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Effectiveness of neuroconstructivism teaching model to enhance students' creative thinking, mathematics achievement, attention, and working memory



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ABSTRACT

This study examines the effectiveness of the Neuroconstructivism (NeuroConstruct) teaching model in enhancing creative thinking, mathematics achievement, attention, and working memory among grade 7 students. A true experimental pre-test and post-test control group design was employed, involving 70 randomly selected students from a total sample of 126 at a secondary school in Phayao, Thailand. The experimental group received instruction through the NeuroConstruct teaching model, while the control group followed the 5E teaching model. Three assessments were utilized: a creative thinking test, a mathematics achievement test, and cognitive ability software to measure attention and working memory. The findings indicate that Grade 7 students from a single Thai secondary school who participated in the NeuroConstruct teaching model demonstrated higher post-test performance in creative thinking, mathematics achievement, attention, and working memory than those who received the 5E teaching model following a five-week intervention. These results provide comparative evidence supporting the instructional potential of a NeuroConstruct teaching model in the studied context. However, outcomes were measured immediately after the intervention, and therefore, the sustainability of these improvements over time cannot be inferred. Moreover, although the observed gains are theoretically consistent with Neuroconstructivism, alternative explanations, such as novelty effects, teacher effects, or Hawthorne effects, cannot be fully ruled out in the absence of an attention or placebo control condition. Accordingly, the findings should be interpreted cautiously and warrant replication across diverse educational settings and extended time frames. This study's key novelty lies in translating Neuroconstructivism—predominantly a theoretical account of developmental, multi-constraint cognition—into a classroom-tested, phase-structured teaching model with actionable lesson procedures. By operationalizing neuroconstructivism principles into six implementable teaching syntaxes and evaluating them in a true experimental classroom design, the study makes an applied contribution that bridges theory and practice in educational neuroscience.

Educational relevance statement

The present research on the NeuroConstruct teaching model has educational relevance by providing an empirically tested, educational neuroscience-based approach to improving cognitive and academic outcomes in secondary education. The findings suggest the model's promising instructional potential in enhancing

creative thinking, mathematics achievement, attention, and working memory, critical components of student success in the 21st-century learning environment. This study provides comparative evidence that implementing the NeuroConstruct model is associated with higher scores in creative thinking, mathematics

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achievement, attention, and working memory than the 5E teaching model in the studied context. Broader instructional recommendations should be based on replication across settings and stronger controls for potential confounds. Importantly, the present study demonstrates strong ecological validity, as the intervention was implemented within an authentic secondary school classroom and aligned with the Thai national core curriculum. The instructional activities, assessment practices, and classroom interactions reflect real-world teaching conditions rather than controlled laboratory settings. This contextual grounding enhances the practical relevance of the findings and supports the applicability of the NeuroConstruct teaching model for actual classroom implementation in comparable educational systems.

1. Introduction

In the context of rapid digital transformation, education systems are increasingly challenged to align learning processes with the demands of Education 4.0, which emphasizes personalized learning, cognitive flexibility, and future-oriented competencies (Bonfield et al., 2020; Chairwut et al., 2025; Thianwan & Srikoon, 2026). The expansion of digital technologies, accelerated by the COVID-19 pandemic, has further reshaped instructional practices and highlighted the need for models that integrate cognitive development with authentic classroom learning (Bilyalova et al., 2020; Duangngern et al., 2025). Although constructivist approaches, such as the 5E teaching model, have been widely adopted to promote inquiry and engagement (Bybee et al., 2006; IPST, 2012), they do not explicitly operationalize underlying neurocognitive processes, such as attention and working memory.

At the same time, contemporary research in Educational Neuroscience and the Mind, Brain, and Education (MBE) movement has emphasized the importance of integrating cognitive and neural mechanisms into instructional design (Fischer et al., 2010; Tokuhama-Espinosa, 2011). In particular, attention and working memory are foundational executive functions that support higher-order outcomes, including creative thinking and mathematics achievement (Lee & Bull, 2016; Sweatt, 2010; Zhao et al., 2021). These domains are especially critical in secondary education, where students are expected to engage in abstract reasoning and complex problem-solving (Menon, 2015). However, despite increasing theoretical insights, classroom practices often remain insufficiently aligned with these neurocognitive principles (Srikoon, 2020a; IPST, 2012).

Within this context, Neuroconstructivism has emerged as a comprehensive developmental framework that conceptualizes learning as the result of dynamic interactions among neural, embodied, social, and environmental constraints (Karmiloff-Smith, 2017; Mareschal, Johnson, et al., 2012; Thomas et al., 2021). The framework offers a theoretically robust basis for instructional design by emphasizing experience-dependent plasticity, interactive specialization, and context-sensitive development (Astle et al., 2023; Johnson, 2011). Nevertheless, a critical gap persists; existing research has predominantly remained at the conceptual or laboratory level, with limited translation into structured, classroom-based teaching models that are experimentally validated in authentic educational settings (Fischer et al., 2010; Thomas et al., 2021; Tokuhama-Espinosa, 2011).

More specifically, prior studies exhibit three key limitations. First, many focus on isolated cognitive constructs (e.g., executive functions, attention, and working memory) without situating them within an integrated developmental framework (Diamond, 2013; Lee & Bull, 2016). Second, neuroscientific principles are often applied metaphorically rather than operationalized into explicit pedagogical procedures. Third, empirical classroom-based studies rarely incorporate concurrent measurement of multiple cognitive and academic outcomes, particularly attention and working memory, despite their central role in learning (Astle et al., 2023). Consequently, there remains a lack of

experimentally tested, classroom-based NeuroConstruct teaching models, representing a significant gap in both theory-to-practice translation and empirical validation.

To address this gap, the present study proposes and experimentally evaluates the NeuroConstruct teaching model, a structured, classroom-implementable framework that operationalizes neuroconstructivist principles into six explicit teaching syntaxes. Grounded in theory-informed experimental research by design approach (McKenney & Reeves, 2019; Plomp, 2013), this approach advances prior work in three respects: (1) it integrates multi-level developmental constraints—neural, embodied, social, and environmental—into instructional design; (2) it explicitly targets attention and working memory as foundational cognitive mechanisms supporting higher-order outcomes; and (3) it provides experimental evidence from an authentic classroom context, thereby moving beyond theoretical interpretation toward empirically validated instructional innovation.

The focus on Grade 7 students is theoretically grounded in developmental neuroscience, as early adolescence represents a critical period of reorganization in executive function networks and cognitive control (Blakemore & Choudhury, 2006; Karmiloff-Smith, 2017). Mathematical topics such as graphs, relations, and functions provide a cognitively demanding context requiring representational coordination, working memory, and attentional regulation (Arsalidou & Taylor, 2011; Menon, 2015). The Thai educational context, characterized by a gap between curriculum expectations and classroom practices, offers an ecologically valid setting for examining the applicability of neuroscience-informed teaching models (Srikoon, 2020a; Srikoon et al., 2026).

The novelty of this study lies in translating Neuroconstructivism from a predominantly theoretical framework into an experimentally validated, classroom-based teaching model with clearly defined instructional procedures, thereby bridging the longstanding gap between educational neuroscience theory and practical classroom implementation (Mirattanaphrai & Srikoon, 2026; Winitisri & Srikoon, 2026).

Accordingly, this study employs a true experimental design to examine whether the NeuroConstruct teaching model produces significantly improved outcomes in creative thinking, mathematics achievement, attention, and working memory compared with the 5E teaching model in authentic classroom conditions. The following section delineates the specific research objectives that guide this investigation.

2. Research objectives

The present study aimed to examine the effectiveness of the NeuroConstruct teaching model in enhancing students' creative thinking, mathematics achievement, attention, and working memory compared with the 5E teaching model. The following research objectives guided the empirical investigation:

1. To investigate the differences in creative thinking between the NeuroConstruct teaching model (experimental group) and the 5E teaching model (control group).
2. To compare the students' mathematics achievement between the experimental and control groups.
3. To assess the differences in attention accuracy between students in the experimental and control groups.
4. To evaluate the differences in working memory accuracy between students in the experimental and control groups.

These objectives are operationalized through specific research questions and testable hypotheses in the following section. The rationale for classifying primary and supporting outcome variables, along with a comprehensive account of the intervention's design and theoretical alignment, is provided in the Research Methodology section.

3. Research Questions and Hypotheses

Grounded in the theoretical framework of Neuroconstructivism and implemented through a true experimental pre-test–post-test control group design, the present study examines whether the NeuroConstruct teaching model produces stronger cognitive and academic outcomes than the widely used 5E teaching model. Specifically, the study investigates four outcome variables: creative thinking, mathematics achievement, attention, and working memory.

Accordingly, the study addresses the following research questions (RQ):

RQ1. Does instruction using the NeuroConstruct teaching model lead to higher creative thinking outcomes among Grade 7 students compared with instruction using the 5E teaching model?

RQ2. Does instruction using the NeuroConstruct teaching model lead to higher mathematics achievement among Grade 7 students compared with the 5E teaching model?

RQ3. Does instruction using the NeuroConstruct teaching model lead to higher attention accuracy among Grade 7 students compared with the 5E teaching model?

RQ4. Does instruction using the NeuroConstruct teaching model lead to higher working memory accuracy among Grade 7 students compared with the 5E teaching model?

Based on the principles of Neuroconstructivism—which emphasize the dynamic interaction between neural processes, cognitive development, and environmental learning constraints—it is expected that a teaching model explicitly designed to engage attention regulation, working memory processes, and cognitive flexibility will produce stronger learning outcomes than a conventional constructivist inquiry model.

Therefore, the following hypotheses (H) were formulated:

H1. Students receiving instruction through the NeuroConstruct teaching model will demonstrate significantly higher post-test scores in creative thinking than students receiving instruction through the 5E teaching model.

H2. Students receiving instruction through the NeuroConstruct teaching model will demonstrate significantly higher post-test scores in mathematics achievement than students receiving instruction through the 5E teaching model.

H3. Students receiving instruction through the NeuroConstruct teaching model will demonstrate significantly higher attention accuracy than students receiving instruction through the 5E teaching model.

H4. Students receiving instruction through the NeuroConstruct teaching model will demonstrate significantly higher working memory accuracy than students receiving instruction through the 5E teaching model.

Together, these research questions and hypotheses establish a clear analytical framework for evaluating whether the NeuroConstruct teaching model yields measurable advantages over the 5E instructional model across cognitive and academic domains.

4. Literature review

4.1. Neuroconstructivism

This section synthesizes contemporary empirical and theoretical developments, with particular attention to multi-constraint interaction, experience-dependent plasticity, and their implications for instructional design (Astle et al., 2023; Thomas et al., 2021). Neuroconstructivism provides a robust theoretical framework that emphasizes the dynamic construction of cognitive representations in the developing brain

(Karmiloff-Smith et al., 2018; Mareschal, Johnson, et al., 2012; Westermann et al., 2007), offering an innovative lens through which educational interventions can be designed to enhance outcomes in areas such as creative thinking, mathematics achievement, attention, and working memory.

Central to Neuroconstructivism is the idea that cognitive development is constrained by several interacting factors, each playing a critical role in shaping brain development and learning outcomes (Johnson & Mareschal, 2012; Mareschal et al., 2007; Westermann et al., 2007). Recent literature has further refined this dynamic, emphasizing context-dependent plasticity and interactive specialization (Astle et al., 2023; Farina, 2020; Thomas & Mareschal, 2020). In Neuroconstructivism theory, the term “constraints” refers not to limitations, but to structured influences that guide cognitive development through complex interactions (Karmiloff-Smith, 2017; Mareschal et al., 2007). These developmental constraints can be classified into six categories:

(1) Epigenetics and Gene–Environment Interaction

Neuroconstructivism emphasizes probabilistic epigenesis, which highlights the bidirectional, dynamic interplay among genetic activity, neural processes, behavior, and environmental context (Karmiloff-Smith, 2017; Westermann et al., 2007). This approach diverges from deterministic genetic models, proposing instead that gene expression is contingent upon both internal signals (e.g., neurochemical states) and external environmental stimuli (Mareschal, Johnson, et al., 2012). Thus, rather than treating genes as fixed blueprints, Neuroconstructivism views them as modulators within a complex developmental system in which experience and context influence how genes are activated and regulated over time. This epigenetic view supports a flexible developmental trajectory, which aligns with the broader interactive specialization framework underpinning Neuroconstructivism theory (Johnson & Mareschal, 2012).

(2) Experience-Based Neuroplasticity

Experience-based neuroplasticity refers to the experience-dependent refinement and reconfiguration of neural architecture at the micro-structural level. Through activity-dependent synaptic modulation, environmental engagement shapes neural representations—distinct, recurring configurations of neuronal firing distributed across brain regions (Bertrand & Camos, 2015; Sweatt, 2010). While these representations are initially influenced by intrinsic constraints such as genetic architecture and cortical microarchitecture (Karmiloff-Smith, 2017; Mareschal et al., 2007), they are continually refined through synaptic plasticity and neurodevelopmental processes, including synaptic pruning and activity-driven reorganization (Johnson, 2011; Karmiloff-Smith, 1992; Quartz & Sejnowski, 1997). Accordingly, the brain’s representational capacity is iteratively expanded through experience-based learning, fostering flexible and adaptive cognitive functioning (Johnson, 2011; Mareschal, Johnson, et al., 2012). This dynamic interplay between neural activity and experiential context constitutes the neurobiological foundation of learning, affirming a central premise of Neuroconstructivism (Karmiloff-Smith, 2017; Westermann et al., 2007).

(3) Embrainment

Neuroconstructivism emphasizes the principle of interactive specialization, wherein brain regions undergo mutual, experience-dependent tuning across development (Johnson, 2011). Rather than experience affecting “isolated” brain regions, this model proposes that functional networks emerge through dynamic and reciprocal interactions among cortical and subcortical areas, gradually supporting more complex cognitive operations (Johnson, 2000, 2011).

For instance, research on creative thinking suggests that it relies on the interplay between the default mode network (DMN), the fronto-

parietal control network (FPCN), and the salience network (Beaty et al., 2015, 2021). Similarly, mathematical reasoning involves coordinated activity across regions such as the intraparietal sulcus, prefrontal cortex, and the angular gyrus, which are integrated over time through experience and formal learning (Arsalidou & Taylor, 2011; Menon, 2015). These findings align with constructivist accounts of neural development, in which foundational networks serve as scaffolds for the emergence of higher-order systems.

(4) Embodiment

Within the Neuroconstructivism framework, embodiment refers to the body's essential role in shaping cognitive development through environmental interactions. Cognitive processes are grounded in the body's morphology, motor systems, and sensorimotor experiences, which actively contribute to the formation and refinement of neural architecture (Mareschal et al., 2007; Westermann et al., 2007). Physical interaction with the environment provides structured input, which is critical for the brain's fine-tuning of neural circuits, especially during early learning and conceptual understanding (Karmiloff-Smith, 2009a, 2009b; Smith & Gasser, 2005). This perspective aligns with embodied cognition, which emphasizes a dynamic, bidirectional relationship between the brain, body, and environment: neural activity modulates bodily actions and perceptual orientations, reinforcing the reciprocity between perception and action (Clark, 2008; Gallagher, 2006; Varela et al., 2017). Educationally, this underscores the importance of learning environments that incorporate bodily movement, physical manipulation, and kinesthetic activity to support knowledge construction (Glenberg et al., 2013).

(5) Ensocialment

Within the Neuroconstructivism framework, ensocialment refers to the social environment's integral role in shaping cognitive development. Rather than being a peripheral factor, the social context functions as a primary mechanism through which neural and cognitive systems adapt and specialize (Bartosovic, Kabbe, & Castelo-Branco, 2021; Nouri et al., 2022; Westermann et al., 2007). Ensocialment extends radical neuroconstructivism by emphasizing that cognition emerges through reciprocal interactions with sociocultural environments, in which language, norms, and technologies serve as scaffolding for brain development (Tokuhama-Espinosa & Borja, 2023; Uden & Ching, 2023). This concept should not be understood as newly claimed but rather as a refinement of existing frameworks situating cognitive development as inherently relational, contextually embedded, and culturally mediated.

From this perspective, interactions with caregivers, peers, and cultural tools shape neural architecture and guide cognitive trajectories through experience-dependent plasticity and social scaffolding (Carpendale & Lewis, 2006; Johnson, 2011; Karmiloff-Smith, 2009a). Cultural practices and institutional norms shape how children encounter and interpret their environment, thereby facilitating the acquisition of cognitive tools for meaning-making (Rogoff, 2003; Tomasello, 1999; Vygotsky, 1978). Educational settings, in particular, structure these interactions by designing environments that facilitate exploration, collaboration, and symbolic representation (Mareschal et al., 2007). In this integrated view, cognitive development is not solely a neurobiological process but also a relational, contextually embedded, and culturally mediated one (Karmiloff-Smith, 2009a; Westermann et al., 2007).

(6) Interaction between Constraints: Neuroconstructivism as a Multi-constraint Framework for Development and Learning

Neuroconstructivism emphasizes that cognitive development is shaped by the dynamic interplay of multiple constraints—genetic activity, neural architecture, embodied action, and environmental

context—which interact recursively throughout the lifespan (Mareschal et al., 2007; Westermann et al., 2007). This systems-based view maintains that no single factor operates in isolation; rather, development is the emergent outcome of continuous cross-level interactions that co-regulate one another. This framework aligns historically with Fischer's dynamic skill theory, which proposed context-sensitive developmental pathways shaped by both internal maturation and external supports (Fischer & Bidell, 2006), and with Fischer and Rose's (2001) emphasis on the inseparability of cognitive, emotional, and social development. Both perspectives reject reductionist views of development and advocate a multilevel systems approach (Overton, 2013).

Contemporary developmental neuroscience reinforces this view. Higher-order cognitive representations emerge through recursive, multi-layered loops involving gene expression, synaptic activity, bodily engagement, and ecological interaction (Johnson, 2011; Quartz & Sejnowski, 1997). Non-primary cortical regions, characterized by high plasticity and sensitivity to sensorimotor and social input, integrate and abstract information to form multimodal, task-relevant representations (Mareschal et al., 2007; Westermann et al., 2007). Together, these insights advance a convergent vision of human development as inherently dynamic, relational, and embodied, synthesizing neuroscientific and educational paradigms rooted in constructivist traditions.

To further clarify the theoretical innovation of the NeuroConstruct teaching model, a visual comparison with historical and contemporary learning models is presented in Table 1. This comparison highlights how Neuroconstructivism integrates multiple levels of constraint, differentiating it from earlier models such as Behaviorism, Piaget's Constructivism, Vygotsky's Sociocultural Theory, and the 5E teaching model. Table 1 and Fig. 1 below present a conceptual map illustrating these theoretical shifts and their educational implications (Aistle et al., 2023; Johnson, 2011; Karmiloff-Smith, 2017; Mareschal, Johnson, et al., 2012; IPST, 2012).

In educational contexts, Neuroconstructivism provides a theoretical foundation for teaching models that leverage interacting constraints to optimize learning outcomes. The NeuroConstruct teaching model applies these principles by systematically engaging multiple neural networks and cognitive domains—including language processing, mathematical reasoning, attentional control, and memory consolidation—through structured activities that promote experience-dependent learning and interactive specialization (Johnson, 2011; Mareschal, Johnson, et al., 2012). Such an approach cultivates higher-order cognitive skills by aligning instructional design with the brain's developmental architecture. A detailed account of the model's design, instructional procedures, and classroom implementation is presented in the Research Methodology section.

According to Neuroconstructivism, the construction of cognitive representations is shaped by dynamic processes of competition and co-ordination. Competition refers to the specialization of neural components for diverse processing tasks, in which different neural circuits vie for resources, leading to the refinement and differentiation of cognitive functions in experience-dependent contexts (Karmiloff-Smith, 2017; Mareschal, Johnson, et al., 2012). Coordination involves integrating separate neural components, enabling the reuse and recombination of existing knowledge to form complex representations (Johnson, 2011; Westermann et al., 2007). The development of these representations crucially depends on children's proactive engagement with their environment, as active exploration provides experiential input that drives experience-dependent plasticity and refines neural architecture (Karmiloff-Smith, 2009a; Smith & Gasser, 2005).

In this study, the Neuroconstructivism-based educational intervention refers explicitly to the NeuroConstruct teaching model, which comprises six instructional phases that systematically engage multiple interacting constraints of cognitive development. Compared with conventional models such as the 5E teaching model, the NeuroConstruct teaching model explicitly targets neurodevelopmental mechanisms to foster higher-order thinking and cognitive flexibility.

Table 1
The comparative learning model.

