

A Picture is Worth a Thousand Words: Self-Generated Drawing Strategy in Multimedia Learning

Authors: Wang Yanqing, Wang Fuxing, Xie Heping, Chen Jiaxue, Wenjing Li, Hu Xiang'en, Wang Fuxing

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Abstract

Self-generated drawing refers to a learning strategy where students employ visual learning methods to create pictures that reflect important ideas from each paragraph of text, thereby promoting learning through the integration of text and images. A review of previous research reveals that prior studies have examined the role of self-generated drawing in learning by manipulating learning materials such as text and animations, finding that the effects of self-generated drawing are not robust: on the one hand, it can enhance learning outcomes by improving students' cognitive and metacognitive abilities and stimulating positive affective states, which is supported by drawing construction generation theory and the cognitive theory of multimedia learning; on the other hand, it can also hinder learning by increasing cognitive load, which is supported by cognitive load theory. Overall, the self-generated drawing strategy remains beneficial for learning, with median effect sizes from existing research on learning outcomes being $d_{\text{retention}} = 0.13$, $d_{\text{comprehension}} = 0.46$, $d_{\text{transfer}} = 0.38$. Future research should continue to focus on material manipulation, effect evaluation, and potential variables related to the self-generated drawing strategy.

Full Text

A Picture is Worth a Thousand Words: Self-Generated Drawing as a Learning Strategy in Multimedia Learning

WANG Yanqing, WANG Fuxing, XIE Heping, CHEN Jiaxue, LI Wenjing, HU Xianguan

School of Psychology, Central China Normal University, Wuhan, 430079

Abstract

Self-generated drawing is a learning strategy in which students construct rep-

representational drawings that reflect the important ideas in each segment of a text, combining text and graphics to facilitate learning. A review of previous research reveals that studies examining the role of self-generated drawing have manipulated learning materials such as text and animations, yet the effects remain inconsistent. On one hand, self-generated drawing can enhance learning outcomes by improving students' cognitive and metacognitive abilities and stimulating positive emotional states, receiving support from both the Generative Theory of Drawing Construction and the Cognitive Theory of Multimedia Learning. On the other hand, it may also hinder learning by increasing cognitive load, as predicted by Cognitive Load Theory. Overall, self-generated drawing strategies are beneficial for learning, with median effect sizes of d retention = 0.13, d comprehension = 0.46, and d transfer = 0.38. Future research should continue to examine material manipulations, outcome assessments, and potential moderating variables of self-generated drawing strategies.

Keywords: self-generated drawing; Generative Theory of Drawing Construction; Cognitive Theory of Multimedia Learning; Cognitive Load Theory; multimedia learning

Imagine a scenario where two students, A and B, simultaneously study a text about how air conditioners work. After reading each paragraph, Student A draws a diagram of the refrigeration process, integrating text and graphics to facilitate learning, while Student B uses other non-drawing methods to process the text. How would their learning outcomes compare? Student A's activity exemplifies the use of self-generated drawing as a learning strategy. If this strategy is effective, Student A should outperform Student B on post-tests. Numerous studies have demonstrated that drawing pictures related to learning content is an effective strategy for improving academic performance (Leutner & Schmeck, 2014). When learners engage in drawing, they utilize prior knowledge to select, organize, and integrate learning materials, externalizing these cognitive processes through visualization (Van Meter & Firetto, 2013). These constructive mental operations and transformations promote understanding of the content. For instance, Schwamborn, Mayer, Thillmann, and Leopold (2010) required students to study an article about chemical reactions between soap and water during laundry. Learners in the drawing group needed to identify main information after reading, organize and integrate it into rich visual representations, and draw pictures representing the main ideas of each paragraph, while the control group simply read the text.

The results showed that the drawing group outperformed the text-only group on both retention and transfer tests. Although these findings support the facilitative effect of drawing strategies on learning outcomes, other studies have reached different conclusions (Leutner, Leopold, & Sumfleth, 2009; Ploetzner & Fillisch, 2017). Potential reasons for these inconsistent results include whether drawing support was provided (e.g., background diagrams, ready-made pictures), drawing quality, learners' prior knowledge levels, and other factors. Therefore, this paper integrates previous empirical research to elaborate on the concept

and experimental manipulations of self-generated drawing, organizes the theoretical foundations that explain how drawing may facilitate or hinder learning, examines the effects of drawing activities on learning outcomes, and analyzes possible reasons for inconsistent findings, aiming to provide insights for better application of self-generated drawing strategies in educational practice.

