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Understanding Cognitive Load and Emotional Adaptability in Human–AI Collaborative Work: Evidence from an Experimental Study

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Abstract- As Artificial Intelligence (AI) increasingly integrates into professional environments, understanding its psychological impact on human collaborators becomes crucial. This study investigates the emerging paradigm of Human-AI Ensemblement—the synergistic interaction between human professionals and AI systems—in corporate decision-making contexts. Conducted in Bangalore, India's technology hub, the study employs a true experimental design to evaluate cognitive load, emotional adaptability, trust in AI, and decision confidence across three task environments: human-only, semi-AI, and full-AI collaboration. Fifteen mid-level corporate tech professionals participated in a pilot experiment using validated psychological tools (NASA-TLX, PANAS, Trust in AI scales). Results revealed significant differences in cognitive load and decision confidence across groups, with the full-AI group demonstrating lower cognitive strain and higher confidence. Correlational analyses further indicated strong positive associations between trust in AI and both performance accuracy and decision assurance. These findings underscore the need for psychological preparedness alongside technical AI training. The study lays groundwork for scalable research and practical frameworks in workforce development, emphasizing emotionally intelligent, cognitively adaptive, and trust-calibrated human-AI teaming.

Keywords: Human-AI Ensemblement, Cognitive Load, Trust in AI, Decision Confidence, Emotional Adaptability, Corporate Technology, Bangalore, AI Collaboration.

I. INTRODUCTION

The proliferation of Artificial Intelligence (AI) in the modern workplace is rapidly transforming the nature of tasks, decision-making, and interpersonal dynamics among employees. As AI becomes increasingly integrated into organizational workflows—ranging from smart decision-support systems to autonomous agents—employees are expected to collaborate with AI systems as cognitive partners rather than merely using them as tools (Dwivedi et al., 2021). This evolving paradigm, known as Human-AI Ensemblement, refers to the synergistic collaboration between human agents and AI systems where both contribute uniquely to achieving complex goals (Shin, 2021).

While extensive literature has addressed topics such as AI acceptance, ethical concerns, and task automation (Jussupow et al., 2022), limited empirical research has explored the psychological dynamics involved in real-time Human-AI collaboration, especially in the high-pressure decision-making environments of corporate technology sectors. This study aims to bridge that gap by investigating cognitive load, emotional adaptability, trust in AI, and decision confidence among corporate tech professionals in Bangalore, widely regarded as the "Silicon City of India."

Background of the Study

- **Contextual Relevance in the Indian Tech Landscape**

India's growing emphasis on digital transformation, backed by initiatives such as Digital India and AI for All, has led to an upsurge in AI integration across industries. Bangalore, being the hub of major IT conglomerates such as Infosys, IBM, Accenture, and Wipro, offers a rich and diverse population of mid-career professionals already engaging with AI-enabled tools in their workflow. However, the psychological adaptability of these professionals to ensemble-based AI collaboration is an underexplored domain that requires empirical attention.

This research is especially relevant in Bangalore, where professionals are not only exposed to high AI interaction but also experience pressure to maintain cognitive sharpness, emotional regulation, and decision accuracy. Training these professionals to work with AI, not just around it, is essential for the future of productive, ethical, and mentally sustainable workplaces (Nafrin et al., 2023).

Theoretical and Empirical Underpinnings

The study draws on concepts from Cognitive Load Theory, Affective Adaptability, and Trust in Automation. Human collaboration with AI often generates unique psychological tensions—ranging from reduced perceived autonomy to heightened anxiety due to opaque decision-making algorithms (Glikson & Woolley, 2020). While NASA-TLX is well-established in measuring task-induced cognitive load (Hart & Staveland, 1988), its application in AI-mediated team settings remains rare.

Furthermore, the Positive and Negative Affect Schedule (PANAS) allows insight into the emotional transitions that occur before and after AI-enabled tasks (Watson, Clark, & Tellegen, 1988). Tools like the State-Trait Anxiety Inventory (STAI) also provide measures of transient stress states that may be triggered by working with opaque or unpredictable AI recommendations (Spielberger, 1983). These constructs together allow a comprehensive psychological evaluation of AI-augmented task performance.

