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AI-Driven Metacognitive Support Systems for Learning: A Survey on Perception, Reasoning, and User-Centric Design

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***Abstract*—There is a rapid growth of digital access to re- sources and learning environments. Due to this, learners face the challenges of cognitive overload, burnout and need person- alized guidance. Currently , AI systems aim to address this by scaffolding Self Regulated Learning (SRL). This survey dives deep into developing such systems based on 24 recent research papers focusing on advancements in knowledge representations, cognitive state modeling and personalized interactions. The work is divided into 3 main fields : First being Knowledge representation where knowledge graphs, concept maps, LLMs are utilized to answer based on complex reasoning. Secondly, there is Cognitive and Affective State Monitoring which utilizes multimodal data to understand the current user state. Finally, we understand how to personalize, interact, scaffolding knowledge and efficacy along with adaptive strategies like Reinforcement learning. Findings show us a trend towards real-time adaptation based on rich models. Despite these, the challenges remain ethical and privacy concerns, efficacy validation. This research paper identifies the gaps and suggests cognitive compass which works on neuro symbolic reasoning, transparent workflow analysis and scaffolding as a potential solution addressing key challenges like user-centric design, state detection and socratic dialogue.**

***Index Terms*—Assistive Technology, Personalized Learning, Cognitive Load, Metacognition, Self Regulated Learning, Knowl- edge Graphs, Brain Computer Interface (BCI), AI Tutors, Con- cept Mapping, Learning Analytics, Neuro-Symbolic AI**

I. Introduction

The Modern education is dominated by vast digital re- sources, online platforms available to user with least effort, which presents challenges like cognitive overload and in turn, leads to reduced learning efficiency [1]. Moreover, online learners lack structured guidance and must independently manage their progress across their learning path [1].

The key aspects to handle these challenges are metacog- nition and Self Regulated Learning (SRL), the process of planning, monitoring, managing, reflecting their own learning [2].

Realistically, multiple learners struggle with these skills [2], [3] and ignore some executive functions that lead to underwhelming learning outcomes, such as managing fatigue [4] or maintaining focus [20]. There is a need in externalizing these executive functions and guiding them throughout the SRL cycle.

AI offers multiple methods to tutor learners; advancements include Intelligent Tutoring Systems (ITS) [5], [7] , a system for personalized path planning [1], real time cognitive state monitoring with sensors like video, EEG and more [8], [9], [20], and conversational tutors like ChatGPT and Socratic playground [13], [21]. There are also data driven insights from Learning Analytics (LA) [22]. Proposed Cognitive Compass builds on neuro symbolic knowledge graphs ,user control and scaffolding based on workflow.

The core purpose of this survey is to review in detail and compile recent research (from 2022-2025) relevant to designing AI based metacognitive support systems. As mentioned before ,the 3 main areas and how they interact are shown in brief in Fig. 1: Knowledge architectures (KG, LLM), cognitive state monitoring, and personalized interaction, and scaffolding. This paper contains Literature survey in depth followed by a summary table. Discussions based on survey including research gaps, limitations and finally ending with conclusion towards future directions on design of cognitive compass, for overcoming the current gaps

II. Literature Survey

This section reviews recent studies grouped into three categories as mentioned.

A. Knowledge Representation and Modeling

Effective support to learners requires robust and clear knowledge representation. KG, concept maps, and LLMs offer powerful modeling capabilities in optimal time and convert unstructured text into meaningful structured notation.

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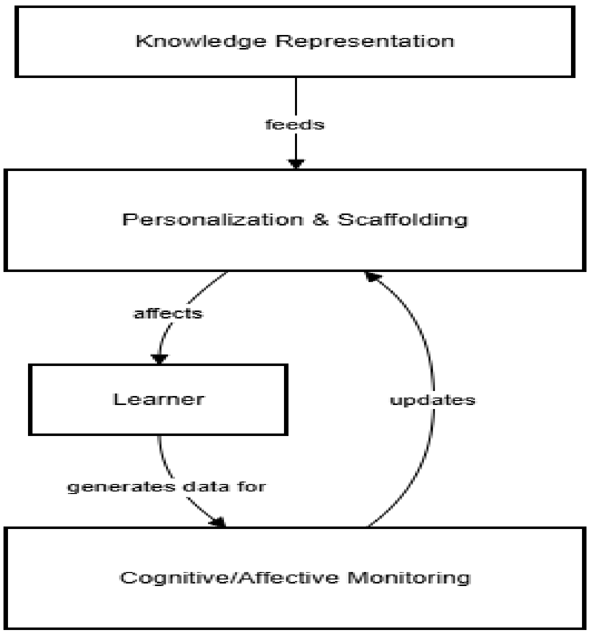

Fig. 1. Conceptual model of an AI driven metacognitive support system.