1 What is Self-Generated Drawing?

Self-generated drawing is a goal-directed learning strategy that requires students to construct, while reading text without pictures, a visual representation that reflects the important ideas in each paragraph, thereby representing the main concepts and relationships through graphics (Van Meter & Garner, 2005)—in essence, “external visualization of learning content.” In this process, learners become active processors rather than passive recipients of information. Self-generated drawing has two main characteristics: First, pictorial representation—the drawings must depict the real-world properties of the learning content (e.g., if the text mentions lightning, learners should draw the shape of lightning) and the spatial relationships among them (Van Meter & Firetto, 2013). Second, self-generation—the pictures must be drawn by the learners themselves, not provided by others (Van Meter & Garner, 2005). Self-generated drawing differs from mind maps and flowcharts because it requires students to engage in constructive activities, such as transforming textual information into vivid visual information. This process involves active cognitive and metacognitive processing that facilitates schema construction and helps learners master knowledge through text-graphic integration (Van Meter & Garner, 2005)—a feature not characteristic of mind maps or flowcharts.

Research on the effectiveness of self-generated drawing strategies primarily involves different manipulations of drawing and control groups. The drawing group manipulation typically requires learners to construct corresponding drawings after reading text materials (pure drawing group). For example, Gobert and Clement (1999) had students learn about plate tectonics, with the drawing group required to draw pictures describing what they had learned from the text. Some studies have provided scaffolding before drawing, such as Lesgold, Levin, Shimron, and Guttman (1975) providing background diagrams and clip art to assist drawing, or Lee (2017) having learners identify keywords before drawing. Control group manipulations vary widely, including studying expert-drawn diagrams (Schwamborn, Thillmann, Opfermann, & Leutner, 2011), orally summarizing text content (Leopold & Leutner, 2012), imagining (Leutner et al., 2009), or repeated reading (Lin et al., 2017).

Currently, considerable controversy remains regarding the conceptual definition and manipulation methods of self-generated drawing. For instance, Van Meter and Garner (2005) defined self-generated drawing as “using visualization methods to draw a picture that reflects the important ideas in each paragraph while reading text without pictures.” However, some studies have used animations as learning materials, asking learners to draw based on dynamic content, thereby

expanding the application scope of self-generated drawing (Mason, Lowe, & Tornatora, 2013; Ploetzner & Fillisch, 2017). Additionally, many studies have not strictly manipulated self-generated drawing. For example, drawing group learners simply drew pictures based on learning materials (Leopold, Sumfleth, & Leutner, 2013; Scheiter, Schleinschok, & Ainsworth, 2017), without considering factors such as drawing time, learners' drawing skills, or material difficulty—all of which may affect drawing effectiveness and could be important reasons for inconsistent learning outcomes across different manipulation conditions. Therefore, when manipulating self-generated drawing, researchers should minimize interference from extraneous variables (e.g., learning time, material difficulty) to better compare differences in learning outcomes and subjective experiences between drawing and non-drawing groups.

2 Theoretical Foundations of Self-Generated Drawing

Researchers hold different views on how self-generated drawing affects learning outcomes. What are the underlying theoretical mechanisms? This study integrates previous theories and practices, focusing on two major perspectives: the facilitation hypothesis and the hindrance hypothesis.

2.1 The Facilitation Hypothesis

The Generative Theory of Drawing Construction (GTDC) emphasizes that when learners construct pictures corresponding to learning content, they engage in cognitive activities involving selection, organization, and integration of materials, while also activating metacognitive activities such as self-monitoring and regulation strategies, thereby promoting deeper understanding of text content (Van Meter & Garner, 2005). The drawing construction process facilitates deeper comprehension because relevant concepts are “integrated into a complex causal chain, establishing a rich mental model” (Gobert & Clement, 1999). This process primarily involves active cognitive and metacognitive processing. The most fundamental cognitive processes include three stages: (1) selection—learners identify relevant key factors from the provided text; (2) organization—learners organize selected information to construct internal verbal and visual (non-verbal) representations; and (3) integration—learners combine verbal and visual representations with prior knowledge (Mayer, 1993). Metacognitive processing emphasizes learners' self-monitoring abilities. During the construction of pictorial representations, learners may encounter various problems, forcing them to re-examine their drawings or even the original text to obtain additional information and continuously improve their constructed pictures. This process is not linear but iterative, thereby enhancing students' self-monitoring abilities, helping them identify comprehension errors, improve drawing accuracy, and ultimately promote learning (see Figure 1 [Figure 1: see original paper]). Although no studies have directly measured these cognitive processing stages, some empirical evidence indicates that self-generated drawing can enhance students' metacognitive processing and facilitate learning (Lesgold et al., 1975; Van

Meter, 2001), supporting GTDC.

