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EVALUATING META-COGNITIVE ACCURACY AND TASK CONFIDENCE UNDER CONDITIONS OF INFORMATION OVERLOAD

DARSHI SHARMA
ASSISTANT PROFESSOR, KALINGA UNIVERSITY, RAIPUR, INDIA.

KHUSHBOO GUPTA
ASSISTANT PROFESSOR, KALINGA UNIVERSITY, RAIPUR, INDIA.

RITU JOON
ASSISTANT PROFESSOR, NEW DELHI INSTITUTE OF MANAGEMENT, NEW DELHI, INDIA,
EMAIL: ritu.joon@ndimdelhi.org, HTTPS://ORCID.ORG/0009-0006-4319-6252

Abstract:
In environments that heavily rely on cognitive demands, the ability to track and evaluate one's own performance or meta-cognitive accuracy is essential to making effective decisions. But in an era of overstimulation and perpetual connectivity, allowing information overload to impact this meta-cognitive capability is becoming more common. After each task, participants reported their confidence in their response. Meta-cognitive accuracy was measured as the relations of confidence judgments and the correctness of the tasks, using Type 2 signal detection theory, as well as calibration metrics. There was slightly increased task confidence under moderate information load conditions, while meta-cognitive accuracy decreased significantly as load conditions increased. Participants who performed under high-load conditions almost always exhibited over-confidence, regardless of performance. The dissociation of perceived and actual competence under overload conditions has significant implications for decision-making in the workplace, especially for decision-makers who must exercise judgment under time-pressed and uncertain circumstances. This study adds value to cognitive psychology and organizational behavior research by developing an empirical model of how overload degrades self-evaluation processes. The results advocate for cognitive ergonomics interventions in stressed environments such as load-aware user interfaces, confidence recalibration training, and real-time meta-cognitive feedback systems

Keywords: Meta-cognitive accuracy, Confidence in task, Information overload, Cognitive accuracy calibration, Decision-making, Cognitive-performance dissociation, Cognitive ergonomics

INTRODUCTION

The Rise of Information Overload and its Cognitive Consequences

Within the context of the digital age professionals are increasingly expected to make quick decisions given large amounts of data. This phenomenoncommonly termed information overloadresults in cognitive overloadcognitive fatigue, attention decline, and deficient reasoning. Although there has been significant research focused on the effect of overload on the accuracy of decision-making, there has been less research investigating the impact of overload on meta-cognitive accuracy, or how accurately a decision-maker is able to assess their own performance [1].

The Importance of Meta-Cognitive Accuracy in High-Load Contexts

Meta-cognitive accuracy governs our confidence judgments, error detection, and whether a decision-maker keeps that error (instead of revising it)[2]. In high-risk contexts like healthcare,
finance, and air traffic control; meta-cognitive inaccuracies can lead to overconfidence, resulting in a defectively considered outcome that might otherwise have been avoided [3]. Critically, understanding how information density impacts self-monitoring will prove useful in constructing tools and workflows to facilitate high-stakes decision-making [4].

LITERATURE REVIEW

Meta-Cognitive Accuracy: Underpinnings and Measurement

Meta-cognition involves both monitoring (the assessment of accuracy) and control (changes to strategy). To study accuracy, researchers often implement calibration curves and/or the Type 2 signal detection theory, which measure the interactions between the presence of confidence and correctness Task confidence is positively associated with performance but may not always parallel performance during moments of stress or complexity, potentially producing the "illusion of knowing." For example, Koriat (2012) found that task-related external cues, such as task format or environmental noise influenced levels of confidence, particularly when attention was taxed. Information Overload: Cognitive Load TheoryCognitive Load Theory (Sweller, 1988) suggests when both intrinsic and extraneous cognitive load are high, they interfere with working memory [5]. This interferes with the quality of both decision outcomes and the process of self-monitoring. While overload studies specifically focus on the accuracy of decisions, there's been minimal investigation about the extent to which the overload experience negatively influences the internal calibration for confidence - this is what these paper hopes to address [6].

Research Gaps

Most research in information overload describes its effects on productivity or error rates, without discussing the potential impacts on mechanisms of self-evaluation. Furthermore, we found minimal amounts of empirical research that attempted to connect information overload to performance and any confidence/performance alignment, with the exception of rigorous applications of meta-cognition [7].

METHODOLOGY

Participants and Experimental Design

The sample included 180 participants (90 male, 90 female; ages 21–45) recruited from educational and professional settings. A within-subjects design was utilized where participants completed three levels of information load (low, moderate, high) in randomized order.

Tasks and Procedure.Participants completed both: Analytical reasoning tasks (e.g., logic puzzles with distracters) Perceptual discrimination tasks (e.g., rapid pattern detection) Participants were asked to complete either task and then provide a self-rating of confidence (0–100%) at the end of the task[8].

Equation 1: Meta-Cognitive Discrepancy Model

$$\Delta MC = C - A$$

where: ΔMC = the meta-cognitive disparity, often called the Overconfidence

- Gap C = average confidence score, representing participants' self-rated certainty about how well they performed
- The task A = average task accuracy, the objective proportion of correct responses
- Meta-Cognitive Accuracy Measures

Two primary measures were calculated:

Type 2 AUC (Area Under the ROC Curve) – to measure discrimination (successfully distinguishing correct vs. incorrect responses at ratings for varying confidence levels)

Calibration Curves – to measures over- or under confidence by plotting the mean confidence across the range of actual performance (observed) [9].