Li et al. [23] proposes **CourseKG**, an educational knowl- edge graph built using advanced NLP combining BERT, BiGRU, MHSA, CRF for entity and relation extraction which address unique needs of educational concepts with deeper rep- resentation. Abu-Rasheed et al. [11] use LLMs that collaborate with human to create KGs in aspects of making curriculum, enhancing personalization. KG is also part of personalized path planning such as KG-PLPPM in [1] which uses cognitive diagnosis and enhanced resource recommendation in LKGA

[15] made using attention mechanisms. These papers arrive to the fact that there is a deep synergy between symbolic representation of KGs and LLMs, Cognitive Compass aims to utilize MeTTa which provides a framework for such synergy. Knowledge shown visually such as digital concept maps in [16] and mind maps [17] help learners in organization, retention of their knowledge.

B. Cognitive and Affective State Monitoring

Every learner behaves differently according to the problem they are learning. Adapting to the learner state in real-time makes the system more meaningful in assisting the learner. LA [22] gives us a framework for collecting and analyzing student data on a large scale.

There are multiple approaches that try to help learners. Mul- timodal approaches which take in various types of data give a rich set of insights. Hossen & Uddin [20] combine computer vision techniques such as face, hand, pose, phone detection for high accuracy attention monitoring. MetaTutor [2] uses an extensive set of sensors from eye tracking to physiological state to model cognitive, affective and metacognitive models (CAMM).

Specific and deeper modalities are also explored. Das & Dev [10] use face muscle movements termed Facial Action Units (AU) for detection, understanding how well a user is engaged. Sallom et al. [6] detect and achieve high accuracy in emotion recognition utilizing CNNs. Physiological under- standing is done using EEG in Beauchemin et al. [9] use EEG-BCIs for cognitive load monitoring and BCI is used to adapt according to user state. Sola et al. [8] use eye- tracking for attention monitoring. This leads us to explore better non-invasive methods that focus on the workflow rather than monitoring user video feed or brain signals. Cognitive Compass aims to track user workflow while respecting user privacy for providing actionable interventions when required. Behavioral indicators such as browser tracking while surfing the web and more are simpler alternatives for monitoring. Smits et al. [4] gives the Flowtime break technique and is effective for managing fatigue, which is detectable through
interaction patterns.

C. Personalized Interaction, Scaffolding, and Efficacy

All metacognitive systems are heavily relying on user interaction and therefore the quality of such interactions with effective interfaces, scaffolding is highly important for long term usage.

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LLMs enable these systems to redefine interaction with learners. Zhang et al.'s [21] Socratic Playground for Learning (SPL) uses GPT-4 and well-defined prompt engineering for Deep questioning, empowers critical thinking. Effective scaf- folding, such as pedagogical agents in [2] are essential. Various adaptive strategies are often optimized using RL [3], [24]. Mermarian & Doleck [24] do highlight the fact that there will be pedagogical conflicts between behaviorism and constructivism, biases. Hence there is a need for a transparent understanding in adaptive systems. Cognitive compass aims to create an audit trail to explain AI reasoning of why it arrived to a certain response.

Evaluation of metacognitive systems is very complex. ITS generally go beyond the traditional methods but not always [5], it highlights the importance of design in such adaptive systems [7]. LA reviews [22] stress on challenges like privacy, fairness and accuracy.

User-centric design for such systems is mandatory as it can make or break the user interactions, human tutors still provide superior emotional support. Personalization is highly necessary for assistive tech based on state of user such as autism [18], visually impaired [12]) along with ADHD [19], these papers clearly identify pain points of specific user and have their own approaches to mitigate or reduce them.

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TABLE I:
Observations On Different Research Papers

