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HEC MONTRÉAL

**Comprendre le rôle des stratégies de recherche visuelle dans la performance des
utilisateurs au sein d'interfaces ERP complexes**

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CERTIFICAT D'APPROBATION ÉTHIQUE

La présente atteste que le projet de recherche décrit ci-dessous a fait l'objet d'une évaluation en matière d'éthique de la recherche avec des êtres humains et qu'il satisfait aux exigences de notre politique en cette matière.

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Résumé

Les systèmes de planification des ressources d'entreprise (ERP) demeurent essentiels au fonctionnement organisationnel, mais leur complexité informationnelle continue de solliciter fortement les capacités cognitives des utilisateurs. Cette étude examine dans quelle mesure les différences individuelles en recherche visuelle influencent la performance lors de tâches ERP de complexité variable, après un module de formation fondé sur l'apprentissage vicariant. L'objectif est d'évaluer l'effet de la complexité des tâches sur la performance et de déterminer si certaines prédispositions visuelles modèrent cette relation, en considérant également la charge cognitive, la frustration, les stratégies de recherche visuelle et la réponse émotionnelle. Un protocole expérimental contrôlé a été mené auprès de 36 participants. Ceux-ci ont d'abord complété trois paradigmes oculométriques mesurant le contrôle inhibiteur, l'exploration visuelle orientée vers un but et le traitement visuel, puis réalisé trois tâches ERP de complexité variable. L'approche multimodale combine mesures oculométriques, indicateurs de performance et évaluations subjectives et physiologiques. Les résultats montrent qu'une complexité accrue augmente la charge cognitive et la frustration, ce qui diminue la performance. De plus, les capacités d'exploration visuelle orientée vers un but et de traitement visuel modèrent significativement ces effets, suggérant que certaines dispositions perceptives soutiennent la navigation dans des interfaces complexes. Une analyse post hoc révèle aussi qu'une meilleure compétence intrinsèque en recherche visuelle est associée à de meilleures performances globales dans les tâches. Cependant, plusieurs effets anticipés ne sont pas confirmés. La complexité des tâches n'a pas modifié la stratégie de recherche visuelle, les réponses émotionnelles positives n'ont pas prédit la performance, et ni la réponse émotionnelle ni la stratégie de recherche visuelle n'ont modéré la relation entre complexité et performance. L'étude propose finalement une méthodologie reproductible et discute des implications pour la transformation numérique et les pistes de recherche futures.

Mots-clés : Complexité des tâches • Stratégies de recherche visuelle • Transformation numérique • Systèmes de planification des ressources d'entreprise (ERP) • Charge cognitive • Performance des utilisateurs

Méthodes de recherche : Transformation numérique • Expérience utilisateur • Suivi oculaire • Analyse d'expression faciale • pupillométrie

Abstract

Enterprise Resource Planning (ERP) systems remain essential to organizational operations, yet their informational complexity continues to impose substantial cognitive demands on users. This study examines how individual differences in visual search propensity influence performance during ERP tasks of varying complexity following a vicarious learning-based training module. The objective is to assess the effect of task complexity on performance and to determine whether visual predispositions moderate this relationship, while also considering cognitive load, frustration, visual search strategies, and emotional responses. A controlled experimental protocol was conducted with 36 participants. They first completed three standardized eye-tracking paradigms measuring inhibitory control, goal-oriented visual exploration, and visual processing, and subsequently performed three ERP tasks of varying complexity. The multimodal approach integrates eye-tracking metrics, performance indicators, and subjective and physiological assessments. Findings show that higher task complexity increases cognitive load and frustration, thereby reducing performance. Moreover, goal-oriented visual exploration and visual processing abilities significantly moderate these effects, suggesting that certain perceptual dispositions help users navigate complex ERP interfaces. A post hoc analysis further reveals that greater intrinsic propensity for visual search is associated with better overall performance. However, several anticipated effects were not confirmed. Task complexity did not alter visual search strategy, positive emotional responses did not predict performance, and neither emotional response nor in-task visual search strategy moderated the relationship between task complexity and performance. The study concludes by offering a reproducible methodology and discussing implications for digital transformation initiatives, as well as avenues for future research.

Keywords: Task Complexity • Visual Search Strategies • Digital Transformation • Enterprise Resource Planning (ERP) systems • Cognitive Load • User Performance

Research methods: Digital Transformation • User Experience • Eye Tracking • Facial Expression Analysis • Pupillometry

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Introduction

Les systèmes de planification des ressources d'entreprise (Enterprise Resource Planning, ou ERP) ont émergé dans les années 1990 pour répondre à la fragmentation croissante des systèmes d'information organisationnels. Avant leur apparition, les entreprises recouraient à une mosaïque d'applications indépendantes, souvent propres à chaque département, comptabilité, production, ventes ou gestion des ressources humaines, rendant la circulation de l'information complexe et source d'erreurs (Davenport, 1998). Cette architecture dispersée entraînait des redondances, des incohérences dans les données et une perte de visibilité sur les opérations. Les ERP ont été conçus comme une réponse intégrée à ces limites en centralisant les données et en reliant les processus d'affaires clés, finance, logistique, production et ressources humaines, ils visaient à renforcer la cohérence opérationnelle et la prise de décision (Klaus et al., 2000). Leur adoption rapide a transformé la gestion des organisations, permettant une meilleure planification de la chaîne d'approvisionnement, l'automatisation de processus comptables et la standardisation des pratiques internes (Jacobs & Weston, 2007).

Si ces promesses ont contribué à faire des ERP des piliers de la transformation numérique, leur mise en œuvre demeure difficile. Les bénéfices attendus se heurtent souvent à des difficultés liées à l'implantation, à la formation et, surtout, à l'expérience utilisateur. Malgré leur puissance fonctionnelle, ces systèmes sont fréquemment perçus comme lourds, rigides et cognitivement exigeants (Somers et Nelson, 2004 ; Aloini & al., 2007). Pour les utilisateurs finaux, des interfaces peu intuitives génèrent désorientation, surcharge cognitive et frustration, affectant directement la performance et la satisfaction (Topi et al., 2005). Les études montrent qu'entre 55 % et 70 % des projets ERP échouent à atteindre leurs objectifs initiaux, principalement en raison de la complexité des interfaces et du manque d'efficacité de navigation (Ali et Miller, 2017). Ces échecs ont des répercussions financières majeures. Dell, par exemple, a dû abandonner un projet ERP de 115 millions de dollars après avoir constaté son inadéquation avec les besoins opérationnels (Nkasu, 2020). Plus largement, près de 70 % des projets ERP dépassent les budgets ou les échéanciers prévus, ce qui témoigne de la persistance de défis humains et organisationnels (Panorama Consulting, 2023).

Bien que les ERP aient été conçus pour rationaliser les opérations, leur architecture informationnelle et visuelle engendre souvent l'effet inverse : inefficacités dans les flux de travail,

perte de temps et insatisfaction des employés. Une étude de Gartner (2022) indique que 45 % des utilisateurs ERP déclarent éprouver des difficultés à trouver les fonctionnalités pertinentes, tandis qu'Asif et al. (2022) estiment que les employés travaillant avec des interfaces à faible découvrabilité consacrent jusqu'à 18 % de leur temps de travail à chercher des fonctions, au détriment de leur productivité. Ces défis persistent malgré l'importance stratégique des ERP, désormais incontournables pour soutenir la compétitivité dans une économie numérique interconnectée (Al-Okaily et al., 2020). Cependant, les bénéfices promis demeurent souvent partiels, freinés par des problèmes d'utilisabilité qui se manifestent particulièrement dans la phase post-implantation, lorsque les gains d'efficacité devraient être les plus tangibles (Costa et al., 2020). Les utilisateurs rapportent alors frustration, erreurs et résistance à l'adoption, un phénomène observé chez plus de la moitié d'entre eux (Ha et Ahn, 2013 ; Salih et al., 2013). Cette faible utilisabilité augmente les coûts de formation et génère des pertes de productivité cachées pouvant atteindre 12 000 \$ par employé chaque année (Ali et Miller, 2017).

La littérature scientifique sur les ERP s'est d'abord concentrée sur les dimensions techniques et organisationnelles, en mettant l'accent sur l'alignement stratégique entre les systèmes d'information et les processus d'affaires (Davenport, 1998 ; Markus & Tanis, 2000), la gestion du changement (Somers & Nelson, 2004) et les modèles de succès post-implantation (Petter, DeLone & McLean, 2013). Ces travaux ont permis de comprendre les causes structurelles des échecs de déploiement, mais ils ont largement négligé la dimension micro-cognitive de l'expérience utilisateur, pourtant déterminante pour l'adoption effective des systèmes. À partir des années 2010, la recherche s'est progressivement orientée vers une approche plus centrée sur l'humain, reconnaissant que la réussite d'un ERP dépend aussi de son utilisabilité, de la charge cognitive qu'il impose et de son acceptation par les employés (Petter, DeLone & McLean, 2013 ; Hekkala & al., 2013). Plusieurs études ont examiné les relations entre la complexité des tâches, la charge cognitive et la performance (Li et al., 2011), ou encore les facteurs psychosociaux de résistance au changement (Ha & Ahn, 2013 ; Salih et al., 2013).

Malgré l'importance stratégique de l'expérience utilisateur dans les ERP, plusieurs écarts subsistent dans la littérature scientifique. D'abord, la plupart des travaux s'appuient sur des mesures déclaratives, questionnaires, auto-évaluations, entrevues, qui permettent peu de saisir les mécanismes attentionnels et perceptifs activés lorsque les utilisateurs interagissent avec des

environnements informationnels complexes. Ensuite, les recherches existantes reconnaissent que la complexité des tâches exerce une influence notable sur la charge cognitive, la frustration et la performance (Li et al. 2011), mais elles ne tiennent pas compte d'un élément central, soit l'existence possible de différences individuelles dans la manière dont les utilisateurs orientent leur attention et parcourent visuellement l'information. À ce jour, il n'existe pratiquement aucune étude examinant si certaines stratégies de recherche visuelle, plus efficaces ou mieux adaptées, aident les utilisateurs à mieux gérer la complexité des tâches dans les ERP. Pourtant, la recherche en psychologie visuelle montre que les individus présentent des différences stables dans leur manière d'explorer visuellement l'information, et qu'ils tendent à adopter des styles de recherche distincts d'une personne à l'autre (Clarke & al., 2022). Le fait que ces variations individuelles soient rarement intégrées aux études sur les ERP constitue un écart important, puisqu'il limite la compréhension des facteurs cognitifs qui influencent la performance et empêche d'adapter adéquatement la formation aux profils réels des utilisateurs.

La présente étude vise à combler cet écart en examinant comment des différences individuelles dans les stratégies de recherche visuelle influencent la manière dont les utilisateurs gèrent la complexité des tâches dans un environnement ERP. Pour ce faire, un protocole expérimental a été conçu dans lequel les participants réalisent trois tâches ERP de complexité variable après avoir reçu une formation fondée sur l'apprentissage vicariant. Ce mode d'apprentissage, également appelé *behavioural modelling*, repose sur l'observation d'un modèle exécutant un comportement ciblé afin que l'apprenant puisse en reproduire les étapes (Bandura, 1977, 2001; Yi & Davis, 2003). Dans la formation des utilisateurs finaux, il prend le plus souvent la forme d'une démonstration vidéo, approche dominante en contexte ERP et qui tend à surpasser les méthodes traditionnelles comme les exposés ou les manuels (Gupta et Huber, 2010). Ensuite, le comportement visuel, cognitif et émotionnel des participants est mesuré à l'aide d'une combinaison de données oculométriques, comportementales et affectives. Cette approche multimodale permet d'observer directement la manière dont les utilisateurs explorent visuellement l'interface, comment ils régulent leur attention et comment ces processus interagissent avec la charge cognitive, la frustration, les stratégies déployées et la performance.

En adoptant cette perspective, l'étude contribue à la littérature de deux façons principales. Premièrement, elle propose une compréhension fine et empirique des différences individuelles

dans les stratégies de recherche visuelle, un aspect jusqu'ici absent des recherches sur les ERP. Deuxièmement, elle montre comment ces différences modèrent les effets de la complexité des tâches sur les réponses cognitives, affectives et comportementales. En d'autres mots, l'étude examine dans quelle mesure les différences de propension à la recherche visuelle permettent aux utilisateurs de mieux gérer la complexité inhérente aux ERP. En éclairant ces mécanismes attentionnels, elle ouvre la voie à des pratiques de formation plus adaptées aux profils des utilisateurs, à la conception de systèmes plus sensibles aux contraintes cognitives et à une compréhension plus nuancée des facteurs humains déterminant la performance dans les environnements ERP.

La présente étude a été réalisée dans le respect des normes éthiques applicables à la recherche avec des participants humains. Le protocole, incluant les procédures expérimentales, les mesures multimodales et les modalités de recrutement, a été approuvé par le comité d'éthique de la recherche de HEC Montréal. Tous les participants ont fourni un consentement éclairé préalable à leur participation. (Certificat #2025-6412).

Le mémoire est structuré en trois volets. Le Chapitre 1 présente la problématique de recherche, les principaux enjeux théoriques ainsi que les écarts identifiés dans la littérature. Le Chapitre 2 correspond à l'article scientifique et suit la structure attendue d'un mémoire académique. Ce chapitre propose une analyse empirique examinant comment la complexité des tâches ERP influence la charge cognitive, la frustration, la performance et les stratégies de recherche visuelle, et analyse dans quelle mesure les différences individuelles dans la propension à la recherche visuelle modèrent ces effets. Il se conclut par une discussion de ses contributions à la communauté scientifique, de ses implications pour les gestionnaires et les projets de transformation numérique, ainsi que des avenues possibles pour la recherche future. Cet article est en préparation pour une soumission à Deloitte Digital ainsi qu'au journal *Information Systems Frontiers*. Le Chapitre 3 correspond à la conclusion générale et offre une synthèse intégrée du Chapitre 2.