Representative Theorists	Model	Key Mechanisms	View of Learner	Brain-Cognition Link	Social/Embodied/ Environmental Factors
Skinner (2014) Piaget (1952)	Behaviorism Piaget’s cognitive constructivism	Stimulus-response conditioning Stages of cognitive development	Passive receiver Active meaning-maker	Ignored Abstract development	Ignored Minimal
Vygotsky (1978)	Vygotsky’s social constructivism	Zone of Proximal Development, scaffolding	Socially interactive	Implicit	Social emphasized
Bybee et al. (2006); IPST (2012)	5E teaching model	Inquiry cycle (Engage–Evaluate)	Inquiry-oriented	Indirect	Experiential context emphasized
Karmiloff-Smith (2017); Mareschal, Johnson, et al. (2012); Astle et al. (2023)	Neuroconstructivism	Multi-constraint interaction: genes, brain, body, society	Pro-active constructor	Central focus	Fully integrated

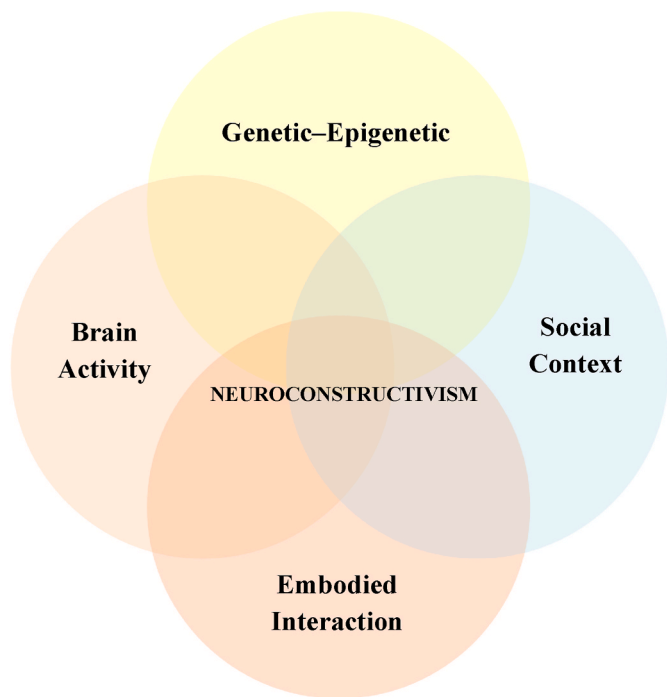


Fig. 1. Schematic representation of the multi-constraint interaction framework in Neuroconstructivism. The four interacting constraints — genetic–epigenetic, brain activity, embodied interaction, and social context — converge to shape cognitive development through dynamic, bidirectional influences (Karmiloff-Smith, 2017; Mareschal, Johnson, et al., 2012).

It should be noted that the present study does not provide direct evidence of neurobiological activation or neural change. No neuro-imaging, electrophysiological, or biological measures were employed. Accordingly, references to neural systems, neuroplasticity, or neuro-modulatory processes are presented as theoretical assumptions derived from the Neuroconstructivism framework, rather than as empirically measured mechanisms. The findings should therefore be interpreted solely in terms of behavioral and cognitive performance.

4.2. 5E teaching model

The 5E teaching model, developed by the Biological Sciences Curriculum Study (BSCS), is a widely adopted inquiry-based instructional framework consisting of five sequential phases: Engage, Explore, Explain, Elaborate, and Evaluate (Bybee et al., 2006). The model has been implemented extensively in science and mathematics education worldwide, including in Thailand, where it is endorsed by the Institute for the Promotion of Teaching Science and Technology (IPST, 2012). Grounded in constructivist principles, the 5E model promotes active

student participation through a cycle of stimulating interest (Engage), hands-on investigation (Explore), data interpretation and knowledge articulation (Explain), application to novel contexts (Elaborate), and summative assessment of learning outcomes (Evaluate). This student-centered approach emphasizes inquiry, conceptual understanding, and the iterative construction of knowledge through experiential learning.

The 5E teaching model was selected as the control condition for methodological rather than theoretical reasons. Although the 5E model represents an effective constructivist framework, it was not originally designed to operationalize neurocognitive mechanisms at the instructional level (Bybee et al., 2006). In contrast, the NeuroConstruct teaching model integrates a multi-constraint developmental framework that explicitly targets neural system activation, attention regulation, and working memory processes (Astle et al., 2023; Karmiloff-Smith, 2017; Mareschal, Johnson, et al., 2012). This comparison is therefore designed to examine whether explicitly embedding neuroconstructivist principles yields additional cognitive and academic benefits beyond those achievable through a widely adopted constructivist inquiry model. Given that alternative neuroscience-based teaching models remain limited and insufficiently standardized for school-based research (Fischer et al., 2010; Thomas et al., 2021), the 5E model serves as an ecologically valid baseline reflecting current mainstream classroom practice.

Recent meta-analytical evidence by Polanin et al. (2024) systematically reviewed the effects of the 5E teaching model across diverse educational contexts, concluding that the model yields moderate positive effects on student learning outcomes, particularly in STEM subjects. However, the effects of the 5E teaching model on cognitive functions, such as attention and memory, remain underexplored. Neuro-constructivism explicitly targets these neurocognitive domains through integrative interventions that engage mechanisms of brain plasticity and cognitive control, suggesting potential advantages for fostering higher-order cognitive skills.

Accordingly, this study hypothesizes that students receiving instruction through the NeuroConstruct teaching model will demonstrate significantly greater improvements in creative thinking, mathematics achievement, attention, and working memory than those taught via the 5E teaching model. The specific hypotheses and expected effect sizes are formalized in the Research Questions and Hypotheses section.

4.3. Creative thinking

Creative thinking is widely recognized as a fundamental cognitive ability for fostering innovation and addressing complex problems, involving the generation of novel and valuable ideas through cognitive processes such as fluent thinking, flexible thinking, and original thinking (Mumford et al., 2012; Runco & Acar, 2012). Fluent thinking refers to the ability to rapidly generate multiple relevant responses; flexible thinking involves producing ideas across diverse conceptual categories; and original thinking denotes the capacity to generate novel ideas that

deviate from conventional approaches (Bicer et al., 2021). This capacity is critical in education for preparing students to meet the demands of the 21st century (Sternberg & Lubart, 1999), and educational neuroscience research supports the effectiveness of interventions aimed at enhancing creative thinking through neuroconstructivist approaches (Srikoon et al., 2018; Zhou & George, 2003).

From a neurocognitive perspective, creative thinking is supported by the prefrontal cortex and associated networks that manage executive functions, including working memory, attention regulation, and cognitive flexibility (Dietrich, 2004; D'Esposito & Postle, 2015). The dorso-lateral prefrontal cortex is critical for maintaining and manipulating information, while the anterior cingulate cortex and frontoparietal networks contribute to attentional control and flexible thinking (Miller et al., 2018; Niendam et al., 2012; Scolari et al., 2015). These neural mechanisms underscore the relevance of instructional approaches that systematically engage executive function networks to foster creative thinking.

4.4. Mathematics achievement

Mathematics achievement is a critical component of academic success, reflecting a student's ability to engage with and comprehend curriculum content (Srikoon et al., 2020). While numerous factors contribute to mathematical performance, including motivation, teaching quality, and socio-emotional variables (Asare et al., 2024; Pajares & Graham, 1999), cognitive functions play a particularly significant role. Attention and working memory have been shown to directly affect mathematics performance by supporting the encoding, manipulation, and retrieval of numerical and spatial information required for mathematical reasoning (Best et al., 2011; Blair & Razza, 2007; Lee & Bull, 2016). These findings underscore the importance of instructional approaches that systematically engage cognitive functions to optimize mathematical learning outcomes (Srikoon, 2020a).

4.5. Attention

Attention is a fundamental cognitive process that enables the brain to selectively focus on relevant stimuli while inhibiting distractions, thereby optimizing information processing and learning outcomes (Thiele & Bellgrove, 2018). Recent advances in developmental cognitive neuroscience emphasize the multifaceted nature of attention, which encompasses alerting, orienting, and executive control networks (Amso & Scerif, 2015; Petersen & Posner, 2012). These networks operate through neuromodulatory systems involving neurotransmitters such as norepinephrine, acetylcholine, and dopamine, which regulate alertness and attentional focus (Lindsay, 2020; Sarter & Paolone, 2011). Adequate attention supports higher-order cognitive functions, including working memory, problem-solving, and creative thinking (Marchetti, 2014; Shi & Qu, 2022).

Attention processes involve complex neural networks rather than a simple linear flow from the thalamus to the neocortex. Specifically, attention is regulated by dynamic interactions among multiple circuits, including the thalamus, prefrontal cortex, and parietal cortex, which form integrated networks such as the fronto-parietal control network and the salience network (Lindsay, 2020; Posner & Petersen, 1990; Sereno et al., 2025; Sweatt, 2010). Recent meta-analyses of neuroimaging studies have further clarified the pivotal role of the dorsal and ventral attention networks in regulating selective attention and executive functions (Dehaene, 2020; Rosenberg et al., 2016). Enhanced functional integrity within these networks has been linked to improvements in academic achievement and cognitive control (Astle et al., 2023).

Attention can be categorized into distinct types, including simple reaction, focused, selective, and sustained attention (Srikoon et al., 2017). Attention and working memory share a dynamic, reciprocal relationship: attention influences the capacity and efficiency of working

memory, while working memory supports the maintenance and manipulation of attentional focus (Baddeley, 2003; Marchetti, 2014). This bidirectional interplay is critical for experience acquisition and for enhancing learning outcomes (Amso & Scerif, 2015; Bertrand & Camos, 2015), and recognizing this mutual influence enables more precise targeting of educational interventions to improve both attentional control and working memory function.

Consequently, attention acts as a foundational cognitive function that enables higher-order processes. Creative thinking relies on attentional flexibility and sustained focus to generate novel ideas (Beaty et al., 2015), while mathematics achievement depends on the efficient allocation of attentional resources to complex problem structures and abstract reasoning (Menon, 2015). By targeting these cognitive sub-processes through interventions that engage executive control, enhance sustained attention, and activate neuromodulatory pathways, neuroconstructivism-based teaching models systematically strengthen attentional control, thereby facilitating improvements in working memory, creative thinking, and mathematical performance (Lindsay, 2020; Srikoon et al., 2017).

4.6. Working memory

Working memory is a multifaceted cognitive system that temporarily maintains and manipulates information required for complex cognitive tasks (Baddeley, 2003; Sweatt, 2010). It encompasses multiple subtypes corresponding to different information modalities — including auditory (phonological), visual, kinesthetic, and spatial processing — each supported by distinct but interacting neural substrates (Baddeley, 2012; Oberauer, Souza, Druet, & Gade, 2013). For example, the phonological loop is responsible for verbal and auditory information, whereas the visuospatial sketchpad processes visual and spatial data (Baddeley, 2003). Baddeley's updated model (2012) further incorporates the episodic buffer, which integrates information across modalities and interfaces with long-term memory, while the central executive orchestrates attentional control and cognitive flexibility according to situational requirements (Miyake & Shah, 1999).

Neuroanatomically, the prefrontal cortex (PFC) plays a central role in working memory, with distinct functional specialization across sub-regions. The ventrolateral PFC is particularly involved in non-spatial, domain-specific maintenance of information, while the dorsolateral PFC contributes to the manipulation and monitoring of spatial and executive components (D'Esposito & Postle, 2015; Lara & Wallis, 2015). Working memory function is further modulated by contextual factors such as autobiographical referencing, familiarity, task demands, and urgency, reflecting its dynamic nature in real-world settings (Cowan, 2017; Ranganath & Blumenfeld, 2005). More recent neuroimaging evidence has further elucidated the dynamic interactions within prefrontal and parietal networks, with neurocomputational models indicating that working memory maintenance and manipulation involve recurrent neural circuits modulated by dopaminergic neuromodulation within the PFC (Braver, 2012; Klaus & Pennington, 2019). This comprehensive understanding underpins the development of educational interventions designed to enhance working memory through experience-dependent plasticity and cognitive training (Melby-Lervåg & Hulme, 2013; Sreenivasan et al., 2014).

Research conducted in Thailand by Srikoon (2019, 2020b) has validated the multidimensional structure of working memory, encompassing basic processing, shifting, updating, and inhibiting components, and demonstrated that working memory significantly influences academic achievement, problem-solving, and creative thinking (Srikoon et al., 2020a). These findings converge with international meta-analyses and longitudinal investigations confirming the critical role of working memory components in supporting academic skills across diverse populations (Dunning et al., 2013; Hu & Hu, 2023; Packiam Alloway and Alloway, 2013). Consequently, interventions targeting working memory through training programs have produced

promising effects on cognitive and academic outcomes, underscoring the need to incorporate working memory considerations into instructional design frameworks grounded in Neuroconstructivism principles (Klingberg, 2010; Melby-Lervåg & Hulme, 2013; Srikoon et al., 2020a).

Additionally, contemporary research highlights the pivotal role of working memory in academic success and creativity (Alloway & Alloway, 2015; Cowan, 2017; Sala & Gobet, 2017). These studies further emphasize the importance of designing educational interventions that specifically target working memory to facilitate enhanced learning and creative performance.

Recent advances in cognitive neuroscience have established that working memory and attention are not localized solely within the prefrontal cortex but rather emerge from the coordinated activity of distributed brain networks. Neuroimaging evidence highlights the pivotal role of the fronto-parietal control network in maintaining and manipulating working memory representations (D'Esposito & Postle, 2015; Miller et al., 2018), with dopaminergic neuromodulation dynamically supporting the updating and flexible allocation of attentional resources (Braver, 2012; Klaus & Pennington, 2019). Contemporary neuroscience further conceptualizes working memory and attention as emerging from dynamic interactions among the executive control network, the default mode network, and salience network dynamics (Beatty et al., 2019; Brissenden & Somers, 2019; Horowitz-Kraus et al., 2023). Similarly, creative thinking and problem-solving are now understood as products of coordinated interactions between the default mode network, the salience network, and the fronto-parietal network, which collectively balance spontaneous idea generation with goal-directed cognitive control (Beatty et al., 2015, 2021; Cubillos-Pinilla et al., 2025).

In summary, these advances reflect a decisive paradigm shift from region-centric to network-based perspectives, demonstrating that working memory, attention, and creative thinking emerge from the coordinated interactions of large-scale brain systems. This systems-level framework — grounded in evidence from neuroimaging, meta-analyses, and neurocomputational modeling — underscores that executive functions and creativity depend on dynamic connectivity rather than localized activity, offering valuable implications for the design of educational models that aim to foster flexible thinking and problem-solving across authentic learning contexts.

Thus, this study examines the NeuroConstruct teaching model as a theory-informed instructional framework, evaluating its effectiveness through behavioral outcomes rather than direct neurobiological evidence.

5. Research methodology

The present study was part of the research project ID: 2.1/006/63, which received ethical approval from the Human Ethics Committee at the University of Phayao. In accordance with established ethical guidelines, all participants provided informed consent prior to participating in this research. This project examines the effectiveness of the NeuroConstruct teaching model in enhancing students' creative thinking, mathematics achievement, attention, and working memory. The methodology adhered to rigorous ethical standards to ensure the integrity of the research process and the protection of participants' rights.

5.1. Research design

This study implemented a true experimental design utilizing a pre-test and post-test control group, a widely recognized methodology for assessing teaching models when multiple sample groups are involved, anticipated learning outcomes are measured, and random assignment is employed. This design is particularly well-suited to investigating the effects of NeuroConstruct teaching models (detailed in the Intervention Process or Appendix A and B), as it enables the collection and

comparison of outcome data across groups, thereby facilitating the analysis and interpretation of results. Drawing on comparative data, this approach thoroughly examines how the dependent variables, students' creative thinking, mathematics achievement, attention, and working memory, are influenced by the applied teaching models (NeuroConstruct and the 5E teaching model). Furthermore, it controls for potential confounding variables, thereby minimizing their influence on the findings and enabling more precise inferences about the impact of the teaching interventions. Importantly, a major methodological strength of the present study lies in its implementation of a true experimental design incorporating both random selection and random assignment. This combination substantially strengthens both external and internal validity by ensuring representativeness of the sample and equivalence between groups prior to the intervention (Creswell & Creswell, 2018; Shadish et al., 2002). Moreover, true experimental designs used in educational research, when combined with true randomization, minimize selection bias and enhance the credibility of causal inference regarding the observed effects of the NeuroConstruct teaching model (Campbell & Stanley, 1963; Cohen et al., 2018). Consequently, differences in post-test outcomes can be more confidently attributed to the teaching intervention rather than to pre-existing group differences or uncontrolled confounding variables.

In the present study, creative thinking and mathematics achievement were treated as the primary educational outcomes because they represent key academic and higher-order learning goals in mathematics education. Attention and working memory were conceptualized as supporting cognitive outcomes that reflect the underlying executive functions targeted by the NeuroConstruct teaching model. Although all four variables were empirically measured as dependent variables, this distinction clarifies the functional role of each outcome within the study design. The simultaneous assessment of creative thinking, mathematics achievement, attention, and working memory enables a comprehensive evaluation of both cognitive and academic outcomes within a single experimental framework, consistent with Neuroconstructivism's emphasis on coordinated cognitive development (Diamond, 2013; Mareschal, Johnson, et al., 2012).

Attention and working memory were selected as key cognitive outcome variables due to their foundational roles within the broader domain of executive functions (Best & Miller, 2010; Diamond, 2013; Pomyoch & Srikoon, 2024). While the study did not explicitly measure other executive function components such as inhibitory control or cognitive flexibility, the focus on attention and working memory was guided by their established empirical links to creative thinking and mathematics achievement (Lee & Bull, 2016; Zhao et al., 2021).

5.2. Participant and sampling procedure

This study employed a true experimental design, in which students were randomly assigned to either an experimental or a control group. The sample comprised 70 students, randomly selected from a population of 126 seventh-grade students enrolled at a secondary school in Phayao, Thailand, during the second semester of the 2020 academic year. Due to the COVID-19 pandemic and its post-pandemic conditions during the second semester of the 2020 academic year, all instructional activities for this study were conducted in a face-to-face classroom setting, with strict adherence to internationally recommended health and safety protocols. These measures included mandatory face mask use for all students and teachers, regular temperature checks at school entry points, physical distancing in classrooms, and frequent hand hygiene. Conducting the study in person under such controlled conditions may affect student engagement and learning outcomes, as face-to-face interaction supports more direct instructional delivery but may also introduce stress or discomfort due to health precautions.

The sampling process involved two key phases: random selection followed by random assignment. Specifically, participants were randomly selected via coin flip, and the selected students were then

randomly assigned to two groups: 35 students in the experimental group, who received instruction using the NeuroConstruct teaching model, and 35 students in the control group, who followed the 5E teaching model.

To ensure procedural transparency and replicability, the randomization process was conducted using a standardized coin-flip protocol administered by the principal researcher, with a classroom teacher serving as an observer. For the random selection phase, each of the 126 eligible students was assigned a unique identification number. A fair coin was flipped sequentially for each student: “heads” indicated inclusion in the sample, whereas “tails” indicated exclusion. This process continued until the required sample size of 70 students was reached.

Following sample selection, a second coin-flip procedure was conducted to randomly assign participants to either the experimental or control group. Each selected student was again assigned a sequential order, and a coin was flipped individually: “heads” assigned the student to the experimental group, and “tails” assigned the student to the control group. This assignment process was conducted before the pre-test to prevent allocation bias.

All coin flips were conducted manually using a standard physical coin to ensure randomness, and no computerized randomization tools were employed. The procedure was completed in a single session before the intervention phase, ensuring that group allocation was finalized prior to instructional implementation.

To further clarify the statistical adequacy of the randomization procedure, the coin-flip method employed in this study can be conceptualized as a Bernoulli randomization process, in which each participant has an equal and independent probability ($p = .50$) of being selected and assigned to either group. This procedure satisfies the fundamental assumption of simple random sampling and random assignment, namely that each unit in the population has an equal likelihood of selection and allocation (Creswell & Creswell, 2018; Shadish et al., 2002). From a statistical perspective, manual coin flipping constitutes a valid mechanical randomization technique that approximates true randomness under conditions of fairness and independence, comparable to computer-generated random number procedures in small to moderate sample sizes (Cohen et al., 2018). The use of a standardized protocol, including sequential assignment, observer verification, and pre-intervention implementation, further enhances procedural reliability and reduces allocation bias. However, it is acknowledged that manual randomization methods may be less reproducible than algorithm-based randomization due to potential human or procedural variability. To mitigate this limitation, the present study ensured transparency by documenting the randomization protocol in detail, thereby aligning with best practices for reproducibility in experimental research (Schulz et al., 2010). Collectively, these procedures support the study’s internal validity while maintaining feasibility within an authentic classroom context.

Random selection and assignment processes were pivotal in ensuring the study’s validity. Random selection played a crucial role in enhancing the study’s external validity, thereby facilitating the generalizability of the findings to a broader population. In contrast, random assignment was crucial for establishing internal validity, thereby enabling the researcher to draw causal inferences about the intervention’s effects. While these procedures serve distinct purposes, both are essential for safeguarding the study’s rigor and ensuring robust, applicable results across different educational contexts.

The sampling procedure employed in this study used simple random sampling. From a population of 126 Grade 7 students, all individuals were given an equal probability of selection (Creswell & Creswell, 2018). A mechanical randomization procedure (coin flipping) was used to randomly select 70 students to participate in the study. Following participant selection, random assignment was conducted to allocate students to either the experimental group ($n = 35$) or the control group ($n = 35$). No individual-matching procedures were applied, as random assignment was considered sufficient to control selection bias

and strengthen internal validity (Shadish et al., 2002). Baseline equivalence between groups was verified by comparing pre-test scores across all dependent variables; no statistically significant differences were observed, indicating comparable initial characteristics between the two groups. The remaining 56 students who were not selected through the random sampling process continued to participate in regular classroom instruction and were not involved in any experimental activities. Their exclusion was solely due to the statistical sampling process, rather than differences in academic performance or demographic characteristics. The use of simple random sampling supports the study’s external validity by reducing systematic selection bias and enhancing the generalizability of the findings to similar educational contexts (Cohen et al., 2018).

To further enhance transparency in participant flow, no attrition occurred during the study. All 70 students who were initially selected and randomly assigned to the experimental ($n = 35$) and control groups ($n = 35$) completed both the pre-test and post-test assessments.

Additionally, no missing data were observed across any of the measured variables. All participants provided complete datasets for creative thinking, mathematics achievement, attention, and working memory. Therefore, all analyses were conducted using the full sample without the need for data imputation or case exclusion.

A summary of participant flow is as follows: from an initial population of 126 eligible students, 70 were randomly selected to participate in the study, while the remaining 56 students continued regular instruction and were not included in the experimental procedures. All selected participants completed the study as planned and were included in the final analysis.

To enhance transparency and align with best practices for reporting experimental studies, a participant flow diagram is provided (Fig. 2). The diagram illustrates the progression of participants through each stage of the study, including the total number of eligible students ($N = 126$), the randomly selected sample ($n = 70$), allocation to experimental ($n = 35$) and control groups ($n = 35$), and final inclusion in the analysis.