S. No.	Title	Year	Methodology	Observed Features	Limitations
1	KG-PLPPM: A Knowl- edge Graph-Based Per- sonal Learning Path Plan- ning... [1]	2025	KG Construction, V- DINA Model, TransR	• Plans personalized learning paths. • Uses cognitive diagnosis for weak points.	• Relies on specific cognitive model (V-DINA). • KG construction is domain-specific. • No real-time cognitive state input.
2	Lessons Learned and Fu- ture Directions of MetaTu- tor... [2]	2022	10-Year Review	• Comprehensive multimodal ITS (logs, eye- tracking, facial, physio). • Uses Pedagogical Agents to scaffold SRL.	• Highly complex, expensive, lab-based. • Difficult for real-world de- ployment.
3	Reinforcement Learning in Education: A Systematic Literature Review [3]	2025	SLR (PRISMA)	• Surveys RL contexts, algo- rithms (Q-learning), and adaptation.	• Limited by source paper qual- ity. • Field-wide gap: "Black box" models.
4	Investigating the Effectiveness of Pomodoro, Flowtime, and Self-regulated Break-Taking... [4]	2025	Online Intervention	• Flowtime technique reduced fatigue increase. • No effect on motivation or task completion.	• Relies on self-reported data. • Short-term intervention.
5	A systematic review of AI-driven intelligent tutor- ing systems (ITS) in K-12... [5]	2025	SLR (28 studies)	• ITS positive effect vs. traditional. • Effect mitigated vs. non- intelligent systems.	• Limited by quasi-experimental designs. • Lacks long-term / diverse sample studies.
6	Emotion recognition for enhanced learning... [6]	2025	Refined CNN	• 95% test accuracy on 7 basic emotions. • Aims to enable adaptive teaching.	• Lab-based dataset (FER2013). • May not generalize to complex "in the wild" emotions.
7	Adaptive intelligent tutor- ing systems for STEM ed- ucation... [7]	2025	Quasi-experimental	• ITS group showed significant improvement. • 80% valued adaptive feed- back.	• Quasi-experimental (no RCT). • STEM-specific, may not generalize.
8	AI Eye-Tracking Technol- ogy: Managing Cognitive Loads for Online Learners [8]	2024	AI Prediction S/W, Eye-Tracking	• Links gaze patterns to cognitive demand. • Potential for load monitoring.	• Relies on proprietary soft- ware. • Correlational, not causal. • Requires specialized hard- ware.
9	Enhancing learning expe- riences: EEG-based pas- sive BCI system... [9]	2024	Experimental, EEG-BCI	• Real-time adaptation to cognitive load. • Motivation (incentive) was key catalyst.	• Invasive hardware (EEG cap). • Lab-based. • Motivation was a confound- ing variable.
10	Optimizing student engagement detection using facial and behavioral features [10]	2025	ML (XGBoost)	• Integrates facial images + Fa- cial Action Units (AUs) to de- tect engagement.	• Lab datasets. • Cannot capture internal cog- nitive engagement (daydream- ing).
11	LLM-Assisted Knowledge Graph Completion for Curriculum... [11]	2025	Human-AI Collab.	• Uses LLMs (GPT-4o) in human-in-the-loop process to build KGs.	• Not fully automated; relies on expert validation. • Dependent on LLM quality (hallucination).
12	AI-Powered Assistive Technologies for Visual Impairment [12]	2024	Survey (AT)	• Highlights ethical and cost barriers.	• General survey; field-wide limits (cost, user acceptance).
13	Socratic wisdom in the age of AI: ChatGPT vs human tutors... [13]	2025	Mixed-Methods	• AI (ChatGPT) v • Humans prefer tailored feedback.	• Based on user perception, not outcomes. • Small, qualitative sample.

S. No.	Title	Year	Methodology	Observed Features	Limitations
14	The Application of Extended Reality Technology in Architectural Design... [14]	2023	Content Review	• XR benefits visualization, motivation.	• Domain-specific (architecture). • Highlights high cost, technical barriers.
15	Enhancing the Recommendation of Learning Resources via an Advanced KG (LKGA) [15]	2025	KG Attention Net.	• Improves recommendations using collaborative signals and attention.	• Evaluated offline, not in a real-time system. • Potential scalability issues.
16	Research and applications of digital concept mapping in education... [16]	2024	SLR	• Reviews DCM trends, use as student org. tool.	• Scope limited to 2012-2022. • Notes gap in pedagogical theory application.
17	Assessing the efficacy of mind mapping as a learning technique... [17]	2024	Quasi-experimental	• Mind mapping improved knowledge retention.	• Quasi-experimental. • Domain-specific (nursing).
18	Breaking Barriers—The Intersection of AI and Assistive Technology in Autism Care... [18]	2024	Narrative Review	• Reviews AI in robotics/wearables for autism.	• Narrative (not systematic) review. • Highlights high cost, ethics, user acceptance.
19	Extended Reality (XR) Technology in ADHD-Friendly Classroom Design [19]	2025	Qualitative	• Explores XR for ADHD support (customization, engagement).	• Small sample. • Relies on educator perceptions, not student outcomes.
20	Attention monitoring of students during online classes using XGBoost... [20]	2023	Computer Vision, XGBoost	• Multimodal (face, hand, pose, phone) attention detection (99.75% accuracy).	• Cannot detect mental disengagement. • High accuracy likely dataset-specific. • Significant privacy concerns.
21	SPL: A Socratic Playground for Learning Powered by Large Language Model [21]	2024	LLM (GPT-4), Prompt Engineering	• ITS using Socratic method via LLM prompts for critical thinking.	• Small pilot study. • Rated low on "human-likeness". • Relies on GPT-4 (cost, latency, hallucination).
22	A Systematic Review of the Role of Learning Analytics in Supporting Personalized Learning [22]	2024	SLR (40 articles)	• Reviews LA for personalization (feedback, prediction).	• Field-wide limits: Data accuracy, privacy, algorithmic fairness, opportunity costs.
23	CourseKG: An Educational Knowledge Graph Based on Course Information... [23]	2024	KG Construction, BERT-BiGRU-CRF	• Method for building domain-specific KGs using advanced NLP.	• Complex model. • KG construction validated, but not its live application.
24	A scoping review of reinforcement learning in education [24]	2024	Scoping Review	• Reviews RL (games, ITS), discusses pedagogical paradigms.	• Limited scope (15 studies). • Highlights RL (behaviorist) vs. constructivist pedagogical conflict.