According to the Cognitive Theory of Multimedia Learning (CTML), humans process information through two distinct channels: a visual representation channel and a verbal representation channel (Mayer, 2009). Numerous studies have shown that learning from well-designed multimedia materials (including text and pictures) is more effective than learning from text alone. When pictures contain spatial relationships among concepts described in the text, students can better understand the meaning of the article (Carney & Levin, 2002; Imhof, Scheiter, Edelmann, & Gerjets, 2012). Therefore, when studying expository texts without provided pictorial representations, learners need to generate and construct corresponding pictures themselves, learning through text-graphic integration to increase interest and motivation, thereby promoting comprehension of learning materials. CTML has also received support from some studies (Leopold & Leutner, 2012; Schmidgall, Eitel, & Scheiter, in press).

In summary, both facilitation perspectives suggest that GTDC emphasizes learners' "self-generation"—the active processing by learners themselves—while CTML focuses on "drawing"—the text-graphic learning approach. These two aspects complement each other and both benefit learners' retention and comprehension of materials. This is why researchers currently use both theories to explain self-generated drawing (Lin et al., 2017). However, reviewing previous studies reveals that the effects of self-generated drawing have only received partial empirical support. Findings showing no differences or even negative effects for self-generated drawing groups compared to control groups do not align with GTDC or CTML assumptions. Future theoretical research should focus on the explanatory power of GTDC and CTML for self-generated drawing strategies.

2.2 The Hindrance Hypothesis

While self-generated drawing can improve learners' text comprehension to some extent, this visualization strategy also imposes higher demands on cognitive load. According to Cognitive Load Theory (CLT), individuals experience three types of cognitive load during information processing: intrinsic cognitive load (ICL), extraneous cognitive load (ECL), and germane cognitive load (GCL) (Sweller, Ayres, & Kalyuga, 2011; Sweller, van Merriënboer, & Paas, 1998). ICL relates to material complexity; ECL addresses additional cognitive demands; GCL reflects cognitive processing essential for learning. From a CLT perspective, using visualization strategies during learning may increase ECL because students need to transform verbal information into pictorial information and execute mechanical drawing operations, consuming substantial cognitive resources and reducing resources available for processing key information and constructing mental models, thereby hindering learning. However, CLT-based hypotheses have received only partial support.

For example, Leutner et al. (2009) found that drawing operations significantly increased ECL and hindered learning. Schwaborn et al. (2011) found that

drawing group students reported higher mental effort and demonstrated poorer learning outcomes than control groups.

Several reasons may explain why CLT's explanation for the hindering effects of self-generated drawing has received limited support. First, research has overlooked GCL effects. Self-generated drawing occurs in text-only conditions and may promote active processing that transforms textual information into pictorial representations, potentially increasing GCL and facilitating deeper understanding. Therefore, which type of cognitive load plays a more critical role? Does drawing operation increase ECL? Does self-generation increase GCL? Do both increase simultaneously? Can increased GCL compensate for increased ECL? These questions require further investigation. Notably, current explorations of the relationship between self-generated drawing and GCL remain speculative (Leutner et al., 2009) and require more empirical validation. Second, cognitive load is a dynamic process influenced by many factors, such as material characteristics, learner characteristics, and environmental factors. Therefore, which factors cause cognitive load during drawing remains undetermined, and whether drawing operations definitively increase cognitive load requires cautious interpretation. Third, cognitive load itself remains controversial. Researchers typically use mental effort and perceived difficulty as cognitive load measures, but whether mental effort belongs to ECL or GCL lacks clear standards (Xie et al., 2017). Consequently, whether mental effort during self-generated drawing facilitates or hinders learning remains undetermined. These controversies limit exploration of relationships among self-generated drawing, cognitive load, and learning outcomes.

Figure 1 The learning process of self-generated drawing based on Generative Theory of Drawing Construction, Cognitive Theory of Multimedia Learning, and Cognitive Load Theory

The difference between the facilitation and hindrance hypotheses lies in whether self-generated drawing promotes understanding by motivating learners to actively apply cognitive and metacognitive strategies to process text content, or whether it hinders acquisition of key knowledge by diverting attention to mechanical drawing operations, resulting in excessive extraneous cognitive load. Overall, both hypotheses have received varying degrees of support. However, neither provides satisfactory explanations for cases where self-generated drawing shows no difference from control conditions. Moreover, many studies cannot precisely specify how self-generated drawing affects cognitive and metacognitive processes, nor do they directly measure cognitive and metacognitive levels or relationships between cognitive load and learning outcomes. Instead, they indirectly infer that self-generated drawing promotes learning by increasing cognitive and metacognitive processing or hinders learning by increasing ECL (Schmidgall et al., 2018). Therefore, future research should directly examine relationships among cognitive processing, metacognition, cognitive load, and learning outcomes to determine whether self-generated drawing affects learning through improved cognitive/metacognitive abilities or reduced ECL.

