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# What Educators Need to Know in the Wake of AI Infiltration in Education?

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The current study examines the role of individual differences in the context of AI (ChatGPT) supported STEM learning. The results showed working memory could influence individual learners' cognitive process in math-related problem solving. It was found high WM learners performed better than low WM learners in terms of performance and cognitive load experienced during the learning.

**INTRODUCTION:** Digital technology such as AI has increasingly played a critical role in learners' learning in terms of their cognitive, metacognitive and affective processes (Amab et al., 2012; Echeverri & Sadler, 2011). Regardless of the promises of new digital technologies in education, researchers and educators have cautioned that digital technology may become less beneficial if the design of digital learning fails to take into consideration individual differences in learning. Greenberg et al. (2021) studied the individual differences in working memory capacity in multimedia learning and found that dual modality (visual and auditory) supports individuals with low visuospatial working memory more than single modality (visual or auditory). They thus concluded that the design of digital learning should take into consideration the individual differences in working memory. Gupta and Zheng (2020) examined the individual differences in math learning by looking into cognitive load experienced by learners during problem solving. Their study revealed that learners varied in their cognitive load and performance when studying the same subject (e.g., math). The researchers attributed the learners' performance variation to individual differences in working memory as learners may experience different cognitive load due to their differences in working memory capacity. Given the individual differences in working memory capacity pertaining to difference in cognitive load in learning, Zheng (2018) proposed a framework for examining individual differences and knowledge acquisition in digital learning. The framework outlines three components which include (a) individual traits, (b) digital technology with enhanced cognitive support (DTECS), and (c) highly intelligent digital technology (HIDT). Zheng (2018) suggests extra cognitive support is needed to improve learners' deep learning skills (Fig. 1).

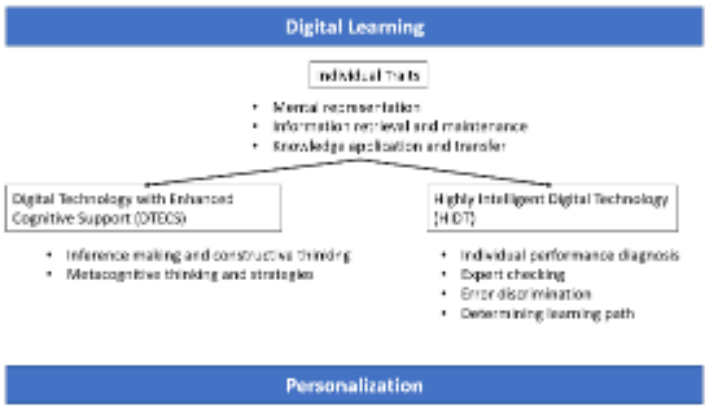


Fig 1. Framework for individualized digital learning

**THE STUDY:** The current study (N=180) tested Zheng's (2018) framework by examining the individual differences in working memory (WM) and cognitive support in the context of AI where ChatGPT was employed to facilitate learners' deep learning like inference making and constructive thinking. Additionally, cognitive support tool like prompts were used to promote learners' deep level thinking such as making inferences, error discrimination, etc. The design of the study therefore included two cognitive support interventions: cognitive prompts (P) and an artificial intelligence tool (ChatGPT),

resulting in four conditions: P+ChatGPT, P+NonChatGPT, NonPrompt+ ChatGPT, and NonPromp+NonChatGPT. The participants were first measured for their WM capacity using symmetry span task for visuospatial memory (Engle, 2018) and audio digit span task for WM capacity (Was & Woltz, 2007). Based on the scores, the participants were divided into high and low WM groups who were randomly assigned into four conditions above. The learning materials include 15 problems in Calculus III covering three topics: permutation, scaling, and conversion. Learners (both high and low WM) solved the problems in one of the four conditions followed by a cognitive load questionnaire (Leppink et al., 2013). A 2 x 4 MANOVA was employed to analyze the data. The results show that overall low WM learners performed less well than high WM learners in problem solving and showed higher cognitive load regardless of the intervention (Fig. 2).

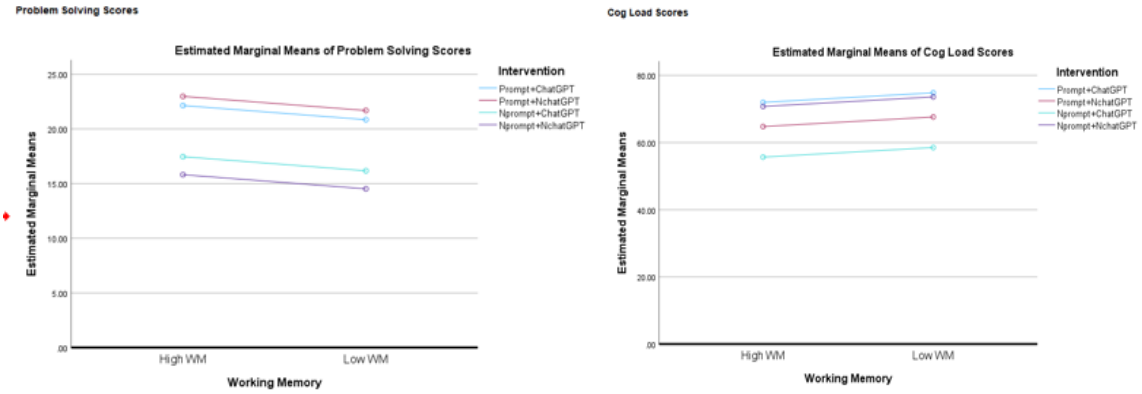


Fig 2. Results of problem solving and cognitive load in cognitive prompts and ChatGPT

**CONCLUSION:** The current study is a preliminary study that examines the relationship between individual differences and cognitive support in STEM learning. The results confirmed the individual differences (e.g., WM) in STEM learning. It was found that low WM learners performed less well in problem solving than did the high WM learners and showed lower cognitive load regardless of interventions (cognitive prompts and ChatGPT), which raised the question of whether cognitive support like cognitive prompts and ChatGPT can compensate for the individual deficiency in WM. Further, the timing and extent the cognitive prompts that are used with ChatGPT have not been fully studied to determine their role in supporting WM process. The results of current do not seem to provide a clear answer to the above questions, suggesting more research is needed to understand the relationship between WM and cognitive support in learning.

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