As shown in Fig. 2, no attrition occurred during the intervention, and all participants completed both pre-test and post-test assessments. Furthermore, no missing data were identified across any of the measured variables. Therefore, all randomized participants were included in the final analysis. This transparent reporting of participant flow strengthens the methodological rigor and replicability of the study.

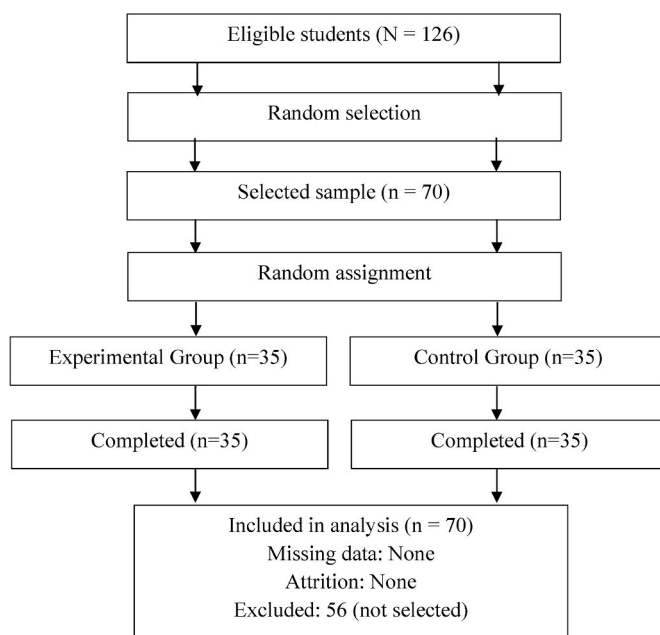


Fig. 2. Participant flow diagram of the study.

The participants in this study comprised 70 Grade 7 students, with a mean age of 12.6 years ($SD = 0.48$; range = 12-13 years). This age range corresponds to early adolescence, a developmental period characterized by rapid reorganization of executive function networks, particularly attention and working memory (Blakemore & Choudhury, 2006; Kamiloff-Smith, 2017).

Regarding gender distribution, the sample included 36 male students (51.4%) and 34 female students (48.6%). No statistically significant differences in gender composition were observed between the experimental and control groups, reducing the likelihood of demographic bias influencing the intervention outcomes.

Baseline equivalence between the experimental and control groups was examined using independent-samples t-tests on all pre-test scores. Results indicated no statistically significant pre-test differences for mathematics achievement, flexible thinking, original thinking, and all attention and working memory subtests (all $p > .05$). However, a statistically significant pre-test difference was observed for fluent thinking ($t(68) = -3.588$, $p < .001$), with the experimental group scoring higher at baseline ($M = 25.11$, $SD = 2.61$) than the control group ($M = 21.91$, $SD = 4.58$). To account for this pre-existing difference, fluent thinking post-test outcomes were interpreted in conjunction with within-group standardized mean gain scores (Becker, 1988), thereby quantifying change relative to each group's own baseline rather than relying solely on between-group post-test comparisons (Morris & DeShon, 2002). This procedure aligns with best practices in true experimental design and supports the study's internal validity by ensuring that post-intervention differences can be attributed to the instructional models rather than to pre-existing academic disparities (Cohen et al., 2018; Shadish et al., 2002).

To control potential confounding variables, several methodological safeguards were implemented. First, both the experimental and control groups were instructed in the same academic semester and participated in an identical five-week intervention (2 h per week), thereby minimizing history and time-related effects. Second, no special academic events, supplemental programs, or differential extracurricular activities occurred during the intervention that could differentially influence the two groups. Both groups were taught in comparable face-to-face classroom settings and were subject to identical COVID-19 health and safety protocols throughout the study period. Finally, students were not formally informed of their assignment to the experimental or control condition. Instruction in both groups was delivered as part of routine classroom practice, which helped reduce expectancy and Hawthorne effects. Collectively, these procedures align with established principles of true experimental design and strengthen the study's internal validity.

To ensure clear reproducibility and procedural transparency, the instructional differences between the experimental and control conditions are explicitly delineated.

The experimental group (NeuroConstruct teaching model) received instruction structured into six sequential phases: neuron stimulation, neuron construction, connecting brain regions, connecting brain and body, connecting body and society, and integration of constraints. Each phase incorporated explicitly designed activities targeting attention regulation, working memory updating, embodied interaction, and social cognition through structured tasks, guided prompts, and phase-specific cognitive activation strategies. Detailed lesson plans, activity sequences, materials, and time allocation are provided in [Appendices A and B](#) to enable replication.

In contrast, the control group (5E teaching model) followed a conventional inquiry-based sequence: Engage, Explore, Explain, Elaborate, and Evaluate. Instruction emphasized conceptual understanding through questioning, discussion, and problem-solving activities, without explicit targeting of neurocognitive processes such as attention or working memory. The same mathematical content, instructional duration (five weeks, 2 h per week), and classroom conditions were maintained across both groups to ensure equivalence, with the primary difference being the instructional design and cognitive emphasis

embedded in each model.

To further ensure comparability, both groups were taught by the same teacher, followed parallel curriculum objectives, and used equivalent assessment procedures. However, only the experimental group received structured neurocognitive activation tasks aligned with Neuroconstructivism principles.

5.3. Intervention Process

5.3.1. Neuroconstructivism teaching model

The Neuroconstructivism teaching model (also known as the NeuroConstruct teaching model) was developed by researchers and is grounded in the Neuroconstructivism approach. The construction of the prototypical NeuroConstruct teaching model followed this approach. Content validity of the NeuroConstruct teaching model was thoroughly evaluated through multiple meetings with a panel of three educational experts from the University of Phayao. To establish the content validity of the NeuroConstruct teaching model, a panel of three experts with recognized expertise in cognitive neuroscience, curriculum and instructional design, and developmental psychology critically reviewed the model. Each expert held a doctoral degree, was an assistant professor, had published extensively in fewer than five peer-reviewed journals, and had more than five years of experience in designing and evaluating educational interventions. Their collective expertise ensured that the model was theoretically aligned with Neuroconstructivism principles, pedagogically applicable in classroom contexts, and developmentally appropriate for adolescent students. The validation process involved iterative cycles of feedback and refinement, confirming the theoretical coherence, pedagogical feasibility, and neurocognitive appropriateness of the NeuroConstruct teaching model, thereby strengthening its content and face validity for implementation.

The expert panel consisted of three scholars with doctoral qualifications and formal academic appointments in cognitive neuroscience, curriculum and instructional design, and developmental psychology. Each expert had more than five years of professional experience in designing and evaluating educational interventions and had published peer-reviewed research in their respective fields. Their role was to evaluate the theoretical coherence, pedagogical feasibility, and neurodevelopmental appropriateness of the model through multiple rounds of structured feedback (Aistle et al., 2023; Thomas & Mareschal, 2020).

The development of the NeuroConstruct teaching model was conducted over a six-month period prior to the experimental study's implementation. The model development process comprised three iterative phases: (1) theoretical design and alignment with Neuroconstructivism principles, (2) expert review and refinement, and (3) pilot implementation and revision. This structured process aligns with established design-based and theory-informed educational research methodologies, which emphasize iterative refinement grounded in theory and empirical feasibility (McKenney & Reeves, 2019; Plomp, 2013).

Grounded in a comprehensive understanding of the Neuroconstructivism framework and aligned with contemporary educational neuroscience, the teaching model was co-developed by three experts with specialized backgrounds in cognitive neuroscience, curriculum design, and developmental psychology. These experts employed an iterative validation process consisting of (1) theoretical alignment verification, (2) pedagogical content mapping, and (3) neurocognitive-developmental appropriateness analysis. This approach is consistent with Neuroconstructivism principles, which emphasize developmental constraints, context-dependent learning, and the interdisciplinary synthesis of neuroscience and education (Aistle et al., 2023; Farina, 2020; Thomas & Mareschal, 2020). The validation ensured the model's alignment with the principles of interactive specialization, neural plasticity, and experience-dependent learning, which are foundational to Neuroconstructivism-informed design.

The experts critically reviewed the model's components, which comprised clearly defined themes, guided teaching practices,

instructional strategies, and explicit pedagogical instructions aligned with Neuroconstructivism principles. Specifically, the panel assessed: (1) the theoretical alignment and accuracy of the Neuroconstructivism concepts integrated into the teaching model; (2) the applicability and feasibility of the teaching strategies and lesson plans in actual classroom settings; and (3) the clarity and usability of the teaching guide provided to educators. Feedback from these expert reviews informed iterative revisions, ensuring that the model was both conceptually sound and practically implementable. Subsequently, it was revised based on expert feedback. These processes established each teaching process for implementing the NeuroConstruct teaching model. Moreover, these issues were discussed to improve the prototypical NeuroConstruct teaching model: (1) the accuracy and clarity of the knowledge about the NeuroConstruct teaching model; (2) the applicability of the NeuroConstruct teaching model and the lesson plans; and (3) the teaching guide to the teaching model. The panel consisted of three distinguished educational experts specializing in curriculum development, instructional design, and cognitive neuroscience in education. Each expert has extensive experience in designing and validating educational interventions and teaching models, holds a doctoral degree, and has published five publications in the fields of curriculum and instruction. Their combined expertise ensured theoretical alignment, practical applicability, and developmental appropriateness of the NeuroConstruct teaching model. Finally, a meeting was held with three experts to assess the face validity of three aspects. Based on the experts' conclusion, the NeuroConstruct teaching model was excellent and feasible. Following expert validation, a pilot implementation of the NeuroConstruct teaching model was conducted with a small group of Grade 7 students ($n = 35$) who were not included in the main experimental sample. The pilot phase aimed to examine the clarity of instructional procedures, the feasibility of classroom implementation, and students' engagement with neurocognitively informed learning activities. Feedback obtained from classroom observations and informal teacher reflections was used to refine lesson sequencing, activity duration, and instructional scaffolding prior to the main intervention. Pilot testing is recommended in educational research to enhance intervention validity and implementation fidelity (McKenney & Reeves, 2019; Plomp, 2013). The NeuroConstruct teaching model is designed as a comprehensive framework that addresses both the content delivered and its teaching approach. The model integrates neuroscience principles into curriculum content development (WHAT?) by focusing on cognitive domains such as creative thinking, mathematics achievement, attention, and working memory. Simultaneously, it incorporates pedagogical strategies and instructional phases (HOW?) that engage learners through six systematic steps, promoting interaction between genetic, neural, bodily, social, and environmental factors to optimize learning outcomes. This dual focus ensures the model's applicability in real classroom settings through detailed lesson plans and teaching guides that facilitate effective implementation. Hence, the NeuroConstruct teaching model, also known as the 'NeuroConstruct teaching model,' could be implemented in classrooms.

The true experimental design enabled the comparison of differences in learning outcomes across four aspects: creative thinking, mathematics achievement, attention, and working memory. This study's research hypothesis was tested using the NeuroConstruct and 5E teaching models.

The NeuroConstruct teaching model comprises four core principles grounded in Neuroconstructivism theory: (1) interactions occur dynamically among genes, neural activity, brain regions, the body, and environmental factors, influencing cognitive development and learning (Karmiloff-Smith, 2017; Mareschal, Johnson, et al., 2012); (2) context dependence critically shapes mental representations through experience-based neuroplasticity and social interactions (Astle et al., 2023; Westermann et al., 2007); (3) cognitive representations are shaped by competition and coordination processes, where specialization enables brain systems to process distinct information types, and coordination integrates these components for flexible learning (Johnson,

2011; Mareschal et al., 2007); and (4) active learner proactivity is essential, as students explore, manipulate, and interact with their environment, driving the construction of new representations (Karmiloff-Smith, 2013).

To enhance procedural clarity and reproducibility, Table 2 presents a structured comparison between the NeuroConstruct and 5E teaching models, highlighting differences in theoretical grounding, instructional procedures, and cognitive emphasis.

As shown in Table 2, both teaching models shared equivalent content, duration, and assessment conditions; however, they differed fundamentally in instructional design and the explicit integration of neurocognitive processes.

The NeuroConstruct teaching model was employed in the experimental group. Its syntax comprises six forms, detailed in Appendix A.

- (1) Neuron stimulation involves activating gene activity regulated by a bidirectional (two-way) interaction between gene activity, neural activity, behavior, and the environment-dependent context. This means that gene expression and neural activity mutually influence one another and are also shaped by behavioral patterns and environmental contexts within a continuous feedback loop.
- (2) Neuron construction involves forming complex cognitive representations in learners. Through activity-based competition, learners' neural structures adapt to experience-dependent contexts, particularly through specific patterns of neural activation.
- (3) Connecting the brain refers to the dynamic integration of multiple functional neural networks, where cognitive abilities emerge from the interaction of distributed but interconnected brain regions. According to network theory, these networks support specialized processes that operate both independently and collaboratively, enabling complex cognitive functions. Learners are trained through cognitive tasks that engage and strengthen large-scale brain networks, promoting efficient communication and functional connectivity across regions to support specific abilities.
- (4) Connecting the brain and body focuses on multiple real-time adjustments in learning activities in an authentic context. Learning occurs through an integrated brain-body-environment system, which enables dynamic coordination between internal cognitive processes ("inside world") and external sensory and contextual inputs ("outside world"). This continuous interaction fosters learners' active engagement and intentional manipulation of their environment, enabling them to select and shape experiences based on their prior knowledge and goals. The term "proactivity" is defined here as a purposeful, embodied interaction that drives cognitive development and learning.
- (5) Connecting the body and society entails developing children in a specific environment. Learners develop in a context that constrains the formation of emotion-related neural representations and social and cognitive development, given their limited experiences. Teachers offer them specific approaches to manipulate the environment.
- (6) Connecting all constraints concerns integrating all constraints into a learning activity. Learners participate in the activity by integrating all constraints and determining all knowledge and processes.

To enhance clarity and reproducibility of the instructional design, the six syntaxes of the NeuroConstruct teaching model are summarized in Table 3. This table summarizes the objectives, instructional activities, and expected cognitive outcomes for each phase. Presenting the teaching model in a structured format supports transparency and aligns with best practices in reporting complex educational interventions, enabling readers to more readily understand the instructional logic and facilitating replication in comparable classroom contexts (Astle et al., 2023;

Table 2
Comparative instructional design between the NeuroConstruct teaching model and the 5E teaching model.

Dimension	NeuroConstruct Teaching Model (Experimental Group)	5E Teaching Model (Control Group)
1. Theoretical foundation	Neuroconstructivism: multi-constraint interaction (gene–brain–body–social–environment)	Constructivism: inquiry-based learning (Bybee et al., 2006)
2. Primary instructional goal	Activation and integration of neurocognitive processes (attention, working memory, cognitive flexibility) alongside academic learning	Conceptual understanding through inquiry, exploration, and student engagement
3. Instructional structure (syntax)	6 phases: Neuron Stimulation → Neuron Construction → Connecting the Brain → Connecting the Brain and Body–Connecting the Body and Society → Integrating All Constraints (1) Neuron Stimulation Activate prior knowledge and initiate neural responsiveness through contextual stimuli and cognitive triggering tasks (2) Neuron Construction Develop cognitive representations through problem-solving, competition, and working memory engagement (3) Connecting Brain Regions Integrate multiple representations (symbolic, numerical, graphical) to strengthen inter-regional neural coordination (4) Connecting Brain and Body Engage embodied cognition through physical interaction, manipulatives, and movement-based learning (5) Connecting Body and Society Embed learning in social interaction, collaborative reasoning, and sociocultural context (6) Integration of Constraints Synthesize neural, cognitive, embodied, and social processes into higher-order understanding and transfer	5 phases: Engage → Explore → Explain → Elaborate → Evaluate (1) Engage NeuroConstruct teaching model explicitly activates attention systems and prior neural representations through targeted prompts; the 5E teaching model focuses on motivation and topic introduction without explicit cognitive activation mechanisms (2) Explore NeuroConstruct teaching model systematically targets working memory updating and cognitive load management; the 5E teaching model emphasizes hands-on exploration without structured cognitive load design (3) Explain NeuroConstruct teaching model emphasizes representational coordination and executive attention; the 5E teaching model focuses on explanation and conceptual clarification without an explicit neural integration focus (4) Elaborate (partial overlap) NeuroConstruct teaching model explicitly incorporates body-based learning to reinforce cognition; the 5E teaching model may extend learning, but does not systematically include embodied cognitive processes (5) Elaborate/Evaluate (partial overlap) NeuroConstruct teaching model structures social cognition as a core phase; the 5E teaching model includes collaboration, but not as a distinct cognitive-development mechanism (6) Evaluate NeuroConstruct teaching model integrates multi-constraint learning and promotes cognitive transfer; the 5E teaching model focuses on assessment of understanding without explicit integration of neurocognitive systems
4. Cognitive targeting	Explicit and systematic targeting of attention, working memory, and executive functions in every phase	No explicit neurocognitive targeting: cognitive processes are implicitly engaged
5. Nature of learning activities	Structured, phase-specific tasks designed to stimulate neural activation, cognitive competition, embodied interaction, and social cognition	Inquiry-based activities, including questioning, exploration, discussion, and conceptual explanation
6. Embodiment (body involvement)	Explicitly integrated (e.g., manipulatives, movement-based learning, physical interaction with concepts)	Limited or indirect; primarily cognitive and discussion-based
7. Social interaction	Structured social cognition phase emphasizing collaborative reasoning and co-construction of knowledge	Collaborative learning occurs, but is not systematically structured as a cognitive mechanism
8. Instructional guidance	Highly structured teaching guide with phase-specific objectives, prompts, and cognitive targets (see Appendix A–B)	General pedagogical guidance based on the inquiry cycle; less prescriptive at the cognitive-process level
9. Teacher role	Cognitive facilitator who actively scaffolds attention, working memory, and neural engagement processes	Inquiry facilitator guiding discussion, questioning, and conceptual understanding
10. Student role	Proactive cognitive agent engaging in neural activation, embodied exploration, and social meaning-making	Active learner engaging in inquiry, exploration, and knowledge construction
11. Content coverage	Same mathematics content (graphs, relations, functions) aligned with the Thai national curriculum	Same content and curriculum alignment
12. Instructional duration	5 weeks (2 h/week), identical across groups	Same duration and schedule
13. Assessment procedures	Identical across groups (creative thinking, mathematics achievement, attention, working memory)	Same assessment instruments and procedures
14. Key distinguishing feature	Integration of neurocognitive mechanisms into structured classroom instruction	Traditional inquiry-based model without explicit neurocognitive integration

Johnson, 2011; Mareschal, Johnson, et al., 2012).

From the above text, a conclusion can be drawn as shown in Fig. 3.

In practice, the NeuroConstruct teaching model was implemented through six structured syntaxes designed to operationalize these principles: (1) Neuron stimulation, activating gene expression via bidirectional interactions between gene activity, neural processes, behavior, and context-dependent environments; (2) Neuron construction, fostering activity-dependent competition to adapt neural structures based on individual experiences; (3) Connecting the Brain through cognitive tasks that promote inter-regional neural coordination; (4) Connecting the Brain and Body, engaging embodied learning in

authentic contexts to coordinate internal neural states with external environmental stimuli; (5) Connecting the Body and Society, guiding learners to manipulate socially embedded contexts to enhance emotional, cognitive, and social development; and (6) Integrating All Constraints, where all constraints are combined in learning activities allowing students to synthesize knowledge and cognitive processes.

To provide a clearer understanding of how the NeuroConstruct teaching model was utilized in classroom settings, detailed lesson plans and teaching guides were developed and distributed to the teachers involved in the intervention. For example, during the instructional period on mathematical concepts such as graphs, relations, and

functions, teachers implemented the six syntaxes of the NeuroConstruct teaching model sequentially.

In the *Neuron Stimulation phase*, teachers facilitated activities that encouraged students to activate prior knowledge and engage in gene–environment interactions through hands-on materials and real-world problems. During the *Neuron Construction phase*, students participated in competitive and collaborative cognitive tasks designed to strengthen neural activation patterns associated with mathematical concepts.

Teachers reported adapting activities to individual student needs during the *Connecting the Brain* and *Connecting the Brain and Body* phases by incorporating physical manipulatives and embodied learning tasks to enhance cognitive integration. In the *Connecting the Body and Society* phase, social and emotional learning strategies were employed to promote cooperative learning and contextualize content within a social framework.

Finally, in the *Integrating All Constraints* phase, teachers facilitated reflective discussions and applied problem-solving exercises that synthesized knowledge and cognitive skills acquired throughout the intervention. This approach was supported by comprehensive teaching guides, which provided scaffolding, suggested activities, and formative assessment tools to help teachers plan and deliver lessons aligned with the Neuroconstructivism framework.

Collaboration among teachers was encouraged through regular

meetings to share best practices and reflect on instructional challenges, fostering a professional learning community focused on improving the effectiveness of the NeuroConstruct teaching model.

This intervention was delivered over five weeks, with 2 h of instruction per week focusing on mathematical concepts, including graphs, relations, and functions. The teaching model explicitly targeted neural and cognitive mechanisms, enhancing creative thinking, mathematics achievement, attention, and working memory through carefully designed activities informed by neuroscientific evidence.

5.3.2. *Experimental group: NeuroConstruct teaching model implementation*

To ensure structural parallelism with the control condition and enhance replicability, the NeuroConstruct teaching model is described here with the same level of procedural detail.

The experimental group received instruction through the NeuroConstruct teaching model, which was operationalized into six structured teaching syntaxes: (1) Activation of prior knowledge and attentional orientation, (2) Guided exploration with embodied and socially mediated tasks, (3) Cognitive engagement through representational coordination, (4) Working memory and attentional regulation activities, (5) Integration and application of knowledge across contexts, and (6) Reflective evaluation and adaptive feedback.