Étant donné que ce mémoire adopte un format fondé sur un article scientifique, le Tableau 1 présente de manière transparente les implications, les contributions et les responsabilités de l'étudiant, allant de la conception de l'étude à la collecte des données, puis à l'analyse et à la rédaction de l'article.

Tableau 1

Implications, contributions et responsabilités de l'étudiant dans ce mémoire

Étape du processus	Contribution
Question de recherche	Identifier les lacunes dans la littérature afin de définir la problématique de recherche et ses implications [90%] – Problématique initialement formulée par le partenaire industriel. – Contextualisation du problème de recherche académique formulé par l'étudiant.
Revue de littérature	Recherche et analyse approfondie des publications scientifiques pertinentes afin de comprendre l'état actuel des connaissances sur les stratégies de recherche visuelle et la complexité des tâches dans les ERP et leurs impacts sur la performance utilisateur [100 %].
Design expérimental	Dépôt de la demande au Comité d'éthique de la recherche (CÉR) de HEC Montréal [70 %] – Préparation de la documentation liée à la soumission par le personnel du Tech3Lab et l'étudiant. – Demande révisée par les co-directeurs de mémoire et le personnel du Tech3Lab. Développement du protocole expérimental et des stimuli [100 %] – Conception de la procédure expérimentale, des questionnaires et des instruments fait par l'étudiant. – Sélection des stimuli par l'étudiant, et approuvé par le partenaire industriel. – Développement d'un protocole de recherche de base par un assistant de recherche et le personnel du Tech3Lab, ensuite adapté à l'étude par l'étudiant. – Développement de courtes formations sur les tâches pour les participants fait par l'étudiant.
Collecte de données	Recrutement des participants pour la collecte de données [70 %] – Recrutement des participants pour la collecte de données par l'étudiant et majoritairement via le panel du Tech3Lab. Préparation du laboratoire [80 %] – Élaboration du protocole et de la ligne de temps de l'oculométrie par l'étudiant sur Tobii. – Assemblage des instruments de collecte multi-appareils avec l'aide du personnel du Tech3Lab. – Tests extensifs et ajustements du dispositif expérimental par l'étudiant. Prétests et gestion des opérations de collecte de données [100 %] – Coordination et préparation des opérations préliminaires par l'étudiant. – Modération et observation de l'ensemble des sessions utilisateurs par l'étudiant. – Soutien technique et organisation de la collecte assurés par la direction du Tech3Lab.
Analyse statistique	Analyse des données psychophysiologiques [90 %] – Extraction et traitement des données pour synchroniser tous les instruments, réalisés par le statisticien du Tech3Lab. – Analyses statistiques sur SAS et R effectuées par l'étudiant avec l'aide du statisticien. – Interprétation et présentation des résultats par l'étudiant.
Rédaction	Rédaction des articles et du présent mémoire [100 %] – Les co-auteurs des articles et les co-directeurs de mémoire ont fourni des commentaires et des révisions.

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Chapter 2

Understanding the Role of Visual Search Strategies in User Performance within Complex ERP Interfaces

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Abstract: This study examines how task complexity and individual propensity for visual search influence user performance in enterprise resource planning (ERP) environments under vicarious training. Using a laboratory experiment combining standardized eye-tracking paradigms with ERP tasks of varying complexity, the findings show that higher task complexity impairs performance by increasing cognitive load, frustration, and negative emotional response. Visual search propensity plays a partial role: goal-oriented visual exploration reduces frustration, whereas weaker visual processing amplifies cognitive load and emotional strain. Although the propensity for visual search does not moderate the effect of complexity on performance, both goal-directed exploration and visual processing independently predict task success across conditions. These results advance understanding of the perceptual and cognitive mechanisms underlying user effectiveness in complex digital work environments. They also suggest that ERP training should emphasize cognitive readiness rather than procedural observation, and that interface design and support strategies should better guide attention and account for users' perceptual differences to improve adoption and performance.

2.1 Introduction

Enterprise Resource Planning (ERP) systems play a crucial role in digital transformation efforts, helping organizations improve their operations, boost efficiency, and consolidate various business processes into a single platform. By consolidating functions such as finance, procurement, and logistics, ERP systems reduce information silos and improve data visibility across departments (Fan et al., 2015; Baluch, 2023). Despite these strategic advantages, many implementations fail to deliver their expected benefits due to persistent challenges in user experience, system adoption, and task usability (Al-Okaily et al., 2021; Ha & Ahn, 2013). These difficulties are particularly evident during the post-implementation phase, when organizations anticipate productivity gains but often encounter frustration, navigation difficulties, and resistance to use (Ha & Ahn, 2013; Costa et al., 2020). The complexity of ERP interfaces frequently emerges as a key obstacle to effective adoption, with over half of users reporting difficulty locating functions or completing tasks due to excessive information density and unclear workflows (Salih et al., 2013). Such usability issues translate into higher training costs, reduced employee efficiency, and hidden productivity losses, estimated at up to \$12,000 per employee annually in some organizations (Ali & Miller, 2017).

One of the main reasons for these difficulties lies in the inherent complexity of ERP environments. Tasks within such systems vary significantly in structure and cognitive demand. While some are procedural and straightforward, others involve multi-step operations that require users to navigate dense, hierarchical interfaces (Eriksson, 2023). This variation in task complexity increases users' cognitive load, often leading to confusion, errors, and reduced performance (Tarafdar & Gordon, 2007). During the training and testing phases, this complexity becomes particularly apparent, as end-users struggle with dense information structures and difficulty identifying relevant functions (Hodgins, 2016). As systems move into deployment, unresolved complexity often leads users to develop compensatory behaviours, such as relying on a limited set of familiar transactions, which can undermine performance and long-term adoption. As organizations move toward cloud-based ERP solutions that emphasize user autonomy, understanding how individuals adapt to varying levels of task complexity becomes increasingly critical for ensuring productivity and satisfaction.

Within this context, user's propensity for visual search plays a critical role in how users interact with complex ERP interfaces. Effective allocation of visual attention enables users to locate relevant information, interpret cues, and complete tasks efficiently (Wolfe, 1994; Kastrati et al., 2021). Visual search refers to the cognitive process through which individuals selectively allocate attention to identify a target among competing stimuli within a visual environment (Wolfe, 1994). It involves both bottom-up mechanisms driven by salient visual features and top-down processes guided by goals and expectations (Wolfe, 1994; Wolfe & Horowitz, 2017). In complex digital interfaces, this process requires users to filter dense information displays and prioritize task-relevant elements. However, these strategies vary across individuals. Some users adopt systematic, goal-directed search patterns that support faster detection, while others rely on more exploratory or reactive scanning (Wagner & Füllgrabe, 2024). Studies show that such differences are linked to cognitive factors like working memory and attentional control, influencing how users manage increasing task complexity (Lanini-Maggi et al., 2021). Users with more efficient visual search strategies are generally better equipped to maintain performance and identify key interface elements even under high cognitive demand (Clarke & al., 2022). By contrast, less efficient search behaviour may amplify the effects of complexity, leading to slower task completion and greater cognitive effort (Tsai & al., 2010).

Understanding these mechanisms is important because, if visual search tendencies are shown to influence how users cope with task complexity, organizations could adapt ERP training and interface design to individual perceptual profiles to improve usability and user performance. This study builds on the assumption that task complexity imposes cognitive and perceptual demands that users must actively manage through their attentional and visual strategies. Individuals differ in their ability to process and prioritize visual information, and these differences may moderate the extent to which increasing complexity affects their performance, frustration, and emotional experience. To investigate these dynamics, the present study draws on multiple theoretical perspectives from Information Systems and cognitive psychology, particularly Guided Search Theory (Wolfe, 1994) and Cognitive Load Theory (Sweller, 2011). It examines how task complexity influences user performance, cognitive load, and emotional response, and how users' propensity for visual search moderates these effects. Accordingly, this research addresses the following question:

“To what extent do individual differences in visual search strategies influence users’ performance across different levels of task complexity in a vicarious ERP training context?”

User training is widely recognized as a critical determinant of successful ERP adoption, and organizations commonly rely on vicarious training to prepare users for system interaction. Vicarious learning refers to the process through which individuals acquire skills by observing someone perform a task and then replicating the demonstrated sequence of actions (Yi & Davis, 2003; Gupta & Huber, 2010). This learning mode relies on four core processes. Attention to the demonstrated behaviour, retention of the observed steps, reproduction of the procedure, and motivation to imitate the behaviour based on its perceived outcomes. Grounded in the observational pathway of Social Cognitive Theory (Bandura, 1977, 1986, 2001), vicarious training is particularly prevalent in ERP implementations, where user training is consistently identified as a key success factor and can account for over 30% of total project costs (Gupta & Anson, 2010; Scott & Walczak, 2009). In line with current industry practice, all participants in the present study completed a vicarious training session prior to performing the ERP tasks. Situating the study within this training framework allows us to examine whether users’ propensity for visual search help them manage task complexity after receiving demonstration-based instruction.

A laboratory experiment was conducted to explore these relationships, focusing on how variations in task complexity and individual visual search strategies influence user performance and experience. This research contributes to the growing body of knowledge on the usability of enterprise systems by emphasizing the role of cognitive and attentional mechanisms in shaping users’ ability to cope with complexity. The remainder of this paper is structured as follows: the next section reviews the relevant literature and identifies the research gap, followed by the presentation of the theoretical framework and hypotheses. The subsequent sections describe the experimental design and measures, report the empirical results, and discuss their implications. Finally, the article concludes with a summary of key findings and directions for future research.

2.2 Literature Review

2.2.1 Task Complexity

Task complexity has been the subject of extensive research in psychology, organizational studies, and information systems, as it constitutes a key determinant of individual performance and

user experience. Early conceptualizations defined complexity as the amount of information processing required to perform a task, shaped by the number of subtasks, information cues, and their interdependencies (Wood, 1986). Subsequent work emphasized its multidimensional nature, arguing that complexity emerges not only from the quantity of information but also from ambiguity, uncertainty, and multiple possible solution paths (Campbell, 1988). More recent frameworks integrate these perspectives and define task complexity as a multidimensional construct that captures the cognitive demands imposed on individuals by factors such as the number of steps, the variety of information types, and the degree of interdependence among elements (Liu & Li, 2012).

Empirical findings consistently indicate that increasing task complexity leads to higher cognitive load, longer completion times, and greater error rates (Sweller, 1988). These effects are particularly pronounced in ERP environments, whose dense information displays, procedural navigation, and interdependent data fields inherently increase the cognitive demands placed on users (Hedman & Borrel, 2004). ERP tasks typically require navigating multiple screens, interpreting domain-specific terminology, and maintaining intermediate values in working memory while ensuring compliance with organizational rules and procedural logic (Lambeck, 2013). The high degree of coupling between modules, such as finance, procurement, and inventory, also means that a single action may propagate system-wide consequences, thereby heightening the stakes associated with errors and further increasing cognitive burden (Janssens & al., 2020). Consequently, users must simultaneously process large volumes of heterogeneous information and integrate perceptual, cognitive, and domain-knowledge resources, which amplifies the perceived difficulty of tasks (Topi & al., 2005). Studies further show that excessive task complexity undermines satisfaction and increases frustration, ultimately reducing the value organizations derive from ERP implementations (Mohanty et al., 2022; Jalil et al., 2016).

Within the field of Human–Computer Interaction (HCI), task complexity has also been shown to heighten the attentional demands placed on users. Eye-tracking studies demonstrate that as complexity increases, users exhibit longer fixation durations, more dispersed scan paths, and reduced efficiency coefficients, all of which reflect greater effort in locating relevant information (Kastrati et al., 2021). These effects are amplified in ERP environments, where dense interfaces and interdependent data fields require users to navigate large volumes of information under time

and accuracy constraints. Such evidence reinforces that task complexity is not only an abstract organizational construct, but a concrete determinant of the cognitive and attentional effort required to perform ERP tasks.

2.2.2 The User Experience of Complex Tasks

Frustration and cognitive load are central constructs in the study of user experience and system usability, particularly in information-rich and cognitively demanding environments such as ERP systems. Frustration is a negative affective state that arises when interactions with a system hinder goal achievement or require excessive effort (Lazar et al., 2006). In digital work settings, it typically emerges from inefficient navigation, ambiguous layouts, or the high mental demands associated with complex, multi-step tasks (Leichtenstern et al., 2006). Empirical research shows that frustration reduces task satisfaction and long-term acceptance, thus becoming a significant barrier to system adoption and sustained use (Tarafdar & Gordon, 2007). It functions not merely as a temporary emotional reaction but as an indicator of users' difficulty coping with complexity and the inefficiencies embedded in system interaction (Bessière et al., 2006).

Cognitive load refers to the mental effort required to process, integrate, and retain information during task execution (Sweller, 1988). It results from the interaction between intrinsic load, determined by task complexity, and extraneous load, generated by suboptimal interface design (Paas & van Merriënboer, 1994). When the overall load exceeds working memory capacity, users experience performance declines manifested through slower completion times, higher error rates, and increased subjective effort (Chandler & Sweller, 1991; Krejtz et al., 2018).