3 Does Self-Generated Drawing Facilitate or Hinder Learning? Evidence from Empirical Studies

The key to self-generated drawing is systematically transforming verbal models into non-verbal models, a conversion process that enhances students' understanding and processing of learning content. However, research findings on the effects of self-generated drawing on learning outcomes remain inconsistent. Comprehensive literature reviews show that researchers have primarily examined three aspects: retention tests, comprehension tests, and transfer tests. To quantitatively describe the relationship between self-generated drawing strategies and learning outcomes, this paper has compiled Cohen's d effect sizes from relevant empirical studies (see Table 1) and calculated median effect sizes.

Literature inclusion criteria were: (1) empirical studies; (2) comparisons between self-generated drawing groups and non-drawing groups (reading, imagining, summarizing, explaining, etc.); and (3) dependent variables measuring learning outcomes or subjective experiences (cognitive load, self-monitoring, etc.).

Retention tests typically assess learners' memory of content (Mayer, 2009). Some studies indicate that self-generated drawing promotes mastery of learning materials (Bock, Verschaffel, & Janssens, 1998; Balemans, Kooloos, Donders, & Van der Zee, 2016; Liao, Lee, & Chan, 2013; Wammes, Meade, & Fernandes, 2016). For example, Mason et al. (2013) tested self-generated drawing in an animation context and found that drawing group learners described more content from the animation than copy-picture and reading groups. However, other studies have not supported positive effects on retention tests (Zhang & Linn, 2013; Stull & Mayer, 2007). For instance, Van Meter et al. (2006) found no significant differences between self-generated drawing and control groups on recognition tests. Ploetzner and Fillisch (2017) found that students who imagined animation content performed better on retention tests than those who generated drawings, suggesting that drawing activities hindered content retention. Among 45 experiments summarized in Table 1, 34 included retention tests: 18 showed positive effects, 12 found no facilitative effects, and 4 found negative effects. The median effect size for self-generated drawing on retention tests was $d = 0.13$.

Comprehension tests primarily assess understanding of important concepts in learning materials (Schmeck, Mayer, Opfermann, Pfeiffer, & Leutner, 2014). Some studies found that self-generated drawing promotes deep understanding (Hall, Bailey, & Tillman, 1997; Lin et al., 2017). For example, Gan (2008) found drawing played an important role in helping fourth-grade students understand "light" and related phenomena. However, other studies found no facilitative effects. Leopold and Leutner (2012, Experiment 2) found no differences among drawing, summarizing, and control groups on comprehension tests. Leutner et al. (2009) found drawing strategies had significant negative effects compared to imagination strategies. Among nine experiments including comprehension tests, seven showed positive effects, one found no difference, and one found negative

effects. The median effect size for self-generated drawing on comprehension tests was $d = 0.46$.

Transfer tests generally examine students' ability to apply learned knowledge to new situations (Mayer, 2009). Researchers hypothesize that transfer problems may require greater understanding of spatial representations, and self-generated drawing group learners develop clearer understanding of spatial relationships during drawing, enabling knowledge transfer. Some studies found drawing groups outperformed control groups on problem-solving tasks (Hall et al., 1997; Van Meter, Meade, & Fernandes, 2006; Schmidgall et al., 2018). However, other studies found no advantages over other strategies (imagination, summarization). For example, Scheiter et al. (2017) found no differences between self-generated drawing and self-explanation groups on transfer tests. Additionally, Schwamborn et al. (2011) showed self-generated drawing not only failed to improve transfer but actually hindered learning compared to provided-picture groups. Among 17 experiments including transfer tests, 10 found positive effects, six found no differences, and one found negative effects. The median effect size for self-generated drawing on transfer tests was $d = 0.38$.

These analyses reveal inconsistent results across retention, comprehension, and transfer tests. On one hand, learners can actively construct mental models related to learning content through selection, organization, and integration of information, continuously monitoring and revising their constructed models and finally externalizing them through drawings to support learning—receiving support from GTDC and CTML. On the other hand, allocating cognitive resources to mechanical drawing operations during the drawing process reduces resources available for learning relevant knowledge, thereby hindering learning—receiving support from CLT. However, neither facilitation nor hindrance hypotheses adequately explain null results, requiring further exploration.

