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AI-Mediated Control–Value Appraisal and Emotional Experiences: A Socio-Technical Extension of Generalized Control–Value Theory

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Abstract: In the era of AI-assisted learning, academic attention to learners' emotional experiences has rapidly increased. Existing research primarily views AI as an external influence (e.g., a risk, motivator, or facilitator), and focuses mainly on individual-level cognitive mechanisms. However, few studies have addressed how AI-assisted environments shape the construction of control and value appraisals underlying emotional experiences. This paper proposes that AI-assisted environments play a structural mediating role in the construction of control and value appraisals, thus extending Generalized Control-Value Theory (GCVT) to the socio-technical field. Specifically, we argue that AI influences these assessments by introducing distributed agency, AI-mediated expectations, and AI-assisted cognition into the formation of control appraisal and the structural reorganization of intrinsic and extrinsic value appraisal. Combining evidence from AI research, cognitive science, and experimental studies, we propose a comprehensive conceptual framework that elucidates how AI contributes to the construction of control and value appraisals, ultimately influencing emotional experiences. This framework positions AI as part of the emotion generating mechanism rather than merely an external situational factor, thus deepening our understanding of emotions in AI-driven digital environments and making it more contextually sensitive and socio-technically grounded. Furthermore, this framework provides theoretical insights for educational psychology and points to future research directions for AI-supported learning systems.

1. Introduction

Artificial intelligence (AI) is increasingly integrated into human performance contexts, from AI-driven feedback and decision-making systems to algorithmic performance metrics across education, organizational, and industrial domains. Existing research has primarily treated AI as an external influence, emphasizing its potential as a risk, a motivator, or a facilitator of human emotional experiences[1-3]. Some studies highlight the motivational and performance-enhancing effects of AI[4, 5], whereas others caution against overreliance or emotional stress induced by algorithmic control[6, 7]. Despite these insights, relatively little attention has been paid to how AI shapes the psychological mechanisms underlying emotional experiences. In particular, the construction of control and value appraisals that is central to emotional responses in the GCVT remains underexplored in AI-mediated settings. To address this gap, this perspective extends GCVT from human-centered to socio-technical contexts and examines AI's mediating role in appraisal construction and emotion formation. Specifically, we propose a framework of AI-mediated appraisal construction and explore how AI shapes the appraisal construction and shifts in emotional experiences.

2. Control–Value Appraisal in Socio-Technical Contexts

2.1 Core Principles of Generalized Control–Value Theory

Generalized control-value theory[8] builds upon classical control-value theory[9, 10] by extending the conceptualization of control and value to account for emotional experiences in complex educational contexts. GCVT explains the role and function of control and value appraisals in the mechanism of emotion generation, capturing the multifaceted influences that shape learners' emotional experiences. Moreover, GCVT[8] incorporates broader contextual dimensions, including cultural factors (e.g., beliefs and gender stereotypes) and social environments (e.g., emotional significance and alignment with personal goals) to further contribute to the formation and regulation of emotions.

According to GCVT, emotions arise from the joint appraisal of perceived control and value across a broad range of domains, including achievement, social, epistemic, and existential contexts[8,10]. Control appraisals refer to an individual's expectation of influencing outcomes and can be assessed through expectancies, attributions, and self-concepts of ability, while value appraisals pertain to the perceived importance or significance of activities and outcomes at intrinsic and extrinsic levels. High control and high value typically promote positive activating emotions, and low control or low value leads to negative or deactivating emotional states[8, 9]. Specifically, achievement emotions (e.g., enjoyment, boredom, hope, anxiety, pride, and shame) are linked to students' competence in academic achievements, epistemic emotions (e.g., surprise, curiosity, and confusion) involve cognitive uncertainty of knowledge, social emotions (e.g., gratitude, guilt, love, hate, and anger) depend on people's perceptions of their own traits and their interpersonal relationships with others, and existential emotions (e.g., happiness and sadness) reflect people's value perceptions of life and health.

2.2 Appraisal Construction in Socio-Technical Contexts

Within the framework of GCVT, control and value appraisals are understood as socially and culturally constructed[8, 11]. Learners' perceptions of their own agency and task significance are shaped by a range of contextual factors, including classroom climate, teacher feedback, institutional norms, and broader cultural expectations[12]. These socio-technical and cultural influences highlight that learners' motivational experiences are not solely individual cognitive processes but are embedded within the social and institutional learning environments. Emotions therefore emerge from context-sensitive appraisal processes embedded in social environments.