These two constructs are closely interrelated. Elevated cognitive load often heightens frustration, while sustained frustration further depletes attentional resources and impairs task focus (Matzen et al., 2016). Assessing both is therefore essential for understanding users' ability to manage complexity. Cognitive load is commonly measured through subjective questionnaires such as the NASA-TLX, whereas frustration can be captured with validated affective subscales (Hart & Staveland, 1988). Objective physiological measures such as pupillometry complement these instruments by providing real-time indicators of momentary cognitive effort (Beatty & Lucero-Wagoner, 2000). Together, these metrics offer convergent evidence on how users process demanding tasks and regulate cognitive effort.

Beyond cognitive and behavioural dimensions, emotional responses represent a key component of interaction with complex systems. Emotions are short-lived, context-specific reactions integrating physiological, cognitive, and behavioural components (Russell, 2003). They are typically described along two axes: valence, indicating the positive or negative quality of the experience, and arousal, reflecting its physiological intensity (Bradley & Lang, 1994). High arousal often corresponds to stress or excitement, while low arousal reflects calmness or disengagement. Monitoring these dimensions provides insight into how individuals respond emotionally to complex ERP tasks. In HCI, emotional responses directly influence engagement, satisfaction, and performance: negative affective states such as frustration are linked to reduced efficiency, whereas positive activation supports learning, persistence, and system adoption (Éthier et al., 2006; Deng & Poole, 2010).

From this perspective, users' experience of complex tasks reflects a dynamic interplay between cognitive load, emotional regulation, and attentional strategies. Individual differences in visual search behaviour may determine how effectively users manage this interplay, shaping whether they sustain performance under high complexity or become overwhelmed by cognitive and emotional demands. Understanding these differences is therefore essential for explaining why some users maintain high efficiency and adaptability in complex ERP environments while others struggle.

2.2.3 Visual Search Strategies and Gaze Behavior

Visual search strategies have been extensively studied in cognitive psychology, neuroscience, and HCI to understand how individuals allocate visual attention and guide eye movements in complex environments (Wolfe, 2020). Visual search refers to the goal-directed process through which individuals locate a target among competing stimuli within a visual field, requiring selective attention under conditions of limited cognitive resources (Treisman & Gelade, 1980; Desimone & Duncan, 1995). This process involves prioritizing task-relevant information while suppressing distractors. In such contexts, users must continuously decide where to look, what to process, and when to shift their focus to locate relevant information efficiently. Visual search behaviour is governed by two complementary mechanisms: bottom-up processes, which are stimulus-driven and capture attention through salient visual properties such as colour, contrast, or brightness, and top-down processes, which are goal-directed and shaped by user intentions, prior

knowledge, and task expectations (Wolfe, 1994; Hollingworth & Bahle, 2019). The dynamic interplay between these two mechanisms determines how effectively individuals can filter out irrelevant information and prioritize task-relevant stimuli.

Eye-tracking research provides detailed insights into these attentional mechanisms by capturing measurable indicators of visual processing, such as fixation duration, saccade amplitude, and scan path dispersion (Rayner, 2009). These indicators reveal the underlying strategies users employ to manage visual information. In this context, a visual search strategy refers to the structured pattern of attentional allocation and eye movements adopted to identify relevant information under task constraints. Inefficient strategies, characterized by frequent regressions, long fixation durations, and scattered scan paths, tend to reflect cognitive overload and uncertainty, leading to slower task completion and greater mental effort (Holmqvist et al., 2011). Conversely, efficient strategies involve targeted, goal-oriented gaze patterns that support rapid information retrieval, lower cognitive load, and higher task performance (Goldberg & Kotval, 1999; Matzen et al., 2016).

2.2.3.1 Individual Differences in Visual Search Propensity

Although visual search mechanisms are universal, individuals differ markedly in how they deploy them. The propensity for visual search refers to a stable individual ability to efficiently allocate visual attention, suppress irrelevant distractions, and adapt gaze behaviour to the demands of complex tasks (Kastrati et al., 2021). This construct encompasses several interconnected cognitive control processes, including inhibitory control, goal-oriented visual exploration, and visual processing (Munoz & Everling, 2004). Inhibitory control denotes the capacity to suppress reflexive eye movements toward irrelevant or salient but non-informative stimuli, thereby maintaining focus on task-relevant elements (Theeuwes, 2010). Goal-oriented visual exploration reflects the ability to plan and execute systematic gaze trajectories aligned with task objectives, thereby facilitating information prioritization and minimizing unnecessary cognitive effort (Eckstein, 2011). Visual processing, in turn, involves identifying and integrating relevant visual cues among distractors, an ability particularly critical in dense, information-rich environments such as ERP interfaces (Wolfe, 1994; Wolfe & Horowitz, 2017). Beyond HCI, robust evidence shows that visual search propensity predicts performance in real-world, high-stakes contexts. In clinical and security environments, neural markers of attentional control such as prestimulus alpha

power and N2pc amplitude reliably forecast detection accuracy and miss rates in low-prevalence tasks like radiology and baggage screening (Van den Berg et al., 2016). A recent meta-analysis further demonstrates that individual differences in inhibitory control and scan efficiency consistently predict outcomes across domains including medical imaging, security screening, and sports (Wagner & Füllgrabe, 2024). These findings highlight the cross-domain relevance of visual search traits as determinants of human performance.

Empirical research shows that these individual differences have substantial predictive value for performance under complexity (Wagner & Füllgrabe, 2024). Users with a higher visual search propensity demonstrate faster target identification, more effective information filtering, and greater resilience to increases in cognitive load (Lanini-Maggi et al., 2021). By contrast, individuals with less efficient attentional control exhibit longer search times, heightened frustration, and greater susceptibility to performance decline as task complexity intensifies (Wagner & Füllgrabe, 2024). These findings suggest that effective visual search is not solely determined by interface design but also by users' perceptual and cognitive adaptability. In the context of ERP systems, this implies that two users may experience the same interface in fundamentally different ways: one navigating efficiently through systematic, top-down scanning, while the other becomes overwhelmed by information density and resorts to reactive exploration. Understanding such individual variations in visual search efficiency provides a theoretical foundation for explaining disparities in performance, emotional response, and cognitive effort when users face complex digital tasks.

2.2.5 Gap

While extensive research has explored the usability and cognitive challenges associated with complex digital environments, most studies have emphasized interface-level factors, that is, how design features can reduce information overload and improve navigability (Norman, 2013; Tarafdar & Gordon, 2007; Topi & al., 2005). However, in enterprise systems such as ERP platforms, the inherent complexity of tasks cannot be fully mitigated solely through design. These systems integrate multiple business processes, require navigation through hierarchically structured interfaces, and impose substantial cognitive and perceptual demands on users (Eriksson, 2023). Consequently, performance outcomes depend not only on the interface but also on how effectively

users allocate attention, manage cognitive load, and regulate their visual behaviour in complex environments.

Despite growing recognition of the role of attention and perception in system usability, few studies have examined how individual differences in visual search strategies influence users' ability to cope with complex enterprise tasks (Clarke & al., 2022). Eye-tracking and HCI research have demonstrated that users adopt diverse gaze patterns, some systematic and goal-directed, others more reactive or exploratory (Wagner & Füllgrabe, 2024; Kastrati et al., 2021). However, the implications of these differences for task performance and cognitive effort in ERP contexts remain largely unexplored. Understanding these variations is critical, as they reflect underlying cognitive mechanisms such as inhibitory control, goal-oriented visual exploration, and visual processing, which together determine how efficiently users can process visual information and maintain performance as task complexity increases (Munoz & Everling, 2004; Wolfe & Horowitz, 2017). Clarifying these individual differences is not only theoretically valuable but also offers practical potential, as it may enable the development of adaptive training strategies that better align ERP learning trajectories with users' attentional profiles.

This study addresses this gap by shifting the analytical focus from the design of interfaces to the users themselves, examining to what extent individual differences in visual search propensity explain performance variations in complex ERP tasks. By doing so, it contributes to the understanding of how perceptual and attentional mechanisms shape user experience and provides new insights for optimizing training, user support, and interface adaptation strategies in enterprise environments.

2.3 Theoretical Development

2.3.1 Theoretical Foundation

This study is grounded in two complementary theoretical frameworks that together explain how users interact with complex enterprise systems: the Guided Search Model (Wolfe, 2020) and the Cognitive Load Theory (Sweller, 2024). These models provide a coherent basis for analyzing how individuals allocate visual attention, process information, and manage cognitive resources as they navigate tasks of varying complexity within ERP environments.

The Guided Search Model posits that visual attention is driven by the interaction between bottom-up (stimulus-driven) and top-down (goal-directed) processes, which jointly determine how users locate relevant elements in complex visual fields (Wolfe, 2020). This model has been widely applied to explain user performance in visual search and interface interaction tasks (Egeth & Yantis, 1997; Zelinsky, 2008). In the context of the present research, it provides the conceptual foundation for understanding individual differences in visual search strategies, specifically the mechanisms of visual inhibition, goal-oriented visual exploration, and visual processing, which were operationalized through distinct experimental paradigms. Each paradigm induces specific attentional states that simulate the visual and cognitive challenges users face during ERP task execution. Guided Search Theory (Wolfe, 1994), therefore, offers a powerful explanatory framework for how individuals differ in their ability to filter, prioritize, and act upon visual information under conditions of high task complexity.

The Cognitive Load Theory (Sweller, 2024) complements this attentional perspective by explaining how the demands of complex tasks impose varying levels of mental effort on users. Cognitive load reflects the amount of working memory resources required to process information, integrate cues, and complete a task efficiently (Sweller, van Merriënboer, & Paas, 2020). As task complexity increases, users must devote greater cognitive resources to interpreting and managing information, which can elevate perceived effort, increase error rates, and reduce task efficiency. Within ERP systems, this relationship is particularly pronounced. Users are often required to attend to multiple data sources, hierarchical menus, and symbolic representations simultaneously, which intensifies cognitive demands and can lead to performance deterioration when cognitive capacity is exceeded.

By integrating these two theoretical perspectives, this study examines how attentional control and cognitive resource management jointly influence user performance under complexity. The Guided Search Model explains how users allocate and direct visual attention, while the Cognitive Load Theory elucidates why these attentional processes become more demanding as task complexity rises. Together, they provide a unified framework for understanding how individual differences in visual search propensity moderate the relationship between task complexity and user performance, thereby shaping cognitive load, frustration, and behavioural efficiency in ERP systems.

2.3.2 Hypothesis Development/Proposed Model

Building on this theoretical foundation, the following hypotheses were developed to examine the relationships between task complexity and user performance, as well as the mediating roles of frustration, cognitive load, emotional response, and visual search behaviour. The model also investigates the moderating influence of users' propensity for visual search on these relationships, reflecting the extent to which individual attentional strategies shape cognitive and performance outcomes. Figure 1 illustrates the conceptual framework and all hypothesized relationships included in the model.

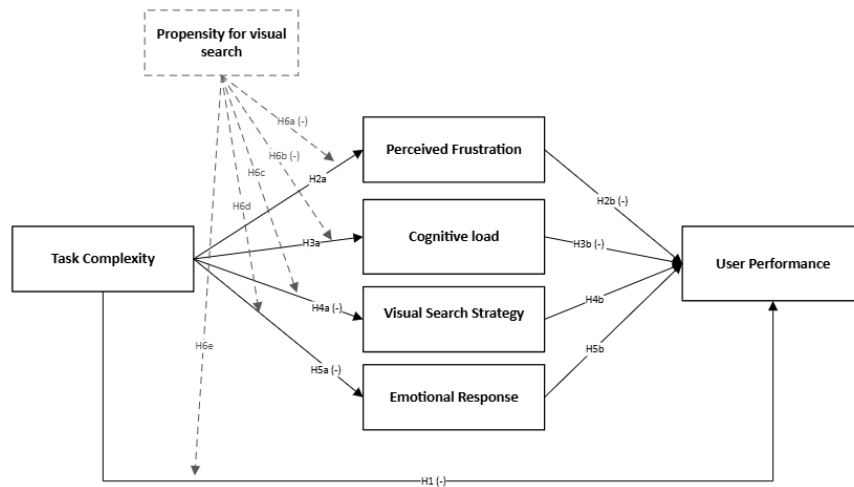


Fig 1. Research Model

In line with previous findings, task complexity has a substantial impact on users' efficiency and accuracy during system interaction. Complex tasks require the coordination of multiple cognitive processes, including information search, decision-making, and working memory management, all of which increase mental demands and the likelihood of errors (Campbell, 1988; Wood, 1986; Zeitlhofer et al., 2024). In ERP systems, complexity varies considerably, from simple, procedural operations to multi-step analytical tasks, forcing users to continually adapt their cognitive and visual strategies. This variation places heavy demands on attentional control and

information processing, often leading to longer search times, elevated frustration, and reduced task performance (Kastrati et al., 2021). Hence, we hypothesize that:

H1: *Task complexity decreases user performance.*

Beyond its direct impact on performance, task complexity also increases emotional strain. As stated previously, complex or ambiguous tasks often evoke greater frustration by amplifying uncertainty, mental effort, and perceived loss of control (Campbell, 1988; Novak et al., 2000; Zeithofer et al., 2024). In ERP environments, where users must navigate dense interfaces and complete multi-step processes under time pressure, the cognitive gap between task demands and available mental resources becomes more salient (Lazar et al., 2006; De Guinea & Markus, 2009). When feedback is unclear or navigation paths are non-intuitive, users' inability to efficiently complete tasks further reinforce perceived frustration, ultimately reducing engagement and satisfaction (Zeithofer et al., 2024).