In the first phase, students’ attention was deliberately activated

Table 3
Summary of the NeuroConstruct teaching model syntaxes.

Syntax	Objective	Key Instructional Activities	Expected Cognitive Outcomes
1. Neuron Stimulation	Activate prior knowledge and initiate neural engagement	Contextual prompts, activating questions, and real-life scenarios	Attention activation; prior knowledge retrieval (Mareschal, Johnson, et al., 2012)
2. Neuron Construction	Develop and refine cognitive representations through task engagement	Problem-solving tasks, adaptive challenges, and collaborative work	Working memory updating; representation building (Astle et al., 2023)
3. Connecting Brain	Integrate distributed neural networks for higher-order cognition	Multi-representational tasks (symbolic, visual, numerical)	Executive attention; cognitive integration (Johnson, 2011)
4. Connecting Brain and Body	Promote embodied cognition through interaction with the environment	Manipulatives, movement-based learning, and real-world tasks	Embodied cognition; attentional engagement (Karmiloff-Smith, 2013)
5. Connecting Body and Society	Situate learning in social and cultural contexts	Peer discussion, collaborative reasoning, explanation tasks	Social cognition; verbal working memory (Vygotsky, 1978)
6. Integration of all Constraints	Synthesize multi-level constraints into a coherent understanding	Reflection, transfer tasks, novel problem-solving	Cognitive integration; creative transfer (Fischer & Bidell, 2006)

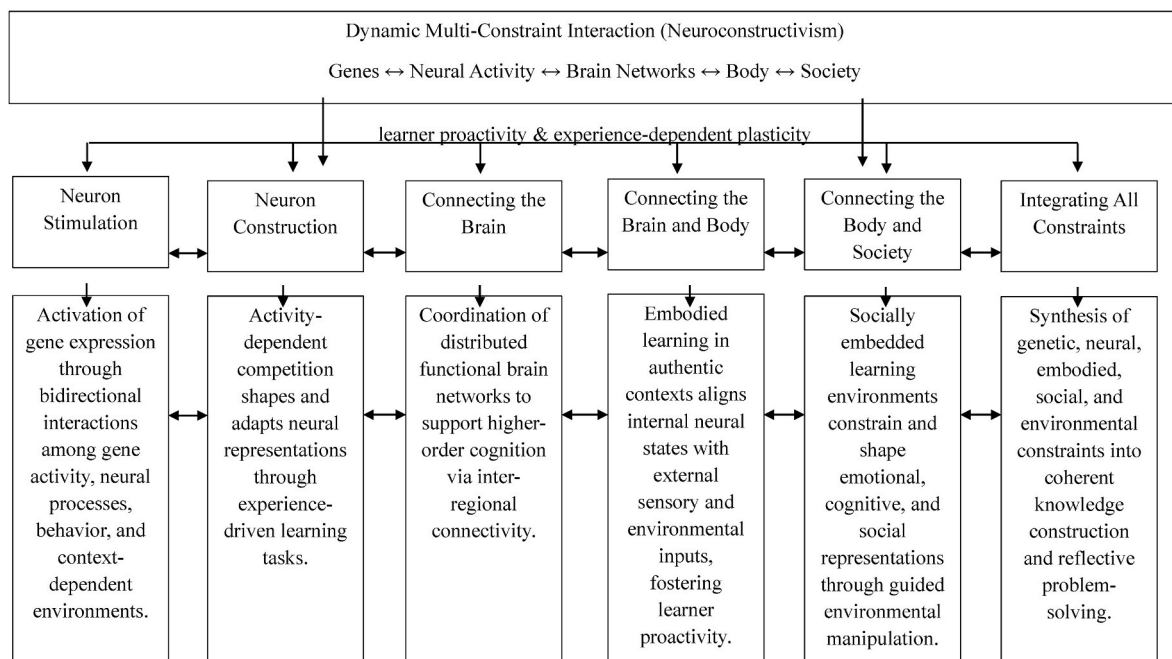


Fig. 3. NeuroConstruct teaching model: A Multi-Constraint, Neurodevelopmental Instructional Process.

through structured prompts and contextually relevant problem situations designed to align with neurocognitive principles of attentional engagement. In the second phase, students engaged in collaborative, embodied learning activities, including manipulating graphical representations and interacting with peers, to support experience-dependent learning.

During the third phase, instructional tasks were designed to promote the coordination of multiple representations (symbolic, graphical, and verbal), requiring students to actively construct meaning through cognitive integration. The fourth phase explicitly targeted working memory and attentional control through scaffolded problem-solving tasks that required maintaining and manipulating multiple pieces of information simultaneously.

In the fifth phase, students applied newly constructed knowledge to novel situations, promoting transfer and flexible thinking. Finally, the sixth phase involved structured reflection, feedback, and evaluation using both formative assessment and guided discussion.

Across all phases, lesson plans, instructional materials, and activity sequences were standardized and aligned with the Grade 7 mathematics curriculum (graphs, relations, and functions). The same teacher delivered instruction using detailed lesson scripts to ensure consistency of implementation. The duration (five weeks), instructional time (10 h), and classroom conditions were equivalent to those of the control group.

To maintain fidelity, implementation was monitored using structured observation checklists, ensuring that each instructional phase was delivered as intended and that the distinguishing features of the NeuroConstruct model were consistently applied.

5.3.3. Operationalization of the NeuroConstruct teaching model in classroom practice

To enhance methodological transparency and replicability, the NeuroConstruct teaching model was operationalized through detailed lesson plans, weekly learning activities, instructional materials, and explicit time allocation across its six syntaxes.

The intervention was implemented over five consecutive weeks (10 instructional hours in total), with 2 h of instruction per week. Each instructional session systematically incorporated all six syntaxes of the NeuroConstruct teaching model within a single lesson, rather than treating each syntax as a separate session. This design reflects the Neuroconstructivist assumption that cognitive development emerges from the dynamic integration of multiple constraints within a single learning episode (Karmiloff-Smith, 2017; Mareschal, Johnson, et al., 2012).

Sample lesson plans were developed to guide teachers in implementing each phase in classroom practice. For example, in a lesson on graph interpretation, the session began with the Neuron Stimulation phase (15 min), where students activated prior knowledge through real-life graph-based problems. This was followed by the Neuron Construction phase (20 min), during which students engaged in competitive and collaborative problem-solving tasks to construct new mathematical representations. The Connecting Brain Regions phase (20 min) involved structured cognitive tasks designed to integrate numerical, symbolic, and graphical representations. The Connecting the Brain and Body phases (15 min) employed embodied learning activities, such as physical manipulation of graph cards and movement-based mapping tasks. Subsequently, the Connecting Body and Society phase (20 min) emphasized social interaction through peer discussion and collaborative explanation of problem-solving strategies. Finally, the lesson concluded with the Integrating All Constraints phase (20 min), during which students reflected on their learning and applied the knowledge they had acquired to novel problem contexts.

Instructional materials and resources included student worksheets, graph cards, physical manipulatives, whiteboard-based visualizations, and structured discussion prompts. These materials were designed to support experience-dependent learning, embodied cognition, and social interaction, consistent with Neuroconstructivism principles (Astle et al.,

2023; Johnson, 2011).

A summary of weekly learning activities, sample lesson plans, instructional materials, and time allocation for each syntax is provided in Appendix B, enabling replication of the intervention in comparable educational contexts.

The pre-test and post-test measured learning outcomes, particularly creative thinking, mathematics achievement, attention, and working memory. The NeuroConstruct teaching model and the 5E teaching model were employed to teach mathematical topics, including graphs, relations, and functions, over a period of 2 h per week, spanning five weeks. In the experimental group, the NeuroConstruct teaching model was implemented through six structured phases: neuron stimulation, neuron construction, connecting the brain regions, connecting the brain and body, connecting the body and society, and integrating all constraints. These phases emphasize bidirectional learning, involving gene activation, neural activity, brain region integration, embodied learning, and social context, thereby fostering neurocognitive development aligned with the Neuroconstructivism framework. In contrast, the control group followed the 5E teaching model, which comprises the phases Engage, Explore, Explain, Elaborate, and Evaluate, focusing on inquiry-based, active learning.

5.3.4. 5E inquiry teaching model

The 5E teaching model is employed in Thailand to develop learning activities and is supported for implementation in public schools by the Institute for the Promotion of Teaching Science and Technology (IPST) (2012). Hence, it was implemented in the control group. It contains five phases: engage, explore, explain, elaborate, and evaluate. This model proposes that active learning should be promoted to enhance learning. Learner development should be attributed to analysis, evaluation, inquiry, and collaborative learning; these processes will provide learners with a clearer understanding and knowledge. Asking questions, observation, analysis, explanation, conclusion, and new questions can construct new knowledge and experiences (IPST, 2012).

Firstly, the engagement phase involves introducing lessons to motivate students and spark their curiosity about current events. It provides a clearer picture of what is to be studied in line with the curriculum's objectives. The exploration phase involves a thorough understanding of the issues at hand. It should be taught through hands-on learning, experiments, and research to obtain sufficient information for subsequent manipulation. Subsequently, the explanation phase involves analyzing, interpreting, and summarizing the collected data, and presenting the results in various formats, such as text, figures, tables, and charts. The results can either support or reject hypotheses; they can also contribute to the construction of new knowledge and broaden learners' understanding. Following this is the elaborate phase, which involves connecting new knowledge with existing knowledge or new ideas derived from research. Students must base their learning on the conclusion to provide explanations for other relevant contexts, thereby improving their expertise. Lastly, the evaluation phase assesses the learning process and outcomes using various tools to enhance learners' knowledge and, in turn, promote their ability to apply new knowledge to other issues.

To ensure comparability and methodological rigor, both the experimental and control conditions are described using parallel structural elements, including teaching syntaxes, teacher roles, student activities, duration, and materials.

For methodological clarity, the distinction between the NeuroConstruct and 5E teaching models lies not only in their theoretical foundations but also in their procedural implementation. While both models employ structured instructional phases, the NeuroConstruct teaching model systematically embeds neurocognitive activation (e.g., attention regulation, working memory engagement, and embodied interaction) within each phase. In contrast, the 5E teaching model follows an inquiry-based sequence without explicit neurocognitive targeting. This distinction ensures that any observed differences in outcomes can be attributed to the integration of neuroconstructivist

principles rather than to general instructional structure.

5.3.5. Control group instructional equivalence

The control group was instructed using the 5E teaching model (Engage, Explore, Explain, Elaborate, and Evaluate) following the guidelines of the Institute for the Promotion of Teaching Science and Technology (IPST, 2012) and Bybee et al. (2006). To ensure methodological rigor and internal validity, several instructional variables were systematically controlled across both groups. First, both the experimental and control groups were taught the same mathematical content, namely graphs, relations, and functions, aligned with the Grade 7 Thai National Core Curriculum. Second, instruction in both groups was delivered by the same mathematics teacher, who had more than 10 years of teaching experience, thereby minimizing teacher-related confounding. Third, the duration and instructional time were equivalent across groups, with both receiving fifth weeks of instruction, totaling 10 instructional hours.

Although using the same teacher across both experimental and control groups was intended to minimize variability due to teacher-related differences (e.g., teaching style, experience, and classroom management), this design choice may also introduce carryover or expectancy effects. Specifically, the teacher's familiarity with both instructional approaches, as well as possible differential enthusiasm or belief in the NeuroConstruct teaching model, may have unintentionally influenced instructional delivery. To mitigate this risk, the teacher was provided with structured lesson plans, standardized instructional materials, and clear procedural guidelines for both conditions. In addition, adherence to each instructional model was monitored using observation checklists to ensure that the distinguishing features of each teaching approach were implemented as intended. Nevertheless, the potential influence of teacher-related factors cannot be entirely excluded and should be considered when interpreting the findings.

The 5E lesson plans were designed by the research team in collaboration with the participating teacher and were reviewed by three mathematics education experts to ensure content validity and alignment with inquiry-based learning principles. While the 5E model emphasizes constructivist inquiry and conceptual understanding, it does not explicitly address neurocognitive processes, such as attention regulation or engagement with working memory. This design allowed the present study to isolate the added value of the NeuroConstruct teaching model beyond a well-established constructivist instructional approach.

By holding content, teacher, and instructional duration constant, observed differences in learning outcomes can be more confidently attributed to differences in instructional design rather than extraneous variables.

5.3.6. Implementation procedure and fidelity

To enhance methodological rigor and internal validity, implementation fidelity was systematically designed, monitored, and evaluated in alignment with established frameworks for educational intervention research (Dusenbury et al., 2003; O'Donnell, 2008) and was explicitly supported by structured instructional materials and fidelity instruments provided in [Appendices B and F](#).

Prior to the intervention, the teacher assigned to the experimental group participated in a 6-h pre-intervention training program focused on (1) the foundational principles of Neuroconstructivism, (2) the instructional logic and sequencing of the six phases of the NeuroConstruct teaching model, and (3) the practical implementation of neuroscience-informed learning activities targeting attention, working memory, and creative thinking. This training was supported by detailed lesson plans, weekly instructional sequences, time allocation structures, and learning materials ([Appendix B](#)), ensuring alignment between theoretical principles and classroom enactment. The training was facilitated by the principal researcher and supported by an external expert in curriculum and instruction.

Teacher readiness was verified through a structured assessment

comprising a checklist-based evaluation of instructional understanding, a microteaching demonstration, and a reflective discussion to confirm alignment between theoretical constructs and planned instructional practices. Implementation commenced only after satisfactory readiness was confirmed.

During the intervention, instructional adherence was continuously monitored using a structured treatment-fidelity checklist aligned with the six teaching syntaxes of the NeuroConstruct teaching model. This checklist was complemented by systematic classroom observations conducted on two occasions during the intervention period by the research team and an external expert, using structured observation protocols and field notes to document instructional practices, student engagement, and alignment between planned and enacted instruction. These procedures ensured consistency in delivery and minimized variability across instructional sessions.

To reduce potential teacher expectancy effects and cross-condition contamination in the single-teacher design, the teacher was required to adhere strictly to condition-specific instructional protocols, supported by standardized lesson plans and instructional guides ([Appendix B](#)). Although these procedures enhanced consistency, minor variations in classroom interaction and instructional dynamics are acknowledged as inherent limitations of classroom-based experimental research.

To further strengthen internal validity, implementation fidelity was operationalized as a quantitative variable using a structured fidelity assessment rubric ([Appendix F](#)). The rubric comprised 12 observable indicators aligned with the six teaching syntaxes of the NeuroConstruct teaching model, with each indicator rated on a 3-point scale (0 = not implemented, 1 = partially implemented, 2 = fully implemented). Fidelity observations were conducted in 2 out of 10 instructional sessions (approximately 20% of the intervention period), selected systematically to represent the full intervention period.

To ensure measurement reliability, two independent observers (a research assistant and an external curriculum expert) underwent a standardized calibration process involving joint observation of pilot sessions, discussion of scoring discrepancies, and refinement of scoring criteria. Inter-rater reliability was assessed using a two-way random-effects intraclass correlation coefficient (ICC) with absolute agreement, which exceeded 0.95, indicating excellent reliability (Koo & Li, 2016). Discrepancies were resolved through consensus discussions, and periodic debriefings were conducted to prevent rater drift.

Fidelity scores were calculated as the percentage of the maximum possible score per observed session, consistent with the scoring procedure defined in [Appendix F](#), and were aggregated across observed sessions to generate an overall implementation fidelity index. The average fidelity score is approximately 91%, indicating a high level of adherence to the intended instructional design.

By integrating structured instructional design ([Appendix B](#)) with a transparent and reliable fidelity assessment framework ([Appendix F](#)), this study treated implementation fidelity not only as a procedural control but also as an empirical indicator of implementation quality. This approach strengthens the internal validity, transparency, and replicability of the findings (Durlak & DuPre, 2008).

5.3.7. Testing procedure

All participants completed pre-test assessments one week prior to the intervention and post-test assessments within one week of its completion. The assessments were administered under standardized classroom conditions. The computerized attention and working memory tests were conducted in a school computer laboratory using identical devices and software settings for all participants. Each student completed the attention battery (approximately 30 min) followed by the working memory battery (approximately 30 min), with a short break between sessions to minimize fatigue.

To ensure procedural consistency and replicability, all testing sessions were conducted under strictly controlled and standardized conditions. The assessments were administered in a quiet computer

laboratory with stable lighting, minimal external noise, and controlled temperature (approximately 25 °C). All students were tested in the same room and at similar times of day to minimize variability due to environmental or circadian factors.

The testing procedure followed a fixed sequence for all participants. Students first completed the attention test battery, followed by a short standardized break of approximately 5–10 min, and then completed the working memory test battery. No deviations from this order were permitted.

All testing sessions were supervised by the principal researcher and a trained research assistant to ensure adherence to standardized instructions. Prior to testing, all students received the same verbal instructions delivered from a standardized script. Students were instructed not to communicate with peers during the assessment, and compliance was monitored throughout the session.

Importantly, all participants completed the assessments under identical conditions regarding environment, instructions, timing, and supervision. This standardization was implemented to minimize extraneous variability and enhance the study's internal validity and reproducibility.

5.3.8. Statistical analysis

All statistical analyses were conducted using SPSS version 29. Prior to hypothesis testing, the assumptions underlying parametric analyses were systematically evaluated. Normality of distribution was assessed using the Shapiro–Wilk test, and homogeneity of variances was examined using Levene's test. The results indicated that all dependent variables met the assumptions for parametric tests ($p > .05$), supporting the use of parametric statistical procedures.

To examine differences between the experimental (NeuroConstruct teaching model) and control (5E teaching model) groups, two primary analytic strategies were employed. Mathematics achievement, as a unidimensional construct, was analyzed using an independent-samples *t*-test on post-test scores. Creative thinking, attention, and working memory, which are conceptually and empirically interrelated multidimensional constructs, were analyzed simultaneously using one-way multivariate analysis of variance (MANOVA), with follow-up univariate ANOVAs conducted when significant multivariate effects were observed. This dual approach ensured that each outcome was analyzed using a method aligned with its dimensionality while controlling for Type I error inflation.

Effect sizes were reported using partial eta squared (η_p^2) for multivariate and univariate analyses, providing an estimate of the magnitude of group differences beyond statistical significance. In addition, 95% confidence intervals (CI) for between-group differences were calculated and reported to enhance the precision and interpretability of the findings. These confidence intervals refer to the differences between the experimental and control groups in post-test, depending on the analysis, and were used to support inferences regarding both statistical and practical significance.

Implementation fidelity was assessed separately (see Methods section) and treated as an indicator of implementation quality; it was not included as a covariate in the statistical analyses. A structured fidelity checklist (Appendix F), comprising 12 observable indicators aligned with the six instructional phases of the NeuroConstruct teaching model, was used to evaluate instructional adherence during classroom observations. Each indicator was rated on a 3-point scale (0 = not implemented, 1 = partially implemented, 2 = fully implemented), enabling computation of session-level fidelity scores.

Fidelity scores were computed based on observations conducted in approximately 20% of instructional sessions (2 out of 10 sessions), and were calculated as the percentage of the maximum possible score per observed session, consistent with the scoring procedure defined in Appendix F. The mean fidelity score was 1.82 (SD = 0.14), corresponding to an overall adherence rate of approximately 91%, indicating high implementation fidelity. Given the consistently high-fidelity scores

($M = 1.82$, $SD = 0.14$; approximately 91% adherence) and low variability across observed sessions, fidelity was not included as a covariate in the statistical models.

To ensure measurement reliability, two independent observers (a research assistant and an external curriculum expert) were trained using a standardized calibration procedure. Inter-rater reliability was assessed using a two-way random-effects intraclass correlation coefficient (ICC [2,1]) with absolute agreement, which exceeded 0.95, indicating excellent agreement (Koo & Li, 2016). Discrepancies were resolved through consensus discussion, and periodic calibration was conducted to minimize rater drift.

Overall, the high level of implementation fidelity, together with strong inter-rater reliability, provides empirical support that the intervention was delivered consistently and as intended. This strengthens the internal validity of the study and increases confidence that observed differences in outcomes can be attributed to the instructional intervention rather than to implementation variability.

Finally, to enhance methodological transparency and replicability, detailed descriptions of the instructional procedures, teaching syntaxes, lesson plans, activity structures, and time allocation are provided in Appendices A and B. A structured comparison between the NeuroConstruct and 5E teaching models is presented in Table 2, further clarifying procedural differences between experimental conditions.

Supplementary Materials Availability. The following supplementary materials are provided to support methodological transparency and reproducibility: Appendix A (NeuroConstruct teaching model), Appendix B (operationalization of the NeuroConstruct teaching model), Appendix C (creative thinking test with sample items), Appendix D (mathematics achievement test with sample items), Appendix E (computerized cognitive test specifications, administration protocols, and sample task screenshots), and Appendix F (implementation fidelity assessment rubric with scoring criteria). All appendices are available as supplementary files submitted alongside this manuscript. These materials will be made available as online supplementary materials through the journal's repository. The proprietary computerized cognitive assessment software is available for research purposes upon reasonable request to the corresponding author, subject to a data-sharing agreement with the instrument developer.

Replication Summary. To facilitate replication, the essential design parameters are summarized as follows. The study employed a true experimental pre-test–post-test control group design with 70 Grade 7 students randomly assigned to two conditions ($n = 35$ per group). The experimental group received the NeuroConstruct teaching model (6 instructional syntaxes grounded in Neuroconstructivism), while the control group received the 5E teaching model (Engage, Explore, Explain, Elaborate, Evaluate). Both conditions covered identical mathematical content (graphs, relations, and functions) over 5 weeks (10 h total; 2 h per week), delivered by the same teacher under equivalent classroom conditions. Pre-tests were administered 1 week prior to the intervention, and post-tests were administered immediately upon completion. Four outcome variables were measured: creative thinking (5-item essay test, 50 min), mathematics achievement (40-item multiple-choice test, 60 min), attention (computerized battery, 4 subtests, 30 min), and working memory (computerized battery, 4 subtests, 30 min). Mathematics achievement was analyzed using independent-samples *t*-tests on post-test scores; creative thinking, attention, and working memory were analyzed simultaneously using one-way MANOVA with follow-up univariate ANOVAs. Detailed lesson plans, instruments, and fidelity procedures are provided in Appendices A–F.