The robustness of self-generated drawing strategies has been questioned by many researchers. Possible reasons for inconsistent findings include: First, whether drawing support is provided may produce different learning outcomes. Studies show that providing drawing backgrounds (Lesgold et al., 1975), offering ready-made pictures for comparison (Van Meter, 2001), or listing keywords before drawing (Lee, 2017) produces better post-test performance than no support. Second, multimedia learning is a complex process, and generating drawings is not the only factor affecting it. Learners' prior knowledge levels (Slominski, Momsen, & Montplaisir, 2017), drawing quality (i.e., accuracy) (Rellensmann, Schukajlow, & Leopold, 2016), and drawing time (Schwamborn et al., 2011) may all affect learning outcomes. For example, Leutner et al. (2009) found drawing hindered understanding for high-knowledge students but provided scaffolding that improved performance for low-knowledge students (Zhang & Linn, 2013). Greene (1989) found students producing high-quality drawings scored higher on post-tests than those producing low-quality drawings. Schmeck et al. (2014) found drawing and control groups no longer differed significantly on comprehension post-tests when learning time was covaried. Some researchers suggest

that differences in outcome measures themselves may contribute to inconsistent findings, with advantages of drawing construction more likely to appear on advanced knowledge tests such as transfer and problem-solving tests (Alesandrini, 1981; Van Essen & Hamaker, 1990) rather than simple recognition tests (Van Meter et al., 2006). Van Meter et al. argue these claims are grounded in knowledge representation theory, which emphasizes that self-generated drawing is a process of elaborately constructing mental representations requiring learners to integrate current knowledge with prior experiences for detailed reasoning and flexible processing rather than simple storage of text. Therefore, different test formats may affect results. The median effect sizes also show $d_{\text{transfer}} = 0.38 > d_{\text{retention}} = 0.13$. Finally, material characteristics affect drawing effectiveness. Most self-generated drawing studies use text-only materials (Schleinschok et al., 2017), with results tending to support drawing effects. However, using complex four-stroke engine animations as materials found self-generated drawing did not affect performance (Ploetzner & Fillisch, 2017). Different animation difficulties also produced different results: Mason et al. (2013) used relatively simple five-ball pendulum animations and found supportive results. Attention to these potential boundary conditions (Mayer, 2010) may help explain the inconsistent relationship between self-generated drawing strategies and learning outcomes.

Table 1 Effects of Self-Generated Drawing on Learning Outcomes and Subjective Perceptions (Cohen' s d values)

| Study | Sample Size | Experimental Manipulation | Learning Outcome d values |
|-------------------------------|-------------|--|-----------------------------|
| Alesandrini, 1981 | | Drawing vs. reading | $U^*=0.279$ |
| Balemans-et al., 2016 | | Drawing vs. reading | $R^*(\#)$ |
| Csíkos et al., 2011 | - | Drawing vs. reading | $R(-0.049)$ |
| De Bock et al., 1998, Exp. 2 | - | Drawing vs. reading | $R^*(\#)$ |
| Dean & Kulhavey, 1981, Exp. 1 | - | Drawing vs. providing diagrams vs. reading | $R^*(1.08)$ |

| Study | Sample Size | Experimental Manipulation | Learning Outcome d values |
|---------------------------------|-------------|---|---------------------------|
| Edens & Potter, 2003 | - | Drawing vs. reading | T*(1.097) |
| Gobert & Clement, 1999 | - | Drawing vs. copying provided diagrams vs. writing | R(-) |
| Hall et al., 1997 | - | Drawing vs. summarizing vs. reading | C*(-) |
| Lin et al., 2017 | - | Drawing vs. providing diagrams vs. reading | R*(0.738) |
| Lee, 2017 | - | Drawing vs. imagining vs. reading | T*(0.714) |
| Leopold et al., 2013 | - | Reading vs. listing keywords vs. drawing vs. (listing keywords + drawing) | C*(0.464) |
| Leopold & Leutner, 2012, Exp. 1 | - | Battery electrochemistry concepts | C*(0.461) |
| Leopold & Leutner, 2012, Exp. 2 | - | Human tissue structure | R*(0.066) |
| Lesgold et al., 1975, Exp. 1 | - | Math word problems | C*(0.245) |

| Study | Sample Size | Experimental Manipulation | Learning Outcome d values |
|------------------------------------|-------------|---|---------------------------|
| Lesgold et al., 1975, Exp. 2 | - | Imaginary African tribe | T(0.053) |
| Lesgold, De Good, & Levin, 1977 | - | Energy conservation law | C*(0.61) |
| Leutner et al., 2009 | - | Plate tectonics | T*(0.808) |
| Mason et al., 2013 | - | Manual air pump operation | C(0.277) |
| Ploetzner- & Fillich, 2017 | - | Human cardiovascular system | T*(0.817) |
| Scheiter et al., 2017 | - | Human skeletal muscle system | R&(-0.98) |
| Schleinschöck et al., 2017, Exp. 1 | - | Drawing vs. summarizing vs. providing diagrams vs. providing summaries | R*(0.129) |
| Schleinschöck et al., 2017, Exp. 2 | - | Water molecules and chemical bonds | R*(#) |
| Schmeck et al., 2014, Exp. 1 | - | Drawing vs. viewpoint selection vs. (drawing + viewpoint selection) vs. reading | C&(-0.37) |