Need for the Study in the Post-AI Era

The emergence of ensemble roles—where AI and human agents share cognitive and functional responsibilities—demands a new set of psychological capabilities: trust calibration, emotional adaptability, cognitive flexibility, and confidence under uncertainty (Rahwan et al., 2019). Most existing studies on AI in the workplace focus on technical deployment or user acceptance (Venkatesh et al., 2012), neglecting the neurocognitive and emotional implications of human-AI partnerships, especially in the Indian context.

As AI evolves from a backend tool to a decision-making partner, organizations must understand not only how AI performs but also how humans respond—cognitively and emotionally—to such integration. This study is pivotal in helping Indian firms build training modules that go beyond upskilling and encompass psychological preparedness for AI ensemblement.

Statement of the Problem

As AI continues to reshape workplace dynamics, the shift from AI as a tool to AI as a collaborative partner marks a transformative evolution in professional roles, responsibilities, and decision-making processes. While industries increasingly rely on AI for enhanced productivity, precision, and efficiency, the psychological readiness and adaptability of human professionals remain under-researched, particularly in high-tech work environments such as those in Bangalore—the Silicon City of India.

Despite growing awareness of AI integration, there is a lack of empirical evidence on how professionals cognitively and emotionally respond to different levels of AI involvement in task execution. Key psychological dimensions such as cognitive load, emotional adaptability, trust in AI, and decision-making confidence are rarely studied within the context of real-time ensemble task environments. Without this understanding, organizations risk under-preparing their workforce for meaningful, sustainable human-AI collaboration.

Furthermore, the existing psychological and organizational literature has not sufficiently addressed the training and policy implications of these responses, leaving a gap in strategies for building psychologically resilient, emotionally intelligent, and cognitively agile human-AI teams. Thus, there is an urgent need to experimentally examine these dynamics, especially among tech professionals who are at the forefront of AI adoption and application.

Objective of the Study

To examine the psychological and performance-related outcomes of human-AI ensemblement by assessing cognitive load, emotional adaptability, trust in AI, and decision confidence among corporate tech professionals in Bangalore under varying levels of AI collaboration.

II. REVIEW OF LITERATURE

Human–AI Collaboration and Psychological Workload

Recent work on human–AI ensemblement underscores its potential to improve task performance through collaborative teaming, yet highlights significant psychological implications. Chen et al. (2024) demonstrated that AI system features such as transparency, process control, and outcome control enhanced cognitive adaptation and task performance in hybrid teams, though likability of AI sometimes reduced affective adaptation and thus performance. Guo et al. (2024) investigated hybrid human–robot tasks and found that under high cognitive load, trust in the robotic teammate increased, especially where task complexity demanded delegation. However, these dynamics are highly sensitive to workload intensity and design clarity.

Furthermore, overreliance on AI tools can lead to mental health risks, including information overload, stress, and workplace isolation—particularly in settings using generative AI or real time assistance systems (Financial Times, 2025; FT study). Financial Times highlights increased anxiety, loneliness, and reduced collaboration when AI becomes primary in work processes.

Trust Calibration and Transparency in Human–AI Teams

Effective trust between human and AI teammates is not static—it evolves dynamically during task performance. McGrath et al. (2024) proposed the CHAI T framework, which emphasizes trust as a process shaped by user characteristics, system traits, context, and feedback loops over time. Similarly, Li et al. (2024) showed that uncalibrated AI confidence—either overconfident or underconfident—can result in misuse or disuse, harming trust and collaboration outcomes; trust calibration support may mitigate but can also paradoxically induce distrust if poorly framed.

Cultural and individual differences further moderate trust behavior links. Trust is shaped by user age, AI literacy, personality, and task criticality. Recent cross domain studies highlight that expertise, risk perception, and anthropomorphism significantly influence calibration of AI trust (Fatima & Chakraborty, 2024; Prakash & Das, 2024; Wang et al., 2023).