5.4. Research instruments

Three tests were administered to evaluate learning outcomes in creative thinking, mathematics achievement, attention, and working memory.

5.4.1. Creative thinking test

The creative thinking test was employed to evaluate students' abilities in fluent thinking, flexible thinking, and original thinking, three key components of creative thinking as established in the literature (Mumford et al., 2012; Runco & Acar, 2012). This test consists of five essay items, administered over 50 min. An example of the creative thinking test is provided in Appendix C, which is explicitly designed to capture diverse aspects of creative cognition. Although the test was developed by Srikoon (2015) and Wongpratum (2000), the intervention and instructional model used in this study were developed independently. The process of measuring creative thinking involves administering a five-item test within a total time limit of 50 min, with 10 min per item. Students are required to generate as many original, relevant, and innovative ideas as possible, emphasizing fluent thinking, flexible thinking, and original thinking in their work. Responses are scored according to the number of ideas, the diversity of perspectives, and the novelty of solutions, with higher scores awarded to logical and creative responses that extend beyond conventional thinking. The instrument demonstrates excellent content validity, as confirmed by expert reviews, and good reliability (coefficient of 0.79). This test has been widely used in previous studies in the Thai educational context to effectively measure creative thinking outcomes.

The creativity test, developed by Srikoon (2015) and Wongpratum (2000), was designed to assess three dimensions of creative thinking: fluent thinking, flexible thinking, and original thinking. Student responses were evaluated using an analytic scoring rubric that specifies performance criteria for each dimension. All responses were scored independently by two raters with formal training in educational measurement and assessment. Prior to scoring, the raters participated in a calibration session to establish a shared interpretation of the scoring criteria; details are provided in Srikoon (2015) and Wongpratum (2000). Inter-rater reliability was assessed using the intraclass correlation coefficient ($ICC = 0.86$), indicating satisfactory agreement relative to recommended benchmarks for performance-based assessments (Cohen et al., 2018; Stemler, 2004). Discrepancies in scoring were resolved through discussion to reach a consensus. This scoring procedure enhances the reliability and transparency of the creativity assessment and supports the study's methodological rigor.

To ensure methodological transparency while maintaining conciseness, the detailed analytic scoring rubric for evaluating creative thinking (i.e., fluent thinking, flexible thinking, and original thinking) is based on the established frameworks developed by Srikoon (2015) and Wongpratum (2000). Due to the extensive and highly specific nature of the scoring criteria, the full rubric, including descriptors, scoring levels, and exemplars, is not reproduced in full within this research. However, it is available in the original sources and can be accessed for replication purposes.

In the present study, these established criteria were strictly followed. Fluent thinking was assessed by the number of relevant ideas generated, flexible thinking by the diversity of conceptual categories, and original thinking by the novelty and statistical infrequency of responses within the sample. All scoring procedures adhered to the standardized guidelines specified in the original instruments.

All responses were independently evaluated by two trained raters with expertise in educational assessment. Prior to scoring, raters participated in a calibration session to ensure a shared understanding of the rubric criteria. Inter-rater reliability was assessed using the intraclass correlation coefficient ($ICC = 0.86$), indicating high agreement.

In cases of scoring discrepancies, a structured consensus procedure was employed. Both raters first reviewed the discrepant responses independently and then discussed them to reach agreement based on the predefined rubric criteria. When consensus could not be achieved, a third expert was consulted to adjudicate the final score. This procedure ensured consistency, minimized subjective bias, and enhanced the reliability and reproducibility of the scoring process.

In addition to the creative thinking test, two other assessments were

used to evaluate learning outcomes: a mathematics achievement test, comprising 40 multiple-choice items aligned with the national curriculum and validated by mathematics experts ($KR-20 = 0.89$), and a computerized cognitive function battery assessing attention and working memory, with high reliability (0.84 to 0.95) and confirmed construct validity (Srikoon, 2019). Collectively, these three tests provide a comprehensive evaluation of cognitive and academic performance relevant to the objectives of the NeuroConstruct teaching model.

In addition, inter-rater reliability was established through independent scoring by two trained raters, yielding high agreement coefficients, thereby ensuring the consistency and objectivity of the scoring process.

5.4.2. Mathematics achievement test

Mathematics achievement was measured using a multiple-choice test comprising 40 items about graphs, relations, and functions, following Thailand's core curriculum for grade 7 students (an example of a mathematics achievement test is provided in Appendix D). Three experts in mathematics teaching at the University of Phayao assessed the test's content validity. The index of objective congruence (IOC) ranged from 0.67 to 1.00. KR-20 internal consistency of reliability was 0.89.

The internal consistency reliability coefficient (KR-20) was 0.89, indicating high reliability and supporting the instrument's use for group comparisons and inferential analysis.

5.4.3. Cognitive Function Computerized Software Test: attention and working memory

Two computerized battery tests were conducted: an attention and a working memory test to evaluate attention and working memory accuracy, respectively (an example of a Cognitive Function Computerized Software Test is provided in Appendix E). Specifically, the computerized attention battery test consisted of four subtests: simple reaction accuracy, focused attention accuracy, selective attention accuracy, and sustained attention accuracy. These tests had reliability of 0.84, 0.88, 0.93, and 0.95, respectively. Srikoon's (2019) assessment of construct validity showed that all indicators had good fit. The 30-item subtests in the Thai language were distributed to the students. The attention computerized battery test lasted 30 min in total.

Similarly, the working memory computerized battery test consisted of four subtests: basic processing accuracy, shifting working memory accuracy, updating working memory accuracy, and inhibiting working memory accuracy, with reliabilities of 0.88, 0.90, 0.89, and 0.88, respectively. The construct validity was confirmed by Srikoon (2019), who reported good model fit indices across all subtests. Each subtest was timed to ensure consistency in administration and to capture not only accuracy but also processing speed, which is an essential aspect of working memory function (Srikoon, 2019). The entire battery took approximately 30 min to complete, striking a balance between comprehensiveness and participant fatigue.

Attention and working memory were assessed using computerized cognitive ability tests developed and validated by Srikoon (2019). The tests consist of multiple subtests targeting core cognitive processes, including focused attention, updating, shifting, and working memory accuracy. The software is a research-based assessment tool and is not publicly distributed. It was installed on school-based computer laboratory systems and administered under standardized conditions by the research team. Each participant completed the tests individually using pre-assigned user accounts, with identical instructions, timing parameters, and hardware specifications across sessions. Access to the software is restricted to educational and research purposes under agreement with the developer. Detailed technical specifications and administrative protocols are available upon reasonable request, facilitating replication in comparable research contexts.

To enhance replicability and methodological transparency, additional details about the computerized cognitive tests are provided below.

The attention battery comprised four computerized subtests (simple

reaction, focused, selective, and sustained attention), each consisting of 30 trials presented in randomized order. In each trial, visual stimuli (e.g., geometric shapes or symbols) were presented at the center of the screen, and participants were instructed to respond as quickly and accurately as possible by pressing designated keys on a standard keyboard. For selective and sustained attention tasks, distractor stimuli were included to increase cognitive load and require attentional control.

Each stimulus was displayed for 500 ms, followed by an inter-stimulus interval of 1000 ms. Participants were given a maximum response window of 1500 ms per trial. Reaction time (in milliseconds) and response accuracy (correct/incorrect) were recorded automatically by the software. Accuracy scores were computed as the percentage of correct responses across trials, while reaction time measures were averaged across correct trials only.

The working memory battery consisted of four subtests (basic processing, shifting, updating, and inhibition), each designed to assess different components of executive functioning. In the updating task, for example, participants were required to continuously monitor and update stimulus sequences, whereas in the inhibition task, they were required to suppress prepotent responses to conflicting stimuli. Each subtest included 30 trials, with timing parameters similar to those of the attention tasks.

All tasks were administered using a proprietary computerized assessment program developed by Srikoon (2019), Version 1. The software was installed on desktop computers in the school computer laboratory, with standardized hardware specifications (Intel Core i5 processors, 8 GB RAM, 19-inch monitors, 60 Hz refresh rate). All participants completed the tasks individually under identical testing conditions, using the same equipment, instructions, and environmental settings to minimize variability.

Prior to the formal assessment, participants completed a short practice session to familiarize themselves with the task procedures and response format. Detailed technical specifications, administration protocols, and sample task screenshots are provided in Appendix E to facilitate replication in future studies.

Although the proprietary software used in this study is not publicly distributed, the underlying task paradigms are based on well-established cognitive assessment principles, including reaction time, selective and sustained attention, and working memory updating and inhibition. Therefore, researchers seeking to replicate this study may employ equivalent computerized cognitive assessments that capture these core executive function components. Examples include widely used paradigms such as continuous performance tasks (CPT), n-back tasks, and task-switching paradigms. The use of such equivalent measures, in combination with the detailed procedural descriptions and sample tasks provided in Appendix E, supports the reproducibility of the study in diverse research contexts.

Creative thinking was assessed using an essay-based test comprising five open-ended items targeting fluent thinking, flexible thinking, and original thinking (Srikoon et al., 2018). The 50-min duration was chosen to provide students with sufficient time to thoughtfully generate diverse and original ideas, consistent with established practices in creativity assessment (Runco & Acar, 2012). Although the test is not strictly timed per item, the overall time frame encourages focused cognitive engagement while allowing ample opportunity for idea development.

The pre-test and post-test measured learning outcomes in creative thinking, mathematics achievement, attention, and working memory using validated instruments developed and/or adapted by the research team and experts. Specifically:

Creative Thinking was assessed using an essay-based test developed by Srikoon (2015) to measure fluent thinking, flexible thinking, and original thinking. This instrument has demonstrated content validity and a reliability coefficient of 0.79.

Mathematics Achievement was measured using a 40-item multiple-choice test aligned with the Thai national core curriculum for Grade 7, focusing on graphs, relations, and functions. The test was validated by

mathematics experts and exhibited high reliability ($KR-20 = 0.89$).

Attention and Working Memory were evaluated using computerized cognitive battery tests developed and validated by Srikoon (2019). These tests include subtests covering simple reaction time, focus, selective and sustained attention, as well as working memory components such as basic processing, shifting, updating, and inhibiting. Reliability coefficients ranged from 0.84 to 0.95, and construct validity was confirmed through confirmatory factor analysis.

These assessments are not international standardized tests but were rigorously developed or adapted to fit the Thai educational context and were psychometrically validated prior to this study.

Furthermore, construct validity was confirmed through confirmatory factor analysis (CFA), which supported the multidimensional structure of attention and working memory, ensuring alignment between theoretical constructs and observed indicators.

To further strengthen the methodological rigor of the present study, additional evidence regarding the reliability and validity of the measurement instruments is explicitly reported. First, the creative thinking assessment, which involved open-ended responses, was evaluated using a structured scoring rubric, and inter-rater reliability was established to ensure scoring consistency. Two independent raters were trained prior to scoring, and inter-rater reliability was quantified using inter-rater reliability coefficients, demonstrating high consistency in evaluating fluent thinking, flexible thinking, and original thinking. Second, the mathematics achievement test demonstrated strong internal consistency reliability, as indicated by a Kuder-Richardson Formula 20 ($KR-20$) coefficient of 0.89, which is considered satisfactory to high for educational measurement. This coefficient confirms that the test items function cohesively in measuring a single underlying construct of mathematical understanding in the domain of graphs, relations, and functions. Third, the computerized cognitive measures used to assess attention and working memory demonstrated both reliability and construct validity. Internal consistency reliability coefficients ranged from 0.84 to 0.95 for attention and from 0.88 to 0.90 for working memory, indicating high measurement precision. In addition, construct validity was established through confirmatory factor analysis (CFA), which verified the theoretical structure of the cognitive constructs, including subcomponents such as updating, shifting, and inhibition. Collectively, the use of multiple instruments with established inter-rater reliability, internal consistency reliability, and construct validity provides strong psychometric support for the measurement framework. This enhances the study's internal validity, reduces measurement error, and increases confidence in the interpretation of the observed effects.

Overall, the integration of inter-rater reliability procedures, high internal consistency coefficients, and confirmatory construct validation provides robust psychometric evidence supporting the measurement framework. This methodological strength contributes to the credibility, reproducibility, and interpretability of the study findings.

5.5. Instruments and testing procedure

To evaluate the effectiveness of the NeuroConstruct teaching model, pre- and post-tests were administered across all outcome variables. Creative thinking was measured using an essay-based test comprising five open-ended items. Students were allotted 50 min to respond, with 10 min per item. Responses were assessed on fluent thinking, flexible thinking, and original thinking, following the rubric validated by Srikoon (2015) and Wongpratum (2000), which demonstrated content validity ($IOC = 1$) and acceptable reliability ($\alpha = 0.79$).

Mathematics achievement was assessed using a 40-item multiple-choice test that covered graphs, relations, and functions, aligned with Thailand's Grade 7 core curriculum. The test was reviewed by three mathematics education experts, yielding an IOC of 0.67-1.00, and demonstrated high internal consistency ($KR-20 = 0.89$). Students completed this test in both the pre-test and post-test stages, each within a 60-min time frame.

Attention and working memory were measured using computerized cognitive ability tests developed and validated by Srikoon (2019). Attention was assessed through subtests of simple reaction time, focus, shifting, updating, and inhibition, with reliability ranging from 0.84 to 0.95. Working memory was evaluated through tasks that measured updating, storage, and manipulation processes, with reliability ranging from 0.88 to 0.90. Confirmatory factor analysis further established construct validity for both measures.

All instruments were administered as pre-tests 1 week prior to the intervention and as post-tests immediately after the 5-week instructional period, which consisted of 10 h of instruction (2 h per week). This procedure allowed for direct comparisons of learning gains between the experimental and control groups.

5.6. Data analysis

Data were analyzed using a combination of descriptive and inferential statistical techniques to address the research objectives and test the study hypotheses. All analyses were conducted using standard statistical procedures, and statistical significance was determined at the 0.05 level.

First, descriptive statistics, including means (M) and standard deviations (SD), were computed for all variables to summarize students' performance across pre-test and post-test measures. Gain scores (post-test minus pre-test) were also calculated to provide an index of learning improvement during the intervention period, following the approach proposed by Kanjanawasee (1989).

Prior to conducting inferential analyses, a systematic series of assumption checks was performed to verify the statistical appropriateness of each analytical procedure employed in the study.

For the independent-samples and paired-samples *t*-tests, univariate normality was evaluated using the Shapiro–Wilk test, with skewness and kurtosis indices examined as supplementary indicators. Results indicated that the distributions of scores did not significantly deviate from normality across all outcome variables ($W = 0.914–0.987$, $p > .05$), with skewness and kurtosis values falling within acceptable ranges (± 1), consistent with recommended benchmarks for parametric analyses (Field, 2018; Kim, 2013). Homogeneity of variance across groups was assessed using Levene's test, which yielded non-significant results for most variables ($F = 0.000–2.486$, $p > .05$), thereby satisfying the univariate variance homogeneity assumption. Where Levene's test indicated unequal variances — specifically for fluent thinking (pre-test: $F = 9.739$, $p = .003$; post-test: $F = 5.668$, $p = .020$) and Basic Processing Accuracy post-test ($F = 4.330$, $p = .041$) — results were interpreted with appropriate caution and supplemented by effect size reporting. During preliminary data screening, outlier screening identified no cases sufficiently extreme to warrant exclusion from the analyses.

For the MANOVA procedures, multivariate normality, linearity among dependent variables, and equality of covariance matrices were systematically evaluated. The homogeneity of covariance matrices across groups was assessed using Box's M test, applied at the more stringent significance threshold of $p < .001$, consistent with recommendations for this test given its well-documented sensitivity to minor departures from multivariate normality (Tabachnick & Fidell, 2019). For Attention outcomes, Box's M indicated that the assumption of equal covariance matrices was tenable ($M = 6.712$, $\chi^2(10) = 6.288$, $p = .791$). Similarly, for Working Memory outcomes, the assumption was not violated ($M = 18.244$, $\chi^2(10) = 17.090$, $p = .072$). For Creative Thinking outcomes, however, Box's M reached statistical significance ($M = 40.098$, $\chi^2(6) = 38.182$, $p < .001$), indicating a departure from the homogeneity of covariance matrices assumption. Importantly, when group sizes are equal — as in the present study ($n_1 = n_2 = 35$) — MANOVA has been demonstrated to maintain robustness against violations of this assumption, as balanced group sizes stabilize Type I error rates and preserve the validity of the *F*-approximation (Huberty & Olejnik, 2006; Tabachnick & Fidell, 2019). The MANOVA results for

Creative Thinking were therefore retained and interpreted accordingly, with the recommendation that replication in larger and more heterogeneous samples would further strengthen the generalizability of these findings. Collectively, the results of the assumption checks supported the appropriateness of the parametric statistical procedures employed in the present study.

To enhance transparency and methodological rigor, detailed results of assumption testing are reported. For normality, the Shapiro–Wilk test indicated that the distributions of scores did not significantly deviate from normality across all outcome variables ($W = 0.914–0.987$, $p > .05$). Additionally, skewness and kurtosis values were within acceptable ranges (± 1), supporting the assumption of approximate normality (Field, 2018; Kim, 2013).

To ensure analytical consistency, statistical procedures were aligned with the dimensionality and theoretical structure of each outcome variable.

Mathematics achievement was analyzed using a gain-score approach, selected to evaluate whether students in the NeuroConstruct group achieved higher post-test performance than those in the 5E group while maintaining analytic consistency with the pre-test–post-test control-group design. Although analysis of covariance (ANCOVA) is often recommended to control for pre-test differences, preliminary analyses revealed no statistically significant difference between groups at baseline in mathematics achievement ($t(68) = -0.59$, $p = .560$). Therefore, the use of independent-samples and paired-samples *t*-test procedures was considered methodologically appropriate and sufficient, avoiding unnecessary model complexity while maintaining statistical validity (Cohen et al., 2018; Field, 2018).

In contrast, creative thinking, attention, and working memory were conceptually and empirically interrelated and were therefore analyzed simultaneously using one-way multivariate analysis of variance (MANOVA). Prior to the main analysis, baseline equivalence for these outcome domains was examined using independent-samples *t*-tests on pre-test scores. Results indicated no statistically significant pre-test differences for flexible thinking, original thinking, and all attention and working memory subtests (all $p > .05$). However, a statistically significant pre-test difference was observed for fluent thinking ($t(68) = -3.588$, $p < .001$), with the experimental group scoring higher at baseline ($M = 25.11$, $SD = 2.61$) than the control group ($M = 21.91$, $SD = 4.58$). Given this pre-existing advantage, fluent thinking post-test outcomes are interpreted in conjunction with within-group gain scores rather than solely from between-group post-test comparisons.

Given that multiple outcomes and sub-dimensions were examined simultaneously, particular consideration was given to the risk of familywise Type I error inflation arising from multiple comparisons. For outcome domains comprising theoretically and empirically interrelated dependent variables — specifically, creative thinking, attention, and working memory — a one-way multivariate analysis of variance (MANOVA) was employed as the primary omnibus test prior to any univariate follow-up. Follow-up univariate ANOVAs were conducted exclusively when the corresponding multivariate effect attained statistical significance, thereby constraining the number of inferential tests performed and preserving an appropriate error-control structure across related outcome dimensions. No additional formal multiplicity correction procedure (e.g., Bonferroni adjustment) was applied to the follow-up univariate tests. Accordingly, univariate findings should be interpreted in conjunction with the multivariate test results, effect size estimates, and confidence intervals to support sound and appropriately qualified statistical inference.

Effect sizes were reported to indicate the magnitude of observed differences. Partial eta squared (η_p^2) was used for MANOVA and follow-up ANOVA results. For mathematics achievement, within-group effect sizes were computed using the standardized mean gain index (Becker, 1988; Morris & DeShon, 2002), defined as the gain score (post-test minus pre-test) divided by the pre-test standard deviation for each group. This approach uses the pre-test standard deviation as the

standardizer because it reflects baseline variability prior to the intervention, thereby providing an interpretable index of pre-to-post change magnitude uncontaminated by treatment effects (Lakens, 2013).

To enhance clarity and analytical coherence, the overall data analysis strategy was structured in a sequential, theoretically aligned manner, corresponding to the study's research questions and hypotheses.

First, baseline equivalence between the experimental and control groups was examined using independent-samples *t*-tests on pre-test scores to ensure comparability prior to the intervention.

Second, within-group changes from pre-test to post-test were assessed using paired samples *t*-tests to determine whether significant improvements occurred in each group over time.

Third, between-group differences in mathematics achievement were analyzed using an independent-samples *t*-test on the post-test scores.

Fourth, for the interrelated cognitive outcomes (creative thinking, attention, and working memory), a one-way multivariate analysis of variance (MANOVA) was conducted to examine overall group differences while controlling for Type I error inflation. When significant multivariate effects were identified, follow-up univariate ANOVAs were performed.

This structured analytic approach ensured that each statistical procedure was appropriately aligned with the dimensionality of the outcome variables and directly addressed the corresponding research questions and hypotheses. Collectively, this strategy improves the transparency, consistency, and reproducibility of the analytical framework.

To further enhance transparency and reproducibility, all statistical procedures were conducted in accordance with established reporting standards. Assumption testing results were systematically evaluated prior to hypothesis testing to ensure the appropriateness of parametric analyses. The selection of statistical techniques was theoretically aligned with the dimensionality and structure of each outcome variable. Effect sizes were interpreted using conventional benchmarks (Cohen, 1988) and reported alongside 95% confidence intervals to facilitate practical interpretation of magnitude. This comprehensive analytical framework ensures methodological rigor, supports reproducibility, and aligns with recommended reporting standards in educational and psychological research.