Frustration, in turn, impairs task performance by diverting cognitive resources from goal-oriented actions to emotional regulation (Calvo & D'Mello, 2010). In HCI, high levels of frustration are consistently linked to longer task completion times, reduced accuracy, and decreased persistence (Hertzum & Hornbæk, 2023; Lazar et al., 2006; Kastrati et al., 2021). When users experience frustration, attentional focus becomes fragmented, limiting efficient visual search and problem-solving. In complex and cognitively demanding ERP interfaces, this frustration directly undermines user performance. Hence, we hypothesize that:

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H2a: *Task complexity increases perceived frustration.*

H2b: *Higher perceived frustration decreases user performance.*

Empirical findings further indicate that increasing task complexity substantially elevates users' cognitive load, leading to longer completion times, higher error rates, and diminished performance accuracy (Sweller, 1988). Cognitive load theory posits that individuals possess a limited working memory capacity that can be easily overwhelmed when task demands exceed available cognitive resources (Sweller, 1994). In complex environments such as ERP systems, users must often process multiple information streams simultaneously, navigating between transaction codes, data fields, and interface elements, while maintaining a coherent understanding of procedural sequences. This multitasking amplifies both intrinsic and extraneous cognitive load,

leaving fewer resources for effective problem-solving and decision-making (Paas & van Merriënboer, 1994; Wickens, 2008).

When cognitive demands exceed the user's processing capacity, mental fatigue and attentional lapses emerge, slowing task completion and increasing the likelihood of errors (de Jong, 2010). Eye-tracking studies have similarly shown that higher cognitive load is associated with longer fixation durations and less efficient visual scanning patterns, reflecting the heightened effort required to extract relevant information from complex interfaces (Kastrati et al., 2021). Therefore, as task complexity increases, users' cognitive resources become progressively depleted, constraining their ability to maintain optimal performance. Hence, we hypothesize that:

H3a: Task complexity increases cognitive load.

H3b: Higher cognitive load decreases user performance.

As established earlier, inefficient strategies often result in prolonged search times, increased cognitive load, and reduced task performance, whereas efficient strategies enable faster, more targeted information retrieval (Goldberg & Kotval, 1999; Matzen et al., 2016). Efficient strategies are characterized by shorter fixations and longer saccades, reflecting faster and more goal-directed visual exploration, whereas inefficient strategies involve dispersed scanning and repeated fixations on irrelevant elements, indicative of uncertainty and cognitive overload (Matzen et al., 2016; Krejtz et al., 2018).

In ERP environments, where interfaces contain numerous fields and hierarchical menus, task complexity can disrupt these strategies by increasing the number of visual elements to process and the uncertainty regarding where relevant information is located (Kastrati et al., 2021). As a result, complex tasks tend to elicit less efficient, more exploratory search behaviour, which increases cognitive load and slows performance. On the other hand, adopting a more focused and systematic visual search pattern facilitates faster information retrieval, reduces mental effort, and enhances task success. Hence, we hypothesize that:

H4a: Task complexity impairs users' visual search strategy.

H4b: More efficient visual search strategy improves user performance.

As previously mentioned, increasing task complexity substantially elevates users' cognitive load (Sweller, 1988). Measurable affective responses, including variations in valence and arousal, often accompany this escalation in mental effort. According to cognitive load theory, when task demands exceed users' cognitive capacity due to complexity, individuals experience affective discomfort, frustration, and reduced perceived control (Paas & van Merriënboer, 1994; Schmeichel & Tang, 2015). Empirical research in HCI confirms that high cognitive load typically correlates with negative valence and high arousal, reflecting stress or frustration, whereas lower cognitive load correlates with positive valence and moderate arousal, associated with engagement and satisfaction (Calvo & D'Mello, 2010).

In ERP environments, the complexity of multi-step procedures and dense information displays can therefore trigger negative emotional responses that hinder focus and efficiency. Conversely, positive emotional states tend to enhance cognitive flexibility, motivation, and performance accuracy (Fredrickson, 2001). Hence, we hypothesize that:

H5a: Task complexity increases negative emotional response.

H5b: More positive emotional response improves user performance.

Following earlier observations, individual differences in visual search propensity, measured by inhibitory control, goal-oriented visual exploration, and visual processing, may play a moderating role in how users experience and respond to task complexity. Visual search propensity reflects the efficiency and control of attentional deployment during interaction, encompassing one's ability to filter irrelevant information, maintain focus, and adapt scanning strategies to environmental demands (Kastrati et al., 2021; Rayner, 2009). Users with stronger visual search skills tend to process information more selectively and effectively, which may mitigate the adverse effects of complex interfaces.

Users with stronger visual search skills can more rapidly locate relevant interface components, sustain attention, and maintain a sense of control over the interaction. This efficiency mitigates feelings of uncertainty and prevents frustration from escalating as task complexity increases (Calvo & D'Mello, 2010; Hertzum & Hornbæk, 2023). In contrast, inefficient searchers experience fragmented attention and repeated scanning of irrelevant elements, amplifying emotional strain and perceived loss of control. Therefore, the negative effect of task complexity

on perceived frustration is expected to be weaker among users with high visual search propensity. Hence, we hypothesize that:

H6a: *Users' propensity for visual search weakens the effect of task complexity on perceived frustration.*

Similarly, since visual attention control directly influences information processing efficiency, individuals with higher visual search propensity are expected to experience lower cognitive load when performing complex tasks. By filtering irrelevant stimuli and prioritizing relevant cues, these users reduce extraneous cognitive processing and maintain greater mental efficiency (Paas & van Merriënboer, 1994; Wickens, 2008). Those with less efficient search behaviour, in contrast, allocate more cognitive resources to scanning and orientation, thereby exacerbating mental workload. Hence, we hypothesize that:

H6b: *Users' propensity for visual search weakens the effect of task complexity on cognitive load.*

In terms of visual search strategy, task complexity generally induces more exploratory and less focused gaze patterns (Goldberg & Kotval, 1999). As tasks become more demanding, users tend to spend more time in fixations and less time proportionally in saccades, reflecting higher processing complexity and reduced search efficiency. This shift suggests that users invest greater effort in local information processing rather than efficient scanning, leading to slower target detection and greater attentional dispersion. Increased task complexity, therefore, promotes less-structured, more exploratory scanpaths, indicating that users' visual attention becomes less goal-directed under high cognitive demands. However, users with a higher propensity for visual search are better able to maintain efficient, adaptive gaze behaviour in complex contexts. Their ability to regulate attention, inhibit irrelevant stimuli, and sustain goal-oriented scanning enables them to make shorter fixations and longer saccades, which support faster and more targeted information retrieval (Krejtz et al., 2018; Wolfe & Horowitz, 2017). This adaptive control of visual attention allows them to maintain consistent search efficiency and mitigate the detrimental impact of complexity on performance. Hence, we hypothesize that:

H6c: *Users' propensity for visual search weakens the effect of task complexity on visual search strategy.*

When individuals can efficiently direct their attention toward relevant information, they experience a greater sense of control and mastery over the task at hand, which fosters positive emotions such as satisfaction and engagement (Fredrickson, 2001). According to affective-cognitive interaction models, effective attention regulation reduces cognitive conflict and uncertainty, which often give rise to frustration or stress (Calvo & D'Mello, 2010). Users with a higher propensity for visual search can suppress irrelevant distractions and maintain a coherent visual strategy, thereby supporting fluent task progression and strengthening their perception of competence. This alignment between attentional control and task demands promotes positive valence and moderate arousal levels, an affective state associated with optimal performance and psychological well-being (Pekrun, 2006).

However, inefficient visual search behaviours, characterized by frequent refixations, prolonged fixations, and attentional dispersion, are associated with heightened cognitive effort and a loss of perceived control. These breakdowns in attentional focus generate negative affective states such as confusion, irritation, and frustration, particularly when users struggle to identify task-relevant elements (Hertzum & Hornbæk, 2023; Calvo & D'Mello, 2010). Therefore, individuals with higher visual search propensity are expected to maintain more stable and positive emotional responses even under conditions of elevated task complexity. Hence, we hypothesize that:

H6d: Users' propensity for visual search weakens the effect of task complexity on emotional response.

Finally, efficient visual search directly enhances user performance by optimizing information retrieval and reducing unnecessary cognitive effort. According to eye-movement research, users who can maintain focused attention and systematically direct their gaze toward relevant interface elements achieve shorter completion times, fewer errors, and higher task success rates (Kastrati et al., 2021; Matzen et al., 2016). This is because effective search behaviours minimize the time spent on irrelevant fixations, freeing cognitive resources for decision-making and action execution (Goldberg & Kotval, 1999).

Within complex ERP environments, where numerous visual cues compete for attention, such attentional control allows users to rapidly identify critical information and maintain workflow continuity. From a cognitive efficiency perspective, this mechanism aligns with theories of

selective attention and information processing, which propose that attentional filtering enhances performance by reducing mental load and enabling faster information encoding (Wickens, 2008; Sweller, 1988). Users with a higher propensity for visual search demonstrate superior attentional regulation, allowing them to sustain effective scanning patterns and integrate perceptual information more efficiently (Rayner, 2009). This not only accelerates task completion but also stabilizes performance under high task complexity by preventing overload and error propagation. Hence, we hypothesize that:

***H6e:** Users' propensity for visual search weakens the effect of task complexity on user performance.*

The research model in Figure 1 outlines how task complexity affects user performance through key cognitive, emotional, and perceptual mechanisms. It posits that task complexity increases perceived frustration, cognitive load, visual search strategy demands, and emotional response, which in turn shape performance outcomes. The model also incorporates users' propensity for visual search as a moderating factor that may weaken the impact of task complexity on these mediating processes. Taken together, this framework captures both the demands imposed by complex ERP interfaces and the individual differences that help explain variability in user performance.

2.4 Methods

2.4.1 Research Design

To address the research question, an experimental approach was necessary to isolate the cognitive, emotional, and perceptual mechanisms through which task complexity influences user performance. A controlled laboratory design enabled systematic manipulation of task complexity while holding all other interface characteristics constant, thereby ensuring that differences in cognitive load, visual search behavior, and emotional response could be attributed to the manipulation rather than to extraneous factors. This approach also allowed for the precise assessment of individual visual search tendencies using standardized eye-tracking paradigms, a level of measurement that would not have been achievable through field data or self-reported methods.

This study used a within-subjects experimental design in which every participant completed all levels of the experimental manipulation. The experiment consisted of two sequential phases, each targeting a different aspect of users' visual and cognitive processing. The factor of interest, task complexity, was operationalized through three ERP task blocks representing low, medium, and high complexity. These three conditions differed in interface density, number of steps required, and the extent of cross-screen information integration. All participants completed the three complexity conditions in a fully randomized order to control for learning and fatigue effects.

Phase 1 assessed individual differences in visual search propensity using three eye-tracking paradigms adapted from the EEGEyeNet framework (Kastrati et al., 2021). Each paradigm targeted a specific component of visual search behavior. Inhibitory control (Pro- and Antisaccade Paradigm), goal-directed visual exploration (Large Grid Paradigm), and visual processing efficiency (Feature-detection Paradigm). These tasks established a baseline profile for each participant, allowing measurement of visual search strengths and limitations independently of ERP task exposure.

Phase 2 consisted of the ERP task blocks, each containing three trials. Before each block, participants watched a short vicarious training video showing the exact steps needed to complete the upcoming task. This ensured that all participants had access to the same procedural knowledge prior to interacting with the ERP system. Participants were then given an instruction sheet specifying the information they would need to recall during the task, introducing a working-memory component consistent across conditions. The ERP tasks required participants to navigate hierarchical menus, locate relevant fields, extract information from multiple screens, and execute transaction steps, mirroring realistic finance-related operations.

This design provided a controlled yet ecologically valid environment for examining how variations in task complexity interact with users' visual search propensity to influence cognitive load, emotional response, and performance outcomes.

2.4.2 Participants

We recruited 36 participants for this study through the HEC Montréal participant pool. The sample had a mean age of 29 years (-18/+66) and included 18 females and 18 males, ensuring a balanced composition that supported the generalizability of the findings. Each participant received

\$30 in compensation for their participation. The inclusion criteria were being 18 years of age or older; having advanced oral and written proficiency in French and/or English; being able to view a computer screen without corrective eyewear; not having skin allergies or sensitivities; and not suffering from epilepsy. No exclusion criteria were applied. The study protocol was reviewed and approved by the Research Ethics Board (CER) of our institution (certificate #2025-6412).

2.4.3 Experimental Stimuli

To manipulate task complexity, three ERP transactions within the SAP S/4HANA system and the Fiori interface were selected, each varying in the cognitive demands placed on the user. This variability was intentionally incorporated to examine how differences in task complexity influenced users' visual search strategies and their ability to discover system functionalities, regardless of the order in which tasks were completed. The tasks differed in the number of steps, the user inputs required, the working memory load, and the volume of data displayed, thereby reflecting distinct levels of information-processing demands.

Task 1, which involved paying a customer invoice (Transaction F-28), is illustrated in Figure 2. This task was classified as the high-complexity condition. Participants were required to process an incoming payment by entering specific financial details, such as customer account numbers and invoice references, into designated fields. Completing the transaction involved nine steps and eleven clicks, with multiple fields requiring manual input. Participants also had to retain up to 4 items in working memory while simultaneously attending to 42 visible data fields across 10 information types. The combined demands of navigation, data entry, and information retention substantially increased the cognitive load and the effort required to complete the transaction. This task mirrored the Pro- and Anti-saccade Paradigm, which assesses inhibitory control, that is, the ability to suppress reflexive eye movements toward irrelevant stimuli and maintain focus on task-relevant visual targets.