In the AI-mediated learning era, the context of appraisal construction is no longer exclusively social but increasingly situated within technologically augmented environments. Technical scaffolds are embedded into learners' cognitive and motivational architecture. Algorithmic recommendation and human-AI collaborative systems are participating in cognition, task organization, feedback generation, and outcome prediction[13-15]. AI does not merely add another environmental influence but becomes integrated into the mechanisms through which individuals interpret their causal influence, competence, and task value. This integration suggests that appraisal construction in AI-mediated settings may involve more than contextual modulation. AI has the potential to reshape how control and value perceptions are formed. The next section elaborates how AI structurally mediates the construction of these appraisals.

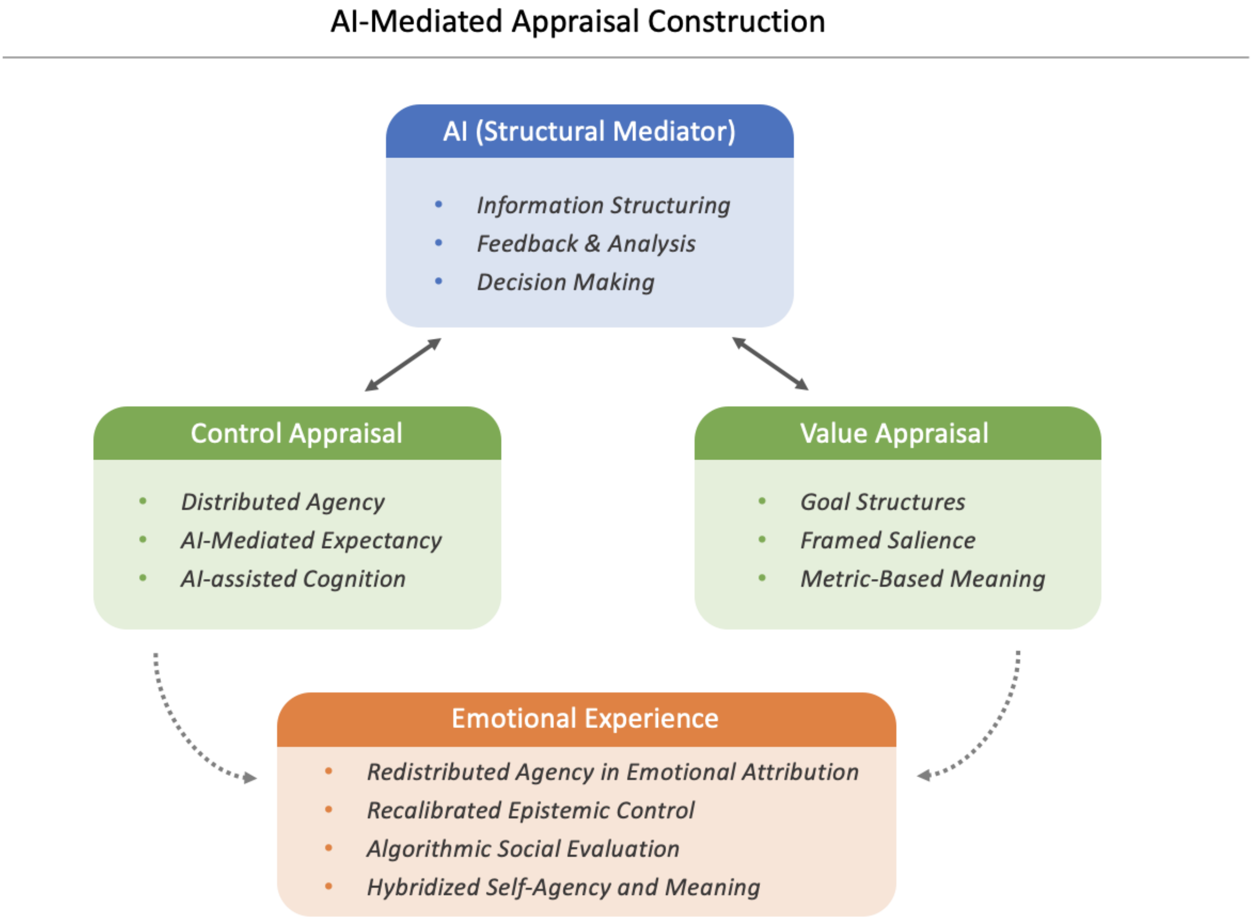

Figure 1: AI-Mediated Appraisal Construction

3. AI-Mediated Appraisal Construction

AI mediates control and value appraisals in dynamic ways. On the one hand, AI mediates the construction of control appraisal through distributed agency, AI-mediated expectancy, and AI-assisted cognition. On the other hand, AI mediates the construction of value appraisal both intrinsically and extrinsically. (See Figure 1.)