To ensure full consistency and transparency in the analytical framework, an alignment matrix was developed to explicitly link research questions, statistical models, and reporting strategies across the Methods, Results, and Tables sections. This alignment clarifies the primary analytic approach for each outcome variable and distinguishes it from supplementary analyses, thereby minimizing ambiguity in statistical interpretation, as shown in Table 4.

To ensure analytical coherence and methodological transparency, each outcome variable was examined using a single, clearly specified primary statistical model aligned with its dimensionality. Mathematics achievement, as a unidimensional construct, was analyzed using an independent-samples *t*-test on post-test scores. Creative thinking, attention, and working memory, as interrelated multidimensional constructs, were analyzed simultaneously using one-way MANOVA, with follow-up univariate ANOVAs conducted when significant multivariate effects were observed. Supplementary within-group analyses (paired-samples *t*-tests) were conducted solely to support interpretation and were not used as the primary basis for hypothesis testing.

To enhance clarity and accessibility, Table 5 provides a concise summary of the research design. This table synthesizes the key methodological components, enabling readers to readily comprehend the overall experimental structure and analytic framework.

A key methodological strength of the present study lies in the adoption of a true experimental pretest–posttest control-group design with random assignment. In educational research, where these designs are often necessitated by practical constraints, the use of true randomization offers a rigorous methodological advantage. Specifically,

random assignment enhances internal validity by reducing selection bias and mitigating the influence of potential confounding variables. As a result, this design supports stronger causal inference, allowing observed differences in creative thinking, mathematics achievement, attention, and working memory to be more confidently attributed to the NeuroConstruct teaching model rather than to pre-existing group disparities or extraneous influences (Creswell & Creswell, 2018; Shadish et al., 2002).

6. Results

This study aimed to examine the effectiveness of the NeuroConstruct teaching model in enhancing four key student outcomes: creative thinking, mathematics achievement, attention, and working memory. Specifically, the research compared these outcomes between the experimental group, which received the NeuroConstruct teaching model, and the control group, which used the 5E teaching model. The following sections present the detailed findings corresponding to each objective.

To provide an overall descriptive overview of students' performance across outcome variables, Fig. 4 presents the pre-test and post-test mean scores for both the NeuroConstruct and 5E teaching models. The figure illustrates consistent post-test improvements across all domains, with higher gains observed in the NeuroConstruct group.

The results of this research are reported following the research objectives. This section presents detailed analyses of students' creative thinking, mathematics achievement, attention, and working memory outcomes before and after the implementation of the NeuroConstruct and 5E teaching models. The subsequent subsections describe the findings for each cognitive domain, supported by statistical analyses and descriptive data. To improve clarity and consistency, 95% confidence intervals (CIs) for the principal between-group differences are reported systematically across the main outcomes.

To ensure full consistency across results tables, the following conventions are applied throughout Tables 6–9: (a) all tables report pre-test and post-test means and standard deviations for both groups; (b) gain scores (post-test minus pre-test) are included for supplementary within-group interpretation only; (c) between-group comparisons are reported using the primary statistical model specified in Table 4 (one-way MANOVA with follow-up univariate ANOVAs for creative thinking, attention, and working memory; independent-samples *t*-test on post-test scores for mathematics achievement); and (d) effect sizes are reported as partial eta squared (η_p^2) for MANOVA-based analyses and SMG for the *t*-test comparison.

6.1. Creative thinking

Scores measured creative thinking. Table 6 shows each element's pre-post-test *M* (Mean Scores) and *SD* (Standard Deviation) of the experimental and control groups.

6.1.1. Multivariate test

All multivariate tests (Wilks' Lambda) were significant for creative thinking accuracy. The teaching models significantly influenced creative thinking at the 0.05 significance level ($F(3, 66) = 5.26, p = .003$) and accounted for 19.30% of the variance in creative thinking ($\eta_p^2 = 0.193$).

Table 6 presents the descriptive statistics and inferential results for creative thinking outcomes across three subdimensions: fluent thinking, flexible thinking, and original thinking, for both the experimental group (NeuroConstruct teaching model) and the control group (5E teaching model). Mean scores and standard deviations are reported for pre-test and post-test assessments, along with gain scores reflecting changes following the intervention. In addition, univariate analysis results, including *F* statistics, partial eta squared (η_p^2), and 95% confidence intervals for between-group differences in post-test scores, are provided to support the interpretation of instructional effects.

Across all dimensions of creative thinking, students in the

Table 4
Alignment of analytical models across Methods, Results, and Tables.

Outcome Variable	Research Question	Primary Statistical Model	Supplementary Analysis	Results Reporting Structure	Table Alignment
Creative Thinking	RQ1: Does the model improve creative thinking?	One-way MANOVA	Mean, standard deviation, follow-up univariate ANOVA, and gain score for within-group change	Report Wilks' Lambda, F, p, η_p^2 ; then mean, standard deviation, gain score, and univariate results per dimension	Table 6: Align with MANOVA outputs (mean, standard deviation, multivariate and univariate effects), and gain score
Mathematics Achievement	RQ2: Does the NeuroConstruct model improve mathematics achievement compared to 5E?	Independent-samples t-test on post-test and standardized mean gain index (SMG) (Becker, 1988)	Mean, standard deviation, and gain score for within-group change	Report between-group difference in post-test scores (t, p, between-group SMG, 95% CI)	Table 7: Emphasize the independent-samples t-test; pre/post shown descriptively, and the gain score
Attention	RQ3: Does the model improve attention?	Like creative thinking	Like creative thinking	Like creative thinking	Table 8: Like creative thinking
Working Memory	RQ4: Does the model improve working memory?	Like creative thinking	Like creative thinking	Like creative thinking	Table 9: Like creative thinking

Table 5
Summary of research design.

Component	Description
Research design	True experimental pre-test-post-test control group design
Participants	70 Grade 7 students (mean age = 12.6 years, SD = 0.48)
Sampling method	Simple random sampling followed by random assignment
Group assignment	Experimental group (n = 35); Control group (n = 35)
Teaching model of the experimental group	NeuroConstruct teaching model (Neuroconstructivism-informed)
Teaching model of the control group	5E teaching model (Engage-Explore-Explain-Elaborate-Evaluate)
Research duration	One academic year overall; 5-week intervention period
Learning content	Graphs, relations, and functions (Grade 7 mathematics curriculum of Thailand)
Outcome variables	Creative thinking, mathematics achievement, attention, and working memory
Research instruments	Essay-based creative thinking test; mathematics achievement test; computerized cognitive ability tests (attention and working memory)
Data analysis	Independent-samples t-test on post-test scores and SMG for mathematics achievement; one-way MANOVA with follow-up univariate ANOVAs for creative thinking, attention, and working memory; mean, standard deviation, and gain score used only for supplementary within-group interpretation

experimental group demonstrated consistently greater improvements from pre-test to post-test compared with those in the control group.

For fluent thinking, the experimental group showed a substantial increase from pre-test (M = 25.11, SD = 2.61) to post-test (M = 41.34, SD = 7.83), yielding a gain score of 16.23. In contrast, the control group improved from pre-test (M = 21.91, SD = 4.58) to post-test (M = 36.23, SD = 5.15), with a gain score of 14.32. The between-group difference was statistically significant, $F(1, 68) = 10.43, p = .002$, with a medium effect size ($\eta_p^2 = 0.133$). The 95% confidence interval [-8.274, -1.954] did not include zero, indicating a reliable advantage for the

Table 6
Creative thinking outcomes by group: pre-test, post-test comparison, gain score, and between-group effects.

Creative thinking	NeuroConstruct teaching model					5E teaching model					F (df= (1,68))	Partial eta squared (η_p^2)	95% Confidence Intervals (CI) of Difference	
	Pre-test		Post-test		Gain score	Pre-test		Post-test		Gain score			Lower bound	Upper bound
	M	SD	M	SD		M	SD	M	SD					
Fluent thinking	25.11	2.61	41.34	7.83	16.23	21.91	4.58	36.23	5.15	14.32	10.43**	0.133	-8.274	-1.954
Flexible thinking	26.51	5.27	43.54	9.86	17.03	24.54	6.08	36.37	10.16	11.83	8.97**	0.117	-11.949	-2.394
Original thinking	27.06	5.17	40.86	8.93	13.80	25.66	6.29	33.66	11.08	8.00	8.96**	0.116	-12.000	-2.400

Note. η_p^2 = partial eta squared. Gain scores were calculated as post-test minus pre-test. The 95% CI for the difference refers to the 95% confidence interval for the between-group difference in post-test. **p < .01.

experimental group.

A similar pattern was observed for flexible thinking. The experimental group improved from pre-test (M = 26.51, SD = 5.27) to post-test (M = 43.54, SD = 9.86), with a gain score of 17.03, whereas the control group showed a smaller increase from pre-test (M = 24.54, SD = 6.08) to post-test (M = 36.37, SD = 10.16), with a gain score of 11.83. This difference was statistically significant, $F(1, 68) = 8.97, p = .004$, with a medium effect size ($\eta_p^2 = 0.117$). The confidence interval [-11.949, -2.394] further supports the robustness of the group difference.

For original thinking, the experimental group demonstrated a marked improvement from pre-test (M = 27.06, SD = 5.17) to post-test (M = 40.86, SD = 8.93), corresponding to a gain score of 13.80. The control group improved from pre-test (M = 25.66, SD = 6.29) to post-test (M = 33.66, SD = 11.08), with a gain score of 8.00. The between-group difference was statistically significant, $F(1, 68) = 8.96, p = .004$, with a medium effect size ($\eta_p^2 = 0.116$). The 95% confidence interval [-12.000, -2.400] did not cross zero, confirming the effect's reliability.

Overall, the results summarized in Table 6 indicate that the NeuroConstruct teaching model led to statistically significant improvements across all dimensions of creative thinking compared with the 5E teaching model. The consistent pattern of medium effect sizes ($\eta_p^2 = 0.116-0.133$) suggests that these differences are not only statistically significant but also educationally meaningful, highlighting the effectiveness of the NeuroConstruct teaching model in enhancing higher-order creative thinking skills.

6.2. Mathematics achievement

Accuracy scores measured mathematics achievement. Table 7 presents the pre- and post-test M (Mean Scores) and SD (Standard Deviation) for the experimental and control groups.

Table 7

Report between-group difference in post-test scores as the primary comparison; gain scores included for supplementary within-group interpretation.

Mathematics achievement	NeuroConstruct teaching model					5E teaching model					t(df = 68)	95% CI of the Difference			
	Pre-test		Post-test		Gain score	SMG	Pre-test		Post-test					Gain score	SMG
	M	SD	M	SD			M	SD	M	SD					
Score	15.09	2.62	29.40	2.80	14.31	5.46	15.46	2.60	22.49	3.11	7.03	2.70	-9.78**	-8.33	-5.50

Note. SMG represents the within-group (pre-to-post) effect size for mathematics achievement and is calculated as the gain score divided by the pre-test standard deviation for each group (Becker, 1988). This standardizer was selected because the pre-test standard deviation reflects performance variability uncontaminated by the intervention. Gain scores were calculated as post-test minus pre-test. **p < .01.

Table 8

Attention outcomes by group: pre-test, post-test comparison, and between-group effects.

Attention	NeuroConstruct teaching model					5E teaching model					F (df=(1,68))	Partial eta squared (η_p^2)	95% CI of the Difference	
	Pre-test		Post-test		Gain score	Pre-test		Post-test		Gain score				
	M	SD	M	SD		M	SD	M	SD					
Simple reaction accuracy	19.74	2.73	25.23	2.92	5.49	19.03	3.04	22.94	3.12	3.91	9.94**	0.13	-3.73	-0.84
Focus attention accuracy	17.94	2.67	22.57	3.62	4.63	17.31	2.83	19.94	3.56	2.63	9.36**	0.12	-4.34	-0.91
Selected attention accuracy	19.43	2.74	23.11	3.36	3.68	18.26	2.69	20.51	3.29	2.25	10.69**	0.14	-4.19	-1.01
Sustained attention accuracy	20.09	3.29	22.06	3.49	1.97	19.06	3.17	19.03	3.36	-0.03	13.66**	0.17	-4.66	-1.39

Note. η_p^2 = partial eta squared. Gain scores were calculated as post-test minus pre-test. The 95% CI for the between-group difference in post-tests refers to the 95% confidence interval for the between-group difference in post-tests. **p < .01.

Table 9

Working memory outcomes by group: pre-test, post-test comparison, and between-group effects.

Working memory	NeuroConstruct teaching model					5E teaching model					F (df=(1,68))	Partial eta squared (η_p^2)	95% CI of the Difference	
	Pre-test		Post-test		Gain score	Pre-test		Post-test		Gain score				
	M	SD	M	SD		M	SD	M	SD					
Basic processing accuracy	17.91	3.50	25.77	2.10	7.86	18.40	2.80	23.54	3.17	5.14	12.04**	0.15	-3.51	-0.95
Shifting working memory accuracy	17.03	3.76	22.23	3.59	5.20	17.94	2.73	19.34	3.64	1.40	11.16**	0.14	-4.61	-1.16
Updating working memory accuracy	16.74	3.17	22.49	3.65	5.75	17.09	3.27	18.66	3.93	1.57	17.86**	0.21	-5.64	-2.02
Inhibiting working memory accuracy	15.11	3.72	22.66	3.51	7.55	15.66	3.51	17.77	4.39	2.11	26.45**	0.28	-6.78	-2.99

Note. η_p^2 = partial eta squared. Gain scores were calculated as post-test minus pre-test. The 95% CI for the between-group difference in post-tests refers to the 95% confidence interval for the between-group difference in post-tests. **p < .01.

6.2.1. Independent-sample T-Test

Table 7 summarizes mathematics achievement outcomes for the experimental group taught using the NeuroConstruct teaching model (n = 35) and the control group taught using the 5E teaching model (n = 35). Pre-test results indicated comparable baseline performance between groups (NeuroConstruct: M = 15.09, SD = 2.62; 5E: M = 15.46, SD = 2.60).

Post-test results showed improvement in both groups; however, gains were substantially greater for the experimental group. Students receiving the NeuroConstruct teaching model achieved a post-test (M = 29.40, SD = 2.80), corresponding to a gain score of 14.31 and a very large effect size (SMG = 5.46). In contrast, the control group attained a post-test score (M = 22.49, SD = 3.11), with a gain score of 7.03 and a smaller, though still large, effect size (SMG = 2.70).

An independent samples t-test was conducted to compare post-test mathematics achievement between the experimental and control groups. Levene’s test indicated that the assumption of homogeneity of variances was not violated, F(1, 68) = 0.632, p = .429. Therefore, the equal-variance assumption was interpreted. The results revealed a statistically significant difference between the two groups, t(68) = -9.78, p < .001, with a mean difference of -6.91 (95% CI [-8.33, -5.50]), indicating that the experimental group outperformed the control group.

6.3. Attention

The accuracy scores also measured attention. Table 8 shows the pre-post-test M (Mean Scores) and SD (Standard Deviation) of the experimental and control groups measured by each subtest.

6.3.1. Multivariate test

All the multivariate tests (Wilks’ Lambda) were significant for attention accuracy. It suggested that the teaching model significantly influenced attention at the 0.05 significance level (F(4, 65) = 4.57, p = .003) and accounted for 22.00% of the variance in attention (η_p^2 = 0.220).

Table 8 presents descriptive statistics and inferential results for attention outcomes across four subdimensions: simple reaction accuracy, focus attention accuracy, selected attention accuracy, and sustained attention accuracy, for both the experimental group (NeuroConstruct teaching model) and the control group (5E teaching model). Mean scores and standard deviations are reported for pre-test and post-test assessments, along with gain scores reflecting changes following the intervention. In addition, univariate analysis results, including F statistics, partial eta squared (η_p^2), and 95% confidence intervals for between-group differences in post-test scores, are provided to

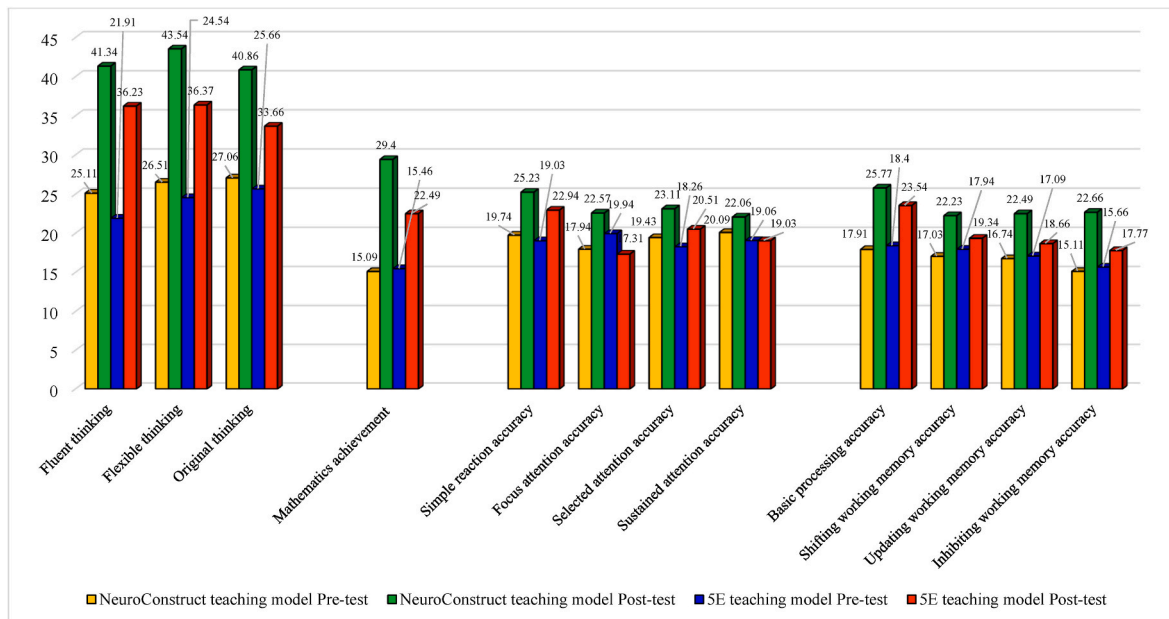


Fig. 4. Pre-test and post-test mean scores across outcome variables for the NeuroConstruct teaching model and the 5E teaching models.

support the interpretation of instructional effects.

Across all attention dimensions, students in the experimental group demonstrated consistently greater improvements from pre-test to post-test than those in the control group.

For simple reaction accuracy, the experimental group showed a notable increase from pre-test ($M = 19.74$, $SD = 2.73$) to post-test ($M = 25.23$, $SD = 2.92$), yielding a gain score of 5.49. In contrast, the control group improved from pre-test ($M = 19.03$, $SD = 3.04$) to post-test ($M = 22.94$, $SD = 3.12$), with a gain score of 3.91. The between-group difference was statistically significant, $F(1, 68) = 9.94$, $p = .002$, with a medium effect size ($\eta_p^2 = 0.13$). The 95% confidence interval $[-3.73, -0.84]$ did not include zero, indicating a reliable advantage for the experimental group.

For focus attention accuracy, the experimental group improved from pre-test ($M = 17.94$, $SD = 2.67$) to post-test ($M = 22.57$, $SD = 3.62$), with a gain score of 4.63. In contrast, the control group also improved from pre-test ($M = 17.31$, $SD = 2.83$) to post-test ($M = 19.94$, $SD = 3.56$), with a gain score of 2.63. The between-group difference was statistically significant, $F(1, 68) = 9.36$, $p = .003$, with a medium effect size ($\eta_p^2 = 0.12$). The confidence interval $[-4.34, -0.91]$ further supports the robustness of the group difference.

For selected attention accuracy, the experimental group demonstrated an increase from pre-test ($M = 19.43$, $SD = 2.74$) to post-test ($M = 23.11$, $SD = 3.36$), corresponding to a gain score of 3.68. The control group improved from pre-test ($M = 18.26$, $SD = 2.69$) to post-test ($M = 20.51$, $SD = 3.29$), with a gain score of 2.25. The between-group difference was statistically significant, $F(1, 68) = 10.69$, $p = .002$, with a medium effect size ($\eta_p^2 = 0.14$). The 95% confidence interval $[-4.19, -1.01]$ did not cross zero, confirming the effect's reliability.

For sustained attention accuracy, the experimental group showed a modest increase from pre-test ($M = 20.09$, $SD = 3.29$) to post-test ($M = 22.06$, $SD = 3.49$), yielding a gain score of 1.97. In contrast, the control group remained relatively stable, with pre-test ($M = 19.06$, $SD = 3.17$) and post-test ($M = 19.03$, $SD = 3.36$) scores, resulting in a negligible change (gain score = -0.03). The between-group difference was statistically significant, $F(1, 68) = 13.66$, $p < .001$, with a medium-to-large effect size ($\eta_p^2 = 0.17$). The confidence interval $[-4.66, -1.39]$ indicates a consistent advantage for the experimental group.

Overall, the results summarized in Table 8 indicate that the NeuroConstruct teaching model led to statistically significant improvements

across all attention dimensions compared with the 5E teaching model. The consistent pattern of medium-to-moderately large effect sizes ($\eta_p^2 = 0.12$ – 0.17) suggests that these differences are not only statistically significant but also educationally meaningful, highlighting the effectiveness of the NeuroConstruct teaching model in enhancing multiple components of attentional functioning.