| Study | Sample Size | Experimental Manipulation | Learning Outcome d values |
|----------------------------------|-------------|---|---------------------------|
| Schmeck - et al., 2014, Exp. 2 | | Drawing vs. summarizing vs. (drawing + summarizing) vs. reading | R*(0.418) |
| Schwambørn et al., 2011 | | Drawing vs. reading | R&(-0.164) |
| Schwambørn et al., 2010 | | Drawing (with support) vs. reading | R(0.414) |
| Schmidgall et al., 2018, Exp. 1 | | Drawing vs. reading | T(0.211) |
| Schmidgall et al., 2018, Exp. 2 | | Drawing vs. imagining vs. reading | R(0.063) |
| Snowman & Cunningham, 1975 | | Five-ball pendulum animation | R(-0.143) |
| Stagg & Verde, 2018 | - | Four-stroke engine animation | CL(-0.35) |
| Van Essen & Hamaker, 1990, Exp.1 | - | Introductory chemistry text | JOL*(-) |
| Van Essen & Hamaker, 1990, Exp.2 | - | Aurora astronomical phenomenon | CL(-0.066) |

| Study | Sample Size | Experimental Manipulation | Learning Outcome d values |
|-----------------------------|-------------|---|---------------------------|
| Van Meter et al., 2006 | - | Fluena biological knowledge | JOL*(-) |
| Van Meter, 2001 | - | Drawing vs. providing diagrams vs. (drawing + providing diagrams) vs. reading | ME*(0.766), PD(-0.124) |
| Wammes-et al., 2016, Exp. 1 | | Soap and water chemical reaction | C*(0.85) |
| Wammes-et al., 2016, Exp. 2 | | Drawing vs. providing diagrams vs. (drawing + providing diagrams) vs. reading | ME*(0.333) |
| Wammes-et al., 2016, Exp. 3 | | Soap and water chemical reaction | R&(-0.169) |
| Wammes-et al., 2016, Exp. 4 | | Drawing vs. (drawing + selection) vs. (drawing + organization/integration) vs. (drawing + selection + organization/integration) vs. reading | T&(0) |
| Wammes-et al., 2016, Exp. 5 | | Human swimming biomechanics | R*(0.87) |
| Wammes-et al., 2016, Exp. 6 | | Drawing vs. copying diagrams vs. viewing | T*(0.91) |

| Study | Sample Size | Experimental Manipulation | Learning Outcome d values |
|-------------------------------|-------------|---|---------------------------|
| Wammes - et al., 2016, Exp. 7 | | Drawing vs. imagining | R (0.002) |
| Zhang & Linn, 2013, Exp. 1 | - | Drawing vs. explaining | T*(0.174) |
| Zhang & Linn, 2013, Exp. 2 | - | Drawing vs. reading | CL*(0.72) |
| Zhang & Linn, 2011 | - | Drawing vs. reading | R(0.009) |
| Zhang, 2010 | - | Drawing vs. reading | R(-0.047) |
| | | Drawing vs. reading | T(-0.439) |
| | | Drawing vs. providing diagrams vs. providing problems vs. reading | R*(0.774) |
| | | Drawing vs. providing diagrams vs. providing problems vs. reading | T*(0.67) |
| | | Drawing (careful) vs. writing (repeated) | R(0.043) |
| | | Drawing (repeated) vs. writing (careful) | T*(0.234) |
| | | Drawing vs. keywords vs. writing | R*(0.337) |
| | | Drawing vs. imagining vs. writing | S-M*(-) |
| | | Drawing vs. providing diagrams vs. writing | R*(1.23) |
| | | Drawing vs. writing (longer study list, shorter encoding time) | R*(1.3) |

| Study | Sample Size | Experimental Manipulation | Learning Outcome d values |
|-------|-------------|--|---------------------------|
| | | Pure drawing vs. pure writing | R*(0.86) |
| | | Drawing vs. simple selection | R*(0.87) |
| | | Drawing vs. complex selection | R*(0.67) |
| | | Drawing vs. viewing | R*(2.27) |
| | | Drawing vs. commenting | R*(1.63) |
| | | Battery car hydrogen combustion process | R(-0.139) |
| | | Hydrogen combustion molecular interactions | T*(0.668) |
| | | | R(-0.107) |
| | | | T(-0.256) |
| | | | T*(0.516) |

Note: R = retention test; C = comprehension test; T = transfer test; U = combined test (total score of retention, comprehension, and transfer); CL = cognitive load; ME = mental effort; PD = perceived difficulty; L = preference level; B = learning beliefs; S-M = self-monitoring; JOL = judgment of learning; # indicates the study measured percentage of correct responses; - indicates values not reported or missing in the study; / indicates values not measured in the study; * indicates self-generated drawing strategy performed better than comparison groups; & indicates self-generated drawing strategy hindered learning compared to other strategies; values in parentheses represent Cohen's d effect sizes comparing self-generated drawing and control groups, where larger d values indicate greater effects of drawing versus non-drawing groups.

