

CONCEPTUALIZING THE TRIADIC MODEL OF AI COMPETENCY (TMAC): THE ROLES OF COGNITIVE, ENVIRONMENTAL, AND EFFICACY DRIVERS IN ACADEMIC RESEARCH PRACTICE

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Abstract: *Usage of Artificial Intelligence (AI) tools in research setting has become a phenomenon. Many research has already explored AI adoption and usage behavior. Limited considerations has been given towards cognitive capability in using AI effectively and ethically in research setting. Although there are benefits of AI usage in this domain, the issue persist on whether the AI-generated outputs assessment also move together with AI utilization. To address this gap, this study proposes the Triadic Model of AI Competency (TMAC). Grounding in Social Cognitive Theory, this study contributes by redefining AI competency from a multidimensional literacy perspective to a cognitively grounded capability. The model emphasize how AI-assisted research practice is influenced by active Cognitive Drivers, Environmental Drivers, and Efficacy Drivers.*

Keywords: *AI Competency, Social Cognitive Theory, Cognitive Drivers, AI Risk Vigilance, AI-Assisted Research Practice*

Introduction

Artificial intelligence (AI) has become increasingly embedded in academic research practices because it helps researchers in generating ideas, synthesizing literature and discussion (Apriani et al., 2025; Črček & Patekar, 2023; Wang & Ren, 2024). Despite the efficiency provided, major concerns emerges regarding hallucinations consist of fabricated content creation and fake citations (Dziri et al., 2022; Ji et al., 2023). Academic related in research practices require more than literacy and adoption, academics should equipped with the ability in verifying the output.

Existing research on AI usage is largely grounded in adoption-based models that explain technology use through factors such as perceived usefulness, ease of use, and social influence (Chatterjee et al., 2020; Osman & Mohamad, 2024). The models measure AI tool usage by testing whether people use the tools, but they do not assess the high-stakes environment of scholarly publishing and hallucination risks. Multiple frameworks have developed AI competency assessment methods that measure three areas of human ability: technical skills and cognitive abilities and ethical understanding (Carolus et al., 2023; Laupichler et al., 2023; Pinski & Benlian, 2023). The frameworks recognize cognitive elements, but they do not identify specific cognitive functions and peer environments as the primary research process used in academic settings.

The research provides a solution to this existing research gap through the development of the Triadic Model of AI Competency (TMAC) which uses Social Cognitive Theory (SCT) (Bandura, 1986, 1998) as its foundation. The study establishes that cognitive processing, environmental collaboration, and risk vigilance determine AI competency for academic research more than technical proficiency.

Literature Review

Social Cognitive Theory

As in measuring the human behavior in term of cognitive process and self-belief. The existing theory from Bandura 1986 and 1998 known as Social Cognitive Theory laid out measurement that can be utilize in measuring how individual interpret and evaluate information. As for the self-efficacy, this theory provided the base in measuring how confidence or self-belief affecting the competency.

In the context of AI usage. The critical ability of evaluating AI outputs is necessary, and this requires active cognitive capability, supportive environmental norms, and the self-efficacy in measuring the confidence of an individual in utilizing AI effectively. The intention in measuring AI competency and its determinants, SCT laid out a good foundation to built on.

Conceptual Development: The TMAC Framework

This study using an approach of synthesizing previous research grounding in Social Cognitive Theory. The framework shifts the focus from passive technical skills to active drivers categorized into three SCT dimensions.

Cognitive Drivers

In assessing AI-generated information, cognitive capabilities plays a role in determining how individuals assess them. This study conceptualizes cognitive capabilities across two constructs: AI Sensemaking (AIS) and Information Verification Process (IVP). AIS refers to the capability of individuals in recognizing AI tools' capabilities and limitations, together with interpreting AI text against human judgment. The tools enable users to generate results through prompt-

based interactions with less technicality complexion. While IVP refers to the ability of individuals in identify, evaluate, verify and apply information in problem solving (Brand-Gruwel et al., 2005; Walraven et al., 2008). These constructs together represent cognitive mechanism of individuals in assessing AI outputs.

Environmental Drivers

Academic environments deeply influence scholarly works. Environmental drivers act as catalysts for responsible AI usage. Collaborative Influence (CI) refers to peer influence that drives academics to cross-check outputs together in scholarly networks (Kwiek, 2015; Šimčisko, 2025). Institutional Support (IS) refers to universities providing clear policies and digital infrastructure to support research activities.