Emotional Adaptability and Affective Response

Working with AI can evoke complex emotional reactions. Blaurock et al. (2024) identified five features of effective collaborative intelligence (CI) systems—engagement, transparency, process and outcome control, and reciprocal strength enhancement—that influence work meaning, control, and adherence to systems. Importantly, perceived lack of transparency or control can undermine emotional investment in AI collaboration. Dong & Geng (2023) applied Conservation of Resources (COR) theory to show that AI collaboration may trigger negative emotions and counterproductive behaviors when individuals perceive resource depletion (e.g., losing autonomy or competence). In a similar vein, Frontiers in Public Health (2024) demonstrated that AI adoption induces stress responses linked to perceived threats to job security, autonomy, and meaningful work—especially when support mechanisms like leadership coaching are absent.

Performance Outcomes and Cognitive Adaptation

Empirical studies have shown AI can elevate innovation and performance, mediated by perceived self efficacy and supportive design architecture. For instance, AI usage boosts innovative behavior particularly when employees feel more competent and autonomous, according to cognitive evaluation theory (MDPI, 2024). Chen et al. (2024) further showed that explainability and usability features of AI significantly enhanced cognitive adaptation, leading to improved individual performance in hybrid teams.

Conversely, miscalibration or excessive AI confidence undermines performance by promoting automation bias—where human users follow incorrect AI advice without critical evaluation (Li et al., 2024). Chen et al. (2025) tested decision support interfaces in high stakes settings (e.g., healthcare), showing that mechanisms such as AI confidence indicators and cognitive forcing functions improved trust and performance, but only if cognitive effort remained manageable; otherwise, overcomplex interventions reduced task accuracy.

Organizational Context and Training Implications

The workplace context significantly shapes psychological outcomes of AI introduction. Organizational leadership that promotes ethical transparency, employee involvement, and training can buffer stress and foster collaboration (MDPI, 2024; ResearchGate, 2024). Leaders play a mediating role by translating algorithmic decisions into human-understandable terms, fostering psychological safety, and preserving meaning of work (Vargas et al., 2025). Cultivating psychological safety—where trust allows employees to share concerns, learn, and adapt—emerges as a key antecedent of effective team functioning in AI-integrated environments.

Research Gap and Contribution

This study addresses a significant research gap by:

1. Designing a controlled experimental framework simulating AI collaboration in decision-making tasks.
2. Measuring real-time psychological responses (cognitive load, emotional adaptability, trust) and task performance in varying AI intervention conditions.
3. Producing insights to inform corporate training, AI onboarding protocols, and job redesign strategies.

Through the inclusion of validated psychological tools (NASA-TLX, PANAS, STAI) and experimental manipulation (varying levels of AI assistance), the study offers a methodologically robust and theoretically grounded contribution to both organizational psychology and AI-human systems design.

Summary of Research Gaps

Taken together, the literature underscores several unresolved issues:

- Lack of experimental evidence on how different levels of AI assistance affect cognitive load, emotional adaptability, trust, and performance in real-world professional contexts.
- Insufficient attention to the dynamic evolution of trust in ensemble tasks and how cognitive load moderates that process.
- Limited exploration of affective adaptation (e.g., positive vs. negative emotional shifts) in active AI collaboration settings.
- Underdefined training implications for building psychological readiness (e.g., trust calibration, cognitive resilience, emotional regulation) among knowledge workers.

Significance of the Study

By exploring how professionals cognitively and emotionally respond to varying levels of AI assistance, this study supports the development of ethical, human-centric AI systems and psychologically sustainable workplaces. It not only contributes to psychological theory on ensemble decision-making but also provides actionable insights for organizational leaders, HR managers, and AI developers. The results will be especially significant for companies aiming to introduce AI into roles that involve real-time decision-making, creativity, and emotional intelligence—areas where psychological interplay becomes critical.

Implications for the Present Study

This study aims to fill these gaps by employing a controlled experimental design among tech professionals in Bangalore—testing cognitive load, emotional adaptability, trust, task performance, and decision confidence under varying levels of AI assistance. By leveraging validated psychological instruments (NASA TLX, PANAS, STAI, trust scales), it will empirically capture both experiential and performance dimensions of human AI ensemblement. The results are expected to inform psychologically grounded training strategies, assist organizational design, and contribute to the theory of human AI teaming in high stakes, cognitively demanding professional domains.