3.1 Control Appraisal Construction

In terms of control appraisal, AI structurally mediates the appraisal through distributed agency, AI-mediated expectancy, and AI-assisted cognition by providing AI feedback, content generations, and AI guidance. First, distributed agency is being formed since control appraisal shifts from individual-centric to distributed construction. Learners partially rely on AI feedback to complete assignments or tasks. AI-powered learning technologies offer several pedagogical opportunities, including personalized reminders, automated real-time feedback for improving writing, and recommendations for study strategies[16, 17]. Collaboration and co-construction with AI enable learners to redistribute perceptual control over outcomes. Second, AI-mediated expectancy is affecting people's expectation of activities and outcomes. Outcome expectancy moves from personal prediction to AI-assisted prediction. AI's efficient content generation capabilities and risk prediction functions have influenced people's expectations and judgments regarding the relationship between behavior and outcomes. AI can generate personalized feedback that not only assesses current performance but also forecasts the impact of specific learning strategies on future academic success[18, 19]. Individual’s expectation of success and failure is partially informed by AI outputs, not solely self-generated. Third, AI-assisted cognition is integrating with sole individual cognition. AI guidance is playing a crucial role in people's cognitive processes, including knowledge understanding, decision making and problem solving. When using AI to scaffold learning and task completion, learners tend to become metacognitively lazy and reduce the motivation for self-regulated learning[20, 21]. With personal cognitive processes integrate AI support, the construction pathway of perceived control has been changing.

3.2 Value Appraisal Construction

In terms of value appraisal, AI structurally mediates the appraisal via intrinsic value and extrinsic value by influencing goal structures, framed salience, and metric-based meaning. As for intrinsic value, AI affects the perception of learning interest, task challenge, and personal growth. Positive relationships are found between the AI-driven personalized feedback and students’ willingness to learn and engage in schoolwork[22]. AI significantly influences individuals’ learning interests by affecting basic psychological needs such as autonomy and competency[23]. Individual perception of intrinsic value becomes partially structured by AI-mediated task framing and feedback. As for extrinsic value, AI influences the perception of external rewards and punishments. AI highlights certain task aspects or outcomes and provides metric-based meaning making contexts. Task salience is algorithmically framed by AI through the explicit encoding, weighting, and optimization mechanisms embedded within an AI system's design and operational objective functions[24]. AI-provided metrics give individuals the hint of the task importance and potential consequences[25]. Extrinsic value evaluation is structured by AI suggested priorities and metrics.

4. AI-Mediated Appraisal and Emotional Experiences

Building on the AI-mediated reconstruction of control and value appraisals, emotional experiences are expected to shift along multiple domains outlined by GCVT. As AI-mediated systems redistribute agency, recalibrate expectations, and frame value salience through algorithmic metrics, the configuration of control and value appraisals become structurally different from traditional human-centered contexts. Consequently, the resulting emotional experiences are expected to exhibit distinct patterns, particularly in domains of achievement, epistemic engagement, social comparison, and existential meaning. Below we illustrate how structural changes in control and value appraisal construction may modulate these emotional patterns.

4.1 Distributed Achievement Emotions

According to GCVT[8, 9], achievement emotions depend on perceived control over outcomes and perceived value of achievement of tasks. Building on the preceding discussion of AI-mediated appraisal construction, when perceived control becomes partially redistributed between learners and AI systems, the locus of agency underlying performance outcomes may become less clearly bounded. Such redistribution of control[26, 27] may lead to attributional ambiguity[28] since activity results cannot be solely attributed to individual competence or efforts, but also algorithmic recommendations. For example, pride may involve hybrid attributions that integrate both personal efforts and technological support. Conversely, when algorithmic judgments are opaque, reduced perceived control may heighten anxiety[29] or contribute to hopelessness. These shifts do not constitute new emotional categories but reflect how achievement emotions are shaped by structurally mediated control and value appraisals in AI-mediated performance environments.