Payment

General Information

Company Code: DD
Posting Date: 2025-08-08
Journal Entry Date: 2025-08-08
Value Date: yyyy-MM-dd
Reference:
Period: 08
Journal Entry Type: 02
Header Text:
Profit Center:
Clearing Text:

Bank Data

House Bank/Account:
GL Account: 11305393
Amount: 4,161.00 EUR
Fees: 0.00 EUR
Assignment:
Amount/Code: 0.00 EUR
Currency:
Transaction Date: 2025-08-08

Open Item Selection

Account Type/Account ID: Customer
Payment Reference:
Pay Advice No.:

Proposed Items (4,161.00 EUR)

Comp...	Account	Journal...	Journ...	Item Text	Journal...	Net Du...	Amount...	Assign...	Clear
DD	80148	90000817	RV		2025-05...	2025-05...	4,161.00	0090000...	✓
DD	80148	90000895	RV		2025-05...	2025-05...	3,854.40	0090000...	Clear

Items to Be Cleared (1)

Remove	Journ...	Open...	Allocat...	Discou...	Invoice...
	90000817	161.00	4,16...	0.00	

Post Simulate

Fig 2. ERP Task 1 (SAP Transaction F-28)

Task 2, which involved completing a journal entry (Transaction F-01), is illustrated in Figure 3. This task represented the moderate-complexity condition. Participants were asked to analyze a general ledger account by reviewing and interpreting financial statement data. Although the transaction displayed the most visible data points (126) across 11 information types, it required no manual input and retained only 2 items in working memory. The interface layout was denser than in Task 1 but involved fewer procedural steps, reducing some of the navigational burden. The complexity in this case stemmed primarily from the need to scan and interpret a large volume of financial data to identify relevant information. This task reflected the Large Grid Paradigm, which evaluates goal-oriented visual exploration, or the capacity to plan and execute systematic gaze movements in alignment with task objectives.

Description	GL Account	Period Balance	Comparison Balance (Actu...)	Absolute Difference	Relative Difference
Balance Sheet		0.00 EUR	0.00 EUR	0.00 EUR	0.0
Assets		20,782,802.33 EUR	0.00 EUR	20,782,802.33 EUR	0.0
Current Assets		3,059,468.97 EUR	0.00 EUR	3,059,468.97 EUR	0.0
Bank Cash Account	113300	1,197,676.52 EUR	0.00 EUR	1,197,676.52 EUR	0.0
Customers - Domestic Receivables	140000	1,794,719.37 EUR	0.00 EUR	1,794,719.37 EUR	0.0
Raw materials	300000	18.20 EUR	0.00 EUR	18.20 EUR	0.0
Finished goods	780000	87,064.88 EUR	0.00 EUR	87,064.88 EUR	0.0
Long-Term Assets		17,723,333.36 EUR	0.00 EUR	17,723,333.36 EUR	0.0
Land	1000	500,000.00 EUR	0.00 EUR	500,000.00 EUR	0.0
Buildings	2000	1,500,000.00 EUR	0.00 EUR	1,500,000.00 EUR	0.0
Accumulated Depreciation - Buildings	2010	-10,000.00 EUR	0.00 EUR	-10,000.00 EUR	0.0
Machinery and equipment	11000	16,000,000.00 EUR	0.00 EUR	16,000,000.00 EUR	0.0
Accumulated depreciation - machinery and equipment	11010	-266,666.64 EUR	0.00 EUR	-266,666.64 EUR	0.0
Liabilities and Owners' Equity		-20,782,802.33 EUR	0.00 EUR	-20,782,802.33 EUR	0.0
Equity		-20,782,802.33 EUR	0.00 EUR	-20,782,802.33 EUR	0.0
Shareholders' Equity		-20,000,000.00 EUR	0.00 EUR	-20,000,000.00 EUR	0.0
Common stock	70000	-20,000,000.00 EUR	0.00 EUR	-20,000,000.00 EUR	0.0
Retained Earnings		-782,802.33 EUR	0.00 EUR	-782,802.33 EUR	0.0
Net Income		-782,802.33 EUR	0.00 EUR	-782,802.33 EUR	0.0

Fig 3. ERP Task 2 (SAP Transaction F-01)

Task 3, which involved the customer line-item display (Transaction FBL5N), is illustrated in Figure 4. This task was defined as the low-complexity condition. Participants were instructed to search a list of customer invoices and identify specific entries that match predefined criteria (e.g., amounts, statuses, or dates). The transaction required only one step and one click, with no user input necessary. Although 96 data fields across nine information types were displayed, the task imposed minimal demands on working memory and navigation. As a result, it was the least cognitively demanding of the three conditions. This task mirrored the Visual Symbol Search Paradigm, which assesses visual processing, or the ability to identify relevant visual cues among distractors in structured displays efficiently.

Customer	Company	Assignment	Journal Entry D...	Journal Entry	Journal ...	Spec...	Due N...	Amount (CoCode Crq)	Clearing Int
80134	AA		2025-09-15	140000011	DZ			-5,270.00	EUR 140000011
80134	AA		2025-09-15	140000010	DZ			-13,858.52	EUR 140000010
80134	AA	0900000920	2025-09-15	90000920	RV			13,858.52	EUR 140000010
80134	AA	0900000919	2025-09-05	90000919	RV			5,270.00	EUR 140000011
80134	AA		2025-04-30	140000005	DZ			-22,042.80	EUR 140000005
80134	AA	0900000647	2025-01-31	90000647	RV			18,914.84	EUR
80134	AA	0900000646	2025-01-31	90000646	RV			23,212.38	EUR
80134	AA	0900000645	2025-01-31	90000645	RV			22,042.80	EUR 140000005
80134	AA	0900000642	2025-01-31	90000642	RV			13,857.48	EUR
								56,984.70	EUR

Fig. 4. ERP Task 3 (SAP Transaction FBL5N)

2.4.4 Paradigms

To assess participants' propensity for visual search, this study employed three paradigms adapted from the EEGEyeNet framework (Kastrati et al., 2021). Each paradigm isolates a distinct attentional mechanism, visual inhibition, goal-oriented visual exploration, and visual processing, providing a multidimensional portrait of the cognitive abilities that shape how users navigate complex digital environments such as ERP systems. These mechanisms are well-established in cognitive psychology and oculomotor neuroscience and are operationalized through structured visual tasks that yield reliable behavioural and eye-tracking indicators.

Visual inhibition was measured using the Pro- and Anti-saccade Paradigm, a canonical paradigm assessing the ability to suppress reflexive eye movements toward irrelevant stimuli. In pro-saccade trials, participants execute an automatic gaze shift toward a suddenly appearing cue. In contrast, anti-saccade trials require them to inhibit this reflex and instead direct their gaze to the mirror-opposite location. This ability to override bottom-up attentional capture reflects top-down inhibitory control, a core executive function supported by frontal-lobe networks (Munoz & Everling, 2004). High error rates or prolonged latencies in anti-saccade trials indicate weaker inhibitory control and a greater tendency to be distracted by visually salient but irrelevant elements. Given that ERP interfaces frequently present competing visual cues and dense information, visual inhibition is a critical mechanism for maintaining goal-directed focus during complex workflows.

Goal-oriented visual exploration was assessed through the Large Grid Search Paradigm, which requires participants to scan a wide array of spatially distributed elements systematically. This paradigm captures users' ability to deploy strategic, top-down exploration, maintain an organized search pattern, and monitor visited versus unvisited locations, capacities essential for navigating visually cluttered or information-rich digital interfaces. Metrics such as fixation distribution, path efficiency, and grid coverage quantify how effectively participants plan and execute structured exploration. This behaviour aligns with theories of goal-driven attention, which emphasize the active selection of task-relevant regions while suppressing irrelevant spatial zones (Eckstein, 2011). By simulating high-density, multi-element environments, the task provides a controlled analogue to ERP screens requiring systematic review of numerous fields, tabs, or data points.

Visual processing efficiency was measured using the Visual Symbol Search Paradigm, which evaluates the speed and accuracy with which individuals discriminate relevant from irrelevant symbols under time pressure. Participants must rapidly determine whether a target symbol is present among distractors, a process that relies on perceptual encoding, rapid matching, and psychomotor decision speed. This paradigm aligns with established measures of processing speed in cognitive assessment, such as the Symbol Search subtest of the WAIS. It provides insight into how quickly users can parse and act on visual information (Wolfe & Horowitz, 2017). In ERP contexts, where users often scan lists, verify details, or locate specific entries within dense displays, efficient visual processing directly supports performance by reducing the time needed to interpret and validate information.

Taken together, these three paradigms offer a comprehensive and theoretically grounded assessment of visual search propensity. By isolating inhibitory control, strategic exploration, and processing speed, they enable a precise characterization of how individuals allocate, shift, and sustain attention in visually complex environments. When combined with eye-tracking indices such as fixation duration, saccadic latency, and scanpath structure, they provide robust empirical measures linking attentional efficiency to user performance in complex digital systems. This multidimensional approach is particularly relevant for ERP-driven digital transformation projects, where user performance depends not only on interface design but also on intrinsic visual-cognitive abilities that shape how individuals cope with task complexity and information load.

2.4.5 Instruments & Measures

The experimental setup combined multiple instruments designed to capture both physiological and behavioural indicators of user experience in a controlled laboratory environment. Facial expression data were collected using FaceReader 9.1 (Noldus Information Technology, Wageningen, Netherlands), an automated facial analysis software that detects and quantifies facial Action Units (AUs) based on the Facial Action Coding System (FACS). The software uses advanced computer vision and machine learning algorithms to estimate participants' emotional states in real time by computing valence and arousal scores derived from facial muscle activations. FaceReader's methodology has demonstrated high validity and reliability for assessing affective responses during HCI tasks (Loijens & Krips, 2025). Emotional responses were measured using valence and arousal. Arousal was presented as a continuous activity measure ranging from

0 (inactive) to +1 (active), calculated based on the corrected activation values (CAV) of facial Action Units and averaged over the five most active AUs at each time point (Loijens & Krips, 2025). Valence was presented as a continuous variable ranging from -1 (negative, unpleasant emotions) to +1 (positive, pleasant emotions), calculated as the difference between the mean activation of negative and positive Action Units at each time point (Loijens & Krips, 2025).

To ensure optimal accuracy in facial recognition and expression detection, each session was recorded using a high-definition camera positioned at eye level, under standardized lighting conditions with a neutral background and minimal environmental distractions. This configuration provided consistent facial tracking and high-quality affective data for analyses of emotional responses.

Eye movement data, pupil size, fixations, and saccades data were recorded using two eye-tracking systems: a Tobii Pro Nano (60 Hz, Tobii AB, Stockholm, Sweden) and a GazePoint device (60 Hz, GP3 Eye Tracker, Vancouver, Canada). Both trackers were mounted on the monitor to capture gaze behaviour under standardized conditions. Participants were positioned approximately 65 cm from the screen to ensure consistency across sessions. Data acquisition was managed through Tobii Pro Lab software (Tobii AB, Stockholm, Sweden), which processed the raw recordings. The laboratory was equipped with a dual-monitor setup: one screen mirrored the participant's display, while the second allowed the experimenter to control the eye-tracking software and monitor gaze data in real time.

From this eye-tracking data, the visual search strategy was assessed using three gaze-based indicators: the K coefficient, average fixation duration, and average saccade amplitude. These measures were collected using Tobii Pro Lab and GazePoint eye-tracking systems. The K coefficient quantifies the balance between focal (goal-directed) and ambient (exploratory) visual attention (Sodhi et al., 2002; Krejtz et al., 2016). Lower K values indicate more targeted and efficient search behaviour, whereas higher K values reflect more dispersed and exploratory gaze patterns. Fixation duration, measured in milliseconds, is the average time a participant's gaze remains stable on a specific interface element. Longer fixations generally indicate greater cognitive processing or greater difficulty in extracting information (Rayner, 2009; Krejtz et al., 2018). Saccade amplitude, measured in degrees of visual angle, captures the distance between successive fixations. Larger saccade amplitudes indicate faster scanning and broader visual exploration,

whereas smaller amplitudes reflect a narrower attentional focus and potentially greater cognitive effort (Goldberg & Kotval, 1999).

The propensity for visual search, defined as users' ability to efficiently direct attention and extract relevant information within complex visual environments, was assessed using three standardized scores derived from eye-tracking paradigms adapted from the EEGEyeNet framework (Kastrati et al., 2021). The Pro- and Anti-saccade Paradigm score (inverse measure) indexed visual inhibitory control and corresponded to the proportion of correct anti-saccade responses. Scores ranged from 0 to 1, with higher values indicating poorer inhibition performance and greater difficulty suppressing reflexive eye movements toward irrelevant stimuli. The Large Grid Paradigm score represented goal-oriented visual exploration efficiency. It ranged from 0 to 1, with higher scores denoting more effective scanning behaviour, that is, faster and more accurate fixation on task-relevant elements. This score provided a reliable indicator of users' ability to guide visual attention in line with task demands strategically. Finally, the Visual Symbol Search Paradigm score (inverse measure) captured visual processing ability, reflecting participants' accuracy and reaction times when identifying relevant targets among distractors. Scores ranged from 0 to 5, where higher values indicated poorer detection performance. Complementarily, the Visual Symbol Search Paradigm accuracy variable (0–1) represented the proportion of correct responses, with lower values corresponding to reduced feature discrimination. Together, these indices provide a structured assessment of individual differences in visual search propensity, integrating inhibitory control, goal-oriented visual exploration, and visual processing as key components of efficient attentional processing. Lower Pro- and Anti-saccade Paradigm and Visual Symbol Search Paradigm scores and higher Large Grid Paradigm scores jointly reflect stronger visual search capability, a construct closely associated with user performance and cognitive efficiency in HCI (Wolfe, 1994; Munoz & Everling, 2004; Wolfe & Horowitz, 2017).