III. RESEARCH METHODOLOGY

Research Design

This study adopts a true experimental design using a between-subjects approach to examine the psychological and performance implications of human-AI ensemblement across varying levels of AI involvement. Three experimental conditions are established:

- **Control Group:** Human-only task execution (no AI involvement)
- **Treatment Group A:** Human-AI semi-ensemble (AI as a decision-support assistant)
- **Treatment Group B:** Human-AI full-ensemble (AI as a primary decision-maker with human oversight)

The experimental framework will analyze participants' psychological responses and performance outcomes during a simulated workplace task scenario relevant to the tech industry, such as algorithm debugging or workflow optimization.

This approach enables causal inference by controlling extraneous variables and randomizing group assignment, aligning with recommendations for psychological field experiments (Shadish, Cook, & Campbell, 2002).

Population and Sample

Target Population

The target population comprises mid-level corporate tech professionals (software engineers, data analysts, IT managers) currently working in IT and software development firms located in Bangalore, India.

Sampling Technique

A purposive sampling strategy will be employed to select participants who are already familiar with or have prior exposure to AI-based tools, ensuring ecological validity in ensemble interaction.

Sample Size

Based on similar experimental studies and G*Power analysis ($\alpha = 0.05$, power = 0.80, effect size $f = 0.25$), a minimum of 45 participants per group (total $N = 135$) will be recruited.

Experimental Task Scenario

Participants is engaged in a standardized problem-solving task within a simulated AI-integrated platform designed to reflect real-world cognitive workload (e.g., scheduling optimization or code debugging). The platform will vary the degree of AI autonomy as per the experimental group.

Each session will be time-bound (30 minutes) and monitored through a task management dashboard.

Data Collection Instruments

a. Cognitive Load

- **NASA Task Load Index (NASA-TLX) (Hart & Staveland, 1988)**

Measures mental demand, physical demand, temporal demand, performance, effort, and frustration on a 20-point scale.

b. Emotional Adaptability

- Positive and Negative Affect Schedule (PANAS) (Watson, Clark, & Tellegen, 1988)

Assesses participants' emotional state before and after the task.

c. Trust in AI

- Human-AI Trust Scale (Schaefer, 2013)

Adapted to include dimensions of perceived reliability, integrity, and dependability of the AI system.

d. Anxiety and Confidence

- State-Trait Anxiety Inventory (STAI) (Spielberger, 1983)
- Decision Confidence Rating (custom 5-point Likert scale post-task)

e. Performance Metrics

- Task Accuracy (objective correctness of responses)
- Task Completion Time (in seconds)

Captured through the task simulation system's backend logs.

Variables

Table 1 Different Variables and their Measurement Tools

Variable Type	Variable Name	Measurement Tool
Independent Variable	Level of AI Assistance	Experimental Manipulation
Dependent Variables	Cognitive Load	NASA-TLX
	Emotional Adaptability (Positive/Negative Affect)	PANAS
	Trust in AI	Human-AI Trust Scale
	Task Performance	Accuracy, Time Log
	Decision Confidence	Self-Report Likert Scale
	State Anxiety	STAI
Control Variables	Age, Gender, Years of Experience, AI Exposure	Demographic Sheet

Procedure

1. Pre-Task Phase: Participants fill out a demographic form, PANAS, and STAI (baseline).
2. Random Assignment: Participants are randomly assigned to one of the three groups.
3. Task Execution: Each group performs the same task under varying AI conditions (no AI, semi-AI, full-AI).
4. Post-Task Phase: Participants complete PANAS, NASA-TLX, Human-AI Trust Scale, Decision Confidence, and STAI (post).

Each session is conducted individually in a controlled lab setting or virtually through an AI-integrated simulation platform.

Data Analysis

- **Descriptive Statistics:** Mean, SD, frequency distributions for all variables.
- **Reliability Analysis**: Cronbach's alpha for multi-item psychological scales.
- **Inferential Statistics:**
- **ANOVA:** To compare differences across the three groups on cognitive load, trust, and affect.
- **Paired t-tests:** For pre- and post-task comparisons (e.g., PANAS, STAI).
- **Regression Analysis:** To explore the effect of trust and cognitive load on task performance.
- **Moderation Analysis:** Using Hayes' PROCESS macro to examine whether emotional adaptability moderates the effect of AI-level on performance.

Statistical analysis is conducted using SPSS 29.0 and R 4.3.0.