4.2 Co-Constructed Epistemic Emotions

In GCVT, epistemic emotions are linked to perceived control over understanding and perceived value of knowledge acquisition[8]. As is previously illustrated, AI-mediated appraisal construction is shifting the personal knowledge construction to co-construction with AI involvement. Such co-constructed understanding may change the perceived value of knowledge acquisition. When knowledge is easier to acquire with less or little personal efforts, AI partially becomes the delegation of cognitive effort[30, 31] and may further decrease learning motivation[32]. For example, individuals may become less confused with AI-guided problem solving and lack enough curiosity[33] for exploring the underlying mechanisms in complex knowledge learning. AI-mediated epistemic environments redistribute the experience of uncertainty, thereby modulating epistemic emotions through altered control and value perceptions.

4.3 Algorithmically Modulated Social Emotions

GCVT claims that social emotions arise from perceived individual value and social relationships, including self-related emotions and other-related emotions[8]. Building on the preceding discussion of AI-mediated appraisal construction, AI may modulate control and value appraisals via salience of rankings[34] and engagement metrics[35]. The algorithmic amplification may intensify comparison in social relationships[36, 37] and therefore affect social emotional experiences. For example, people may feel intensified shame and envy due to persistent comparison, and the feeling of belonging may depend on social platform visibility governed by algorithms. AI systems amplify and stabilize value hierarchies that shape their occurrence.

4.4 Technology-Mediated Existential Emotions

GCVT claims that existential emotions are decided by perceived value of health and life[8]. As is previously discussed, individuals' value perception is shared with AI participation. The authorship is partially redistributed[38], decision-making process is assisted by AI feedback, task meaning is structured by external metrics, and goal hierarchies are suggested by AI systems. Such shared value perception may affect people's perceived autonomy[39] and coherence of self-agency[40, 41]. For example, people may feel instability in perceiving happiness and sadness due to AI assessment and algorithmic-contingent evaluation. In AI-mediated contexts, existential emotions may fluctuate as perceptions of agency and value become partially externalized.

5. Discussion

This perspective extends GCVT to socio-technical contexts by situating appraisal construction within AI-mediated environments. Rather than treating AI as a peripheral contextual factor, the present framework conceptualizes it as a mediator of control and value appraisal construction. In AI-supported settings, perceptions of agency, competence, and task value may become partially distributed across human–AI systems. Accordingly, emotional changes observed in AI-supported learning should not be interpreted as direct technological effects, but as shifts in perceived control and value configurations shaped by AI-mediated appraisal structures. By reframing appraisal as distributed and technologically scaffolded, this perspective clarifies how emotional experiences in socio-technical systems can be understood as structurally modulated rather than technologically determined.

These theoretical considerations also carry practical implications for AI system design and implementation. AI systems should preserve perceivable human agency by maintaining visible human authorship in task processes. In addition, attention should also be given to the emotional influences of algorithmic visibility since excessive reliance on metric-based value signals may intensify externally driven appraisal patterns. More balanced feedback structures that extend beyond metric-dominant signals may reduce the amplification of social comparison and support more stable forms of motivation. At the educational and organizational levels, fostering more balanced human–AI engagement patterns may encourage sustained cognitive participation and active intrinsic engagement.

Future research is needed to empirically examine the structural propositions advanced in this framework. Experimental studies could manipulate levels of AI assistance to assess their effects on perceived control, intrinsic value, epistemic curiosity, and emotional variability. Such designs would help determine whether reduced cognitive outsourcing enhances more stable forms of human engagement. Further investigation may explore how diffusion of agency in human–AI collaboration influences the intensity or attribution of achievement emotions. Longitudinal research is also warranted to examine whether prolonged exposure to AI-mediated evaluation systems recalibrates baseline control–value appraisals over time. Together, such empirical work would deepen understanding of the structural mechanisms through which AI-mediated contexts modulate emotional experience.

6. Conclusion

This perspective extends GCVT from traditional human-centered to socio-technical settings, highlighting how AI reshapes control and value appraisal processes. Such shifts in appraisal construction lead to changes in emotional experiences through perceived control and value evaluations under AI-mediated conditions. Theoretically, this work contributes to a more nuanced understanding of emotion as emerging from context-sensitive appraisals that integrate both social and technological influences. Practical implications for AI system design include careful consideration of human-perceived autonomy and the impact of algorithmic rankings on emotional experiences. Furthermore, suggestions are proposed for fostering balanced human-AI collaboration in educational and organizational contexts. Despite these insights, empirical evidence on AI's mediating role in appraisal construction remains limited, calling for systematic investigations across different tasks, contexts, and populations. Future empirical research could employ experimental and longitudinal designs to clarify how AI-mediated appraisal processes shape emotions and inform interventions for human–AI interaction.

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