners cannot rely on letter–sound mappings but build detailed representations of stroke patterns, radicals, and whole-character configurations in order to map print to sound and meaning (Ke & Koda, 2019; Wang et al., 2003). Recent work comparing L1 and L2 beginners' handwriting further highlights how effortful it is for L2 learners to encode and retrieve orthographic forms accurately (Liang & Cai, 2025). For many learners, weaknesses in orthographic knowledge, rather than phonological awareness, are the primary bottleneck in decoding written Chinese.

Beyond single-character recognition, Chinese L2 readers must also cope with the pervasive use of compounding and morphosyllabic word formation. Understanding how characters combine into multi-character words requires sensitivity to morphological structure, semantic transparency, and the positioning of morphemes within compounds (Arcodia, 2007; Ke & Koda, 2019). Studies show that morphological awareness is strongly associated with vocabulary growth and reading comprehension, supporting learners infer the meanings of unfamiliar words from familiar morphemes (Tong & McBride-Chang, 2010; Zhang et al., 2023). These demands mean that challenges in morphological analysis can quickly cascade into broader difficulties in reading for meaning.

In summary, successful L2 Chinese reading comprehension requires the coordination of fine-grained orthographic knowledge and morphological awareness. L2 learners who have

not yet established stable orthographic and morphological representations often adopt compensatory strategies such as relying heavily on dictionaries or translation tools, which can further slow down reading (Guo & Huang, 2020; Ke & Koda, 2019). These persistent challenges form the backdrop against which new AI-powered supports for reading are now being introduced, raising the question of what additional competencies learners need in order to use such tools in ways that genuinely support the development of core reading skills.

7.2.2 Artificial intelligence in education and language learning

Artificial Intelligence (AI) broadly refers to computational systems designed to mimic human intelligence in performing cognitive tasks such as learning and problem-solving. In education, AI has evolved to data-driven, learning systems that can model complex learner behaviour and adapt instruction in real time (Chen et al., 2020; Zhuang et al., 2017). This strand of research, often termed Artificial Intelligence in Education (AIED), has developed a range of tools including automated assessment systems, adaptive learning platforms, and conversational agents (e.g. chatbots) that provide personalised guidance and feedback to students (Diwan et al., 2023). Within language learning, AI-driven systems have progressed from early Computer-Assisted Language Learning (CALL) programmes to more sophisticated Intelligent CALL (ICALL) environments that incorporate natural language processing and learner modelling. These systems move beyond static drills to create dynamic, communicative learning experiences and to address the complexities of real-world language use (Amaral & Meurers, 2011; Eswaran et al., 2025; Yuan, 2025).

Recent advances in generative AI have opened new possibilities for L2 learning. These tools can engage learners in interactive dialogues, provide instant feedback on language output, and generate contextually appropriate examples (Dynel, 2023; Liu et al., 2025; Wu & Zhang, 2025). Emerging studies suggest that generative AI can facilitate L2 writing and reading by enabling learners to practice language in realistic contexts, obtain summaries of

texts, and receive adaptive support, including metacognitive prompts and strategy suggestions (Feng, 2025; Mehmood et al., 2025; Xia et al., 2024). For instance, L2 learners can use chatbots to ask for definitions or explanations of unfamiliar words, practice reading comprehension through question–answer dialogues, and generate alternative phrasings for complex sentences. These affordances have been found to increase learner motivation and help manage cognitive load during reading tasks. At the same time, effective use of these tools requires learners to develop new strategies; users often must employ metacognitive tactics such as prompt refinement, comparison of multiple AI outputs, and critical evaluation of AI-generated information to optimise learning (Frank, 2024; Wu & Zhang, 2025; Yuan, 2025). In other words, simply having access to AI tools is not enough. Students need specific competencies to harness AI effectively for language learning. This has led to growing interest in what educators term AI literacy for learners.

7.2.3 Concepts and frameworks of AI literacy

As AI becomes increasingly embedded in everyday technologies and learning environments, scholars have argued that learners need a broad form of AI literacy rather than just basic technical skills. AI literacy is typically defined as the set of knowledge and skills that enable individuals to understand how AI systems work and engage with AI in an effective and ethical manner (Chiu et al., 2024; Long & Magerko, 2020; Wang et al., 2024). This concept goes beyond programming content to include understanding data-driven decision-making and recognising the limits and biases of AI. Recent work in AI education further highlights that AI literacy also involves learning to collaborate with AI systems, taking into account how human strengths and weaknesses interact with algorithmic ‘intelligence’ (Chandra et al., 2022; Korteling et al., 2021; Tedre et al., 2021).

Building on this conceptual work, several frameworks have been proposed to structure AI literacy for curriculum design. For instance, Chiu et al. (2024) distinguish between AI

literacy and AI competency, emphasising that learners need both conceptual understanding and practical capabilities to operate in AI-rich societies. In the context of schooling, Touretzky et al., (2019) and Tedre et al. (2021) outline trajectories for K–12 AI education that cover foundational concepts, human–AI interaction, and societal implications. More recently, the ABCE framework (Ng et al., 2024) has organised AI literacy into four dimensions: the Affective dimension, the Behavioural dimension, the Cognitive dimension, and the Ethical dimension. Related work in language education stresses that teachers and learners alike must develop these multidimensional competencies to integrate AI tools productively (Pokrivčáková, 2019; Bushnell, 2025; Sun & Chan, 2025). In the present study, this ABCE perspective is adopted to conceptualise AI literacy among adolescent L2 Chinese learners and to examine how their affective, behavioural, cognitive, and ethical engagement with AI may relate to reading comprehension.

7.2.4 Theoretical framework of the present study

Research on Chinese reading shows that comprehension depends on multiple linguistic components, particularly orthographic and morphological knowledge. Readers must form precise representations of characters and understand how they combine into words and larger meaning units (Shen, 2018; Wang et al., 2003). Longitudinal work further indicates that weaknesses in orthographic processing and morphological analysis are key markers of later reading difficulties (Leong et al., 2011). In this study, orthographic knowledge and morphological awareness are therefore treated as core cognitive–linguistic foundations for L2 Chinese reading comprehension. At the same time, AI-based tools are increasingly used to support reading. These systems can augment learners’ abilities by providing explanations, feedback, and adaptive prompts, while leaving goal setting and interpretation to human users (Khosravi et al., 2022; Soyoo et al., 2023; Wu & Zhang, 2025). From this perspective, the benefits of AI for reading depend not only on access to tools, but also on how learners

understand and manage them. Integrating these strands, the present study proposes a model in which AI literacy, orthographic knowledge, morphological awareness, and reading comprehension are linked in a coherent structure. AI literacy, conceptualised through the ABCE dimensions, is expected to relate directly to reading comprehension and indirectly via its associations with orthographic and morphological skills. The hypothesised model therefore specifies AI literacy as an exogenous construct with both direct and indirect paths to Chinese L2 reading comprehension.

7.3 Methodology

This study adopted a quantitative design to investigate the relationships among AI literacy, orthographic knowledge, and Chinese L2 reading comprehension in senior-secondary learners. Multiple regression was used to gauge the unique variance each predictor explains in reading performance. Subsequently, a path analysis was employed to test the hypothesised framework. Given the moderate sample size, the model was specified as a path analysis with observed composite variables to reduce model complexity. This approach is appropriate for probing previously unexamined associations and for estimating potential direct and indirect associations among variables in a modest sample (Cohen, 1992; Takona, 2024).

7.3.1 Participants

The study included 155 Form 4 South-East Asian students (67 girls, 88 boys) recruited from four secondary schools in Hong Kong. These schools were selected because they offer less-intensive Chinese curricula, which is relevant for students learning Chinese as a second language. Participants were specifically ethnic minority students whose primary languages included Urdu, Hindi, Nepali, Tagalog, and English, with Chinese predominantly used in

academic settings. Their socioeconomic status ranged from middle- to lower-income households, reflecting the typical profiles of ethnic minority students in Hong Kong secondary schools.

A key inclusion criterion was that participants had prior experience using AI-assisted Chinese learning platforms that provided by schools, which included tools such as digital flashcards, interactive character recognition exercises, and adaptive reading comprehension tasks. Usage was verified through a pre-study questionnaire, ensuring that participants had sufficient exposure to AI-supported Chinese learning.

Regarding sample size adequacy, a power analysis using G Power (Faul et al., 2009) for multiple regression with predictors and a medium effect size ($f^2 = 0.15$) at $\alpha = 0.05$ and power = 0.80 indicated a minimum required sample of 77 participants. The actual sample size of 155 students exceeds this requirement, providing sufficient power to detect medium effect sizes and ensuring the reliability of the regression and structural equation modeling (SEM) analyses conducted in this study.

7.3.2 Measures

Chinese Reading Comprehension was assessed using selected items from the Territory-wide System Assessment (TSA) Chinese Reading Comprehension Test for Form 3 students. This test included multiple-choice, true-or-false, short-answer, and open-ended questions based on two articles, totaling 28 marks. The TSA is a government-administered standard assessment widely used in Hong Kong, with well-documented validity and reliability (Lau et al., 2018). Prior studies have confirmed that TSA reading scores correlate strongly with other measures of Chinese language proficiency, supporting its construct validity for assessing L2 reading comprehension among secondary students (Sun, 2019; Liang et al., 2020; Lin & Chen, 2021).

Orthographic knowledge was assessed applying Orthographic Choice in Context Task, which was modified from Leong et al. (2011), measures students' knowledge of orthography within sentence contexts. Each item presents a sentence with a missing word, and participants are asked to choose the most appropriate two-character word from four options. The distractors are designed based on orthographic or phonological similarity and include three types: (a) regular-consistent, (b) regular-inconsistent, and (c) exception real or pseudowords. The task consists of 20 items and requires approximately 5 minutes to complete. Each correct answer is awarded one point, resulting in a maximum score of 20.

Morphological awareness was assessed by the Morpheme Recognition Task (Ku & Anderson, 2003). The Morpheme Recognition Task evaluates students' understanding of morphological relationships between morphemes that form compound words. Participants are presented with word pairs and are asked to judge whether the meaning of the second word is derived from the first, based on shared morphemes. This task consists of 20 items and requires approximately 5 minutes to complete. One point is awarded for each correct response, with a maximum score of 20.

AI literacy was assessed using a 32-item AI Literacy Questionnaire (AILQ) adapted from Ng et al. (2024), grounded in the ABCE framework, which encompasses Affective, Behavioral, Cognitive, and Ethical dimensions. Sample items include: (1) Affective: "I feel confident using AI tools to support my learning". (2) Behavioral: "I can effectively use AI tools to complete learning tasks independently". (3) Cognitive: "I understand how AI systems generate suggestions or predictions". (4) Ethical: "I consider the ethical implications of using AI-generated content in my learning".

Responses were collected on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire has demonstrated good internal consistency in prior studies (Cronbach's $\alpha = 0.89$; Ng et al., 2024). In the present study, the AILQ also

showed high reliability (Cronbach's $\alpha = 0.91$), indicating that it is a robust measure of students' AI literacy across multiple dimensions relevant to language learning.

7.3.3 Procedure

Data collection took place during regular school hours in the computer rooms. Prior to the study, ethical approval was obtained from the authors' institution, and written consent was collected from school principals, parents or guardians, and participating students. At the start of each session, students were reminded that participation was voluntary and that their responses would be kept confidential and used only for research purposes.

Assessments were administered across two sessions within the same week, each lasting approximately 40–45 minutes. In the first session, students completed the Chinese reading comprehension test followed by the orthographic knowledge task. In the second session, they completed the morphological awareness task and the AI Literacy Questionnaire. The order of tasks within each session was fixed for all students to ensure standardisation of administration conditions. For each task, the examiner first provided standardised oral instructions and worked through one or two practice items with the whole class to familiarise students with the response format before they proceeded to the test items.

The reading comprehension, orthographic knowledge, and morphological awareness tasks were administered using printed booklets and answer sheets. The AI Literacy Questionnaire was completed on desktop computers using an online survey platform provided by the schools. Students were instructed to work individually and silently, and they were explicitly asked not to use dictionaries, translation applications, or AI tools during the assessments. Classroom teachers were present but did not provide assistance with the test content. Two trained research assistants monitored the sessions, answered procedural questions, and ensured that instructions were followed. At the end of each session, all materials were collected and checked for completeness.

7.3.4 Data analysis

Data analysis followed a systematic approach. First, internal consistency indices and descriptive statistics (means, standard deviations, skewness, and kurtosis) were computed for all measures. Pearson correlation analyses were then carried out to examine bivariate relations among AI literacy, orthographic knowledge, morphological awareness, and reading comprehension. Next, hierarchical multiple regression analyses were conducted to assess the unique contribution of AI literacy to reading comprehension after accounting for orthographic knowledge and morphological awareness. Finally, an observed-variable path analysis was used to test the hypothesised relations among AI literacy, orthographic knowledge, morphological awareness, and reading comprehension. AI literacy, orthographic knowledge, morphological awareness, and reading comprehension were entered into the model as observed composite variables. Model fit was evaluated using the chi-square statistic (χ^2), the Comparative Fit Index (CFI), the Root Mean Square Error of Approximation (RMSEA), and the Standardised Root Mean Square Residual (SRMR). A significance level of .05 was adopted for all inferential tests. Bias-corrected bootstrap confidence intervals (5,000 resamples, 90%) were used to evaluate the significance of indirect paths.