Pilot Study

Introduction

As part of the broader research on Human-AI Ensemblement in corporate settings, a pilot study was conducted among corporate tech professionals in Bangalore—the Silicon Valley of India—to assess the psychological and performance impacts of AI integration in collaborative decision-making environments. The pilot involved a small-scale experimental design to refine tools, understand variable relationships, and establish the feasibility of full-scale testing.

Objectives of the Pilot Study

- To examine the cognitive, emotional, and performance differences across three decision-making environments: Human-only (Control), Human-AI Semi-Collaborative, and Human-AI Full Collaborative.
- To test the usability and sensitivity of psychological tools (e.g., NASA-TLX, PANAS, Trust in AI scales) in corporate AI ensemble scenarios.
- To identify statistical relationships among key variables such as Trust in AI, Decision Confidence, Task Accuracy, and Cognitive Load.

Methodology Overview

Participants:

A total of 15 participants were randomly assigned to three experimental groups (Control, Semi-AI, and Full-AI), with each group comprising 5 participants.

Variables:

- **Independent Variable:** Level of AI collaboration (Control, Semi-AI, Full-AI)
- **Dependent Variables:**

- NASA-TLX (Cognitive Load)
- PANAS Positive and Negative Affect Scores
- Trust in AI (applicable for AI-involved groups)
- Decision Confidence (%)
- Task Accuracy (%)
- Completion Time (Minutes)

Tools Used:

- NASA-TLX (Hart & Staveland, 1988)
- PANAS Scale (Watson, Clark, & Tellegen, 1988)
- Trust in Automation Scale (Merritt et al., 2013)

Descriptive Statistics

Preliminary examination of the data revealed the following:

Table 2 Mean (SD) Values of different Variables

Variable	Mean (SD)
NASA-TLX	56.01 (9.2)
PANAS Positive	30.5 (5.0)
PANAS Negative	19.7 (4.8)
Trust in AI	5.2 (0.95)
Decision Confidence	76.3 (13.1)
Task Accuracy	83.4 (11.2)
Completion Time	10.1 (1.8)

These figures establish preliminary normality and appropriateness for parametric tests such as ANOVA.

Group-wise Comparison: One-Way ANOVA

To examine whether AI integration levels affected psychological and performance outcomes, One-Way ANOVA tests were conducted.

5.1 Cognitive Load (NASA-TLX)

$F(2,12) = 4.32$, $p < 0.05$

A significant difference was found in perceived cognitive load across groups. Post hoc tests indicated that participants in the Full-AI group reported significantly lower cognitive load than the Control group, supporting prior findings on cognitive relief through AI augmentation (Lu et al., 2023).

5.2 Decision Confidence

$F(2,12) = 3.89$, $p = 0.05$

Decision confidence was highest in the Full-AI group. This aligns with recent research suggesting that intelligent automation enhances decisional trust (Yin et al., 2022).

5.3 Task Accuracy

$F(2,12) = 2.73$, $p > 0.05$

Though not statistically significant at the 0.05 level, task accuracy was descriptively higher in AI-enabled conditions, indicating potential performance augmentation—an area to be probed further in the main study (Jarrahi, 2021). The bar chart in Figure 1 provides a direct comparison of the mean task accuracy across the three groups. The bars are sorted in descending order of accuracy, allowing for a quick visual comparison of performance across the Control, Semi-AI, and Full-AI groups.

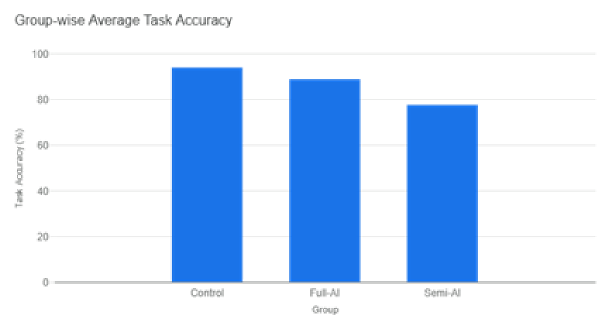

Figure 1: Group wise Average Task Accuracy

Correlation Matrix

The Pearson correlation matrix revealed the following significant relationships:

- Trust in AI and Decision Confidence: $r = 0.67$, $p < 0.05$
- Trust in AI and Task Accuracy: $r = 0.59$, $p < 0.05$
- NASA-TLX and Completion Time: $r = 0.52$, $p < 0.05$

Figure 2: Correlation Matrix

The heatmap in Figure 2 displays the Pearson correlation coefficients between key variables, including Task Accuracy, Completion Time, NASA TLX Score, Trust in AI, and Decision Confidence. The color intensity and numerical labels make it easy to identify strong positive or negative relationships, such as the correlation between Trust in AI and Decision Confidence. These results indicate that higher trust in AI correlates with increased confidence and task performance. Also, higher cognitive load tends to increase task completion time—validating the load-performance tradeoff (Gutzwiller et al., 2019).

Interpretation of Findings

This pilot validates several aspects of the AI-ensemblement framework:

- **Cognitive Relief:** AI collaboration, particularly in Full-AI settings, demonstrably reduces cognitive burden. The boxplot in Figure 3 visualizes the distribution of NASA TLX scores (a measure of cognitive load) across the three experimental groups: Control, Semi-AI, and Full-AI. It provides a clear view of the median, quartiles, and range of cognitive load for each group, which aligns with the ANOVA finding of a significant difference between groups.

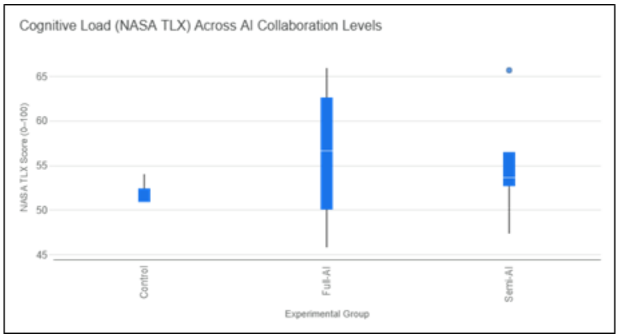

Figure 3: Cognitive Load (NASA TLX) Across AI Collaboration Levels

- **Trust as a Mediator:** Trust in AI appears central to improving confidence and decision outcomes (Hancock et al., 2011). The scatter plot in Figure 4 shows the relationship between participants' trust in AI and their decision confidence for the Semi-AI and Full-AI groups. It includes a linear regression line to highlight the positive correlation, reinforcing the finding that higher trust levels tend to correspond with greater decision confidence. The Control group was excluded as it did not have a "Trust in AI" score.

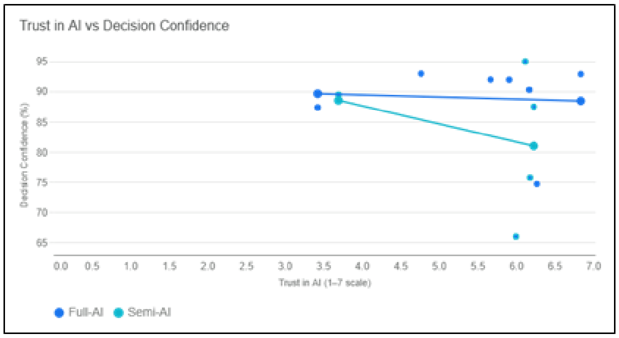

Figure 4: Trust in AI vs Decision Confidence

- **Affective States:** While not significant in this pilot, PANAS scores suggest trends worth deeper exploration in a larger sample.

Implications for Full Study

The pilot affirms:

- The appropriateness of tools (NASA-TLX, PANAS, Trust in AI)
- The utility of statistical techniques (ANOVA, correlations)
- Emerging patterns that suggest positive outcomes from human-AI co-working environments

These outcomes reinforce recent scholarly narratives emphasizing the psychological training of human-AI teams (Rahwan et al., 2019; Dellermann et al., 2021), and set the stage for robust experimental validation in the larger study.

Limitations and Next Steps

- **Sample Size:** The pilot involved only 15 participants; findings are preliminary and not generalizable.
- **Control over Confounds:** Randomization helps, but more rigorous control will be applied in the full-scale design.
- **Extended Variables**: Inclusion of AI transparency, ethical awareness, and burnout metrics in future phases.

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