User performance was assessed using two objective indicators: task completion time and success rate for each trial across the three ERP tasks. At the beginning of each trial, the moderator initiated a timer from the moment the stimulus appeared on the screen until the participant verbally indicated task completion or until the maximum time limit was reached. Task completion time was thus recorded as the duration taken by the participant to complete the trial, with longer times indicating lower performance. Task completion time is a widely recognized indicator of user

performance in usability studies, as it reflects both efficiency and the cognitive demands associated with task execution (Hornbæk, 2006). The moderator documented the success rate in a log file and coded it dichotomously (1 = success, 0 = failure). A trial was considered a failure if the participant exceeded the allotted time or failed to complete the task according to the instructions.

Task complexity was measured using the Task Complexity Index (TCI) (Braarud, 2001), which includes four items rated on a 7-point Likert scale (1 = "strongly disagree," 7 = "strongly agree"). See Annexe A for the complete scale items. To validate the intended variability in task complexity, we conducted an independent manipulation check based on objective task characteristics. Complexity ratings were derived from predefined criteria, including the number of clicks required, user input, steps to complete, working memory load, and the volume and diversity of visible data points, all within the transaction interface in SAP Fiori. This systematic evaluation allowed us to classify Task 1 as high complexity, Task 2 as moderate complexity, and Task 3 as low complexity. These distinctions were established prior to the experiment to ensure that the manipulation of task complexity reflected meaningful differences in cognitive demands. In addition to this objective assessment, participants' perceptions of complexity were measured through post-task questionnaires to provide a dependent manipulation check. We were able to confirm our independent manipulation check using participants' questionnaire results. The combination of both approaches ensured that the experimental manipulation was both theoretically grounded and empirically validated, providing a robust foundation for interpreting task complexity.

Perceived frustration and cognitive load were measured using the NASA Task Load Index (TLX) (Hart & Staveland, 1988). The NASA-TLX is a multidimensional measure of subjective workload that has demonstrated strong reliability and validity across experimental and applied contexts. Perceived frustration was assessed using the single-item frustration subscale, rated on a percentage slider (0 = "low," 100 = "high"). Perceived cognitive load was measured using the single-item mental load subscale, also rated on a percentage slider (0 = "low," 100 = "high"). See Annexe A for the complete scale items.

Refer to Table 2 for an overview of all the constructs, instruments, and measurement scales.

Table 2

Constructs, Instruments, and Measurement Scale

Construct	Instruments/Source	Measured Variables	Measurement Scale/Range
Emotional Response	FaceReader 9.1 (Noldus Information Technology, Wageningen, Netherlands)	Valence	Valence = -1 (negative) to +1 (positive)
		Arousal	Arousal = 0 (inactive) to +1 (active)
Visual Search Strategy	Tobii Pro Nano (60 Hz) & GazePoint Eye Tracker (60 Hz) + Tobii Pro Lab software	K Coefficient	Low = goal-directed (efficient); High = exploratory (inefficient)
		Average Fixation Duration (ms)	Longer = higher cognitive effort; shorter = fluent processing
		Average Saccade Amplitude (°)	Larger = broader exploration; smaller = focused processing
		Visual Inhibition	Pro- and Antisaccade : 0–1 (range), higher = poorer inhibition (inverse measure)
Propensity for Visual Search	EEGeyeNet-based paradigms (Kastrati et al., 2021)	Goal-oriented visual exploration	Large Grid: 0–1 (range), higher = better goal-oriented visual exploration
		Visual processing	Visual Symbol Search: 0–5 (range), higher = poorer visual processing (inverse measure)
User Performance	Experimental task logs (Lab Observations)	Success Rate (binary)	Dichotomous (1 = success, 0 = failure)
		Task Completion Time (s)	Continuous (seconds)
Cognitive Load	NASA Task Load Index (TLX) (Hart & Staveland, 1988)	Mental Demand Subscale	Continuous slider, 0 (“Low”) to 100 (“High”)
	Tobii Pro Nano (60 Hz) & GazePoint Eye Tracker (60 Hz) + Tobii Pro Lab software	Pupil Adj	Continuous (change in pupil diameter, mm)
Frustration	NASA Task Load Index (TLX) (Hart & Staveland, 1988)	Frustration Subscale	Continuous slider, 0 (“Low”) to 100 (“High”)
Task Complexity	Task Complexity Index (TCI) (Braarud, 2001)	Task complexity classification	7-point Likert scale (1 = “Strongly disagree”, 7 = “Strongly agree”)

2.4.6 Procedure/Data Collection

Before participants arrived, the researcher prepared the laboratory by powering up the computers, launching the required software, and configuring data recording and synchronization

tools. Individual profiles were created for each participant using a standardized naming convention. Upon arrival, participants were instructed to store personal belongings in secure lockers, silence their phones, and discard chewing gum. They were offered a restroom break before reading and signing the consent form on an iPad in the participant's room. The moderator answered any questions participants had before beginning the experiment.

The physiological setup began with the calibration of two eye-tracking devices (Tobii Pro Lab and GazePoint) using standardized procedures, with participants seated approximately 65 cm from the monitor. Once calibration of both devices was complete, the moderator activated the Cobalt Bluebox and launched Cobalt Capture recording, a system developed by Tech3Lab at HEC Montréal (Courtemanche et al., 2022). A short baseline video was shown to establish initial measures. Participants then completed a short demographic questionnaire followed by the pre-study questionnaire.

The study followed a Latin square design to randomize the order of the paradigms, ERP tasks, and the eye-tracking device assigned to each condition. Participants completed the three paradigms in the randomized order assigned to them, with the moderator re-entering the room to switch the recording device when required. For each ERP task, participants received instructions via Qualtrics and then viewed a three-minute vicarious training video before beginning the task. Each task was performed across three trials, with three minutes allocated per trial for Task 1 and one minute per trial for Tasks 2 and 3. The moderator recorded observations on task success and completion time for each trial. After each task, participants completed a post-task questionnaire.

At the conclusion of the session, all recordings were saved under the appropriate naming convention. The researcher facilitated the compensation process, after which participants were thanked and escorted out of the laboratory.

2.4.7 Data Analysis

The data analysis employed a series of advanced statistical techniques to test the research hypotheses and examine the relationships among task complexity, visual search behaviour, and user performance within the SAP environment. The analysis followed a structured, multi-step approach integrating both descriptive and inferential statistics. All statistical models were

implemented using SAS OnDemand for Academics and SAS Studio, a web-based SAS development environment supporting cloud-based data processing and model execution.

Descriptive statistics (means, standard deviations, and frequencies) were computed for all variables across the three ERP tasks to provide an overview of the data distribution and to ensure completeness and comparability across participants. Following data preprocessing, the eye-tracking datasets obtained from the Tobii and GazePoint systems were standardized onto a common measurement scale and appended into a single dataset, enabling comprehensive analyses across all experimental conditions within a unified structure. A one-way ANOVA was then conducted as a manipulation check to verify the effectiveness of the task complexity manipulation within the SAP tasks. Subsequently, linear mixed-effects regression models with random intercepts were estimated to account for inter-individual variability while testing the fixed effects of task complexity and visual search parameters on user performance and experience-related outcomes. These random intercepts captured the hierarchical structure of the data by accounting for repeated measures at the participant level.

To explore the relationships in greater depth, hierarchical linear regression models were used to test the direct and mediated effects among key constructs. Specifically, task complexity (independent variable) was modelled as predicting user performance (dependent variable), with mediating factors including frustration, cognitive load, visual search strategies, and emotional responses. A subsequent moderation analysis was conducted to assess the interactive influence of users' propensity for visual search on these mediating mechanisms. Additionally, supplementary regression analyses were performed to investigate the direct predictive effects of the eye-tracking paradigm accuracy scores (users' propensity for visual search) on user performance, independent of the primary model, thereby providing complementary insights into individual-level differences.

Given that the hypotheses were unidirectional, one-tailed significance testing was applied. When the direction of the effect was consistent with the hypothesized relationship, the p-value (α) was divided by two to reflect the directional nature of the test. When effects were bidirectional or inconsistent with the hypothesis, the adjusted value was computed as $1 - (p/2)$. To ensure model validity and reliability, diagnostic and residual plots were systematically inspected, confirming normality, homoscedasticity, and residual independence. Multicollinearity tests verified that the independent variables were not excessively correlated. The combination of random-intercept

modelling and robust diagnostic evaluation ensured the reliability and interpretability of the results.

2.5 Results

2.5.1 Manipulation check

During data analysis, a manipulation check was performed to ensure the validity of the differences in task complexity across the three experimental conditions. A one-way repeated-measures ANOVA test was conducted to verify the effectiveness of the task complexity manipulation. The results revealed a significant main effect of task complexity, $F(2, 70) = 18.94$, $p < .001$. Perceived complexity decreased progressively across tasks (Task 1: $M = 2.93$, $SE = 0.20$; Task 2: $M = 2.69$, $SE = 0.20$; Task 3: $M = 1.71$, $SE = 0.20$). Post hoc comparisons using the Tukey-Kramer adjustment indicated that Task 3 was perceived as significantly less complex than Task 1 ($p < .001$) and Task 2 ($p < .001$), whereas the difference between Tasks 1 and 2 was not significant ($p = .46$). These results confirm that the manipulation of task complexity was effective, as illustrated in Figure 5, which depicts the mean perceived complexity for each ERP task.

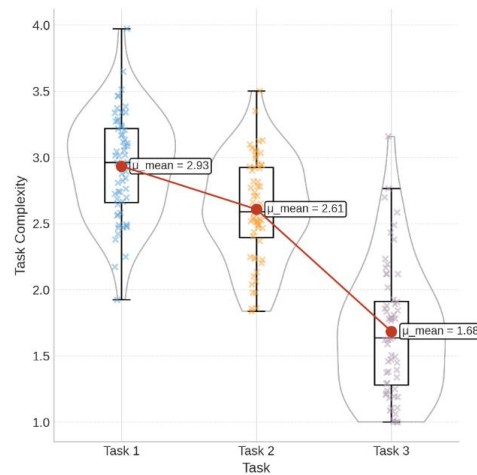


Fig 5. Mean perceived task complexity across ERP tasks

2.5.2 Descriptive statistics

Table 3 presents the descriptive statistics for all variables measured across the three tasks completed by participants within the ERP system. The variables encompass task complexity, users' propensity for visual search, frustration, cognitive load, emotional responses, visual search strategy, and overall user performance. For each variable, the table reports the mean and standard deviation across tasks, along with the total number of valid observations (n) collected.

Table 3
Summary of Descriptive Statistics

Variable	Task 1*			Task 2**			Task 3***		
	n	M	SD	n	M	SD	n	M	SD
Task Complexity	36	2.93	1.38	36	2.68	1.23	36	1.71	0.85
Inhibitory Control	31	0.24	0.16	31	0.24	0.16	31	0.24	0.16
Goal-oriented visual exploration	36	0.69	0.11	36	0.69	0.11	36	0.69	0.11
Visual processing	34	3.80	0.77	34	3.80	0.77	34	3.80	0.77
Perceived Frustration	35	20.17	18.17	35	18.06	21.07	35	7.74	10.14
Perceived Cognitive Load	36	27.19	21.86	36	21.58	16.04	35	14.43	13.44
Pupil Size	35	0.51	0.64	35	0.16	0.36	35	0.16	0.51
K Coefficient	35	-0.11	0.34	35	0.37	0.23	35	0.11	0.19
Fixation Duration	35	357.15	64.81	35	412.75	76.61	35	359.67	59.53
Saccade Amplitude	35	199.27	51.29	35	172.18	46.11	35	196.97	47.76
Valence	16	-0.13	0.11	18	-0.10	0.11	16	-0.08	0.10
Arousal	16	0.28	0.03	16	0.29	0.03	16	0.29	0.03
Success Rate	36	0.60	0.47	36	0.44	0.30	36	0.94	0.19
Task Completion Time (s)	36	80.15	31.06	36	27.06	10.91	36	16.13	9.12

The descriptive results presented in Table 3 reveal clear and consistent patterns across the three ERP tasks, confirming the effectiveness of the task complexity manipulation. As expected, task complexity decreased across tasks, with means of $M = 2.93$ ($SD = 1.38$) *, $M = 2.68$ ($SD = 1.23$) **, and $M = 1.71$ ($SD = 0.85$) ***, indicating that participants perceived increasing complexity across tasks. This trend was accompanied by a reduction in perceived frustration, which declined from $M = 20.17$ ($SD = 18.17$) * to $M = 18.06$ ($SD = 21.07$) ** and $M = 7.74$ ($SD = 10.14$) ***, and in perceived cognitive load, which decreased from $M = 27.19$ ($SD = 21.86$) * to $M = 21.58$ ($SD =$

16.04)** and $M = 14.43$ ($SD = 13.44$)***. These patterns suggest that lower task complexity was associated with reduced emotional strain and cognitive effort.

Performance indicators showed the same direction. The success rate increased from $M = 0.60$ ($SD = 0.47$)* in the first task to $M = 0.94$ ($SD = 0.19$)*** in the final task, whereas task completion time decreased from $M = 80.15$ seconds ($SD = 31.06$)* to $M = 27.06$ seconds ($SD = 10.91$)** and $M = 16.13$ seconds ($SD = 9.12$)***. Together, these results indicate that participants completed simpler tasks more efficiently and accurately.

Eye-tracking metrics further supported these findings. The K coefficient, which reflects visual search efficiency, shifted from $M = -0.11$ ($SD = 0.34$)* to $M = 0.37$ ($SD = 0.23$)** and $M = 0.11$ ($SD = 0.19$)***, suggesting more systematic and goal-directed visual search strategies as task complexity decreased. Fixation duration and saccade amplitude remained relatively stable across tasks, indicating consistent gaze dynamics but more effective allocation of visual attention in simpler interfaces.