7.4 Results

7.4.1 Preliminary Analyses

Descriptive statistics were examined for all variables to ensure that the assumptions for parametric analyses were reasonably satisfied. As shown in Table 7.1, the distributions of AI literacy, orthographic knowledge, morphological awareness, and reading comprehension did not display severe skewness or kurtosis, suggesting approximate normality. Internal consistency estimates indicated satisfactory reliability for all scales. A methodological point

is important for interpreting the findings is that AI literacy was modelled as an overall composite score to capture general competence in AI-rich learning contexts. This choice was theoretically aligned with the study’s focus on AI literacy as a broad “meta-resource” shaping students’ ability to engage with AI tools productively

Table 7.1. Descriptive Statistics of Variables (n = 155)

Variable	Mean	SD	Skewness	Kurtosis	Cronbach’s α
Reading Comprehension	15.85	4.12	-0.18	-0.38	0.83
Morphological Awareness	22.42	6.28	0.08	-0.25	0.80
Orthographic Knowledge	17.63	5.94	0.12	-0.19	0.78
AI Literacy	3.68	0.57	-0.22	0.09	0.89

7.4.2 Pearson Analyses

Pearson correlation analyses revealed significant relationships among AI literacy, Chinese reading skills, and reading comprehension (Table 7.2). AI literacy showed a moderate positive correlation with reading comprehension ($r = .319$, $p < .01$) and a weak but significant correlation with orthographic knowledge ($r = .174$, $p < .05$). Morphological awareness was not significantly correlated with AI literacy ($r = .065$, $p = .422$). Among reading-related skills, orthographic knowledge demonstrated the strongest association with reading comprehension ($r = .365$, $p < .01$), while morphological awareness showed no significant relationship ($r = .180$, $p = .065$).

Table 7.2. Matrix of correlation coefficients among AI literacy, reading comprehension, and reading related skills of L2 Chinese learners in Hong Kong.

	1	2	3	4
1. Reading comprehension	-	.180	.365**	.319**
2. Morphological awareness		-	.207**	.065
3. Orthographic knowledge			-	.174*
4. AI literacy				-

Note. * $p < .05$ ** $p < .01$, *** $p < .001$. Correlations were correlation coefficients among L2 Chinese learners in Hong Kong (n = 155).

7.4.3 Hierarchical Regression Analysis

Hierarchical regression analyses examined the unique predictive contributions of AI literacy and reading-related skills to L2 Chinese reading comprehension (Table 7.3). The analysis proceeded in two sequential steps, with each model building upon the previous one. The final model incorporating AI literacy explained an additional 3.7% of variance ($\Delta R^2 = .037$, $p = .012$), with total explained variance reaching 32.3% ($R^2 = .323$, $F(6,148) = 11.76$, $p < .001$). AI literacy demonstrated a significant unique contribution ($\beta = .187$, $p = .012$) alongside orthographic knowledge ($\beta = .261$, $p = .002$). These results indicate that AI literacy explains variance in reading comprehension beyond traditional predictors, highlighting its emerging importance in digital learning contexts.

Table 7.3. Hierarchical regression analysis of reading skills and AI literacy predicting to reading comprehension

Predictor	ΔR^2	B	SE	β	t
Model 1	.018				
Age		0.42	0.41	0.82	1.02
Model 2	.115				
Orthographic knowledge		0.38	0.12	.261	3.17**
Morphological awareness		0.21	0.11	.172	1.91
Model 3					
AI literacy	.037	1.05	0.43	.187	2.44*

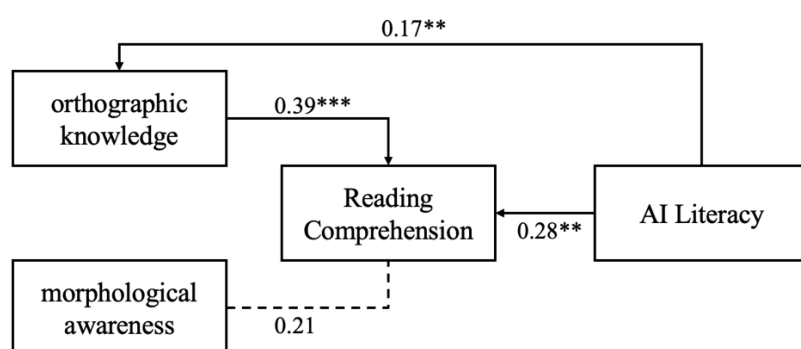
Note. * $p < .05$ ** $p < .01$, *** $p < .001$.

7.4.4 Path analysis

The hypothesised path model was examined using observed-variable path analysis. The model specified direct paths from AI literacy, orthographic knowledge, and morphological awareness to reading comprehension, as well as a path from AI literacy to orthographic knowledge to test a potential indirect association via orthographic knowledge. AI literacy and morphological awareness were allowed to covary, as both served as exogenous predictors in the model. The path analysis indicated an acceptable fit to the data, $\chi^2(1) = 2.05$, $p = .152$, CFI = 0.954, RMSEA = 0.071, SRMR = 0.067. The model accounted for approximately

42.3% of the variance in reading comprehension scores ($R^2 = .423$). Figure 1 illustrates the estimated significant and non-significant pathways.

Figure 7.1. SEM path diagram among L2 Chinese learners in Hong Kong



Note. The solid line represented significant path using 95% confidence interval on bootstrap analysis with 5000 bootstrapped sample. The dash line represented insignificant path.

7.5 Discussion

The present study examined how AI literacy relates to Chinese L2 reading comprehension when core linguistic skills including orthographic knowledge and morphological awareness are taken into account. The findings showed that AI literacy was positively associated with reading comprehension and remained a significant predictor even after controlling for orthographic and morphological skills. In the path model, AI literacy showed a small-to-moderate direct association with reading comprehension and a further indirect association via orthographic knowledge, whereas morphological awareness did not contribute uniquely to reading once the other predictors were considered. Together, the predictors accounted for a substantial proportion of variance in reading performance, suggesting that AI literacy should be considered alongside traditional linguistic skills in understanding adolescent L2 Chinese reading in AI-rich environments.

7.5.1 AI literacy and reading comprehension in context

The positive association between AI literacy and reading comprehension aligns with a growing body of research linking AI-related competencies to students' academic outcomes. Studies in general education contexts have indicated that students with higher AI literacy or stronger AI-related skills tend to show better engagement, self-regulation, and performance, particularly when they are able to use AI tools strategically for information seeking and problem solving (Chen & Gong, 2025; Chiu et al., 2024; Wang et al., 2024). In language education, recent work has reported benefits of generative AI and intelligent language-learning systems for reading and writing, through adaptive feedback, explanations, and metacognitive prompts (Dyner, 2023; Liu et al., 2025; Xia et al., 2024).

Compared to these studies, the present findings contribute two nuances. First, the association between AI literacy and reading comprehension was small-to-moderate once key linguistic skills were controlled, indicating that AI literacy appears to play a supportive and enabling role in adolescents' L2 reading comprehension, contributing incremental explanatory value beyond core linguistic skills such as orthographic knowledge. The pattern here is more consistent with research suggesting that students who already possess stronger skills are often better able to capitalise on AI-based supports (Guerra et al., 2025; Soyoof et al., 2023). Second, the present study focuses specifically on adolescent L2 Chinese readers, a group largely absent from existing AI literacy work, which has tended to examine either computer science education or English-medium contexts. As such, the results extend AI literacy research into a different language and script system, showing that the AI literacy–achievement link also holds in morphosyllabic L2 reading.

7.5.2 Orthographic knowledge as a pathway from AI literacy to reading

The partial mediating role of orthographic knowledge provides a more fine-grained view of how AI literacy may translate into reading advantages. The strong association

between orthographic knowledge and reading comprehension is consistent with established models of Chinese reading, which emphasise that precise visual–orthographic representations of characters are fundamental for efficient word recognition and comprehension (Shen, 2018; Wang et al., 2003). Longitudinal and risk-identification studies likewise show that weaknesses in orthographic processing, such as unstable stroke patterns or radical positions, are early markers of later reading difficulties (Leong et al., 2011; Chang et al., 2014).

The new contribution of this study lies in showing that AI literacy is linked to orthographic knowledge and that this link helps explain its association with reading comprehension. This pattern is compatible with research on digital and AI-enhanced literacy practices, where learners who are more confident and strategic in using technology tend to engage more frequently in activities that reinforce orthographic representations, such as digital handwriting practice, character-recognition games, and multimodal character learning (Ke & Koda, 2019; Liang & Cai, 2025). Recent intervention work suggests that AI-based systems can further support such activities by providing immediate feedback on stroke order, character formation, and visual similarity, leading to measurable gains in character recognition and related reading skills (He, 2024; Shafiee Rad, 2025; Xu et al., 2025). In comparison to these studies, the present findings do not test a specific AI intervention but indicate that students who report higher AI literacy may be better positioned to identify, access, and use such AI-based resources in ways that ultimately strengthen their orthographic knowledge.

7.5.3 Rethinking the role of morphological awareness

By contrast, morphological awareness did not uniquely predict reading comprehension once AI literacy and orthographic knowledge were taken into account. At first glance, this finding appears to diverge from a substantial literature in both L1 and L2 Chinese, where morphological awareness has been identified as a key predictor of vocabulary development

and reading comprehension, especially from upper primary and early secondary school onwards (Arcodia, 2007; Tong & McBride-Chang, 2010; Wang et al., 2003). Intervention studies have also demonstrated that explicit morphology instruction or enquiry-based activities focusing on morphological relationships can enhance word learning and reading-related outcomes (Mulder et al., 2022; Suadi et al., 2024).

Several factors may account for this apparent discrepancy. First, the participants in this study were mid-secondary L2 learners in Hong Kong, whose morphological skills may still be emerging relative to their orthographic decoding needs. For such learners, basic character identification and orthographic accuracy may remain the most immediate bottlenecks, with morphological sensitivity playing a secondary role in the types of comprehension tasks used here. This interpretation is consistent with stage-based models suggesting that orthographic demands dominate earlier phases of Chinese reading development, while morphological contributions become more pronounced as character recognition becomes more automatic (Chang et al., 2014). Second, the morphology measure used in this study tapped specific aspects of compound structure and morpheme recognition; it did not cover other dimensions such as derivational morphology, semantic radical awareness, or cross-linguistic transfer from students' L1 morphology, any of which might show stronger unique links to reading. Third, the inclusion of AI literacy in the model may have absorbed some of the variance otherwise attributed to strategic use of morphological cues: learners with higher AI literacy may increasingly rely on AI tools to unpack complex words and phrases, reducing the extent to which individual differences in independent morphological analysis explain reading performance.

Rather than concluding that morphology is unimportant for L2 Chinese reading, the findings therefore point to a more conditional role that may depend on developmental stage, task demands, and learners' patterns of AI use. Future studies could explore this by including

a broader battery of morphological tasks and by directly observing how learners with different AI literacy profiles use morphological versus AI-based strategies when reading morphologically complex texts.

7.5.4 The supportive role of AI literacy in human–AI collaboration

The pattern of results supports a view of AI literacy as a form of meta-resource that shapes how students mobilise both technological and linguistic resources for reading. From the perspective of the ABCE framework (Ng et al., 2024; Sun & Chan, 2025), the behavioural and cognitive dimensions seem particularly salient in this study that students who know how to formulate effective prompts, evaluate AI-generated explanations, and integrate feedback into their own reading strategies are better positioned to benefit from AI-enhanced environments. This interpretation is in line with broader discussions of human–AI collaboration, which emphasise the importance of appropriate division of labour and informed delegation of tasks to AI systems (Chandra et al., 2022; Fügener et al., 2022; Godwin-Jones, 2024).

Compared with highly technical accounts of AI that focus on algorithmic performance, the present study resonates more strongly with human-centric perspectives, which argue that AI systems should augment rather than replace human capacities and that users need competencies to recognise AI limitations and biases (Estevez Almenzar et al., 2022; Korteling et al., 2021; Tedre et al., 2021). In this sense, the finding that AI literacy is positively related to reading comprehension without diminishing the role of orthographic knowledge can be seen as an empirical illustration of intelligence augmentation that learners with higher AI literacy appear to use AI in ways that support, rather than undermine, the development and deployment of core reading skills.

7.5.5 Implications

The findings have several implications for Chinese L2 teaching. First, they suggest that AI literacy training should be integrated into reading instruction rather than treated as an optional or purely technical add-on. For example, teachers can design reading tasks in which students use AI tools to generate stroke animations and obtain alternative explanations of challenging passages. Crucially, such tasks should not end with AI output. Instead, students can be guided to compare AI explanations with textbook definitions, identify inaccuracies or omissions, and articulate what they have learned about orthographic or morphological patterns. In this way, AI activities explicitly serve the dual goals of strengthening orthographic representations and fostering the behavioural and cognitive aspects of AI literacy.