Efficacy Drivers

Self-efficacy is the psychological state of an individual, where an individual has the confidence level in completing the task (Bandura, 1998). In this study, self-efficacy is represented by Perceived AI Confidence (PAC) and AI Risk Vigilance (ARV). Individuals with higher self-efficacy tend to utilize AI tools more in their work (Bewersdorff et al., 2025; Ma & Li, 2024). However, academics must also possess healthy skepticism. ARV means academics strictly adhere to research ethics to prevent data privacy risks and biased results (Cui & Alias, 2024; Delikoura et al., 2025; Harsh Shukla, Kshama Pandey & Neeraj Kumar, 2025).

Conceptual Framework

This study proposes a conceptual framework consist of AI competency influenced by three types of determinants: Cognitive drivers, Environmental drivers, and Efficacy drivers. Which in turn affected AI-assisted research practice effectiveness. While AI competency treated as cognitive central of multidimensional construct consist of ability in evaluate, verify and apply AI-generated outputs.

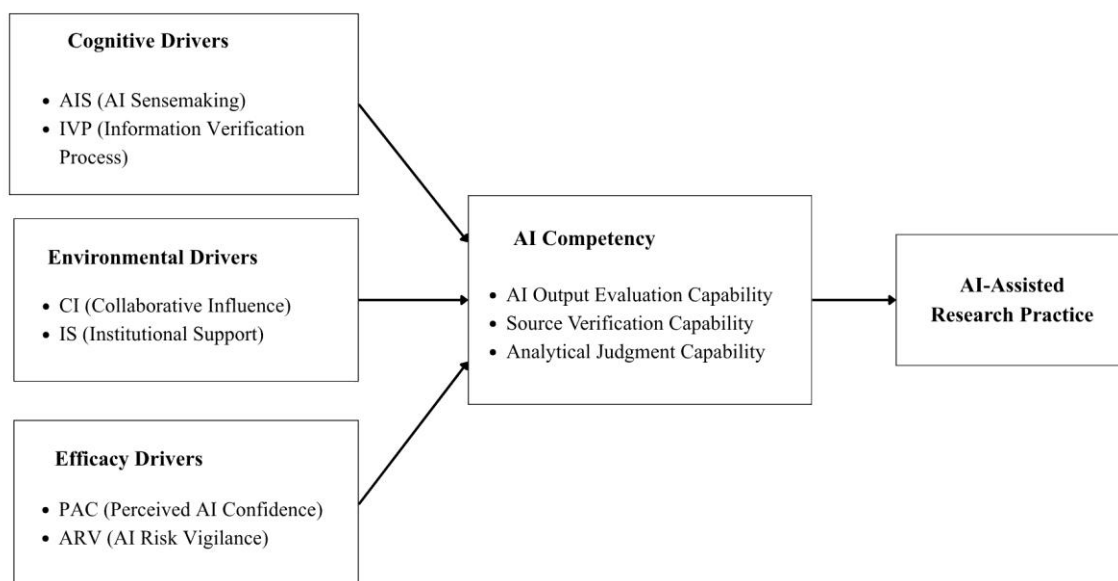


Figure 1: Triadic Model of AI Competency (TMAC)

Conceptual Development Approach

This study using an approach of synthesizing previous research grounding in Social Cognitive Theory. The constructs and relationships are derived from previous studies. The empirical studies are critically analyzed to develop the conceptual model.

Theoretical Contribution

Table 1: Theoretical Contribution

Contribution	Explanation
Redefinition of AI competency	shifts from multidimensional literacy to cognitive evaluation
Theoretical extension	applies SCT to AI competency in academic research
Integration of healthy scepticism determinant	introduces AI Risk Vigilance (ARV) into efficacy construct
Integration of peer validation determinant	introduces Collaborative Influence (CI) as peer-driven verification into environmental construct

Implications

Theoretical implication can be derived from this study is the extension of SCT into TMAC framework. It clarifies role of cognitive processing, peer-driven collaboration, and risk vigilance in effective AI utilization in academic research practices. As for the practical implication, the approach can be more focus on evaluation and verification skills training.

Conclusions

This study proposes a cognitive focus framework of AI competency based on Social Cognitive Theory. The focusing on cognitive, environmental and self-efficacy provides more focused measurement and explanation towards AI competency in academic research setting. The framework offer a ground for future empirical studies to validate the proposed relationships. Future research need to empirically validate the TMAC framework using quantitative approach. Structural Equation Modeling (SEM) can be utilize to test the strength of relationship between the drivers and AI competency. Also, future empirical works should examine how this competency influence actual research outcomes.

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