2.5.3 Hypothesis testing

Since most of the hypothesis focused on mediation analysis, we first examined the direct effects of task complexity on user performance to determine if significant results were present. Since they were, we then proceeded to the analysis of each mediating variable, their effect on the independent variable and on the dependent variable. We then conducted the analysis of the moderating variables on the mediating effects of the independent variables on each of the mediating variables. Figure x outlines the indirect effects, focusing on variables that were collected during the study to evaluate each of the effects.

2.5.3.1 Task Complexity & User Performance

To assess the direct impact of task complexity on user performance, two linear mixed-effects regression models were estimated. The first analysis revealed that task complexity significantly predicted task success rate, $\beta = -0.16$, $SE = 0.03$, $t(103.40) = -5.63$, $p < .0001$, 95% CI $[-0.21, -0.10]$. This negative and statistically robust association indicates that as the level of task complexity increases, the probability of successfully completing the task decreases.

A second model further demonstrated that task complexity exerted a significant positive effect on task completion time, $\beta = 11.60$, $SE = 2.35$, $t(106) = 4.94$, $p < .0001$, 95% CI [6.94, 16.25]. This finding confirms that users required substantially more time to complete tasks of greater complexity, suggesting an escalation in cognitive and operational demands associated with increased task difficulty.

These results show that task complexity was associated with lower success rates and longer task completion times across participants, thereby supporting H1.

2.5.3.2 Frustration

A series of linear mixed-effects regressions were conducted to examine the relationship between task complexity and user frustration, as measured through self-reported scales. Task complexity significantly predicted perceived frustration, $\beta = 8.31$, $SE = 1.05$, $t(94.67) = 7.92$, $p < .0001$, 95% CI [6.23, 10.40]. Higher task complexity was thus associated with higher levels of reported frustration.

Additional analyses assessed the relationship between perceived frustration and user performance metrics. Perceived frustration significantly predicted average task completion time, $\beta = 0.65$, $SE = 0.18$, $t(103) = 3.61$, $p < .001$, 95% CI [0.29, 1.01], and task success rate, $\beta = -0.005$, $SE = 0.002$, $t(90.37) = -2.32$, $p = .011$, 95% CI [-0.01, -0.001]. As frustration increased, users tended to spend more time completing tasks and achieved lower success rates.

These results indicate that higher task complexity consistently increased frustration, which was subsequently associated with longer task completion times and lower success rates, thereby supporting H2a and H2b.

2.5.3.3 Cognitive Load

A series of linear mixed-effects models were conducted to examine the relationship between task complexity and cognitive load using both subjective and physiological indicators. Task complexity significantly predicted self-reported cognitive load, as measured by the NASA-TLX mental demand score, $\beta = 8.83$, $SE = 1.02$, $t(93.29) = 8.69$, $p < .0001$, 95% CI [6.81, 10.85]. Higher task complexity was therefore associated with greater perceived mental demand.

In contrast, the physiological indicator of cognitive load, mean pupil diameter, exhibited a positive but non-significant trend, $\beta = 0.04$, $SE = 0.04$, $t(95.31) = 0.94$, $p = .174$, 95% CI $[-0.04, 0.13]$. Although the direction of the effect was consistent with theoretical expectations, it did not reach statistical significance under the current experimental conditions.

Further analyses examined the relationship between cognitive load and user performance. Self-reported cognitive load (NASA-TLX mental demand) was negatively associated with task success rate, $\beta = -0.004$, $SE = 0.002$, $t(89.97) = -1.83$, $p = .03$, 95% CI $[-0.008, 0.0003]$. The physiological indicator (pupil size) showed a non-significant positive association with success rate, $\beta = 0.004$, $SE = 0.07$, $t(102.9) = 0.06$, $p = .53$, 95% CI $[-0.14, 0.15]$.

Additionally, higher perceived cognitive load was associated with significantly longer task completion times, $\beta = 0.49$, $SE = 0.18$, $t(105) = 2.72$, $p = .004$, 95% CI $[0.11, 0.82]$. Physiological measures showed a similar pattern, with larger pupil size predicting longer task completion times, although this relationship did not reach significance, $\beta = 8.10$, $SE = 6.29$, $t(103) = 1.29$, $p = .10$, 95% CI $[-4.37, 20.57]$. Taken together, these results provide support for H3a and H3b.

A complete summary of the descriptive and inferential statistics is presented in Table 4.

Table 4
Summary of Mediation Effects of Cognitive Load on User Performance

Predictor	Outcome Variable	β	SE	$t(df)$	p	95% CI [LL, UL]
Perceived Cognitive Load	Success Rate	-0.004	0.002	-1.83 (89.97)	.03	[6.81, 10.85]
Pupil Size	Success Rate	0.004	0.07	0.06 (102.9)	.53	$[-0.14, 0.15]$
Perceived Cognitive Load	Average Task Completion Time (s)	0.49	0.18	2.72 (105)	.004	$[0.11, 0.82]$
Pupil size	Average Task Completion Time (s)	8.10	6.29	1.29 (103)	.10	$[-4.37, 20.57]$

2.5.3.4 Visual Search Strategy

A series of linear mixed-effects models were conducted to examine the relationship between task complexity and visual search behavior. Task complexity did not significantly predict the K coefficient, $\beta = -0.02$, $SE = 0.02$, $t(103) = -0.80$, $p = .21$, 95% CI $[-0.07, 0.03]$. Similarly,

no significant effect was observed between task complexity and average saccade amplitude, $\beta = -5.14$, $SE = 3.79$, $t(103) = -1.36$, $p = .09$, 95% CI $[-12.66, 2.37]$. The average fixation duration also showed a positive but non-significant association with task complexity, $\beta = 0.19$, $SE = 5.52$, $t(103) = 0.03$, $p = .49$, 95% CI $[-10.76, 11.14]$. Although none of these relationships reached statistical significance, the direction of effects suggests that increases in task complexity were accompanied by slightly longer fixations and smaller saccades.

Further analyses examined the relationship between visual search indicators and user performance. The K coefficient was significantly and negatively associated with task completion time, $\beta = -34.11$, $SE = 10.07$, $t(103) = -3.39$, $p < .001$, 95% CI $[-54.09, -14.13]$, indicating that participants with more focused gaze patterns tended to complete tasks more rapidly. Average fixation duration was negatively associated with task success rate, $\beta = -0.0002$, $SE = 0.0006$, $t(102.5) = -0.37$, $p = .35$, 95% CI $[-0.001, 0.0009]$, whereas saccade amplitude showed a positive association with success rate, $\beta = 0.001$, $SE = 0.0008$, $t(103) = 1.46$, $p = .07$, 95% CI $[-0.0004, 0.0027]$. No significant relationships were observed between the K coefficient and success rate, $\beta = -0.08$, $SE = 0.12$, $t(93.47) = -0.65$, $p = .74$, 95% CI $[-0.32, 0.16]$, nor between fixation duration and completion time, $\beta = -0.06$, $SE = 0.05$, $t(103) = -1.19$, $p = .88$, 95% CI $[-0.15, 0.04]$, or between saccade amplitude and completion time, $\beta = 0.07$, $SE = 0.07$, $t(103) = 0.99$, $p = .84$, 95% CI $[-0.07, 0.20]$.

Overall, these analyses reveal that specific gaze indicators, particularly the K coefficient and fixation duration, were systematically related to task efficiency and accuracy, while other visual measures did not show significant effects. Taken together, these results indicate that H4a was not supported, while H4b received empirical support.

A complete summary of the descriptive and inferential statistics is presented in Table 5.

Table 5

Summary of Mediation Effects of Visual Search Strategy on User Performance

Predictor	Outcome Variable	β	SE	$t(df)$	p	95% CI [LL, UL]
K Coefficient	Average Task Completion Time (s)	-34.11	10.07	-3.39 (103)	<.001	[-54.09, -14.13]
K Coefficient	Success Rate	-0.08	0.12	-0.65 (93.47)	.74	[-0.32, 0.16]
Average Fixation Duration	Success Rate	-0.0002	0.0005	-0.37 (102.5)	.35	[-0.001, 0.0009]
Average Fixation Duration	Average Task Completion Time (s)	-0.06	0.05	-1.19 (103)	.88	[-0.15, 0.04]
Saccade Amplitude	Success Rate	0.001	0.0008	1.46 (103)	.07	[-0.0004, 0.0027]
Saccade Amplitude	Average Task Completion Time (s)	0.07	0.07	0.99 (103)	.84	[-0.07, 0.20]

2.5.3.5 Emotional Response

Linear mixed-effects models were conducted to examine the effects of task complexity on emotional responses, specifically valence and arousal, and to assess the associations between these emotional measures and user performance. Due to a measurement artefact in the GazePoint recordings, only data collected with the Tobii eye-tracking system were retained for analysis, as these provided more reliable and consistent emotional response estimates.

Task complexity was significantly and negatively associated with valence, $\beta = -0.02$, $SE = 0.01$, $t(46.25) = -2.11$, $p = .02$, 95% CI [-0.04, -0.001], indicating lower positive affect with increasing task complexity. The relationship between task complexity and arousal was not significant and positive, $\beta = 0.003$, $SE = 0.003$, $t(43.61) = 0.97$, $p = .83$, 95% CI [-0.003, 0.01].

Analyses examining the association between emotional responses and user performance revealed no significant effects. The effect of valence on success rate was not detected, $\beta = 0.31$, $SE = 0.55$, $t(48) = 0.56$, $p = .29$, 95% CI [-0.80, 1.42], or to average task completion time, $\beta = -66.93$, $SE = 51.92$, $t(48) = -1.29$, $p = .10$, 95% CI [-171.32, 37.47]. Similarly, arousal was not significantly associated with success rate, $\beta = -2.86$, $SE = 1.85$, $t(48) = -1.55$, $p = .06$, 95% CI [-

6.59, 0.86], or with average task completion time, $\beta = 18.15$, $SE = 180.76$, $t(48) = 0.10$, $p = .46$, 95% CI [-345.30, 381.60].

These results indicate that higher task complexity was associated with lower valence but not with changes in arousal, and that emotional responses did not significantly predict performance outcomes. Accordingly, H5a was supported, whereas H5b was not supported.

A complete summary of the descriptive and inferential statistics is presented in Table 6.

Table 6
Summary of Mediation Effects of Emotional Response on User Performance

Predictor	Outcome Variable	β	SE	$t(df)$	p	95% CI [LL, UL]
Task Complexity	Valence	-0.02	0.01	-2.11 (46.25)	.02	[-0.04, -0.001]
Task Complexity	Arousal	0.003	0.003	0.97 (43.61)	.83	[-0.003, 0.01]
Valence	Success Rate	0.31	0.55	0.56 (48)	.29	[-0.80, 1.42]
Valence	Average Task Completion Time (s)	-66.93	51.92	-1.29 (48)	.10	[-171.32, 37.47]
Arousal	Success Rate	-2.86	1.85	-1.55 (48)	.06	[-6.59, 0.86]
Arousal	Average Task Completion Time (s)	18.15	180.76	0.10 (48)	.46	[-345.30, 381.60]

Note. Only data collected with the Tobii system were analyzed due to measurement artefacts in the GazePoint dataset, which produced inconsistent emotional response recordings.

2.5.2.6 Propensity for Visual Search

A series of linear mixed-effects models were conducted to examine whether users' visual search propensity moderated the relationship between task complexity and various user experience outcomes, including frustration, cognitive load, visual search behavior, and performance.

2.5.2.6.1 Frustration

Task complexity and users' visual search propensity interacted significantly for two of the three dimensions tested. The moderating effect of inhibitory control on the relationship between task complexity and frustration was not significant, $\beta = 2.05$, $SE = 8.41$, $t(86.91) = 0.24$, $p = .40$, 95% CI [-14.66, 18.77]. In contrast, a significant negative interaction was observed for goal-oriented visual exploration, $\beta = -24.38$, $SE = 10.25$, $t(92.73) = -2.35$, $p = .01$, 95% CI [-44.45, -

3.74], indicating that participants with stronger goal-directed search abilities reported lower frustration as task complexity increased. A significant positive interaction emerged for visual processing, $\beta = 3.36$, $SE = 1.31$, $t(95.58) = 2.56$, $p = .006$, 95% CI [0.75, 5.97], showing that participants with weaker visual processing abilities experienced higher frustration under complex task conditions. Accordingly, H6a is supported, with moderation emerging only for goal-oriented visual exploration.

A complete summary of the descriptive and inferential statistics is presented in Table 7.

Table 7

Summary of the Moderating Effect of Visual Search Propensity on Frustration

Moderator	β	SE	$t(df)$	p	95% CI [LL, UL]
Inhibitory Control	2.05	8.41	0.24(86.91)	.40	[-14.66, 18.77].
Goal-oriented visual exploration	-24.38	10.25	-2.35 (92.73)	.01	[-44.45, -3.74].
Visual processing	3.36	1.31	2.56 (95.58)	.006	[0.75, 5.97].