4 Does Self-Generated Drawing Affect Subjective Experience?

As an artistic learning approach, self-generated drawing requires students to actively construct knowledge externally, promoting learning outcomes to some extent. However, what subjective experiences (cognitive load, emotional states, motivation levels, self-monitoring) do students have when using this strategy? This has been a focus of previous research.

The purpose of self-generated drawing is to encourage learners to actively process information by drawing pictures representing text content, thereby improving academic performance. However, some studies suggest self-generated drawing may hinder learning by increasing cognitive load (Leutner et al., 2009). When learners draw based on text content, they need to switch between text and pictures to search for key information that can be visualized. This repeated

switching consumes additional cognitive resources, reducing resources available for knowledge processing and producing negative effects that hinder learning. Comprehensive reviews show that among seven studies measuring cognitive load effects of self-generated drawing, four found increased cognitive load (Schmidgall et al., in press; Schmeck et al., 2014) (see Table 1). However, given the small number of studies measuring cognitive load, the stability of these effects requires continued examination.

Students' emotional states are crucial for learning success. When students experience positive emotions, they become more motivated, investing more time and effort in learning (Bransford, Brown, & Cocking, 2000). Currently, only two empirical studies have measured emotional states during self-generated drawing. One found self-generated drawing improved learning beliefs, making learners prefer drawing strategies and believe drawing helps solve problems (Csíkos et al., 2011). Another found drawing group learners preferred drawing over written summarization, possibly because drawing generates pleasant feelings that increase interest and enthusiasm for further learning, leading to greater cognitive resource investment (Stagg & Verde, 2018). Many researchers argue self-generated drawing deserves attention because it positively affects emotional processes, increases motivation (Ainsworth, Prain, & Tytler, 2011), and enhances engagement (Quillin & Thomas, 2015). Notably, learning motivation plays a vital role, yet the relationship between self-generated drawing and motivation remains largely theoretical, requiring more empirical research on how drawing affects motivation and subsequent learning outcomes.

Metacognitive monitoring refers to learners' ability to evaluate their learning status according to learning goals during cognitive processing (Bjork, Dunlosky, & Kornell, 2013). During drawing generation, learners actively select, organize, and integrate information, improving self-monitoring abilities, detecting inconsistencies between internal representations and external descriptions, and increasing error detection and correction, thereby promoting more comprehensive and accurate understanding (Van Meter, 2001; Van Meter & Firetto, 2013). Only five studies have reported relationships between self-generated drawing and self-monitoring, with four finding improved monitoring abilities. For example, Zhang and Linn (2013) showed students generated more self-monitoring events during drawing, such as self-questioning and reviewing previous text. Schleinschok et al. (2017) used judgment of learning (JOL) to measure monitoring accuracy and found higher accuracy in self-generated drawing groups than control groups.

An important purpose of manipulating self-generated drawing is to examine differences in internal perceptions between drawing and non-drawing students. This subjective measurement approach directly assesses learners' feelings, indirectly inferring learning outcomes with simplicity and efficiency advantages, but also limitations. Both cognitive load measurement and emotional state assessment rely on learners' subjective reports, which may deviate from actual experiences when reporting mental effort, perceived difficulty, or preference levels.

Therefore, future research could incorporate physiological indicators, combining subjective and objective measures to better understand learners' internal experiences. Additionally, reviews show that only 13 of 45 empirical studies (29%) measured learners' mental activities during learning, with relatively single indicators. Future studies could include measures of mind wandering (MW) (Wilson et al., 2018), delayed JOL (Xie, Wang, Wang, & An, 2016), etc., to more deeply understand learners' engagement and metacognitive processing during self-generated drawing.

5 Summary and Future Directions

5.1 Summary

This review of self-generated drawing strategies reveals effects on both external learning outcomes and internal subjective perceptions. Regarding learning outcomes, GTDC and CTML suggest that learners actively select, organize, and integrate textual information during drawing, engaging in generative processing that improves academic performance. However, some studies do not support self-generated drawing strategies, consistent with CLT predictions (see Figure 1), suggesting that drawing increases extraneous cognitive load and reduces learning outcomes. Overall, self-generated drawing strategies are beneficial for learning (d retention = 0.13, d comprehension = 0.46, d transfer = 0.38). The effect size on retention tests is less than 0.2 (small), while effect sizes on comprehension and transfer tests are around 0.5 (medium). Therefore, in the opening example, Student A using self-generated drawing should outperform Student B on post-tests. Inconsistent findings may result from many potential boundary conditions, such as support provision, learning time, and learners' knowledge levels. Regarding subjective perceptions, learners must focus on mechanical drawing operations, potentially increasing extraneous cognitive load and reducing resources for processing key information, thereby decreasing learning outcomes. Conversely, self-generated drawing can enhance self-monitoring abilities, improve emotional states, increase engagement, help learners develop clearer understanding of content structures and relationships, positively affect subjective experiences, and thereby promote learning.