Second, the findings highlight the need to scaffold students' decision-making about when and how to rely on AI support. Research on human–AI delegation shows that uncritical reliance on AI can lead to over-trust and reduced independent reasoning, whereas carefully calibrated use can enhance performance (Fügener et al., 2022; Korteling et al., 2021). In reading classes, this suggests that teachers should help students distinguish between tasks where AI can provide useful support and tasks where overreliance might undermine learning. Explicit reflection activities, such as asking students to justify when they chose to consult AI, or to revise AI-generated responses based on their own orthographic and morphological knowledge, can make these decisions visible and open to discussion.

Third, the study underscores the importance of teacher AI literacy. Prior work has argued that teachers' beliefs, competencies, and ethical stances towards AI strongly shape how AI is introduced in the classroom and what opportunities students have to develop their own literacy (Bushnell, 2025; Sun & Chan, 2025). If teachers are themselves uncertain about how to evaluate AI outputs, manage bias, or design tasks that leverage rather than circumvent

linguistic learning, students may receive inconsistent or superficial messages about AI use. Professional development programmes that combine technical familiarity with pedagogical design and ethical reflection are therefore critical for realising the potential suggested by the present findings.

Several limitations should be noted. First, the cross-sectional design means that causal directions among AI literacy, orthographic knowledge, morphological awareness, and reading comprehension cannot be firmly established. It remains plausible that stronger readers are more inclined to develop higher AI literacy. Longitudinal and intervention studies are needed to test whether targeted AI literacy instruction leads to measurable gains in reading outcomes and whether changes in AI literacy precede improvements in orthographic and morphological skills.

Second, AI literacy was measured via self-report, which may not fully capture actual competencies or behaviours when interacting with AI. Self-perceptions can be influenced by confidence and social desirability. Future work could incorporate performance-based measures from AI-enhanced reading platforms to provide more objective indicators of AI literacy.

Third, the sample comprised 155 Form 4 students from four Hong Kong secondary schools serving ethnic minority learners. This specific context is important but limits the generalisability of the findings to other age groups, proficiency levels, and educational systems, particularly where access to AI tools or classroom norms around AI use differ. Larger-scale studies that sample across school types, regions, and policy environments would help to clarify the extent to which the observed patterns are context-specific. It would also be valuable to examine whether the role of AI literacy differs for learners with different first-language backgrounds or varying levels of Chinese proficiency.

Fourth, AI literacy was operationalised as an overall composite score, which provides a parsimonious index of students' general AI-related competence but does not allow the present study to disentangle the potentially distinct roles of its sub-dimensions. Prior theorising suggests that different components of AI literacy may relate to academic outcomes through different mechanisms. By collapsing across dimensions, the current analyses may have masked differential or even opposing associations between specific AI literacy facets and reading-related skills. Future research should therefore model AI literacy at the subscale level and test dimension-specific pathways, as well as whether the relative importance of each facet varies by proficiency level, access to AI tools, and instructional context.

Finally, the study focused on a single measure of reading comprehension and did not differentiate among types of AI tools or usage contexts. Students likely drew on a mixture of general-purpose chatbots, translation applications, and education-specific platforms when engaging with AI. Future research could distinguish between different categories of AI tools and investigate how particular AI use patterns relate to orthographic and morphological outcomes. Including multiple reading tasks that vary in genre and cognitive demand would also provide a richer picture of how AI literacy functions in different aspects of L2 Chinese reading.

7.6 Conclusion

This study investigated the role of AI literacy in Chinese L2 reading comprehension among adolescent learners from Southeast Asian backgrounds applying AI-assisted learning platform for Chinese language. Findings suggest that AI literacy functions as a complementary factor that supports adolescent L2 reading comprehension, alongside established linguistic and cognitive predictors, rather than serving as a primary determinant of reading outcomes. Learners with greater proficiency in interacting with AI tools

demonstrated stronger reading performance, highlighting that AI literacy contributes incremental explanatory value beyond core linguistic skills such as orthographic knowledge.

AI literacy was also positively associated with orthographic knowledge, suggesting that digital tools can effectively support the visual-form processing necessary for reading Chinese characters. The lack of a significant link with morphological awareness indicates that AI's impact may vary across specific reading subskills, depending on the linguistic nature and design of the AI tools employed..

Overall, this study underscores that AI literacy play a supportive and enabling role in adolescents' L2 reading comprehension. AI literacy should be integrated into frameworks of L2 reading development and actively cultivated in instructional practice. Future research should examine longitudinal effects, explore how different AI tools influence specific reading subskills, and develop assessment methods beyond self-report to capture learners' authentic digital competencies. Integrating AI literacy into language education prepares learners to navigate and thrive in AI-enhanced learning environments.

Chapter 8 Study 4: Second Language Learning in the Age of Artificial Intelligence: An Integrated Model of Executive Function, AI Literacy and Reading Comprehension

8.1 Introduction

The integration of Artificial Intelligence in Education (AIED) is rapidly transforming second language (L2) pedagogy, with a growing emphasis on personalized learning pathways (Tapalova & Zhiyenbayeva, 2022). However, a significant gap persists between the technological capabilities of AI application and their pedagogical alignment with human cognition. This is particularly evident in the context of logographic languages like Chinese, where the cognitive demands of mastering its orthographic system are profound, yet often overlooked in AIED design. Situated at the confluence of AIED, cognitive science, and L2 acquisition, this study investigates a critical yet under-examined question: How can AI systems be purposefully engineered to scaffold the specific cognitive skills that positive predict reading comprehension?

L2 acquisition is a cognitively intensive process that goes beyond the accumulation of vocabulary or grammar rules (Ellis & Robinson, 2008). It engages an array of interdependent cognitive and communicative skills, among which executive functions (EFs) play a foundational role. EFs, comprising working memory, inhibitory control, and cognitive flexibility, are particularly critical in acquiring complex writing systems such as Chinese (Lehtonen et al., 2023; Perfetti & Harris, 2013; Rivera et al., 2023). Working memory enables learners to retain and manipulate unfamiliar orthographic forms while simultaneously integrating semantic content. Inhibitory control is essential for managing cross-linguistic interference, especially from the first language (L1), and cognitive flexibility allows for efficient switching between character structures, syntactic patterns, and contextual cues.

Collectively, these cognitive capacities support not only basic skills such as character recognition and vocabulary acquisition but also higher-order processes such as inference, discourse integration, and reading comprehension (Kintsch, 1998).

The importance of these cognitive mechanisms is amplified in digital learning environments, where learners must navigate not only linguistic input but also complex interactions with AI-powered tools (Sarnovska et al., 2024; Yousaf et al., 2024). In such contexts, AI literacy, the ability to understand, interpret, and critically engage with AI systems, emerges as a crucial skill. AI tools now provide features such as personalized reading content, real-time grammar correction, character recognition support, and adaptive learning pathways. Outside the classroom, AI technologies also enable communication for non-verbal learners and deliver tailored instruction via machine learning algorithms (Kim et al., 2018). These affordances, while transformative, introduce additional cognitive demands: learners must monitor their attention, evaluate automated feedback, and decide which AI-generated suggestions to integrate into their learning strategies. Thus, the intersection of EFs and AI literacy becomes particularly salient for learners seeking to achieve proficiency in a second language in technologically mediated settings.

Despite the growing relevance of both constructs, research on EFs and AI literacy in L2 contexts has advanced largely in isolation. Few empirical studies have examined how these domains interact within authentic learning environments where technologies such as intelligent tutoring systems, adaptive testing platforms, and generative AI chatbots are regularly employed (Lin et al., 2023). Yet it is precisely within these settings that the dynamic interplay between EF, AI literacy, and L2 learning becomes most critical. Learners must manage limited cognitive resources while interpreting AI feedback, shifting across linguistic modes, and applying system-generated recommendations to their ongoing language development.

This study addresses this gap by investigating how AIED tools can be designed not merely to deliver content, but to actively scaffold the cognitive processes essential for effective language learning. The current study argues that EFs and AI literacy are not discrete competencies, but mutually reinforcing dimensions of a broader skill set needed for successful L2 acquisition, particularly in demanding contexts such as learning Chinese. Understanding and leveraging this synergy has important implications for educators, curriculum designers, and AI developers alike, as they seek to equip learners with the cognitive and technological fluency required to thrive in an increasingly global and digitized linguistic landscape.

8.2 Literature Review

8.2.1 Challenges of Chinese L2 learning

Chinese L2 presents a uniquely complex challenge for learners, particularly due to the logographic nature of its script, the opacity of its orthography-phonology mapping, and the cognitive demands of character-based decoding and comprehension (Cheng, 2023). Existing literature on reading comprehension and cognitive models provides a foundational understanding of how these challenges manifest for L2 learners of Chinese. This review synthesizes cognitive and linguistic perspectives to highlight the multi-dimensional obstacles faced by L2 learners.

One of the most widely acknowledged challenges in Chinese L2 learning lies in its complex writing system (Wong et al., 2011). Unlike alphabetic systems that rely on phoneme-grapheme correspondence, Chinese uses morphosyllabic characters, often composed of semantic and phonetic radicals. These characters provide limited phonological clues, making phonological decoding strategies which commonly employed in alphabetic L1s

ineffective for Chinese learners (Li & Woore, 2023). As a result, orthographic knowledge becomes central to successful reading. Studies indicate that orthographic awareness, including sensitivity to radical positions and visual configuration, significantly predicts L2 reading comprehension outcomes (Loh et al., 2018). Moreover, word segmentation in Chinese adds another layer of difficulty. Due to the absence of inter-word spacing, learners must rely on morphological awareness to identify meaningful units in the text (Bassetti & Masterson, 2012). Many Chinese words are compounds, and successful comprehension depends on the ability to analyze morphemes, infer meaning from their combinations, and suppress irrelevant character-level interpretations. This is particularly important when characters have multiple meanings or function differently depending on context, further reinforcing the need for morphological processing skills (Zhou et al., 2022).

Recognizing the inherent challenges associated with acquiring Chinese as a second language, educators and researchers have increasingly turned to AI applications to support the learning process. Although the integration of AI technologies into L2 instruction remains in its early stages, their growing presence in digital learning environments necessitates a critical examination of their pedagogical impact. Specifically, it is important to explore how these technologies reshape the processes of second language acquisition and redefine the cognitive and metacognitive skill demands placed on learners.

8.2.2 L2 learning in AI Era

The integration of AI into language education has advanced markedly in recent years, propelled by developments in computational linguistics, natural language processing, machine learning, and deep learning (Kuddus, 2022). These technological innovations have facilitated the incorporation of sophisticated AI tools into various dimensions of L2 learning, spanning both formal classroom instruction and independent study. This trend signifies a

paradigmatic shift in pedagogical practice, opening new pathways for language acquisition through technology-enhanced learning environments.

A wide range of AI-driven tools has been developed to support various facets of L2 acquisition (AbuSahyon et al., 2023). In the context of Chinese L2 education, learners regularly engage with multiple AI applications that facilitate distinct areas of language development. Duolingo, for instance, employs adaptive algorithms to personalize instruction in grammar and vocabulary for second language learning (Dekhakhena, 2025); ChatGPT enables L2 learners to generate sentences, receive grammar corrections, and experiment with alternative phrasing (Phieanchang, 2024); and Google Translate provides sentence-level translation and pronunciation support for real-time communication (Niño, 2025). Additionally, mLang developed by a team from the University of Hong Kong, offers the system that utilizes AI to provide automated feedback on Chinese writing, assisting learners in improving their composition skills (Loh, 2024). Together, these platforms constitute the digital ecosystem through which participants in this study have cultivated AI literacy, both within formal instructional settings and through self-directed learning.

AI literacy, as conceptualized in this study, refers to the composite of knowledge, skills, and attitudes required to critically and effectively interact with AI technologies in educational settings (Chiu et al., 2024; Ng et al., 2021). This construct was operationalized using a revised 23-item AI Literacy Questionnaire (AILQ) (Ng et al., 2024), adapted for the L2 Chinese context and grounded in the framework, which comprises affective, behavioral, cognitive, and ethical dimensions (ABCE). Each dimension reflects a distinct yet interconnected aspect of human–AI interaction and is aligned with specific competencies recognized in the field of AIED. Table 8.1 presents a conceptual mapping of the four AI literacy dimensions as assessed in the AILQ to their corresponding AIED competencies, along with example questionnaire items and contextualized illustrations of how each

dimension manifests in Chinese L2 learning. This framework situates AI literacy as a cognitively demanding, multifaceted construct that extends beyond basic technological proficiency.