TABLE II
COMPARATIVE INSIGHT: CURRENT STATE VS. IDENTIFIED GAPS IN SURVEYED DOMAINS

Domain	Current State (What We Have)	Identified Gaps (What We Lack)
I. Knowledge Representation [15].	Structured KGs for path planning [1], Advanced NLP (BERT) for building domain-specific KGs [23]. LLMs assisting in human-in- the-loop KG creation [11]. Visual tools (Mind Maps) proven effective [17].	Fully automated, high-accuracy KG generation. Standardization for interoperability between KGs. Native, deeply integrated neuro-symbolic reason- ing frameworks. Real-time, dynamic KG updating from user interaction.
II. Cognitive/Affective Monitoring atten-	High-accuracy, multimodal CV for tion/emotion [6], [20]. High-fidelity (but in-vasive) physiological sensors (EEG) [9]. Non-invasive proxies (eye-tracking, behavioral patterns) [4], [8]. Learning analytics (LA) frameworks for data collection [22].	Reliable detection of *internal* states (e.g., mental disengagement vs. focused attention) [20]. Scalable, non-invasive, low-cost hardware. Robust solutions for privacy, data consent, and algorithmic bias [22].
III. Personalized Interaction meth-	ITS efficacy proven superior to traditional ods [5], [7]. LLM-driven, flexible Socratic dialogue agents [21]. RL models for optimizing pedagogical policies [3], [24]. Human–AI comparison (AI for access, Human for empathy) [13].	Pedagogical alignment (e.g., RL's behaviorism vs. constructivism) [24]. AI agents that can replicate human emotional support [13]. Explicit transparency and explainability ("Why?"). Clear proof of ITS superiority over *non-intelligent* (but well-designed) digital tools [5].

III. DISCUSSION

After a deep dive into 24 research papers, Table II summarizes them in aspects of what is present and what are the gaps identified in each domain, this reveals deep interconnection of domains and challenges in AI driven support systems.

Firstly, there is a deep interlink between knowledge graphs and LLMs for enhancement of knowledge representation. KG provides structured reasoning [1], [15] , which can further use NLP pipelines

[23] while LLMs speed up KG creation [11]. However, beyond linking components, moving towards native integrated neuro sym- bolic frameworks like hyperon is core of cognitive compass utilizing MeTTa lang.

Secondly, Cognitive and Affective State Monitoring gives an important but necessary trade off, privacy and cost for quality in system interactions such as EEG [9] offer high level analysis but it is practically not scalable to real world deployment, whereas computer vision [20] or behavioral analysis [4] face challenges in accurately understanding the user and raise ethical concerns [22].

Thirdly, Personalized interaction is constantly evolving with LLM based conversations [21] and RL optimization [3], [24]. Still there is a challenge of replication of human empathy [13], [24].

Learners need to know why a system is suggesting a certain pathway, needs to be highly transparent, Cognitive compass aims to develop a clear audit trails. User motivation to learn [9] and deep personalization for users [18], [19] are also important.

IV. CONCLUSIONS

This survey has analyzed 24 recent research papers in AI driven systems designed to support learners with externalizing self regulated learning. This literature shows us the significant progress in building systems capable of real time adaptation and personalizing based on user. Knowledge representation has a synergy with KG, advanced NLP and LLMs [11], [23]. Learner state can be assessed based on multimodal inputs that user allows for LA [2], [20], [22].Interfaces evolved through use of LLMs and RL [3], [21].

However, realistically the path to highly accessible , effective deployment faces various challenges. Understanding the user internal state non-invasively, ensuring ethical standards and local processing if possible for LA [22], achieving pedagogical alignment i.e selecting which type of learning [24] dynamically, and demonstrating clear efficacy over other tools [5], remain main hurdles.

Future directions would involve in creation Cognitive Compass which consists of hybrid human AI models with neuro symbolic reasoning at its core, explicit transparency, and workflow based SRL scaffolding. The field still lacks standardized evaluation metrics, and solutions for ethical LA and sufficient evidence of generalization in real world environments.

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