ANALYSIS AND RESULTS

Confidence Development in Loading Conditions

Participants in the low load condition performed with well-calibrated confidence; their mean accuracy aligned with their mean confidence. In the moderate load, confidence increased slightly and performance leveled off indicating slight overconfidence. In the high loading condition, the gap between accuracy and confidence was even larger with confidence surpassing accuracy more than 20% correct in analytical tasks. Declined Meta-Vigilance in High Load Type 2 AUC scores declined 0.82 (low load), 0.71 (moderate), 0.59 (high), reflecting a statistically significant deterioration of meta-cognitive discrimination particularly as time pressure increased. Calibration curves confirmed always overestimating ability in an overload, particularly in time pressured tasks. Subgroup Patterns with Implicit Classification [10]

Clustering solutions revealed three meta-cognitive profiles:

- Accurate-Calibrated (28%) – performed in accuracy in all conditions.

- Overconfidence (45%) – confident but low accurate when overload.
- Underconfident-Cautious (27%) – low confidence despite high accurate.

Regression analysis confirmed information density and time pressure were significant predictors of confidence-performance misalignment ($p < 0.001$) [11].

DISCUSSION

The Dissociation of Confidence and PerformanceResults confirm that when dealing with information overload, a confidence engagement and performance dissociation occurs whereby participants can be increasingly certain of increasingly incorrect answers [12]. This presents significant challenges in operational contexts when self-monitoring is required. Implications for Workplace Design and Human Resource SystemsCognitive tools should be built into workflow and operations to surface when confidence is no longer aligned with accuracy. Human Resource representatives and managers can benefit from real time cognitive feedback systems, surfacing when employees were approaching information overload and more likely to misjudge, or second guess their decisions. Identification of confidence-performance dissociation is particularly significant in technical, medical and analytical role [13].

The Future of Cognitive Ergonomics

The findings of this study suggest that adaptive information interfaces, confidence- adjusted dashboards, and meta-cognitive training programs would support individuals in better calibrating when their confidence beliefs may not be anchored to reality [14]. Such interventions could improve safety, performance, and accountability in decision making [15].

Table 1: Meta-Cognitive Accuracy and Confidence Measures Under Varying Information Load Conditions

Load Condition	Mean Task Accuracy (%)	Mean Confidence (%)	Meta-Cognitive Accuracy (Type 2 AUC)	Overconfidence Gap (%)
Low	89.2	87.5	0.82	-1.7
Moderate	81.5	85.2	0.71	3.7
High	68.7	90.1	0.59	21.4

The **table 1**above summarizes the effects of information overload and its impact on task performance, confidence, and metacognitive accuracy. Participants exhibited high task accuracy (89.2%) and well-aligned confidence (87.5%) under low load conditions, which led to high metacognitive discrimination (AUC = 0.82) and a minor underconfidence gap of (-1.7%). The increased load led to lower task accuracy and relatively fixed confidence, producing a moderate overconfidence gap (+3.7%) and lower AUC (0.71). The standard deviations are worth noting, as they show the variability in self-evaluations changing while task performance was lower than counterfactual (i.e. performance was expected to be lower based on display information). Under high load, the gap of confidence and task performance was even larger: actual performance tended to be lower (like under moderate load) but confidence was held at a higher number (90.1%). Overconfidence gap of (+21.4%) and a Low metacognition accuracy (AUC = 0.59) show the substantial risk of overload. The data highlights how as the amount of information we are overloaded with increases, the accuracy of self-evaluations decreases dramatically.

CONCLUSION

Summary of Findings

The current study found information load has a considerable effect on meta-cognitive accuracy, so participants incorrectly judged their own performance level. As the amount and complexity of information increases, participants are less likely to accurately judge whether their decisions or responses to the task are correct. This created a larger gap in task confidence and actual performance, and this effect was more pronounced in high-load conditions, especially in high-pressure environments. Error rates were noticeably higher for participants in high load conditions and they tended toward overconfidence in these conditions, frequently expressing extreme certainty in wrong answers. This was especially true of tasks that involved cognitive burden such as analytical tasks that taxed both working memory and attentional resources. These results highlight the perils of relying on self-assessment only in overloaded environments, especially when making an immediate or accurate decision is important.

Contributions

This research represents a unique value through the theoretical application of cognitive psychology to applied occupational contexts, specifically in situations where information overload and self-regulation of information processing are critical. This research proposes a validated model that captures how information overload undercuts the alignment between perceived task performance and actual task performance. Beyond models and theories, this research provides empirical metrics (e.g. Type 2 AUC scores and calibration curves) and behavioral profiling tools that organizations can use. These empirical outputs provide the foundation for practical strategies like meta-cognitive training programs aimed at increasing awareness of people's own biases of overconfidence, real-time feedback mechanisms to signal users when their confidence exceeds their actual accuracy, and adaptive human-computer interfaces that adjust information input based on user load conditions (volume and complexity). By taking cognitive research and converting it into actionable strategies, this study serves to bridge the gap between cognitive scientists' research on mental workload and the demands of workplaces on efficient worker performance (and safety, and system design).

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