Table 8.1. Mapping AI Literacy Dimensions (AILQ) to AIED Competencies in L2 Chinese Learning

AI Literacy Dimension	AIED Competency	Example revised AILQ Item	Application in L2 Chinese Learning
Affective	Emotional readiness to engage with AI	“I feel confident using AI tools like ChatGPT to support my Chinese learning.”	Learners demonstrate openness and willingness to engage with AI for L2 Chinese learning.
Behavioral	Strategic use of AI tools	“I regularly use AI apps to practice Chinese characters and review my mistakes.”	Learners develop structured study routines using AI for L2 Chinese learning.
Cognitive	Metacognitive evaluation of AI output	“I understand how AI-generated feedback is produced and can decide when to trust it.”	Learners critically assess the accuracy of AI outputs and adjust their use in L2 Chinese learning accordingly.
Ethical	Critical awareness of algorithmic bias	“I consider how AI recommendations might reflect certain cultural or algorithmic biases.”	Learners reflect on the limitations of AI-generated example sentences in terms of cultural nuance and context-appropriateness.

For effective L2 learning, particularly in AI-enhanced environments, learners must engage in complex decision-making, exercise judgment regarding the reliability of AI-generated feedback, and adapt their strategies based on a contextual understanding of language use (Muthmainnah et al., 2024). These practices inherently engage EFs. Specifically, cognitive flexibility is required to navigate diverse platforms and integrate varied forms of feedback; inhibitory control helps learners filter out misleading or irrelevant AI-generated content; and working memory supports the real-time integration of AI feedback into ongoing comprehension and production tasks (Zhang et al., 2013). This interplay

highlights how strong EFs are crucial for learners to effectively leverage AI tools, allowing them to critically evaluate, integrate, and apply AI-generated content, thereby advancing both their digital and linguistic competencies. In essence, EFs act as the cognitive regulators that enable learners to harness the potential benefits of AI while mitigating its challenges in L2 acquisition (Neugnot-Cerioli & Laurenty, 2024).

8.2.3 The role of EF in L2 learning and AI literacy

Defining EFs within the context of L2 learning necessitates an understanding of how core cognitive processes underpin the multifaceted task of language acquisition (Yao et al., 2024). The primary components of EFs, working memory, inhibitory control, and cognitive flexibility, are critically implicated in a wide range of language processing activities, from comprehending syntactically complex sentences to producing grammatically accurate utterances. Working memory enables the temporary storage and manipulation of linguistic information, facilitating both comprehension and production. Inhibitory control allows learners to suppress irrelevant or competing information, such as interference from the L1. Cognitive flexibility supports the ability to shift between different linguistic structures, rules, and communicative contexts, thus enhancing adaptability and fluency (Vogel, 2023).

Empirical research consistently demonstrates robust associations between EFs and L2 learning outcomes (Garcia et al., 2019; Musskopf & Barbosa, 2022). A growing body of evidence reveals both correlational and, in some cases, causal relationships between specific EF components and distinct aspects of L2 proficiency (Lehtonen et al., 2023; Shokrkon & Nicoladis, 2022). For example, strong working memory capacity has been found to predict success in vocabulary acquisition, sentence parsing, and grammatical accuracy (Verhagen & Leseman, 2016). Effective inhibitory control is essential for managing cross-linguistic interference, particularly in bilingual or multilingual learners (Poarch & Van, 2012). Meanwhile, cognitive flexibility plays a pivotal role in enabling learners to adapt to novel

linguistic input, transfer strategies across tasks, and engage in metalinguistic reflection that are fundamental to language development and communicative competence (Hung & Loh, 2021). In recognition of the integral role of EFs in L2 learning, various intervention strategies have been explored to enhance these cognitive abilities with the aim of improving language acquisition. These interventions include direct cognitive training programs targeting specific EF components, as well as pedagogical approaches that implicitly support EF development through complex, cognitively engaging language tasks. A review of this literature highlights how insights from cognitive science can inform instructional design, offering educators practical avenues for optimizing L2 pedagogy.

Furthermore, the examination of EFs in AI-mediated L2 learning environments is essential for the development of effective and cognitively supportive educational technologies (Liu & Fan, 2025). EFs directly enable effective interaction with AI tools. For example, working memory facilitates the retention and manipulation of AI-generated feedback while cognitive flexibility allows learners to adapt strategies when navigating diverse AI interfaces. On the other hand, inhibitory control helps filter irrelevant or unreliable AI outputs. Thus, well-designed AI systems can leverage these EF capacities by structuring adaptive tasks that align with learners' working memory limits or offering multimodal input to stimulate cognitive flexibility. Conversely, systems that ignore EF demands may hinder both AI literacy development and language acquisition. Thus, AI-driven platforms must intentionally harness EF strengths to foster learners' ability to critically evaluate, integrate, and apply AI-generated content, a synergy vital for advancing digital and linguistic competencies (Mohebbi, 2025).

8.2.4 Theoretical framework

This literature review proposes an integrated model for understanding Chinese L2 reading comprehension in this AI era, focusing on the dynamic interactions among EFs, AI

literacy, and reading-related linguistic skills. This model is guided by the Reading Systems Framework (RSF). RSF by Perfetti and Stafura (2014) serves as a comprehensive cognitive architecture for understanding the intricate processes involved in reading comprehension. It views reading as an interaction of knowledge sources including linguistic, orthographic, and general knowledge as well as cognitive processes like decoding, word recognition, inference generation, and comprehension monitoring. These processes are constrained by limited working memory and processing resources. The RSF is particularly well-suited for analyzing Chinese L2 reading comprehension, which involves navigating the visual complexity and unique structure of Chinese script, while also being mediated by EFs and, increasingly, AI literacy in digital reading environments (Perfetti & Helder, 2022). The distinct features of the Chinese writing system, such as visually complex characters and opaque form-sound mappings, place considerable demands on cognitive control for L2 learners.

Within the RSF, EFs play a critical role in modulating these cognitive demands. Working memory allows readers to hold and manipulate text information across characters and clauses, facilitating the integration of local meaning with broader discourse. Inhibitory control helps suppress irrelevant or misleading interpretations, such as homophone confusion or incorrect L1-based reading strategies. Cognitive flexibility enables learners to alternate between decoding individual characters and applying context-driven inference strategies. These EF components are essential for both lower-level visual-orthographic processing and higher-level meaning construction, acting as regulatory mechanisms within the RSF's reading system (Sun, 2022).

In addition to EFs, the growing use of AI in language learning introduces AI literacy as a new variable. In the current study, AI literacy refers to a learner's ability to effectively interact with AI-powered tools, such as intelligent dictionaries, translation apps, or adaptive reading platforms, for educational purposes. Within the RSF, AI literacy can be

conceptualized as an external scaffold that enhances the learner's internal cognitive architecture. For Chinese L2 learners, AI tools can compensate for orthographic or morphological difficulties by offering real-time support in character recognition, vocabulary lookup, and syntactic parsing. These tools can reduce cognitive load, allowing processing resources to be reallocated toward deeper comprehension tasks. However, the benefits of AI support are not automatic but depend on learners' executive control in strategically using these tools. Learners with stronger EFs are better equipped to determine when and how to use AI assistance, enabling them to maintain focus on comprehension goals without becoming overly reliant on technology.

This integrated view posits Chinese L2 reading comprehension as a result of dynamic interactions among word-level processing, executive control, and the learner's ability to engage with supportive technologies (Li & Clariana, 2019). The RSF accommodates these interactions by recognizing the role of lexical access in bridging decoding and comprehension, and by allowing for individual differences in cognitive capacity and learning strategies. When extended to include EFs and AI literacy, the RSF becomes a robust framework for analyzing the multilayered nature of reading comprehension in digitally mediated, second-language contexts. This theoretical framework guides the present study in examining how EF and AI literacy jointly mediate reading comprehension outcomes in Chinese L2 learners. By situating these variables within a unified model, it becomes possible to explore not only how learners process text, but also how they manage cognitive resources and digital tools to optimize comprehension. Such a model is particularly relevant in an era where reading increasingly involves complex interactions between cognition and technology. Thus, the extended RSF provides a theoretically grounded and context-sensitive foundation for understanding the evolving demands of second language reading in the age of AI.

Building on the extended Reading Systems Framework, the present study aims to investigate how cognitive control and digital literacy jointly contribute to Chinese L2 reading comprehension. It hypothesizes that executive functions, particularly cognitive flexibility, will not only directly predict L2 Chinese reading comprehension but will also exert a significant indirect influence by enabling the development and effective application of AI literacy. By conceptualizing EF as an internal regulatory mechanism and AI literacy as an external scaffold that supports reading processes, this study explores the dynamic interactions among these constructs in digitally mediated contexts. Accordingly, the research is guided by the following questions:

1. How do EF including working memory, inhibitory control, and cognitive flexibility influence Chinese L2 reading comprehension within the framework of the Reading Systems Framework (RSF)?

2. How does AI literacy interact with EF to support or mediate Chinese L2 reading comprehension, particularly in managing cognitive demands and optimizing learning in AI-assisted reading environments?

8.3 Methodology

8.3.1 Research Design

This study employed a quantitative correlational design to examine the relationships among EFs, AI literacy, and Chinese L2 reading comprehension in senior secondary students. Multiple regression analyses were conducted to assess the unique contribution of each predictor to reading performance. Additionally, structural equation modeling (SEM) was used to evaluate a hypothesized causal model, in which EFs was posited to influence reading comprehension both directly and indirectly via AI literacy.

8.3.2 Participants

The sample consisted of 155 Form 4 Chinese L2 learners (Mage = 15.32, SD = 0.58), including 67 females and 88 males, recruited from four secondary schools in Hong Kong known for offering less-intensive Chinese curricula. All participants were Southeast Asian ethnic minority students whose primary languages included Urdu, Hindi, Tagalog, or Nepali. Chinese was primarily used in academic contexts, confirming their L2 learner status.

To ensure alignment with the study's focus on AI literacy, participants were required to have prior experience with AI-assisted tools for Chinese language learning. This criterion was confirmed through a pre-study screening questionnaire, in which learners reported their familiarity with one or more commonly used AI-based platforms. These included Duolingo (for adaptive vocabulary and grammar exercises), ChatGPT (used for generating sentence-level feedback and vocabulary explanations), and Google Translate (for AI-driven sentence translation and pronunciation support). Collectively, these tools reflect a representative sample of AI-integrated applications frequently employed by L2 Chinese learners in both classroom settings and self-directed learning environments.

8.3.3 Measures

The instruments employed in the study were categorized into three main types. For literacy measures, Chinese reading comprehension was assessed using selected items from the Form 3 Territory-wide System Assessment, comprising multiple-choice, true/false, short-answer, and open-ended questions across two passages (total score of 28). Orthographic knowledge was measured using the Orthographic Choice in Context Task, adapted from Leong et al. (2011). Participants selected the appropriate two-character word to complete a sentence from four options, with distractors based on orthographic or phonological similarity (regular-consistent, regular-inconsistent, and exception items). The task included 20 items and had a maximum score of 20. Morphological knowledge was evaluated using the

Morpheme Recognition Task (Ku & Anderson, 2003), where participants judged semantic relationships between compound word pairs. The task included 20 items, with one point awarded per correct response.

Second, this study assessed the three core components of EF. Inhibitory control was assessed using the Color–Word Interference Test, which consisted of 24 baseline trials and 30 mixed trials (24 incongruent and 6 congruent). Each stimulus was presented for 3,500 milliseconds, with a 1,200-millisecond interstimulus interval. An interference score was calculated by subtracting the mean reaction time for baseline trials from that of incongruent trials. Higher interference scores indicated greater cognitive cost in resolving conflict between competing stimuli, and therefore reflected poor inhibitory control. Cognitive flexibility was evaluated via the D-KEFS Sorting Test, where participants grouped six cards into two sets based on varying attributes (size, shape, color, and semantic category), with eight possible sorting rules per set. Working memory was measured using a backward Digit Span task involving randomized digits (1–9) to minimize lexical bias.

Third, AI literacy was measured using a revised 23-item AI Literacy Questionnaire (AILQ) (Ng et al., 2024), grounded in the ABCE framework: Affective, Behavioral, Cognitive, and Ethical dimensions. Responses were collected using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Internal consistency reliability (Cronbach’s alpha) for the full AILQ was $\alpha = 0.88$, with subscale reliabilities.

8.3.4 Procedure

Assessments were conducted in school IT rooms, where each participant used a desktop computer with a keyboard and mouse. Although parental consent was obtained in advance, students could opt out prior to testing. Participants completed measures of orthographic awareness, morphological awareness, inhibitory control, working memory, cognitive flexibility, AI literacy, non-verbal intelligence, and Chinese reading comprehension. Testing

occurred over two sessions, each lasting approximately 35 minutes with a 10-minute break between sessions, totaling around 80 minutes. The primary researcher and a class teacher supervised the sessions; standardized visual instructions were provided, and no assistance was given during testing.

8.3.5 Data analysis

In addition to the descriptive and correlational analyses conducted to examine the association between Chinese reading comprehension and inhibitory control, the measurement properties of the latent constructs were evaluated through confirmatory factor analysis (CFA), with the aim of validating the factor structure underlying EFs, AI literacy, Chinese reading comprehension, and related reading skills. This step was critical to ensure construct validity prior to testing structural relationships. To assess the multivariate associations among the study variables and to test the hypothesized model, structural equation modeling (SEM) was then conducted. SEM enabled simultaneous estimation of both measurement and structural components, offering a comprehensive framework for analyzing the direct and indirect pathways linking EFs, AI literacy, and reading comprehension.