Although both groups showed improvements in focus attention accuracy from pre-test to post-test, the magnitude of improvement differed substantially between the two instructional conditions. The experimental group's gain of 4.63 points was notably larger than the control group's gain of 2.63 points, and the between-group difference in post-test scores was statistically significant, $F(1, 68) = 9.36$, $p = .003$, $\eta_p^2 = 0.12$. This differential gain pattern suggests that while the 5E teaching model may facilitate modest attentional improvements through its inquiry-based instructional sequence, the NeuroConstruct teaching model produces substantially greater improvements in focused attention. This finding aligns with the theoretical premise of the NeuroConstruct teaching model, which systematically targets attentional control mechanisms through neuroscience-informed instructional strategies grounded in the principles of neuroconstructivism (Mareschal, Johnson, et al., 2012). In contrast, although the 5E teaching model is effective at promoting inquiry-based learning and conceptual understanding, it is not explicitly designed to systematically stimulate or sustain executive attention (Diamond, 2013). The fact that the control group nonetheless improved—rather than declined—in focus attention accuracy indicates that engagement in structured science instruction may confer some degree of attentional benefit, even without targeted neurocognitive training. However, the significantly larger gain in the experimental group underscores the added value of embedding explicit neurocognitive stimulation within the instructional design, which appears to amplify the attentional benefits beyond what conventional inquiry-based instruction alone can achieve.

6.4. Working memory

The accuracy scores also measured working memory. Table 9 shows the pre-post-test M (Mean Scores) and SD (Standard Deviation) of the experimental and control groups measured by each subtest.

6.4.1. Multivariate test

All multivariate tests (Wilks' Lambda) were significant for working memory accuracy. That is, the teaching models significantly influenced working memory at the 0.05 significance level ($F(4, 65) = 8.89, p < .001$) and accounted for 35.40% of the variance in working memory ($\eta_p^2 = 0.354$).

Table 9 presents descriptive statistics and inferential results for working memory outcomes across four subdimensions: basic processing accuracy, shifting working memory accuracy, updating working memory accuracy, and inhibiting working memory accuracy for both the experimental group (NeuroConstruct teaching model) and the control group (5E teaching model). Mean scores and standard deviations are reported for pre-test and post-test assessments, along with gain scores reflecting changes following the intervention. In addition, univariate analysis results, including F statistics, partial eta squared (η_p^2), and 95% confidence intervals for between-group differences in post-test scores, are provided to support the interpretation of instructional effects.

Across all dimensions of working memory, students in the experimental group demonstrated consistently greater improvements from pre-test to post-test compared with those in the control group, indicating the effectiveness of the NeuroConstruct teaching model in enhancing executive function processes.

For basic processing accuracy, the experimental group showed a substantial increase from pre-test ($M = 17.91, SD = 3.50$) to post-test ($M = 25.77, SD = 2.10$), yielding a gain score of 7.86. In contrast, the control group improved from pre-test ($M = 18.40, SD = 2.80$) to post-test ($M = 23.54, SD = 3.17$), with a gain score of 5.14. The between-group difference was statistically significant, $F(1, 68) = 12.04, p < .001$, with a medium effect size ($\eta_p^2 = 0.15$). The 95% confidence interval $[-3.51, -0.95]$ did not include zero, indicating a reliable advantage for the experimental group.

A similar pattern was observed for shifting working memory accuracy. The experimental group improved from pre-test ($M = 17.03, SD = 3.76$) to post-test ($M = 22.23, SD = 3.59$), with a gain score of 5.20, whereas the control group showed a smaller increase from pre-test ($M = 17.94, SD = 2.73$) to post-test ($M = 19.34, SD = 3.64$), with a gain score of 1.40. This difference was statistically significant, $F(1, 68) = 11.16, p < .001$, with a medium effect size ($\eta_p^2 = 0.14$). The confidence interval $[-4.61, -1.16]$ further supports the robustness of the group difference.

For updating working memory accuracy, the experimental group demonstrated a marked improvement from pre-test ($M = 16.74, SD = 3.17$) to post-test ($M = 22.49, SD = 3.65$), corresponding to a gain score of 5.75. The control group improved from pre-test ($M = 17.09, SD = 3.27$) to post-test ($M = 18.66, SD = 3.93$), with a gain score of 1.57. The between-group difference was statistically significant, $F(1, 68) = 17.86, p < .001$, with a medium-to-large effect size ($\eta_p^2 = 0.21$). The 95% confidence interval $[-5.64, -2.02]$ did not cross zero, confirming the effect's reliability.

For inhibiting working memory accuracy, the experimental group showed a substantial increase from pre-test ($M = 15.11, SD = 3.72$) to post-test ($M = 22.66, SD = 3.51$), yielding a gain score of 7.55. In comparison, the control group improved from pre-test ($M = 15.66, SD = 3.51$) to post-test ($M = 17.77, SD = 4.39$), with a gain score of 2.11. The between-group difference was statistically significant, $F(1, 68) = 26.45, p < .001$, with a large effect size ($\eta_p^2 = 0.28$). The confidence interval $[-6.78, -2.99]$ further confirms the strength and consistency of the effect.

Overall, the results summarized in Table 9 indicate that the NeuroConstruct teaching model led to statistically significant improvements across all dimensions of working memory compared with the 5E teaching model. The consistent pattern of medium to large effect sizes ($\eta_p^2 = 0.14-0.28$) suggests that these differences are not only statistically significant but also educationally meaningful, highlighting the effectiveness of the NeuroConstruct teaching model in enhancing core executive functions, particularly working memory processes essential for higher-order learning.

To support the interpretation of statistical findings, effect sizes were examined alongside p-values to evaluate the magnitude and educational relevance of the observed differences. Across all outcome variables, the NeuroConstruct teaching model consistently demonstrated medium-to-large effect sizes, indicating that the observed improvements are not only statistically significant but also practically meaningful in classroom contexts. Specifically, the magnitude of the effects suggests that a substantial proportion of the variance in students' creative thinking, mathematics achievement, attention, and working memory can be attributed to the instructional model rather than to random variation. From an educational perspective, effects of this magnitude reflect meaningful gains in higher-order cognitive processes and executive functions that are foundational to learning, including attentional control and working memory capacity. These findings indicate that the NeuroConstruct teaching model produces improvements likely to have real-world instructional impact, extending beyond statistically detectable differences to changes that are educationally substantive and relevant to classroom practice. Detailed definitions, calculation procedures, and interpretation criteria for all reported effect sizes are provided in the table notes to ensure transparency and reproducibility of the analysis, as shown in Table 10.

Table 10 shows the results; partial eta squared (η_p^2) represents the proportion of variance in the dependent variable explained by group membership (NeuroConstruct vs. 5E teaching model), controlling for other sources of variance. For mathematics achievement, within-group effect sizes were reported using SMG, computed as the gain score (post-test minus pre-test) divided by the pre-test standard deviation for each group (Becker, 1988). This index reflects the magnitude of pre-to-post change within each condition relative to baseline variability.

Confidence intervals (95% CI) refer to the estimated range of the true between-group difference. For gain-score analyses, the 95% CI represents the difference between the NeuroConstruct and 5E groups (NeuroConstruct minus 5E). A CI that does not include zero indicates a statistically reliable group difference. Gain scores were calculated as post-test minus pre-test. All η_p^2 values reported are between-group estimates; SMG values represent within-group effect sizes unless otherwise specified.

The effect sizes were interpreted using established benchmarks (Cohen, 1988; Lakens, 2013), where $\eta_p^2 \approx 0.01$ indicates a small effect, 0.06 a medium effect, and 0.14 or higher a large effect. For standardized mean differences, SMG values of 0.20, 0.50, and 0.80 correspond to small, medium, and large effects, respectively (Cohen, 1988). Beyond statistical significance, practical significance was evaluated by examining (1) the proportion of variance explained, (2) the relevance of the outcome to classroom learning, and (3) comparison with prior meta-analytic benchmarks in education and cognitive training (Hattie, 2009; Jacob & Parkinson, 2015; Melby-Lervåg & Hulme, 2013; Scott et al., 2004). This multi-criteria interpretation ensures that effect sizes are understood not only as statistical indices but also as indicators of meaningful educational impact.

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The implementation fidelity analysis indicated high adherence to the

NeuroConstruct teaching model. Across the 2 instructional sessions, the mean fidelity score was 1.82 (SD = 0.14), corresponding to an overall adherence rate of 91.0%. All six teaching syntaxes were consistently implemented, with slightly lower adherence observed during early sessions in the “connecting body and society” phase, which improved over time following formative feedback. To examine the potential influence of fidelity on learning outcomes, exploratory correlational analyses were conducted between session-level fidelity scores and students’ gain scores. Results indicated a positive association, suggesting that higher levels of implementation fidelity were linked to greater improvements in cognitive and academic outcomes. Although these analyses were exploratory, they provide preliminary evidence of the importance of high-fidelity implementation for achieving the intervention’s intended effects.

7. Discussion

7.1. Interpretation of key findings

The findings are interpreted at the behavioral level, while drawing on educational neuroscience and Neuroconstructivism as explanatory theoretical lenses rather than as sources of direct neurobiological evidence.

A key strength of the present study lies in its ecological validity. Unlike laboratory-based or highly controlled intervention studies, the NeuroConstruct teaching model was implemented in an authentic school setting under real instructional conditions. The intervention, aligned with the Thai national curriculum, was integrated into regular classroom schedules and delivered through standard pedagogical practices. These features ensure that the findings are grounded in realistic educational contexts, thereby enhancing their external validity and practical applicability. From an educational perspective, this ecological grounding is particularly important, as it provides preliminary evidence that neuroscience-informed instructional models can be feasibly enacted within existing school systems without requiring specialized infrastructure. However, because this evidence derives from a single school and a five-week implementation period, the practical feasibility of broader adoption remains an empirical question requiring further replication.

The findings show that students exposed to the NeuroConstruct teaching model achieved higher post-test scores than those taught using the 5E teaching model across the assessed domains. These results are consistent with the potential promise of a neuroscience-informed instructional design; however, causal claims are not warranted because school-based studies may retain uncontrolled sources of bias and did not include an attention/placebo control condition (Cook & Campbell, 1979; Shadish et al., 2002). Therefore, the present evidence should be interpreted as comparative support and should be extended through replication across contexts and more rigorous control strategies. While the observed improvements in cognitive and academic outcomes are theoretically consistent with Neuroconstructivism principles, it is important to emphasize that the present study did not directly measure neural activity or neurobiological change. Therefore, any references to underlying neural mechanisms should be interpreted as theoretically informed explanations rather than empirical evidence, consistent with established cautions against reverse inference in educational neuroscience (Bruer, 1997; Howell, 2013).

Conducting the present study in an authentic secondary school setting aligned with the Thai national core curriculum substantially strengthens its practical relevance and ecological validity. The NeuroConstruct teaching model was not examined under highly controlled laboratory conditions but rather implemented within the structural constraints of real classrooms, including fixed instructional time, curriculum standards, and prevailing pedagogical practices. This intervention in everyday schooling conditions enhances the credibility of the findings for educational practitioners and policymakers (Fischer et al.,

Table 10
Effect size interpretation matrix for creative thinking, mathematics achievement, attention, and working memory.

Outcome Variable	Statistical Index	Observed Effect Size	Magnitude Interpretation	Variance Explained	Practical (Educational) Significance	Benchmark Comparison	Interpretation Statement
Creative Thinking	η^2	0.193	Large (Cohen, 1988; Lakens, 2013)	19.3%	Substantial improvement in divergent thinking processes (fluent thinking, flexible thinking, original thinking) relevant to 21st-century skills	Comparable to strong creativity interventions ($d \approx 0.64$; Scott et al., 2004)	Indicates that nearly one-fifth of the variance in creative thinking is attributable to the instructional model, reflecting a meaningful shift in higher-order cognitive performance
Mathematics Achievement	SMG	SMG of the NeuroConstruct teaching model = 5.46, SMG of the 5E teaching model = 2.70	Large (Cohen, 1988)	—	Represents meaningful improvement in curriculum-aligned mathematical reasoning and problem-solving ability	Exceeds typical classroom intervention effects (Hattie, 2009; $d \approx 0.40$)	Suggests that the NeuroConstruct model produces gains beyond typical instructional variation, with strong implications for academic achievement
Attention	η^2	0.220	Large (Cohen, 1988; Lakens, 2013)	22.0%	Enhances attentional control (selective, sustained, executive), which underpins learning readiness and engagement	Higher than typical EF interventions (Jacob & Parkinson, 2015)	Demonstrates that the intervention meaningfully improves cognitive control processes critical for classroom learning
Working Memory	η^2	0.354	Very large (Cohen, 1988; Lakens, 2013)	35.4%	Strong enhancement of information processing, updating, and cognitive load management	Substantially exceeds WM training meta-analyses ($g \approx 0.46$; Melby-Lervåg & Hulme, 2013)	Indicates a powerful instructional effect on core executive function, suggesting high practical relevance for learning and transfer

Note. η^2 = partial eta squared; SMG = Standardized Mean Gain of Becker (1988). η^2 values indicate the magnitude of between-group differences attributable to the teaching model; SMG values indicate within-group (pre-to-post) effect sizes standardized by the pre-test standard deviation.

2010; McKenney & Reeves, 2019). Moreover, the alignment of the NeuroConstruct teaching model with mandated curricular content, specifically graphs, relations, and functions, suggests that the model may be integrated into existing curricular frameworks without necessitating structural curricular reform, although this preliminary finding requires replication across different curricula and subject areas. The clearly articulated instructional phases and the absence of reliance on specialized neuroscientific equipment further support the model's potential scalability across diverse school contexts. From a design-based research perspective, these characteristics position the NeuroConstruct teaching model as a feasible and adaptable instructional innovation that may be extended beyond the original research site, subject to further empirical validation (Darling-Hammond et al., 2017; Plomp, 2013).

From a neuroconstructivist perspective, the observed gains can be interpreted as the outcome of systematic engagement with attention and working memory, foundational cognitive resources that support higher-order learning. Attention functions as a gatekeeper for information processing, while working memory enables the temporary maintenance and manipulation of representations necessary for mathematical reasoning and creative problem-solving (Baddeley, 2003; Zhao et al., 2021).

The NeuroConstruct teaching model explicitly embedded instructional activities that required sustained attentional focus, representational coordination, and iterative cognitive updating. These features are theoretically aligned with interactive specialization and experience-dependent plasticity, which suggest that repeated, structured cognitive engagement promotes the refinement of neural representations over time (Johnson, 2011; Karmiloff-Smith, 2017). Accordingly, improvements in attention and working memory may help explain the observed gains in creative thinking and mathematics achievement; however, this mediational pathway was not directly tested in the present study.

The present study highlights distinct theoretical and practical differences between the NeuroConstruct teaching model and the conventional 5E teaching model. While both models foster active engagement and conceptual understanding, Neuroconstructivism integrates a multi-constraint developmental framework emphasizing dynamic interactions among genetic, neural, embodied, social, and environmental factors (Astle et al., 2023; Karmiloff-Smith, 2017; Mareschal, Johnson, et al., 2012). This neurobiological grounding provides structured support for cognitive processes relevant to learning, such as attention, working memory, and creative thinking, which have been empirically shown to improve more significantly under the NeuroConstruct teaching model than under the 5E teaching model.

In contrast, the 5E model, rooted in constructivist pedagogy, primarily facilitates inquiry-based learning through sequential phases of Engage, Explore, Explain, Elaborate, and Evaluate (Bybee et al., 2006; IPST, 2012). Although effective in promoting conceptual understanding and student motivation, the 5E model does not explicitly address neurocognitive mechanisms or integrate principles of neural development.

Therefore, the enhanced learning outcomes observed in this study under the NeuroConstruct teaching model may be theoretically interpreted through the lens of brain plasticity and cognitive control principles, although the present study did not directly measure neural activity. This interpretation suggests that teaching models informed by neuroscientific principles may offer added benefits in developing higher-order cognitive skills, a hypothesis that warrants further investigation using neuroimaging or physiological measures (Polanin et al., 2024). This comparison underscores the potential for educational frameworks to evolve beyond traditional pedagogical models by integrating interdisciplinary insights from neuroscience and cognitive psychology to optimize student learning.

Although the sample of 70 students was relatively small, it was randomly selected from the population of 126 seventh-grade students at the school, thereby supporting the representativeness of the findings. Nevertheless, caution should be exercised when generalizing the results beyond this context. Future studies with larger samples and diverse

educational settings are recommended to validate and extend these findings (Creswell & Creswell, 2018).

This research suggests that Neuroconstructivism provides a contemporary foundation for developing a teaching model that improves learner outcomes. Specifically, the NeuroConstruct teaching model focuses on systematically developing students' creative thinking (including fluent thinking, flexible thinking, and original thinking), mathematics achievement (covering topics such as graphs, relations, and functions), as well as cognitive functions like attention and working memory, grounded in Neuroconstructivism principles (Karmiloff-Smith, 2017; Mareschal, Johnson, et al., 2012; Srikoon et al., 2018). The instructional process comprises six structured phases: neuron stimulation, neuron construction, integration of brain regions, coordination between the brain and body, embedding learning in social contexts, and integration of all developmental constraints (Astle et al., 2023). Detailed lesson plans and teaching guides support teachers in implementing these phases through activities that promote bidirectional learning among neural, bodily, and environmental factors. The findings of this study provide context-specific comparative evidence indicating that the NeuroConstruct teaching model is associated with improvements in creative thinking, mathematics achievement, attention, and working memory among Grade 7 students within the examined instructional setting. However, these results must be interpreted with caution. The data were collected from a single school, involved a relatively small sample size, focused on one grade level and one mathematics topic, and were based on a short intervention period.

Consequently, the present findings should not be generalized to all classrooms, grade levels, subject areas, or educational contexts. Rather, they should be understood as context-bound empirical evidence that demonstrates the potential instructional value of the NeuroConstruct teaching model under specific conditions. Broader instructional recommendations and claims of general applicability require replication across diverse schools, age groups, subject domains, and longer implementation periods, using robust experimental and true-experimental designs (Creswell & Creswell, 2018; Shadish et al., 2002).

These findings suggest the value of instructional approaches informed by Neuroconstructivist principles that attend to the cognitive, embodied, and social dimensions of learning. All constraints are involved at all levels, spanning genes, neural activity, brain region, body, and society, and the integration of these principles may help inform the development of a novel teaching approach aimed at supporting cognitive and academic learning outcomes. (Karmiloff-Smith et al., 2018; Westerman et al., 2007; Winitisiri & Srikoon, 2026). To facilitate effective information processing, the sensory register temporarily stores a large amount of incoming sensory information. This selective storage, which involves attention, allows relevant information to be further processed and encoded into working memory. This will enhance working memory and facilitate the retention of more knowledge in long-term memory (Sweatt, 2010; White, 2020). While the findings suggest that improvements in attention and working memory were associated with better mathematics achievement and creative thinking, these cognitive functions should be understood as foundational supports rather than isolated targets. Effective educational interventions should therefore allocate time and resources to concurrently develop attention, working memory, creative thinking skills, and mathematical competencies. Such a holistic approach aligns with the Neuroconstructivism framework, which emphasizes the interdependent and reciprocal nature of these cognitive processes in fostering academic success (Baddeley, 2003; Lee & Bull, 2016; Mumford et al., 2012). Focusing exclusively on attention and working memory at the expense of direct training in creativity and mathematics might overlook the domain-specific skills and knowledge essential for students' overall development and performance. Moreover, the NeuroConstruct teaching model is grounded in contemporary neuroscience and cognitive psychology, which emphasize the interactive development of neural systems supporting attention, working memory, creative thinking, and

mathematical reasoning (Astle et al., 2023; Karmiloff-Smith, 2017; Srikoon et al., 2018). The present study provides comparative evidence that students in the NeuroConstruct group achieved better mathematics outcomes and demonstrated greater creative thinking than those in the 5E group under the conditions of this study. This suggests that the model effectively engages neural and cognitive mechanisms critical to these domains. Furthermore, enhancing creative thinking and mathematics skills supports learners in developing innovative products and fosters other essential 21st-century skills, including problem-solving, critical thinking, and adaptability (Marchetti, 2014; Mumford et al., 2012). Thus, the assumption that the NeuroConstruct teaching model can enhance mathematics achievement and foster creative thinking, ultimately leading to broader 21st-century competencies, is substantiated by both theoretical foundations and empirical findings.

The present study's findings provide initial evidence that the NeuroConstruct teaching model may contribute to improvements in cognitive and academic skills, particularly creative thinking, mathematics achievement, attention, and working memory. These results align with Neuroconstructivism theory, which emphasizes the dynamic interaction of genetic, neural, embodied, social, and environmental factors in cognitive development (Karmiloff-Smith, 2017; Mareschal, Johnson, et al., 2012). The model's systematic approach to decomposing complex cognitive processes into manageable instructional components is theoretically consistent with principles of targeted cognitive engagement; however, the observed improvements should be interpreted at the behavioral level, as the present study did not include direct measures of neural network activity.

In practice, the teaching model can be further improved by developing tailored lesson plans that incorporate individualized scaffolding tailored to learners' unique neurocognitive profiles, thereby optimizing proactivity and engagement (Astle et al., 2023). Teachers can be trained to implement embodied and socially contextualized learning activities that integrate physical movement, collaboration, and reflective practice, consistent with the model's six instructional phases. For example, incorporating kinesthetic exercises linked to mathematical concepts or problem-solving tasks that require flexible thinking may enhance neural plasticity and cognitive transfer (Johnson, 2011; Karmiloff-Smith, 2009a).

Future applications of the NeuroConstruct teaching model should also include professional development programs for educators that focus on educational neuroscience principles, assessment strategies aligned with neurocognitive outcomes, and the integration of technology to dynamically monitor and adapt instruction (Srikoon, 2020a). Such enhancements can support sustainable implementation and wider adoption across diverse educational contexts.