5.2 Future Directions

Self-generated drawing offers valuable insights for individual learning and educational practice improvement but faces many issues regarding potential variables, material manipulation, and experimental methods that require refinement. Current research has substantial room for exploration, and future studies could proceed in several directions:

First, examine boundary conditions affecting self-generated drawing to optimize the strategy. Previous sections identified many potential moderators (support provision, test format, prior knowledge, etc.), but other uninvestigated variables require exploration, including learning motivation, interest, cognitive style,

drawing skills, material difficulty, and metacognitive prompts. Notably, most drawing strategy research focuses on paper-and-pencil drawing, with few studies using tablets or electronic devices (Lehtinen & Viiri, 2014). As touch-screen media and computers become increasingly common in life and education, future research could compare different drawing media (tablet vs. paper vs. computer). One study already indicates that computer-based drawing requires more effort and time than non-drawing conditions (Schwamborn et al., 2011), suggesting strategy effectiveness relates to media use. Computer drawing requires more manual operations, creating additional cognitive load. Future research could reduce cognitive load through training or optimized drawing tools to better apply self-generated drawing in multimedia learning environments.

Second, integrate self-generated drawing strategies with computer and online learning. With multimedia teaching 普及, students must learn not only static textbook content but also dynamic content reflecting visual-spatial relationships. When learning dynamic content, learners easily extract salient information while neglecting subtle but relevant information. Could drawing help learners extract conceptually relevant information and improve animation learning outcomes? Some studies suggest drawing strategies enable systematic and comprehensive perception and processing of dynamic content (Mason et al., 2013), while others show self-generated drawing in animations does not achieve effects comparable to text materials (Slominski et al., 2017). Do factors such as animation pacing (Wang, Xie, & Li, 2016), playback speed (Qian, Wang, Duan, & Zhou, 2016), or animation content affect drawing effectiveness? Could adding cues (prompting conditions) to animations facilitate drawing (Wang, Duan, Zhou, & Chen, 2015)? These questions require continued investigation.

Third, measure self-generated drawing effects using more ecologically valid methods. Current research primarily measures immediate effects on subjective experiences and learning outcomes, which does not reflect normal educational contexts. In real school instruction, tests typically occur days or weeks after learning. Therefore, future research should measure not only immediate drawing effects but also delayed test performance (Mason et al., 2013). Additionally, when measuring drawing quality, Van Meter (2001) classified quality based on the amount and complexity of systematic and structural knowledge in student-generated drawings. However, some studies used the same scoring criteria for drawing quality and learning performance (Schleinschok et al., 2017), confounding these measures. Selecting more objective evaluation standards for drawing quality represents a potential focus. Reviews show most research focuses on learning outcomes (retention, comprehension, transfer) while neglecting learners' psychological experiences during drawing. Future studies should integrate external learning outcomes with internal subjective perceptions for more comprehensive understanding.

Fourth, analyze effects of self-generated drawing on special student populations. Most research focuses on typical students, with results generally supporting drawing effects. Few studies examine how self-generated drawing affects stu-

dents with reading disabilities. Can self-generated drawing also benefit these students? Only one study has demonstrated effectiveness for children with orthographic dyslexia but weak effects for children with double deficits (phonological and orthographic difficulties) (Wang, Yang, Tasi, & Chan, 2013). This finding requires replication. Future research should examine effects on different types of reading disabilities and consider whether self-generated drawing helps other children (autism, learning difficulties, ADHD) learn better.

Fifth, investigate behavioral patterns and neural foundations of self-generated drawing strategies. Eye-tracking records students' eye movements to trace learning processes, assuming what the eyes fixate on is what the brain processes (Wang, Duan, Zhou, & Chen, 2015; Van Gog & Scheiter, 2010). Eye-movement indicators such as fixation points and durations reveal instantaneous cognitive processing information. Additionally, functional near-infrared spectroscopy (fNIRS) has been widely applied in educational psychology research (Brucker, Ehlis, Häußinger, Fallgatter, & Gerjets, 2015), providing opportunities for educational neuroscience. Cognitive load and self-monitoring events during drawing may be reflected in eye-movement data or brain activity changes. To deeply understand the cognitive mechanisms of drawing, traditional testing alone is insufficient. One study has already applied eye-tracking to self-generated drawing research (Lin et al., 2017), and future studies should adopt such methods to explore the mechanisms underlying self-generated drawing effects.

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