8.4 Results

Prior to conducting inferential analyses, descriptive statistics were calculated for all study variables to assess data distribution and to confirm the assumptions necessary for parametric testing. Table 8.2 reports the means, standard deviations, and distribution characteristics of the raw scores across all measured constructs.

Table 8.2 Means and standard deviations for all variables

Measures	Mean	SD	Skewness	Kurtosis
Reading comprehension	16.32	5.49	-.57	-.19
Orthographic knowledge	11.25	5.58	-.32	-.90
Morphological awareness	9.90	8.43	-.05	-.55
The Color–Word Interference Test	224.10	46.85	.21	1.12
Sorting test	4.90	2.43	.01	1.01
Digit Span task	4.22	3.04	.02	1.16
AI literacy	4.01	.616	-.35	-.42
Raven’s Standard Progressive Matrices	38.2	6.87	-0.34	0.12

N=155

Pearson correlation coefficients were subsequently computed to examine bivariate associations among the key variables, including reading-related linguistic skills, EF components, and AI literacy. The resulting correlation matrix, presented in Table 8.3, indicates several statistically significant relationships across cognitive, linguistic, and digital competencies

Table 8.3 Matrix of correlation coefficients among EF, AI literacy, reading comprehension, and reading related skills of L2 Chinese learners in Hong Kong.

	1	2	3	4	5	6	7
1. RC	-	.365*	.180*	-.264**	.353**	.434**	.319**
2. OK		-	.207**	-.024	.152	.225**	.174*
3. MA			-	-.067	.005	.154	.065
4. IC_CW				-	-.254**	-.100	-.079
5. CF_ST					-	.214**	.278**
6. WM_DST						-	.143
7. AI L							-

Note. * $p < .05$ ** $p < .01$, *** $p < .001$. RC = Reading comprehension task; OK = Orthographic knowledge task; MA = Morphological awareness task; IC_CW = Inhibitory control the Color–Word Interference Test; CF_ST = Cognitive flexibility Sorting test; WM_DST = Working memory Digit Span task; AI L = AI literacy questionnaire. Correlations were correlation coefficients among L2 Chinese learners in Hong Kong ($n = 155$).

Before proceeding with SEM to evaluate the hypothesized relationships among EFs, AI literacy, and L2 reading comprehension, it was necessary to establish the latent structure of EFs within this adolescent sample. Given the developmental variability of EFs and its sensitivity to contextual and measurement factors, the dimensionality of EFs in this dataset

could not be assumed a priori. CFA was therefore conducted using SPSS AMOS 28 to compare competing structural models, including a unidimensional model, three alternative two-factor models, and a hypothesized three-factor model. The CFA results supported the three-factor model comprising working memory, cognitive flexibility, and inhibitory control (Table 8.4).

Table 8.4 Model fit indices for the full confirmatory factor analysis models of EF for L2 Chinese learners (N = 155)

Model	χ^2/df	GFI	CFI	RMSEA	SRMR	AIC
1. Full three factors	1.539	.993	.964	.059	.004	11.539
Two factors						
2. working memory + (inhibitory = flexibility)	Model not identified					
3. flexibility + (working memory = inhibitory)	Model not identified					
4. inhibitory + (working memory = flexibility)	Model not identified					
5. One factor	Model not identified					

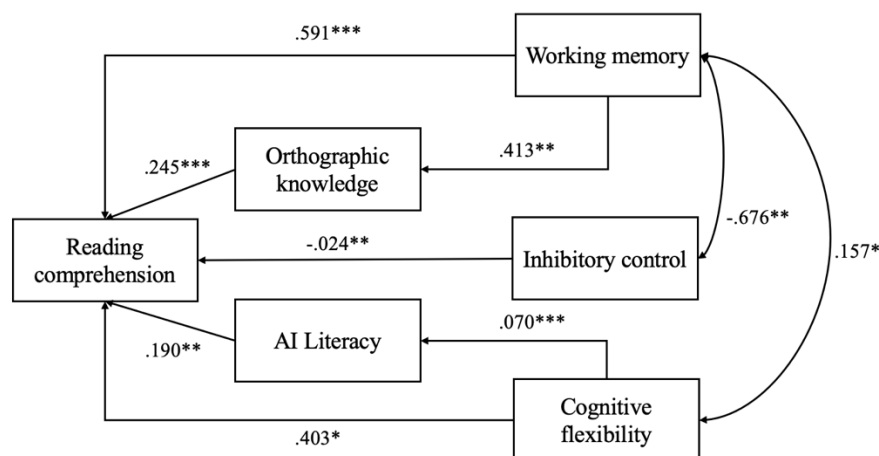
Following the establishment of the EF measurement model, SEM was employed to test the hypothesized structural relationships among executive functions, AI literacy, orthographic knowledge, and reading comprehension (Figure 8.1). The model demonstrated acceptable fit, $\chi^2(10) = 10.72$, $p = .378$, SRMR = 0.0569, RMSEA = 0.071, and CFI = 0.954.

Reading comprehension was significantly predicted by multiple factors. Among EF components, working memory showed the largest standardized direct effect on reading comprehension ($\beta = 0.591$, $p < .001$), followed by cognitive flexibility ($\beta = 0.403$, $p < .05$). Inhibitory control also showed a statistically significant association with reading comprehension ($\beta = -0.240$, $p < .01$). In addition, AI literacy demonstrated a small-to-moderate positive direct association with reading comprehension ($\beta = 0.190$, $p < .01$), above and beyond EF and orthographic knowledge ($\beta = 0.245$, $p < .001$). Although statistically reliable, this coefficient should be interpreted as an incremental effect rather than a large educational impact; substantively, it suggests that a one standard deviation difference in AI

literacy is associated with approximately 0.19 standard deviations difference in reading comprehension, conditional on other predictors in the model.

The model also indicated interdependencies among predictors. Working memory exerted a significant positive effect on orthographic knowledge ($\beta = 0.413$, $p < .001$), consistent with the role of working memory in acquiring and maintaining orthographic representations. Cognitive flexibility was the only EF component that significantly predicted AI literacy ($\beta = 0.070$, $p < .001$). Despite statistical significance, the magnitude of this path is very small, implying that cognitive flexibility explains only a limited proportion of variance in AI literacy in practical terms. One possibility is that the small coefficient reflects attenuation due to measurement limitations (e.g., AI literacy modeled as an observed composite and cognitive flexibility measured with a single task), and/or heterogeneity across AI literacy sub-dimensions that may relate differently to cognitive flexibility.

Figure 8.1 Path diagram of relation among EF, AI literacy, reading comprehension, and reading related skills



Note. The solid line represented significant path using 95% confidence interval.

8.5 Discussion

The findings provide empirical support for a multidimensional model of EF, with distinct but interrelated components of working memory, cognitive flexibility, and inhibitory

control (Karr et al., 2018). All three EF components were significantly associated with Chinese L2 reading comprehension, underscoring their relevance to the cognitive demands of reading in a morphosyllabic writing system. This pattern is consistent with prior work suggesting that successful L2 Chinese reading requires maintaining detailed orthographic information, flexibly integrating contextual cues, and regulating interference from competing interpretations (Shen, 2018).

In addition to EF, the model indicates that AI literacy is positively associated with reading comprehension. However, the standardized coefficient from AI literacy to reading comprehension ($\beta = 0.190$) should be interpreted as a small-to-moderate effect rather than a substantial one. In educational terms, this magnitude suggests incremental explanatory value: students with higher AI literacy tend to show somewhat better reading comprehension, even when core linguistic skill of orthographic knowledge and EF are controlled. Importantly, statistical significance does not by itself imply educational meaningfulness. The present effect size indicates that AI literacy may function as a supportive, enabling resource in AI-rich learning environments, but it is unlikely to be the dominant determinant of reading comprehension compared with core cognitive and linguistic predictors.

A particularly novel contribution of this study lies in the identification of cognitive flexibility as a significant predictor of AI literacy. This finding suggests that the ability to adaptively shift between tasks, representations, or perspectives is a key cognitive resource for effective engagement with AI technologies (Yu et al., 2024). In doing so, the research establishes a theoretical link between cognitive psychology and digital literacy, positing cognitive flexibility as a foundational capacity for navigating the demands of AI-mediated learning environments. Moreover, the observed indirect effect of cognitive flexibility on reading comprehension, mediated through AI literacy, introduces a new explanatory pathway. This pathway highlights the role of EF not only in supporting reading comprehension directly

but also in enabling learners to develop the digital competencies necessary for interacting with intelligent systems that increasingly shape learning experiences (Gkora & Drigas, 2024).

This mediational pathway establishes a proposed Cognitive–AI Literacy–Reading Integration Model (CAR), conceptualizing how higher-order cognitive processes interface with digital competence to support L2 reading in AI-enhanced educational contexts. Specifically, CAR posits that EF enables learners to manage cognitive load, adapt strategies, and transfer knowledge across learning modalities, while AI literacy provides the technological means to operationalize these abilities in digital environments. This integrated framework helps explain how cognitive flexibility not only directly facilitates reading comprehension but also empowers learners to harness AI tools effectively, thereby creating a synergistic cycle that enhances overall L2 literacy development.

Thus, these findings present an integrated theoretical framework that brings together cognitive, linguistic, and technological dimensions of L2 learning. By embedding EF and AI literacy within the Reading Systems Framework, the study offers a comprehensive lens through which to understand reading development in a digitally mediated, cognitively demanding, and linguistically complex environment. As AI technologies become more prevalent in educational contexts, this integrated perspective underscores the need to cultivate both cognitive adaptability and digital literacy to support equitable and effective language learning for diverse learners.

8.6 Implication

By demonstrating the dynamic interplay among L2 reading comprehension, AI literacy, and EFs, the research offers a direct and actionable pedagogical implications for L2 Chinese language education, particularly for ethnic minority students who often face unique linguistic and socio-economic challenges.

Pedagogically, educators should consider integrating activities that explicitly train and scaffold EFs into their curriculum, given their strong predictive power for reading comprehension (Rapport et al., 2020). Explicit instruction in character recognition and visual-orthographic processing is also necessary due to the significant role of orthographic knowledge in L2 Chinese reading comprehension. Most importantly, the positive association between AI literacy and reading comprehension suggests that integrating AI tools into the curriculum, coupled with explicit instruction on AI literacy, can significantly enhance L2 reading outcomes. Educators should focus on developing students' critical understanding of AI's capabilities and limitations, teaching them how to formulate effective prompts, critically evaluate AI-generated content, and adapt their interaction strategies with AI tools to optimize learning (Darwin et al., 2024). This holistic approach is crucial for preparing students for an increasingly AI-mediated world.

For curriculum developers, the findings highlight the urgent need to revise and update L2 curricula to explicitly incorporate AI literacy as a core competency. This means moving beyond basic digital skills to include integrated themes that teach learners about AI's principles, applications in language learning, ethical considerations, and how to critically interact with AI systems. Such revisions should aim to create a seamless integration of cognitive, linguistic, and digital literacies, ensuring that L2 learners are prepared for the demands of a rapidly evolving technological landscape (Musa, 2024).

From the perspectives of developers of AI-powered language learning tools, this research provides valuable insights into designing more cognitively supportive and pedagogically effective platforms. Developers should consider how their tools can explicitly scaffold EFs, for instance, by offering adaptive challenges that incrementally increase working memory load, providing clear feedback that encourages cognitive flexibility, or designing interfaces that minimize cognitive interference (Gkora & Drigas, 2024).

Furthermore, tools should be designed to promote AI literacy by offering transparency about their functionalities, encouraging critical evaluation of outputs, and enabling learners to understand the underlying mechanisms of the AI they are interacting with. Features that allow for personalized learning pathways based on a learner's EFs profile could also be explored.

Despite these insights, several limitations constrain the generalizability of the findings. First, the sample consisted exclusively of Southeast Asian ethnic minority students in Hong Kong, a population with unique sociolinguistic and educational profiles (Michelle et al., 2017). While this group is underrepresented in L2 research and thus valuable to study, findings may not extend to other L2 learner populations or educational contexts. Second, the study employed a cross-sectional design, limiting causal inference. Although SEM allows for the testing of directional hypotheses, longitudinal or experimental studies are necessary to confirm causal pathways between EFs, AI literacy, and reading comprehension. Intervention studies that target specific EF components could also explore whether such training leads to measurable gains in AI literacy and reading performance. Third, AI literacy was assessed through self-report using the AILQ, which, while validated, remains subject to potential biases such as social desirability or limited introspective access (Ng et al., 2024). Although care was taken to clarify items and ensure relevance, future research would benefit from performance-based AI literacy assessments or triangulation with behavioral data from actual tool use. Finally, while the study included a range of cognitive and linguistic predictors, other influential variables, such as motivation, digital access, and teacher scaffolding, were not addressed.