7.2. Theoretical integration with neuroconstructivism

Neuroconstructivism is an interdisciplinary science dedicated to designing innovative teaching models that integrate insights from neuroscience, cognitive psychology, and educational theory (Ramus, 2004; Sirois et al., 2008). This approach involves developing novel concepts and detailed theoretical explanations to enhance pedagogical practices. Specifically, classroom applications of Neuroconstructivism aim to improve teaching effectiveness and enhance students' learning outcomes.

In the present study, the NeuroConstruct teaching model was systematically developed and implemented as an educational intervention. The model comprises six structured instructional phases: neuron stimulation, neuron construction, connecting brain regions, connecting brain and body, connecting body and society, and integrating all developmental constraints. These phases target the dynamic interactions among genetic activity, neural processes, embodied cognition, and social context to facilitate cognitive development.

This intervention was delivered over five weeks, focusing on mathematical concepts aligned with the curriculum. The NeuroConstruct

teaching model is designed to target cognitive processes — including creative thinking, mathematics achievement, attention, and working memory — through instructional activities theoretically informed by neurocognitive principles. The NeuroConstruct teaching model is grounded in Neuroconstructivist theory, which offers one possible framework for interpreting the stronger outcomes observed in the experimental group relative to the 5E group. However, the present study did not directly examine experience-dependent plasticity, brain development, or other neurobiological mechanisms.

Empirical findings from this study indicate that students taught under the NeuroConstruct teaching model outperformed peers in the control group across all measured domains. These results provide preliminary support for the promise of Neuroconstructivism-informed instructional design in improving cognitive and academic outcomes in secondary education, although the single-site, short-term design warrants caution in drawing definitive conclusions.

Drawing on the interdisciplinary foundations of Neuroconstructivism (Ramus, 2004; Sirois et al., 2008), the NeuroConstruct teaching model was designed to operationalize these principles into classroom practice. Although the term “NeuroConstruct teaching model” is derived from the broader Neuroconstructivism theoretical framework, it specifically refers to the structured instructional approach developed and implemented in this study. Neuroconstructivism, as a theoretical paradigm, emphasizes the dynamic, multi-constraint interactions underlying cognitive development. The NeuroConstruct teaching model operationalizes these principles into six actionable instructional phases that target cognitive domains. It is important to distinguish between the theoretical framework and the applied teaching model to avoid conflating the two. Some summary ideas presented in previous sections may unintentionally mix foundational theoretical concepts with novel instructional details, which could lead to misunderstanding if not carefully delineated (Astle et al., 2023; Karmiloff-Smith, 2017).

While this study provides promising evidence in support of the NeuroConstruct teaching model, we acknowledge that educational transformation is a complex and ongoing process that requires further investigation and collaborative efforts. The concept of Neuroconstructivism serves as a comprehensive theoretical framework that integrates multiple interacting constraints, including genetic factors, neural development, bodily engagement, and social context, to explain cognitive development dynamically (Karmiloff-Smith, 2017; Mareschal, Johnson, et al., 2012). This approach emphasizes bidirectional interactions among these factors, which shape the evolution of cognitive representations over time (Astle et al., 2023; Johnson, 2011). Applying this framework to teaching model development, the NeuroConstruct teaching model was systematically designed to operationalize these principles into six instructional phases: neuron stimulation, neuron construction, connecting brain regions, connecting brain and body, connecting body and society, and integrating all constraints. Each phase aligns with core Neuroconstructivism concepts and aims to engage students' neural, cognitive, embodied, and social systems in a coherent and developmentally appropriate manner (Srikoon, 2024). In classroom application, this model promotes active learner engagement through structured activities that foster higher-order cognitive skills such as creative thinking, mathematical reasoning, attention, and working memory. The teaching strategies encourage learners to actively explore and manipulate their environment, facilitating experience-dependent neuroplasticity and social interaction (Karmiloff-Smith, 2013; Westermann et al., 2007). The effectiveness of this approach was empirically supported by the study's findings, which demonstrated significant improvements in students' cognitive and academic outcomes compared to the 5E teaching model (Srikoon, 2024). Moreover, detailed lesson plans and teaching guides were developed to ensure practical feasibility and fidelity in implementation by educators.

To address the need to enhance teachers' understanding of Neuroconstructivism and to develop practical instructional activities, this

paper elaborates on the theoretical foundations and practical implementation of the NeuroConstruct teaching model. The model was co-developed by experts in cognitive neuroscience, curriculum design, and developmental psychology, ensuring its rigorous theoretical alignment and practical feasibility (Astle et al., 2023; Karmiloff-Smith, 2017; Mareschal, Johnson, et al., 2012). It integrates multiple interacting constraints such as genetic, neural, embodied, social, and environmental factors, which are systematically engaged through six instructional phases designed to operationalize Neuroconstructivism principles in classroom teaching (Johnson, 2011; Mareschal, Johnson, et al., 2012). The intervention includes detailed lesson plans and teaching guides that provide clear pedagogical strategies and activities, explicitly targeting cognitive functions such as creative thinking, mathematics achievement, attention, and working memory (Srikoon, 2019; Srikoon et al., 2018). Moreover, the model emphasizes active learner engagement through brain-body-environment interactions and social embeddedness, promoting proactivity and experience-dependent neuroplasticity (Astle et al., 2023; Karmiloff-Smith, 2013). These aspects are described in the Intervention Process section, providing educators with concrete guidance for designing and implementing Neuroconstructivism-informed instructional activities effectively. Therefore, this study not only demonstrates the effectiveness of the NeuroConstruct teaching model on student outcomes but also provides foundational knowledge and practical tools to support teachers in understanding and applying Neuroconstructivism principles in their instructional design.

Several methodological constraints limit the ability to draw causal inferences in the present study. First, as is typical of authentic school-based interventions, residual confounding cannot be fully ruled out, including potential influences of student motivation, classroom conditions, or differential familiarity with computerized assessments. Second, the absence of a placebo or attention-control condition restricts the ability to disentangle instructional effects from nonspecific attention or novelty effects. Third, the practical constraints of classroom research limit the feasibility of blinding participants and instructors.

Consequently, the findings should be interpreted as comparative evidence of instructional effectiveness rather than definitive causal proof (Cook & Campbell, 1979; Shadish et al., 2002). In addition, because the study did not include direct measures of brain activity or neural change, any references to neurobiological mechanisms remain theoretical and cannot be empirically substantiated within the present research design.

7.3. Practical significance of effect sizes

Practical significance and comparison with prior evidence. Beyond statistical significance, the obtained partial eta squared values indicate educationally meaningful magnitudes of impact. Using conventional guidelines for η^2/η_p^2 (small ≈ 0.01 , medium ≈ 0.06 , large ≈ 0.14), the overall effects for creative thinking ($\eta_p^2 = 0.193$) and attention ($\eta_p^2 = 0.220$) can be interpreted as large, while the effect for working memory ($\eta_p^2 = 0.354$) is very large, implying that a substantial proportion of post-intervention variance is attributable to the instructional model rather than random fluctuation (Cohen, 1988; Lakens, 2013). These values correspond to Cohen's f of approximately 0.49 (creative thinking), 0.53 (attention), and 0.74 (working memory), further supporting the conclusion that the NeuroConstruct model was associated with practically meaningful gains in classroom-relevant cognitive outcomes (Cohen, 1988; Lakens, 2013). From an educational perspective, effects of this magnitude suggest that the intervention is not merely producing "detectable" differences, but shifts large enough to plausibly influence students' learning readiness (attention control) and information processing capacity (working memory), which are widely recognized as foundational for academic learning and problem solving (Jacob & Parkinson, 2015; Maher et al., 2013).

Importantly, the magnitude of the present effects compares favorably with prior evidence on interventions. For creativity-focused

interventions, a classic meta-analysis reported an average effect size of 0.64 for creativity-training outcomes, indicating a moderate-to-strong effect under well-designed programs (Scott et al., 2004). In contrast, meta-analytic evidence on working memory training in children often shows moderate near-transfer effects (e.g., around $g \approx 0.46$) but small far-transfer effects to broader academic outcomes (Melby-Lervåg & Hulme, 2013; Schwaighofer et al., 2015). The comparatively large effect observed for working memory in this study ($\eta_p^2 = 0.354$) suggests that the NeuroConstruct model may operate differently from "practice-only" cognitive training by embedding executive demands within authentic mathematics learning activities and sustained instructional routines, thereby increasing the likelihood of functional classroom relevance. Nevertheless, because η_p^2 can be sensitive to design features and may not be directly comparable to standardized mean differences across studies, replication across sites and longer follow-up are needed to confirm generalizability and durability (Lakens, 2013; Maher et al., 2013).

7.4. Strengths of the study

Contribution The study's primary contribution is its systematic translation of Neuroconstructivism — predominantly a theoretical account of multi-constraint cognitive development — into a structured, classroom-implementable teaching model with clearly articulated instructional phases. Whereas prior educational neuroscience research has largely remained at a conceptual or laboratory level (Fischer et al., 2010; Tokuhama-Espinosa, 2011), the NeuroConstruct teaching model operationalizes neurodevelopmental principles into six defined teaching syntaxes suitable for secondary mathematics instruction (Karmiloff-Smith, 2017; Mareschal, Johnson, et al., 2012). This theory-to-practice translation addresses the gap between neuroscience research and classroom application identified in the introduction.

Design and methodological strengths. Several features of the research design enhance the credibility of the findings. First, the study employed a true experimental pretest–posttest control-group design with random assignment, which supports causal inference more strongly than the quasi-experimental alternatives commonly used in classroom research (Creswell & Creswell, 2018; Shadish et al., 2002). Second, and critically, the comparison condition was an active control — the widely adopted 5E teaching model (Bybee et al., 2006) — rather than a no-treatment or passive control group. This design choice provides a more stringent test of the NeuroConstruct model's added instructional value, as any observed differences are less likely to be attributable solely to general instructional engagement or novelty effects (Polanin et al., 2024). Third, the intervention was conducted within an authentic classroom context aligned with the Thai national curriculum, which strengthens ecological validity and practical relevance (Bronfenbrenner, 1977; Brown, 1992). Fourth, the study concurrently assessed creative thinking, mathematics achievement, attention, and working memory using instruments with established validity and reliability ranging from satisfactory to high (Cohen et al., 2018; Srikoon, 2019). This integrated measurement approach is consistent with Neuroconstructivism's premise that academic performance emerges from coordinated cognitive processes (Astle et al., 2023; Lee & Bull, 2016).

7.5. Educational implications

Beyond the specific findings reported above, the present study carries implications across several domains. In educational neuroscience, empirical evaluation of Neuroconstructivist principles through a true-experimental design contributes to efforts to bridge the long-standing gap between neuroscience theory and educational practice (Fischer et al., 2010; Thomas et al., 2021). In instructional design, the six clearly defined teaching syntaxes provide a replicable structure amenable to fidelity assessment and iterative refinement, thereby contributing to the methodological foundations of Educational Design

Research (McKenney & Reeves, 2019; Plomp, 2013).

Next, regarding teacher professional development, the NeuroConstruct teaching model provides a theoretically grounded framework to support teachers in aligning instructional decisions with learners' cognitive and developmental characteristics. By making cognitive mechanisms such as attention and working memory pedagogically visible, the model has potential value for professional learning initiatives that emphasize understanding how students learn, rather than focusing solely on techniques or content coverage (Darling-Hammond et al., 2017).

Finally, at the policy and curriculum innovation level, the model's structured yet low-resource design may offer preliminary implications for scalability and adaptation across educational contexts; however, these possibilities should be interpreted cautiously and require further validation across broader settings. Because the NeuroConstruct teaching model does not require specialized neuroscientific equipment, it offers a feasible approach to curriculum innovation that integrates educational neuroscience principles into mainstream schooling. As such, the findings provide preliminary empirical evidence that may inform curriculum development and policy discussions related to 21st-century learning and neuroscience-informed education.

Although the findings demonstrate statistically significant advantages of the NeuroConstruct teaching model over the 5E model, these results should be interpreted with caution, given alternative explanatory mechanisms. In particular, novelty effects may have contributed to increased student motivation and engagement, as exposure to a new and cognitively stimulating instructional approach can temporarily enhance performance independent of its inherent effectiveness (Clark, 1983; Hidi & Renninger, 2006). In addition, teacher-related influences, including subtle variations in instructional enthusiasm, expectations, or delivery emphasis, may have shaped student outcomes despite efforts to standardize teaching conditions (Darling-Hammond et al., 2017). Furthermore, Hawthorne effects cannot be fully ruled out, as students' awareness of participating in an intervention study may have influenced their engagement and performance (Adair, 1984). Collectively, these factors suggest that the observed improvements may reflect a combination of instructional effects and contextual influences, underscoring the need for cautious interpretation and further replication using more controlled or longitudinal designs.

An important methodological strength of the present study lies in the systematic assessment of implementation fidelity. By operationalizing fidelity as a quantitative construct and demonstrating high inter-rater reliability, the study provides robust evidence that the NeuroConstruct teaching model was delivered as intended. This strengthens the internal validity of the findings by reducing ambiguity regarding whether observed effects can be attributed to the instructional model rather than to variations in implementation (Durlak & DuPre, 2008). Furthermore, the observed positive association between fidelity levels and student outcomes suggests that the effectiveness of the NeuroConstruct teaching model depends on consistent, high-quality implementation. This finding aligns with prior research emphasizing the critical role of fidelity in intervention-based educational studies and underscores the importance of structured teacher support and monitoring mechanisms.

8. Limitations and future directions

Several limitations of the present study should be acknowledged. First, the sample was drawn from a single secondary school and consisted of only 70 Grade 7 students. This relatively small and context-specific sample limits the generalizability of the findings to other educational settings with different sociocultural, institutional, or instructional conditions (Shadish et al., 2002).

Second, the intervention was implemented over a five-week period, which may be sufficient to detect short-term effects but is insufficient to establish the durability of improvements in creative thinking, mathematics achievement, attention, and working memory. Evidence from

educational neuroscience and cognitive training research consistently indicates that sustained and repeated exposure is often necessary for cognitive and academic gains to be consolidated and maintained over time (Diamond & Ling, 2016; Melby-Lervåg & Hulme, 2013; Sala & Gobet, 2017). Accordingly, the observed improvements should be interpreted as immediate post-intervention effects rather than enduring developmental changes.

Third, no follow-up measurement was conducted after the intervention. Consequently, it remains unclear whether the observed gains were maintained over time or reflected only short-term effects immediately following the instructional treatment. Prior research has consistently indicated that short-term intervention effects do not necessarily translate into long-term retention or transfer in the absence of continued reinforcement (Cook & Campbell, 1979; Hattie, 2009; Shadish et al., 2002). Future studies employing longitudinal designs with delayed post-test assessments are, therefore, necessary to determine whether the effects of the NeuroConstruct teaching model are sustained, attenuated, or amplified over time.

Fourth, although a true experimental design with random assignment was employed, conducting the study within an authentic classroom context means that certain sources of residual confounding cannot be fully eliminated. These include teacher effects, novelty effects, and classroom-level dynamics, as well as more nuanced contextual factors such as teacher-student interactions, classroom climate, student motivation, prior learning experiences, and peer dynamics, all of which may have influenced student engagement and performance independently of the NeuroConstruct teaching model itself (Campbell & Stanley, 1963; Shadish et al., 2002). Importantly, these implementation constraints do not invalidate the experimental classification of the study but do warrant caution in interpreting causal inferences. Future research employing multi-site randomized designs or more tightly controlled experimental conditions would further strengthen the generalizability and causal specificity of the findings.

Furthermore, although the same teacher delivered both conditions to control for between-teacher variability, this single-teacher design introduces several potential threats to internal validity. First, expectancy effects may have occurred if the teacher held differential outcome expectations for the two instructional models, consciously or unconsciously favoring the NeuroConstruct condition (Rosenthal & Jacobson, 1968). Second, differential enthusiasm is difficult to rule out: because the NeuroConstruct model was novel and theoretically foregrounded in the study, the teacher may have engaged with it more energetically than with the familiar 5E model, thereby introducing a confound between instructional content and delivery quality. Third, implementation asymmetry may have arisen from differences in the teacher's depth of familiarity with each model: the NeuroConstruct model was the focus of targeted pre-intervention training, whereas the 5E model was part of existing practice, potentially leading to unequal implementation precision. Although standardized lesson plans, instructional protocols, and fidelity monitoring were employed to mitigate these risks, they cannot entirely eliminate within-teacher variability. Future studies should consider employing multiple teachers, counterbalanced designs, or hierarchical modeling approaches (e.g., multilevel analysis) to better isolate instructional effects from teacher-related confounds.

Fifth, although implementation fidelity was systematically assessed using a structured 12-indicator rubric with quantitative scoring ($M = 1.82$, $SD = 0.14$; 91% adherence) and demonstrated excellent inter-rater reliability ($ICC > 0.95$), two limitations of the fidelity assessment warrant acknowledgment. First, observations were conducted in only 2 out of 10 sessions (approximately 20% of the intervention period), which may not fully capture session-to-session variability in implementation quality. Second, the fidelity rubric was developed specifically for this study rather than drawn from an independently validated instrument, which limits the comparability of fidelity data with those reported in other intervention research (Carroll et al., 2007; Century et al., 2010). Future research should extend fidelity observations to a larger

proportion of instructional sessions and adopt independently validated fidelity frameworks to further strengthen internal validity and enable cross-study comparisons (Durlak & DuPre, 2008; O'Donnell, 2008).

Sixth, the potential influence of novelty and Hawthorne effects on the observed outcomes cannot be entirely excluded. Students in the experimental group may have exhibited increased engagement and performance partly because of the perceived novelty of the NeuroConstruct teaching model, rather than solely because of its intrinsic instructional effectiveness. The Hawthorne effect — whereby participants modify their behavior in response to being observed or exposed to new conditions — has been widely documented in educational and experimental research (Adair, 1984; McCarney et al., 2007). Similarly, novelty effects may temporarily enhance motivation and attentional engagement, thereby inflating short-term gains in cognitive and academic performance (Clark, 1983). Although procedural measures were implemented to minimize expectancy effects, including not explicitly informing students of group allocation, these influences cannot be entirely ruled out. Future research should incorporate longer intervention periods, delayed post-tests, and attention-control conditions to more clearly distinguish genuine instructional effects from novelty-driven engagement.

Seventh, the measurement instruments employed in the present study were developed and validated within the Thai educational context. Although these instruments demonstrated satisfactory psychometric properties — including content validity, construct validity, and reliability — they are not internationally standardized measures. As a result, the comparability of the present findings with those from studies conducted in different cultural or educational contexts may be constrained. Cross-cultural differences in cognitive assessment frameworks, scoring criteria, and educational norms may influence the interpretation of constructs such as creative thinking, attention, and working memory (Heine, 2016; van de Vijver & Leung, 1997). Future research should therefore consider employing internationally validated instruments or conducting cross-cultural validation studies to enhance the external validity and cross-contextual comparability of findings (Hambleton et al., 2005).

Future research should address these limitations by employing larger, more diverse samples across multiple schools, extending the intervention duration, and incorporating follow-up assessments to examine the sustainability of learning outcomes. In addition, future studies should include systematic measures of implementation fidelity and adopt research designs that further reduce potential confounding influences. Such efforts would strengthen causal inference and enhance the robustness and transferability of findings from NeuroConstruct teaching models. Future research could extend these findings by incorporating broader executive function assessments, such as inhibitory control and cognitive flexibility, to more fully elucidate the roles of executive functions in educational outcomes.

9. Conclusion

This study provides context-specific empirical evidence that the NeuroConstruct teaching model is associated with improved outcomes in creative thinking, mathematics achievement, attention, and working memory among Grade 7 students compared to the 5E teaching model. By translating Neuroconstructivism into a structured, classroom-applicable instructional model, the study offers preliminary evidence of the practical value of integrating neurocognitive principles into instructional design within authentic school settings. The findings suggest that targeting foundational cognitive processes — particularly attention and working memory — may enhance higher-order learning outcomes. This is consistent with the broader premise that instructional models informed by educational neuroscience can support both cognitive and academic development, though further replication is needed to confirm these initial findings. However, the results should be interpreted with caution. The short intervention duration and immediate post-test

measurement limit conclusions about long-term effects, and alternative explanations cannot be entirely ruled out. Future research should therefore examine the sustainability of these effects across extended timeframes, diverse educational contexts, and more rigorous experimental controls. Overall, the NeuroConstruct teaching model offers a promising, theory-informed approach that bridges neuroscience and classroom practice, with potential implications for instructional innovation and teacher professional development in contemporary education. Importantly, the conclusions of this study are confined to the specific cognitive and academic outcomes measured, and should not be interpreted as direct evidence of underlying neural mechanisms or as broadly generalizable across different educational contexts without further empirical validation.

CRedit authorship contribution statement

Sanit Srikoon: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Chansit Khamput:** Writing – review & editing, Writing – original draft, Resources, Investigation, Data curation. **Ketsaraphan Punsrigate:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Pornpisut Duangngern:** Writing – review & editing, Writing – original draft.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request. The data is not publicly available due to ethical and private considerations involving human participants.

Statement for studies in humans/animals

This study involved human participants and was conducted in accordance with established ethical standards. Ethical approval was obtained from the University of Phayao Ethics Committee for Human Research, Thailand (Project No. 2.1/006/63). Written informed consent was obtained from the parents or legal guardians of all participants, and assent was obtained from the students prior to data collection. Participation was voluntary, and participants were informed of their right to withdraw at any time without penalty. All data were collected and handled anonymously to ensure confidentiality and privacy.

No animals were involved in this study.

Declaration of AI usage statement

During the preparation of this manuscript, the authors used AI-assisted tools (licensed versions of Grammarly and ChatGPT) solely for language editing and grammar-checking. The authors critically reviewed, edited, and validated all content and took full responsibility for the accuracy, integrity, and originality of the work.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Sanit Srikoon reports financial support was provided by University of Phayao. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ssaho.2026.103020>.

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