8.7 Conclusion

This research offers compelling empirical evidence for an integrated model of L2 reading comprehension, positing it as a dynamic synthesis of cognitive control, linguistic

expertise, and digital literacy. The findings yield substantial theoretical insights into these intricate relationships and carry significant practical implications for language education. By emphasizing the cultivation of EFs, particularly working memory and cognitive flexibility, alongside orthographic knowledge and AI literacy, educators can strategically enhance L2 learners' reading outcomes and prepare them for success in the evolving landscape of AI-mediated learning environments. Researchers should further investigate how specific AI tools can be optimized to scaffold EFs and reading skills in real-time. In particular, tailoring AI systems to match learners' EFs profiles could enhance personalization and effectiveness. For example, adaptive reading platforms could adjust the level of scaffolding based on working memory capacity or offer reflective prompts to support cognitive flexibility. Such innovations would move the field beyond passive personalization toward active cognitive support, bridging the gap between AI-driven instruction and individual learner needs.

Chapter 9 General Discussion

9.1 Overview

This dissertation set out to examine how executive function (EF), linguistic knowledge, and digital competence interact to influence Chinese L2 reading comprehension among Southeast Asian ethnic-minority students in Hong Kong. Across four empirical studies, a new theoretical framework, the Cognitive–AI Literacy–Reading Integration (CAR) model, emerged. The CAR model conceptualizes L2 reading as a tri-layered system in which (1) EFs provide the cognitive capacity for control and adaptation, (2) AI literacy supplies the technological means to operationalize those capacities in digital environments, and (3) reading comprehension represents the linguistic manifestation of these combined resources.

Rather than treating cognitive, linguistic, and digital factors as separate predictors, the CAR model unites them in a coherent developmental mechanism that explains how learners manage cognitive load, engage with AI-mediated input, and construct meaning from complex Chinese texts. This chapter therefore interprets all major findings as sequential contributions to the formulation and validation of the CAR framework.

9.2 Research objectives and research questions

The present dissertation had four major research objectives as follows. The research objectives of present study were:

1. To evaluate the structure of executive function (working memory, inhibitory control, and cognitive flexibility) among second language learners.
2. To identify the direct and indirect pathways linking executive function and AI literacy to L2 reading comprehension.

3. To model the relational dynamics between executive function, AI literacy, and L2 reading comprehension performance in the context of AI-mediated learning, considering the specific challenges posed by the orthographic systems and the cognitive demands of AI tools.

These research objectives of present study were to address three research questions:

1. What are the structure of executive function (working memory, inhibitory control, cognitive flexibility) among second language learners?
2. How do learners' levels of executive function and AI literacy individually and interactively relate to their reading comprehension?
3. Does the level of AI literacy influence how effectively learners utilize AI-powered language learning tools in relation to their executive function capacities and their L2 reading development?

9.3 Findings

9.3.1 The structure of executive function

One of the foundational aspect of the present study for CAR model was to clarify the underlying structure of EF within the adolescent sample of Form 4 South-east Asian students, given that the conceptualization and measurement of EF can vary across developmental stages and contexts. Based on the confirmatory factor analysis (CFA) which was employed to evaluate different proposed factor structures of EF, the results of unequivocally supported a three-factor model comprising working memory, cognitive flexibility, and inhibitory control, demonstrating an excellent fit to the data. This finding is consistent with prominent theoretical frameworks of EF and provides a robust basis for interpreting the subsequent analyses in this dissertation.

A growing body of research has extensively reviewed the theoretical underpinnings of EF, highlighting the general consensus in research that identifies these three primary components: inhibitory control, working memory, and cognitive flexibility (Diamond, 2013; Miyake, 2000). Miyake (2000) notably demonstrated through factor analysis that these components, while distinguishable, are also correlated, forming an integrated cognitive system. The current study's empirical validation of this three-factor structure in an adolescent population aligns strongly with Miyake's influential framework and other contemporary models that delineate distinct yet interrelated subcomponents of EF (Miyake & Friedman, 2012; Cragg and Chevalier, 2022). The significant covariances observed between factors in the CFA further support the notion of an integrated system where these components interact, rather than operating in complete isolation.

The confirmation of a robust, three-factor EF structure is pivotal, as it provides the necessary psychometric grounding for the present investigation. Crucially, this finding establishes and anchors the Cognitive (C) layer within the proposed CAR framework. It validates the measurement model used to represent EF as a latent construct, ensuring that the subsequent structural equation modeling (SEM) analyses, which investigated the integrated relationships among EF, reading skills, and AI literacy, were built upon a psychometrically sound foundation. By establishing that working memory, cognitive flexibility, and inhibitory control are distinct yet interconnected domains in this specific adolescent sample, the study provides a clear framework for understanding their individual and combined contributions to complex cognitive outcomes like Chinese L2 reading comprehension. This finding also contributes to the broader literature on the developmental trajectories of EF, suggesting that the differentiated nature of these core components is well-established by Form 4 (adolescent) age.

9.3.2 The Relation between reading skills and L2 reading comprehension

The present study explored the relationship between reading-related linguistic skills and Chinese as a L2 reading comprehension. Specifically, it examined the contributions of orthographic knowledge and morphological awareness, two most essential linguistic skills in Chinese to L2 Chinese reading comprehension.

Research detailed the critical role of various reading-related skills in Chinese reading comprehension, given the unique characteristics of its logographic writing system. Orthographic knowledge, defined as the memory for specific visual and spelling patterns of characters and their components, was highlighted as foundational for word recognition and overall reading proficiency (Apel et al., 2019; Loh et al., 2018). The current study's regression analysis found that orthographic knowledge significantly predicted reading comprehension. This strong positive association aligns perfectly with the literature, which consistently emphasizes the importance of accurate orthographic processing for efficient character and word identification in Chinese, especially due to the absence of clear inter-word spacing (Braze & Gong, 2017; Liao et al., 2022). For L2 learners, as discussed in Chapter 3, accurate orthographic processing and direct visual recognition of characters are essential, as they cannot rely on phonological decoding strategies as readily as readers of alphabetic scripts (Li & Woore, 2023). Thus, the significant predictive power of orthographic knowledge in this study underscores its fundamental role in Chinese L2 reading comprehension.

In contrast, while research presented morphological awareness as a crucial metalinguistic skill for manipulating morphemes and understanding word formation rules, particularly important in Chinese due to its morphosyllabic nature and heavy reliance on compounding (Hung, 2012; Tong et al., 2009), the current study's regression analysis found that morphological awareness did not significantly predict reading comprehension. This

finding, while seemingly contradictory to some literature suggesting a positive association (Tong & McBride, 2017; Xie et al., 2019), is not entirely unprecedented. Chapter 3 also noted that the role of morphological awareness in Chinese reading comprehension is not always consistent across studies, with some finding its direct contribution significant only when certain factors are controlled or at specific developmental stages (Xie et al., 2019). It is possible that in the current sample of Form 4 (adolescent) L2 learners, the variance explained by morphological awareness might be subsumed by other factors, or its contribution might be more indirect, perhaps mediated by other skills not fully captured in this specific regression model. For instance, some mentioned that morphological awareness can mediate the relationship between Chinese writing ability and reading comprehension (Liu & Liu, 2020). Further investigation into the indirect pathways of morphological awareness in this population could provide more clarity.

Overall, the findings regarding linguistic reading skills highlight the paramount importance of orthographic knowledge for Chinese L2 reading comprehension in this adolescent sample. While morphological awareness is theoretically and empirically important in Chinese reading development, its direct predictive role was not evident in the current study, suggesting a need for further exploration of its nuanced contributions, potentially through indirect pathways or in different developmental contexts. These results delineate the Reading layer of the CAR model, demonstrating how linguistic resources manifest the outcomes of cognitive processing. Within CAR, orthographic knowledge functions as the primary linguistic channel through which executive control is expressed in reading, translating cognitive capacity into visible comprehension performance.

9.3.3 Relation among executive function, reading skills, and L2 reading comprehension

The present study investigated the intricate relationship between EF and Chinese L2 reading comprehension in Form 4 South-east Asian students. The results largely align with

and extend the theoretical perspectives and empirical evidence presented in literature review, underscoring the critical role of EF in supporting complex cognitive processes involved in L2 reading. Specifically, the results indicated that working memory and cognitive flexibility were significant positive predictors of reading comprehension, while inhibitory control showed a negative association. These findings provide valuable insights into how distinct EF components contribute to L2 Chinese reading, a process known to be particularly demanding due to the unique characteristics of its orthography. This mediation also clarified how cognitive resources are translated into linguistic performance, thereby defining the Reading layer of the CAR model.

Research highlighted EF as a suite of cognitive processes, comprising working memory, inhibitory control, and cognitive flexibility, that regulate goal-directed behavior and are essential for various cognitive and linguistic tasks (Diamond, 2013; Miyake, 2000). It is emphasized that working memory is crucial for manipulating linguistic information, processing complex sentences, and integrating information across extended discourse, which is highly relevant for reading comprehension (Baddeley, 2021; Shin et al., 2019). The current study's finding that working memory was the strongest positive predictor of Chinese L2 reading comprehension strongly corroborates this established link. This is particularly salient in Chinese reading, where readers must simultaneously store and process phonological and semantic codes, and continuously update their understanding as new information is encountered in unspaced text (Deng, 2025; Huang et al., 2022; Mercer, 2005). The demanding nature of Chinese orthography, with its logographic characters and compound words, necessitates robust working memory capacity to manage the simultaneous decoding and meaning-making processes (Liu et al., 2024).

Furthermore, research posited that cognitive flexibility enables shifting between tasks or perspectives, fostering adaptive problem-solving (Monsell, 2003). In the context of

reading, cognitive flexibility allows readers to flexibly switch between various components such as decoding, vocabulary, syntax, discourse, and visual information when processing text (Cartwright et al., 2019). The current study's finding that cognitive flexibility significantly predicted Chinese L2 reading comprehension supports this theoretical stance. This is especially pertinent for Chinese, where reading often necessitates shifting between different strategies due to the complex visual forms, multiple context-dependent meanings, and absence of clear word boundaries (Pan & Lin, 2023; Sun, 2024). The ability to adaptively switch between character-level recognition and higher-level semantic integration is a hallmark of skilled Chinese L2 reading, and the present results confirm the importance of cognitive flexibility in this process (Lin et al., 2024; Kong, 2006).

The unexpected negative association between inhibitory control and reading comprehension in the current study warrants further discussion. Chapter 2 described inhibitory control as the capacity to resist interference from distracting information or automatic responses and to suppress inappropriate responses (Diamond, 2013; Drijbooms et al., 2015). In Chinese reading, inhibitory control is considered critical for suppressing distractions from neighboring words, managing homophones, and inhibiting irrelevant lexical representations (Liao & Zhao, 2024; Pan & Lin, 2023). While some literature suggests a direct link between inhibitory control and reading comprehension (Locascio et al., 2010), conflicting findings exist regarding its predictive power, with some studies showing its contribution is shared with other metalinguistic skills (Chung & McBride-Chang, 2011). The negative correlation observed here could be interpreted as a suppressor effect or a measurement artifact, as suggested in the Chapter 6 summary, rather than indicating that lower inhibitory control is beneficial for reading. It might imply that in this specific L2 context, or with the particular inhibitory control measure used, a different dynamic is at play, or that the demands of Chinese L2 reading might reconfigure the typical beneficial role of

inhibitory control seen in other contexts. For instance, an over-reliance on inhibition might hinder the flexible activation of multiple possible meanings that could eventually lead to the correct interpretation in a language rich in polysemy and homophony. This finding highlights the complexity of EF interplay in L2 contexts and suggests a need for more nuanced investigations into the specific mechanisms through which inhibitory control operates in Chinese L2 reading.

Given that a higher score on the inhibitory control measure indicates weaker inhibitory control, the observed negative correlation suggests that weaker inhibitory control was linked to lower reading comprehension performance. Thus, the association between inhibitory control and reading comprehension in the current study consistent with the established role of inhibitory control in managing cognitive interference during reading. Research described inhibitory control as the capacity to resist interference from distracting information or automatic responses and to suppress inappropriate responses (Diamond, 2013; Drijbooms et al., 2015). In Chinese reading, inhibitory control is considered critical for suppressing distractions from neighboring words, managing homophones, and inhibiting irrelevant lexical representations (Liao & Zhao, 2024; Pan & Lin, 2023). While some literature suggests a direct link between inhibitory control and reading comprehension (Locascio et al., 2010), conflicting findings exist regarding its predictive power, with some studies showing its contribution is shared with other metalinguistic skills (Chung & McBride-Chang, 2011). This result highlights the complexity of EF interplay in L2 contexts and suggests a need for more nuanced investigations into the specific mechanisms through which inhibitory control operates in Chinese L2 reading.

The interplay between EF and fundamental reading skills is also a crucial area of investigation, particularly in the context of learning a complex orthography like Chinese as a second language. As the correlational analysis showed that orthographic knowledge had

positive associations with working memory, this finding aligns with the theoretical understanding that working memory provides the cognitive resources necessary for the temporary storage and manipulation of visual-orthographic information during character recognition and learning (Carretti et al., 2009; Zhang, 2019). Efficient working memory capacity can facilitate the accurate retrieval and processing of complex visual patterns inherent in Chinese characters, thereby supporting the development of orthographic knowledge.

However, the correlational analysis also revealed that morphological awareness was not significantly correlated with any of the cognitive measures of EF. This lack of a direct significant correlation is notable, especially considering the theoretical importance of EF in language learning. While some studies suggest that EF can influence language-specific abilities like morphological awareness (Xu et al., 2024), the current study's findings do not directly support such a relationship in this adolescent L2 Chinese sample. It is possible that the relationship between EF and morphological awareness is more complex, perhaps indirect, on specific developmental stages. For instance, some research mentioned that morphological awareness can mediate the relationship between Chinese writing ability and reading comprehension (Liu & Liu, 2020), suggesting a more integrated pathway rather than a direct EF influence.

Overall, the results reinforce the theoretical frameworks of the current study by empirically demonstrating the significant contributions of working memory, cognitive flexibility, and inhibitory control to Chinese L2 reading comprehension. The study's findings align with the notion that EF components are not isolated but form a dynamic, integrated system crucial for effective reading comprehension (Miyake & Friedman, 2012; Weaver & Kieffer, 2022). The unique linguistic features of Chinese further emphasize the heightened demands placed on these cognitive functions for L2 learners. These findings contribute to a

deeper understanding of the cognitive underpinnings of Chinese L2 reading, providing empirical support for the theoretical models that highlight the interplay between cognitive processes and textual understanding in complex orthographies.

The study's findings further reveal a crucial cognitive pathway consistent with the CAR framework: a direct link between working memory and orthographic knowledge. This relationship reinforces the idea that working memory provides the necessary cognitive support for processing the visual complexities inherent in the Chinese writing system. Within the CAR model, orthographic knowledge is not a solitary skill but the critical interface that bridges the gap between the Cognitive layer and linguistic outcomes. It channels cognitive control into recognizing complex characters and inferring meaning without relying heavily on phonological cues. However, the non-correlation between the broader EF components and morphological awareness highlights a key nuance in this interplay. This suggests that the relationship between general cognitive control and complex linguistic analysis may be more mediated, necessitating further investigation into potential indirect effects or specific developmental pathways. Taken together, these empirical patterns powerfully substantiate the Cognitive-to-Reading linkage proposed by the CAR model. Specifically, EF components, particularly working memory and cognitive flexibility, constitute the cognitive control system that efficiently channels attention and processing resources toward linguistic decoding and comprehension, dynamically clarifying the interaction between the Cognitive and Reading layers of the CAR model during L2 reading.

9.3.4 The Multidimensional Structure of AI Literacy

A fundamental objective of this dissertation was to establish a robust conceptualization and measurement model for AI literacy, a construct central to the CAR framework. Drawing on the validated ABCE framework (Affective, Behavioral, Cognitive, Ethical), this study operationalized AI literacy not as a unitary technical skill, but as a multidimensional capacity

essential for navigating technology-mediated learning environments. The confirmatory factor analysis conducted in this research unequivocally supported the four-factor ABCE structure, demonstrating excellent fit to the data collected from the ethnic minority adolescent sample. This finding is consistent with contemporary theoretical models that argue for a holistic understanding of AI literacy, one that integrates the motivation to learn about AI (Affective), the ability to use and collaborate with AI tools (Behavioral), the conceptual understanding of how AI works (Cognitive), and the critical awareness of its societal and ethical implications (Ethical) (Long & Magerko, 2020; Ng et al., 2023).

The empirical validation of this four-factor structure is pivotal for the CAR model, as it solidifies the AI Literacy layer within the integrated framework. By confirming that AI literacy comprises these distinct yet interrelated domains, the study provides the necessary psychometric grounding for investigating its role as both an outcome of cognitive processes and a predictor of reading success. Crucially, the strong loadings on the ethical dimension within our sample underscore that for learners navigating cross-cultural and linguistic challenges, an awareness of fairness, bias, and accountability in AI systems is an integral part of their digital competence. This finding aligns with the broader call for human-centered AI education that prepares students to be critical citizens.

The confirmation of this robust structure allows for a precise interpretation of how AI literacy functions within the CAR model. It establishes that the pathway from cognitive flexibility to reading comprehension is mediated not by a vague digital skill, but by a defined competency in engaging with AI—specifically, the adaptability to use AI tools strategically (Behavioral), the confidence to do so (Affective), and the critical judgment to interpret their outputs ethically (Ethical). This provides a granular understanding of how the Cognitive and AI Literacy layers interact to ultimately support the Reading outcome, moving the model

beyond a simple technological determinism to a nuanced account of cognitive-digital integration in L2 learning.

9.3.5 Relation between executive function and AI literacy

The emergence of AI as a transformative force in education necessitates an understanding of how core cognitive abilities, such as EF, interact with the development of AI literacy for second language learning. In this section, the relationship between EF and AI literacy

AI literacy is widely defined as a multifaceted competency encompassing the ability to understand how AI technologies work, their societal impact, and how to use them ethically and effectively. It extends beyond mere technical proficiency to include critical evaluation, communication, and collaboration with AI (Chiu et al., 2024; Long & Magerko, 2020). This implies that engaging with AI requires higher-order cognitive skills, aligning with the functions of EF further posited that strong EF skills provide the cognitive foundation for effectively engaging with AI tools, suggesting that working memory is critical for processing AI outputs, inhibitory control helps filter irrelevant information, and cognitive flexibility enables adaptation to new AI interfaces.

The key finding provides empirical evidence for the theoretical link between the Cognitive and AI Literacy layers of the CAR framework. The correlational analysis revealed that cognitive flexibility was significantly related to AI literacy, a relationship robustly confirmed by the regression analysis, which identified cognitive flexibility as the sole significant predictor of AI literacy among the EF components. This statistical verification strongly supports the theoretical connection that links EF to effective technology engagement. As discussed in Chapter 2, cognitive flexibility—the ability to switch flexibly between tasks, mental sets, and perspectives (Miyake & Friedman, 2012; Uddin, 2021)—is intrinsically required for interacting with AI systems. The inherent demands of AI use, such

as abstract, interdisciplinary reasoning, adapting to novel interfaces, understanding complex algorithms, and critically evaluating AI-generated content, inherently call upon this form of cognitive adaptability. Thus, it is highly logical that greater cognitive flexibility is associated with increased proficiency in AI literacy, enabling learners to adapt their thinking to the unique logic and applications of AI systems.

Conversely, the study found that neither working memory nor inhibitory control significantly contributed to AI literacy. This is a notable finding, especially considering the general importance of working memory for information processing and inhibitory control for managing interference in various cognitive tasks, including language learning. The results suggested that this might indicate that "the cognitive demands of engaging with AI content may differ from those required for traditional language-based tasks and instead depend more on mental adaptability than on information retention or inhibition". This interpretation aligns with the idea that while working memory and inhibitory control are crucial for processing and retaining specific pieces of information or suppressing distractions, AI literacy might be more heavily reliant on the flexible application of knowledge and adaptive problem-solving, which are hallmarks of cognitive flexibility. For instance, rather than simply remembering facts about AI (working memory) or inhibiting irrelevant thoughts (inhibitory control), AI literacy might prioritize the ability to conceptualize how AI works, evaluate its outputs, and adapt one's approach to interacting with AI tools, all of which are central to cognitive flexibility.

In summary, findings substantiates the Cognitive–AI Literacy interface of the CAR framework, illustrating that cognitive flexibility, the ability to shift mental sets, enables learners to navigate and interpret AI-mediated learning environments effectively. Within CAR, this interface represents the developmental bridge through which cognitive adaptability is translated into digital competence.

9.3.6 Relation between AI literacy and L2 reading comprehension

The increasing integration of AI into educational contexts, particularly in language learning, raises important questions about its relationship with traditional academic skills like reading comprehension. This section discusses the interplay between AI literacy and Chinese L2 reading comprehension, drawing upon the empirical findings.

Many research emphasized that AI literacy is not merely about using AI tools but understanding their strengths, limitations, and ethical implications, especially in learning process. It posited that AI tools can enhance L2 reading comprehension by providing personalized support, adaptive learning experiences, and access to diverse linguistic input (Godwin-Jones, 2023; Pokrivčáková, 2019). However, to truly leverage these affordances, learners need to develop critical AI literacy, which involves evaluating AI outputs, understanding how AI processes language, and employing metacognitive strategies. Since reading comprehension is a complex cognitive process involving the active construction of meaning from text, a skill that is particularly crucial for L2 learners navigating linguistic, cognitive, and cultural challenges, AI literacy could be a potential factors that support the L2 Chinese reading comprehension process.

The results provide the necessary empirical bridge to complete the CAR model, demonstrating a direct connection between AI Literacy and Chinese L2 reading comprehension. The linear regression analysis showed that AI literacy significantly predicted reading comprehension, which indicates a moderate positive association. This relationship suggests that students with higher AI literacy tend to exhibit better reading comprehension skills. This could be attributed to several factors. First, AI tools, such as generative AI chatbots, offer extensive affordances for informal digital language learning (IDLE) and self-directed L2 development (Liu et al., 2024; Soyooof, 2023). Learners with higher AI literacy are likely more adept at utilizing these tools for tasks like generating contextually appropriate

texts and engaging in personalized language use, all of which can indirectly bolster their overall reading comprehension abilities. The ability to critically evaluate AI-generated content and adapt interaction strategies with AI tools may also translate into more effective strategies for comprehending complex L2 texts.

Furthermore, the correlational analysis showed that AI literacy exhibited a significant positive correlation with orthographic knowledge, a foundational reading skill in Chinese. This suggests that students who are more proficient in understanding and interacting with AI technologies may also possess stronger foundational skills in recognizing and processing Chinese characters. This connection could be indirect, perhaps through shared cognitive underpinnings or through the use of AI tools that inadvertently enhance orthographic learning. In contrast, AI literacy did not significantly predict morphological awareness, which indicates a more selective relationship between AI literacy and specific linguistic skills, suggesting that while AI literacy may support overall reading comprehension and orthographic processing, its direct impact on other linguistic skills might be limited or mediated by other factors. This nuanced pattern confirms that AI literacy serves as a powerful, but selective, mediator that successfully translates general cognitive abilities into enhanced L2 reading outcomes, finalizing the crucial link between AI Literacy and Chinese L2 reading comprehension within the CAR framework.

In summary, findings demonstrate a significant positive relationship between AI literacy and Chinese L2 reading comprehension, suggesting that competence in navigating and utilizing AI technologies directly contributes to enhanced reading outcomes. This relationship is likely facilitated by the adaptive and interactive learning opportunities provided by AI tools, coupled with the finding that AI literacy specifically correlates with orthographic knowledge, highlighting its intersection with a fundamental L2 Chinese skill. This direct, empirically verified association completes the integrative loop of the CAR

framework. Specifically, the learners' ability to critically interact with and adapt to AI tools acts as the operational mechanism by which cognitive control is successfully channeled and expressed as enhanced reading comprehension. This robust empirical link confirms the full Cognitive–AI Literacy–Reading (CAR) sequence, establishing the model as a valid explanatory framework for L2 Chinese reading development in an AI environment.

9.4 Limitation

Despite its valuable contributions to elucidating the complex interplay among executive function, reading skills, AI literacy, and Chinese L2 reading comprehension, the present study is subject to several limitations that warrant careful consideration when interpreting its findings. These limitations relate to the research design, participant characteristics, measurement instruments, and the overall scope of the investigation.

Firstly, the study adopted a quantitative correlational design. While this methodological approach is suitable for exploring previously unexamined associations and for constructing an a priori causal framework through SEM, it inherently restricts the capacity to draw definitive causal inferences. Specifically, correlational designs are limited to identifying statistical associations among variables, rather than establishing cause-and-effect relationships. Although SEM was employed to test hypothesized pathways and to model both direct and indirect effects, the cross-sectional nature of the data, collected at a single time point, precludes the determination of temporal precedence, which is a fundamental criterion for establishing causality. For example, although the findings indicated that working memory predicted reading comprehension, it remains unclear whether enhanced working memory leads to improved reading comprehension, whether the relationship is reciprocal, or whether both constructs are influenced by an unmeasured third variable. Consequently, interpretations of predictive relationships should be approached with caution, recognizing that the observed

associations do not equate to causation. To more robustly ascertain the directionality and developmental trajectories of the relationships among executive function, AI literacy, and reading comprehension, future research employing longitudinal designs would be necessary.

Secondly, the characteristics of the research participants may constrain the generalizability of the study's findings. The sample comprised 155 Form 4 Chinese L2 students (67 girls and 88 boys) from Southeast Asian ethnic minority backgrounds, recruited from four secondary schools in Hong Kong. This population is distinctive due to several factors that may influence the observed relationships and, consequently, limit the broader applicability of the results. The participants' primary first languages (e.g., Urdu, Hindi, Tagalog, and Nepali) are alphabetic and non-tonal, which contrasts markedly with Chinese, a logographic and tonal language. Such linguistic divergence suggests that the cognitive and linguistic challenges associated with learning Chinese as an L2 for this group may differ substantially from those faced by learners with other L1 backgrounds. Moreover, many participants lack a supportive Chinese language environment at home, thereby restricting their exposure to and reinforcement of Chinese outside the classroom context. Socio-economic disadvantage is also prevalent within this cohort, often accompanied by limited parental proficiency in Cantonese, which may further impact educational attainment and the availability of academic support. These intersecting linguistic, socio-economic, and cultural factors render this sample unique, and thus, the findings may not be readily generalizable to L2 Chinese learners from different age groups, L1 backgrounds, educational systems, or socio-economic contexts. Additionally, the inclusion criterion requiring prior experience with AI applications for Chinese L2 learning introduces a potential self-selection bias, further limiting the generalizability of the findings to L2 learners without such prior exposure.

Next, limitations pertaining to the measurement instruments employed in this study warrant acknowledgment. Although considerable effort was made to select and adapt

validated instruments, certain issues merit further discussion, particularly with respect to the assessment of AI literacy. The measure of AI literacy utilized in this study, a revised version of the AI Literacy Questionnaire (AILQ), primarily evaluates perceived knowledge, confidence, and attitudes toward AI through self-report. Given that AI literacy is an emergent construct and its measurement remains in a developmental phase, this approach presents inherent limitations. Early frameworks for AI literacy, such as those proposed by Burgsteiner et al. (2016) and Kandlhofer et al. (2016), predominantly emphasized foundational knowledge and conceptual understanding of AI. More recent frameworks, including those by Long and Magerko (2020) and Ng et al. (2021), have broadened the scope to encompass critical evaluation, communication, and ethical considerations. Nevertheless, many existing assessments, including self-report questionnaires, continue to focus on perceived competence rather than objectively measured, demonstrated ability. This reliance on self-report may not adequately capture the depth of cognitive engagement or the practical skills that constitute comprehensive AI literacy, thereby potentially constraining the understanding of its relationship with reading comprehension. Furthermore, the presence of a mild ceiling effect and limited variability in AI literacy scores may have restricted the range of detectable associations with other variables, possibly attributable to the characteristics of the scale or the specific context of the participants' AI experience.

Finally, the applicability of the CAR model is shaped by contextual factors such as technological infrastructure, cultural attitudes toward AI, and institutional readiness for digital learning. Developed within Hong Kong's relatively advanced and bilingual educational system, the model may not generalize seamlessly to regions with limited technological access or differing pedagogical traditions. In resource-constrained contexts, restricted exposure to AI tools and insufficient teacher training could weaken the cognitive–digital interactions central to CAR. Likewise, sociocultural perceptions of AI may also

influence learners' engagement and the degree to which AI literacy can function as a meaningful mediator of reading performance. Moreover, exam-driven curricula and rigid policy frameworks may hinder the integration of AI-based instruction that supports EF and adaptive learning. These contextual contingencies underscore that CAR should be viewed as a flexible, context-sensitive framework requiring localized validation and policy-level adaptation before broad educational implementation.

In conclusion, although this study offers important insights into the intricate relationships among EF, AI literacy, and Chinese L2 reading comprehension within the CAR model, the aforementioned limitations should be carefully considered when interpreting the findings and in the design of future research endeavors. Validation across varied educational, cultural, and linguistic contexts, particularly in under-resourced environments, remains an essential direction for future research and policy-level inquiry.

9.5 Implication

Despite the limitations noted above, the findings of this study yield several important theoretical, pedagogical, and practical implications for advancing our understanding of L2 Chinese reading comprehension, particularly within the intersecting frameworks of EF and emerging AI literacy.

9.5.1 Theoretical Implications

This study makes a significant theoretical contribution by empirically validating the CAR Model of L2 reading comprehension that encompasses cognitive (EF), linguistic (reading skills), and digital (AI literacy) dimensions. It reconfigures the traditional psycholinguistic view of reading comprehension as a purely cognitive-linguistic process by embedding it within a digital-cognitive ecology. By incorporating AI literacy, the model

acknowledges that comprehension today often occurs in environments mediated by algorithmic support, adaptive feedback, and multimodal input. This reframing expands established frameworks such as the Construction–Integration Model and the Reading Systems Framework to include technological mediation as a structural component rather than an external aid.

Moreover, the significant predictive roles of working memory and cognitive flexibility in L2 Chinese reading comprehension highlight the substantial cognitive demands imposed by the logographic nature of the Chinese writing system. These findings align with and extend prominent theories of reading, including the Construction-Integration Model and the Reading Systems Framework, by demonstrating how core components of EF are actively involved in key reading processes such as character recognition, lexical access, syntactic integration, and meaning construction. The study supports the theoretical assertion that cognitive control functions are not merely ancillary but foundational in navigating the orthographic and semantic complexities of Chinese, which include the absence of explicit word boundaries and the prevalence of homophones and polysemous characters.

A particularly novel theoretical insight of this study is the discovery that cognitive flexibility significantly predicts AI literacy. This finding suggests that mental adaptability and the ability to shift between perspectives are essential cognitive prerequisites for effective engagement with AI technologies. In doing so, the study bridges cognitive psychology and emerging frameworks of digital literacy, advancing the argument that EF, particularly cognitive flexibility, constitutes a foundational cognitive capacity for functioning in an AI-mediated world. Furthermore, the observed indirect effect of cognitive flexibility on reading comprehension through AI literacy introduces a new conceptual pathway of CAR model. This model conceptualizes how higher-order cognitive processes interface with digital competence to support L2 reading in AI-enhanced educational contexts. CAR posits that EFs

enable learners to manage cognitive load, adapt strategies, and transfer knowledge across learning modalities, while AI literacy provides the technological means to operationalize these abilities in digital environments. This underscores a synergistic developmental model in which cognitive flexibility not only directly facilitates reading comprehension but also enhances learners' ability to utilize AI tools as scaffolds for understanding, thereby promoting deeper and more efficient learning.

Taken together, these findings offer a theoretically enriched lens for examining the evolving dynamics of L2 reading comprehension in the 21st century. The integration of EF and AI literacy into the conceptualization of L2 reading development not only deepens our understanding of the cognitive underpinnings of language learning but also positions learners more effectively within the broader context of digitally mediated education.

9.5.2 Pedagogical Implications

The findings of this study yield direct and actionable pedagogical implications for the instruction of L2 Chinese, particularly for ethnic minority learners who often encounter distinctive linguistic, educational, and socio-economic barriers. The results underscore the importance of integrating cognitive, linguistic, and digital competencies into the design of effective second language reading curricula.

First, the strong predictive roles of working memory, cognitive flexibility, and inhibitory control in L2 Chinese reading comprehension point to the pedagogical value of explicitly supporting the development of EFs within language instruction. For working memory, instructional strategies should incorporate tasks that require active manipulation and integration of information. Examples include guided summarization of texts, structured note-taking that emphasizes synthesis, and reciprocal teaching practices where students' alternate roles in questioning, clarifying, and predicting content. These approaches promote the maintenance and transformation of textual information in working memory.

To support cognitive flexibility, educators should design learning tasks that encourage flexible thinking, such as interpreting texts from multiple perspectives, analyzing non-linear or unfamiliar text structures, or solving open-ended problems that require adaptive reasoning. Particularly relevant for Chinese, activities that prompt students to switch between semantic, visual, and contextual cues when encountering polysemous or visually similar characters can strengthen their ability to shift cognitive sets. This directly targets the adaptive switching component of cognitive flexibility, crucial for navigating the complexity of Chinese orthography.

For IC, pedagogical practices should involve exercises that help students suppress distractions and irrelevant stimuli during reading tasks. Activities such as identifying key information within cluttered or distractor-filled texts, practicing selective attention, or responding to misleading textual cues (e.g., characters used in atypical or deceptive contexts) can enhance inhibitory control by promoting more deliberate and focused processing.

Second, the prominent role of orthographic knowledge in L2 Chinese reading comprehension highlights the necessity of explicit and systematic instruction in visual-orthographic processing. Beyond rote memorization of characters, instruction should emphasize the structural analysis of Chinese script, including radical identification, stroke patterns, positional regularities, and semantic cues embedded within characters. Instructional strategies such as character decomposition, contrastive analysis of confusable characters, and teaching the semantic functions of high-frequency radicals are particularly effective. These methods are especially vital for learners whose first languages are alphabetic and non-tonal, as they cannot draw on phonological decoding strategies in the same way native Chinese readers might.

Third, the positive association between AI literacy and L2 reading comprehension suggests that AI tools can be meaningfully integrated into instructional practices, provided

they are accompanied by explicit instruction aimed at fostering critical AI literacy. Rather than merely permitting the use of AI tools, educators should guide students in understanding the affordances and limitations of such technologies. Instruction should focus on training students to craft effective prompts for AI-generated reading materials or summaries, critically evaluate AI outputs for accuracy and bias, and strategically adapt their interactions with AI tools to support their individual learning goals. Developing such competencies will not only improve L2 reading outcomes but also cultivate responsible digital citizenship in an AI-mediated educational landscape.

Finally, the study underscores the need for a holistic and integrated pedagogical approach to L2 Chinese literacy development. Rather than addressing cognitive, linguistic, and digital skills in isolation, educational programs should aim to foster the synergistic growth of these interrelated domains. This calls for interdisciplinary collaboration among language educators, curriculum developers, and technology specialists to design learning experiences that simultaneously support executive functioning, reinforce foundational reading skills, and promote AI literacy. Such an integrated instructional model is essential for cultivating the comprehensive competencies required for proficient L2 Chinese reading in the 21st-century educational environment.

Chapter 10 Conclusion

This dissertation investigated the cognitive and technological foundations of L2 Chinese reading comprehension among Southeast Asian ethnic-minority adolescents in Hong Kong to formulate the Cognitive–AI Literacy–Reading Integration (CAR) model. It comprised four interconnected studies that collectively traced how executive function (EF), AI literacy, and linguistic skills converge to support reading comprehension performance of Chinese as a second language in AI-enhanced learning environments.

Study 1 established the cognitive architecture underlying reading by confirming a three-factor model of EF and demonstrating its predictive relevance to L2 Chinese reading. Study 2 provided the critical conceptual and psychometric foundation by validating the multidimensional ABCE framework of AI literacy, confirming its robust four-factor structure (Affective, Behavioral, Cognitive, Ethical) and establishing a reliable measurement tool for the subsequent investigations. Study 3 introduced this validated AI literacy construct as a pivotal digital-competence variable, showing it contributed directly to reading comprehension and interacted with orthographic knowledge. Finally, Study 4 integrated these dimensions into a unified structural model, revealing that cognitive flexibility predicted AI literacy, which in turn mediated its effect on reading comprehension. Together, these findings substantiated the CAR framework as a comprehensive account of how cognition and technology jointly shape L2 literacy.

The CAR model contributes theoretically by redefining L2 reading as an adaptive process situated within an AI-mediated ecosystem. It demonstrates that EFs provide the cognitive foundation necessary for managing complex textual information, that AI literacy operationalizes these functions within digital environments, and that reading comprehension emerges as the linguistic manifestation of this integration. In contrast to earlier models confined to psycholinguistic or socio-cultural domains, CAR bridges cognitive control theory

and digital-literacy research, offering a multidimensional explanation that reflects the realities of twenty-first-century language learning.

The empirical findings have significant practical implications. They suggest that enhancing reading comprehension requires more than linguistic instruction: it calls for pedagogical designs that cultivate EF skills and AI literacy concurrently. Educational programs informed by CAR should embed cognitive-flexibility training, promote strategic interaction with AI tools, and emphasize explicit instruction in orthographic and metacognitive strategies. Teachers, meanwhile, must be equipped to guide learners in evaluating AI-generated content, regulating cognitive load, and transferring digital insights to real reading contexts. At the policy level, the model advocates for curricula that integrate AI resources while ensuring equitable access and cognitive scaffolding for learners from diverse linguistic backgrounds.

Despite these contributions, the dissertation acknowledges limitations inherent in the current formulation of the CAR model. The reliance on cross-sectional data limits causal inference, and the self-report nature of the AI literacy measure may not fully capture the complexity of digital engagement. Future research should employ longitudinal and experimental designs, incorporate performance-based assessments, and extend the model to other linguistic and cultural contexts. Such work will be crucial for refining CAR into a universally applicable framework for cognitive-digital literacy.

In conclusion, the CAR model encapsulates the central insight of this dissertation that reading comprehension in an AI-mediated world is not solely a linguistic achievement, but a manifestation of cognitive adaptability expressed through digital competence. By integrating executive function, AI literacy, and orthographic knowledge into a single explanatory structure, the model offers a forward-looking paradigm for second-language education. It envisions learners as cognitively agile and technologically empowered readers who can

navigate complex information landscapes with discernment and flexibility. Through this lens, the teaching and study of L2 Chinese, and, by extension, second-language literacy in general, are redefined for the era of AI.

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