2.5.2.6.1 Cognitive Load

For the moderating effects of visual search propensity on cognitive load, results revealed mixed patterns. For inhibitory control, the interactions were positive but not significant for either perceived cognitive load, $\beta = 11.28$, $SE = 7.76$, $t(87.47) = 1.45$, $p = .08$, 95% CI [-4.15, 26.71], or physiological load, $\beta = 0.31$, $SE = 0.27$, $t(86) = 1.15$, $p = .13$, 95% CI [-0.22, 0.84]. Goal-oriented visual exploration did not significantly moderate the relationship between task complexity and either subjective, $\beta = 6.56$, $SE = 10.29$, $t(91.75) = 0.64$, $p = .74$, 95% CI [-13.88, 27.00], or physiological cognitive load, $\beta = 0.09$, $SE = 0.43$, $t(92.84) = 0.21$, $p = .59$, 95% CI [-0.77, 0.95]. For visual processing, a significant positive interaction was found with perceived cognitive load, $\beta = 2.80$, $SE = 1.59$, $t(96.67) = 1.76$, $p = .04$, 95% CI [-0.36, 5.95], whereas the physiological indicator followed the same positive direction but was not significant, $\beta = 0.03$, $SE = 0.06$, $t(77.78) = 0.24$, $p = .32$, 95% CI [-0.09, 0.15]. These findings indicate that H6b was supported, as visual processing significantly moderated the relationship between task complexity and perceived cognitive load.

A complete summary of the descriptive and inferential statistics is presented in Table 8.

Table 8*Summary of the Moderating Effects of Visual Search Propensity on Cognitive Load*

Moderator	Cognitive Load Measure	β	SE	$t(df)$	p	95% CI [LL, UL]
Inhibitory Control	NASA-TLX Mental Demand	11.28	7.76	1.45 (87.47)	.08	[-4.15, 26.71]
Inhibitory Control	Pupil	0.31	0.27	1.15 (86)	.13	[-0.22, 0.84].
Goal-oriented visual exploration	NASA-TLX Mental Demand	6.56	10.29	0.64 (91.75)	.74	[-13.88, 27.00].
Goal-oriented visual exploration	Pupil	0.09	0.43	0.21 (92.84)	.59	[-0.77, 0.95]
Visual processing	NASA-TLX Mental Demand	2.80	1.59	1.76 (96.67)	.04	[-0.36, 5.95]
Visual processing	Pupil	0.03	0.06	0.24 (77.78)	.32	[-0.09, 0.15]

2.5.2.6.1 Visual Search Strategy

The analyses assessing the moderating effect of visual search propensity on visual search behavior revealed no statistically significant interactions. For inhibitory control, the effects were non-significant for the K coefficient $\beta = -0.01$, $SE = 0.18$, $t(86) = -0.05$, $p = .48$, 95% CI [-0.37, 0.34], and fixation duration, $\beta = 7.35$, $SE = 41.14$, $t(64.34) = 0.18$, $p = .43$, 95% CI [-74.83, 89.52]. The effect on saccade amplitude was also non-significant, and the direction was not confirmed $\beta = 2.88$, $SE = 27.66$, $t(86) = 0.10$, $p = .54$, 95% CI [-52.10, 57.86]. Similarly, goal-oriented visual exploration did not moderate task complexity effects on the K coefficient $\beta = -0.15$, $SE = 0.25$, $t(101) = -0.60$, $p = .73$, 95% CI [-0.64, 0.34], fixation duration $\beta = 16.69$, $SE = 55.18$, $t(101) = 0.30$, $p = .62$, 95% CI [-92.77, 126.16], or saccade amplitude $\beta = 17.50$, $SE = 38.24$, $t(101) = 0.46$, $p = .84$, 95% CI [-58.36, 93.37]. For visual processing, none of the interactions were significant for the K coefficient $\beta = 0.007$, $SE = 0.04$, $t(98) = 0.20$, $p = .58$, 95% CI [-0.06, 0.08], fixation duration $\beta = 1.19$, $SE = 7.94$, $t(74.6) = 0.15$, $p = .44$, 95% CI [-14.64, 17.02], or saccade amplitude $\beta = 17.50$, $SE = 38.24$, $t(101) = 0.46$, $p = .68$, 95% CI [-58.36, 93.37]. These results indicate that H6c was not supported, as none of the visual search propensity dimensions significantly moderated the effect of task complexity on visual search behavior.

2.5.2.6.1 Emotional Response

Linear mixed-effects models were conducted to examine the moderating effects of users' visual search propensity on emotional responses, measured through valence and arousal scores.

Commenté [GU2]: p-values in this section are all for 2-sided tests

Commenté [EL3R2]: Section corrigée pour des 1-sided tests

Across all models, no statistically significant interactions were observed. For inhibitory control, the interaction between task complexity and inhibitory control was not significant for valence $\beta = 0.05$, $SE = 0.08$, $t(37.01) = 0.59$, $p = .72$, 95% CI $[-0.12, 0.21]$ or arousal $\beta = -0.008$, $SE = 0.02$, $t(37.12) = -0.35$, $p = .37$, 95% CI $[-0.05, 0.04]$. Similarly, goal-oriented visual exploration showed no significant moderating effects for valence $\beta = 0.20$, $SE = 0.13$, $t(42.88) = 1.52$, $p = .07$, 95% CI $[-0.07, 0.47]$ or arousal $\beta = -0.05$, $SE = 0.04$, $t(44.11) = -1.41$, $p = .92$, 95% CI $[-0.13, 0.02]$. Finally, visual processing did not significantly moderate the relationship between task complexity and emotional responses for valence $\beta = 0.01$, $SE = 0.02$, $t(44.51) = 0.77$, $p = .78$, 95% CI $[-0.02, 0.05]$ or arousal $\beta = -0.001$, $SE = 0.005$, $t(44.88) = -0.20$, $p = .42$, 95% CI $[-0.01, 0.01]$. Overall, these results indicate that users' visual search propensity did not significantly moderate the effects of task complexity on emotional responses, as measured through valence and arousal. These findings indicate that H6d was not supported, as none of the visual search propensity dimensions moderated the relationship between task complexity and emotional responses.

2.5.2.6.1 Task Complexity & User Performance

The moderating effects of visual search propensity on user performance were also examined. No significant interactions were observed for inhibitory control, either for success rate $\beta = 0.06$, $SE = 0.21$, $t(81.23) = 0.26$, $p = .60$, 95% CI $[-0.36, 0.47]$ or completion time $\beta = 9.34$, $SE = 17.64$, $t(89) = 0.53$, $p = .30$, 95% CI $[-25.70, 44.39]$. Similarly, goal-oriented visual exploration did not moderate the effects of task complexity on success rate $\beta = -0.03$, $SE = 0.29$, $t(101.9) = -0.09$, $p = .54$, 95% CI $[-0.59, 0.54]$ or completion time $\beta = -7.84$, $SE = 24.04$, $t(104) = -0.33$, $p = .63$, 95% CI $[-55.52, 39.84]$. For visual processing, the interaction with success rate was not significant $\beta = 0.05$, $SE = 0.04$, $t(81) = 1.22$, $p = .89$, 95% CI $[-0.03, 0.13]$, and the effect on completion time showed a negative but non-significant trend $\beta = -4.76$, $SE = 3.36$, $t(98) = -1.42$, $p = .92$, 95% CI $[-11.44, 1.91]$. These results indicate that H6e was not supported, as none of the visual search propensity dimensions significantly moderated the effect of task complexity on user performance.

A summary of all hypotheses tested, and their corresponding outcomes is presented in Table 9.

Table 9*Summary of main findings*

Hypothesis		Finding
H1	Task complexity decreases user performance.	Supported
H2a	Task complexity increases perceived frustration.	Supported
H2b	Higher perceived frustration decreases user performance.	Supported
H3a	Task complexity increases cognitive load.	Supported
H3b	Higher cognitive load decreases user performance.	Supported
H4a	Task complexity impairs users' visual search strategy.	Not Supported
H4b	More efficient visual search strategy improves user performance.	Supported
H5a	Task complexity increases negative emotional response.	Supported
H5b	More positive emotional response improves user performance.	Not Supported
H6a	Users' propensity for visual search weakens the effect of task complexity on perceived frustration.	Supported
H6b	Users' propensity for visual search weakens the effect of task complexity on cognitive load.	Supported
H6c	Users' propensity for visual search weakens the effect of task complexity on visual search strategy.	Not Supported
H6d	Users' propensity for visual search weakens the effect of task complexity on emotional response.	Not Supported
H6e	Users' propensity for visual search weakens the effect of task complexity on user performance.	Not Supported

2.5.2.7 Post-hoc Analysis

To further examine the relationship between visual search proficiency and task performance, an additional exploratory analysis was conducted. This analysis, which was not part of the original hypotheses, used accuracy scores from the visual search paradigms as predictors of user performance in the ERP tasks. While the moderation analyses showed that propensity for visual search did not significantly moderate the effect of task complexity, this follow-up analysis aimed to determine whether participants' actual performance in the paradigms could predict their performance in the ERP environment. This approach was particularly relevant because the ERP tasks were intentionally designed to mirror the cognitive processes assessed in the paradigms, such as goal-directed search and visual processing. The results showed that accuracy in the goal-oriented visual exploration paradigm significantly predicted ERP task success, $\beta = 1.58$, $SE = 0.48$,

$t(106) = 3.28, p = .0014, 95\% \text{ CI } [0.63, 2.54]$ Accuracy in the visual processing paradigm was also positively associated with ERP performance, $\beta = 1.40, SE = 0.66, t(106) = 2.13, p = .02, 95\% \text{ CI } [0.10, 2.69]$. Taken together, these results indicate that accuracy in the visual search paradigms reliably predicts ERP task performance, even though it does not moderate the relationship between task complexity and performance.

2.6 Discussion

2.6.1 Summary of Results

This section summarizes how task complexity and individual visual search propensities shaped participants' experience in the study. Despite completing a vicarious training module, participants continued to encounter substantial cognitive and emotional demands when engaging with complex workflows. Although more efficient visual search tendencies provided some support in navigating the interfaces, their influence remained limited. Consistent with research in HCI and visual cognition, users' experiences were shaped not only by interface structure but also by individual differences in how visual information was scanned and prioritized. These general patterns provide the basis for the detailed results presented in the following subsections.

Our findings confirm H1, showing that task complexity has a clear detrimental effect on user performance in ERP contexts. Complex workflows reduced performance efficiency, reinforcing prior evidence that higher structural and cognitive demands hinder users' ability to complete tasks effectively (Sweller, 2011; Wickens, 2008). This result underscores that the challenge of complex ERP tasks stems less from the number of steps than from the cumulative mental and operational load they impose. Importantly, this performance impairment points to deeper cognitive and emotional mechanisms that mere performance metrics cannot capture, motivating the exploration of the mediators discussed in the following sections.

The analyses show a clear and consistent link between task complexity and perceived frustration, supporting H2a. As tasks became more demanding, users reported higher frustration, indicating that complex ERP workflows generate emotional strain alongside cognitive effort. This aligns with prior work showing that negative affect often emerges when task demands exceed users' perceived control or available cognitive resources (Smith & Lazarus, 1990). Frustration thus appears as an early marker of overload in complex digital environments. Further analyses support

H2b, showing that frustration directly undermines performance. Higher frustration was associated with slower execution and lower success, consistent with evidence that emotional states mediate the relationship between task demands and performance efficiency (Matthews et al., 2015; Desmet & Roeser, 2015). Research in HCI similarly indicates that negative affect disrupts attention, increases hesitation, and raises error likelihood (Picard, 1997; Calvo & D'Mello, 2010). In ERP contexts, reducing frustration through clearer task flows or adaptive guidance may therefore help mitigate the performance penalties of complexity.

The analyses revealed a positive association between task complexity and perceived cognitive load, supporting H3a. As workflows became more intricate, participants reported higher mental demand, consistent with Cognitive Load Theory, which posits that increased task complexity raises intrinsic load and constrains working-memory capacity (Sweller, 2011; Paas & van Merriënboer, 1994). Prior HCI research similarly shows that complex interfaces elevate mental workload by increasing the amount of information users must retain and integrate (Wickens, 2008). Although the physiological data followed the same trend, variability in pupillometric responses is common in short tasks (Beatty & Lucero-Wagoner, 2000). Analyses also supported H3b: higher cognitive load impaired performance. Participants reporting greater mental demand were slower and less successful, reflecting the established bottleneck in which limited working-memory resources undermine information monitoring and decision accuracy (Kalyuga, 2011; Young et al., 2014). This aligns with extensive evidence that elevated workload leads to slower processing and increased errors across digital environments (Hart & Staveland, 1988; Xie & Salvendy, 2000).

Although the analyses did not reveal a significant relationship between task complexity and visual search strategy, and H4a was not supported, the directional trends remain informative. As complexity increased, participants showed slightly longer fixations and smaller saccades, suggesting a more localized deployment of attention, an adjustment consistent with how users typically respond to visually demanding tasks (Rayner, 2009; Krejtz et al., 2018). This non-significant effect is expected, this finding is theoretically consistent with research conceptualizing visual search efficiency as a relatively stable attentional trait rather than a state-dependant response to short-term task manipulations (Wolfe, 2021; Eckstein, 2011). Therefore, while task complexity may influence momentary gaze allocation, it is unlikely to fundamentally alter underlying search

efficiency within a single experimental session. Beyond the effect of task complexity, visual search efficiency emerged as a meaningful predictor of performance, supporting H4b. Participants showing more structured and goal-directed gaze patterns, shorter fixations, broader saccades, and lower K coefficients, completed tasks more quickly and accurately. This aligns with findings that shorter fixations and efficient saccades reflect more economical information processing, whereas prolonged fixations are linked to higher cognitive effort and reduced performance (Rayner, 2009; Krejtz et al., 2016). The results also fit with Guided Search Theory, which emphasizes that efficient visual search occurs when attentional goals align with interface structure (Wolfe, 2021).

The analyses revealed a significant association between task complexity and negative emotional response, supporting H5a. As complexity increased, participants reported more negative emotions, indicating that demanding ERP workflows elicit affective strain alongside cognitive effort. This aligns with research showing that negative affect intensifies under conditions of high uncertainty, disrupted task goals, or reduced predictability (Norman, 2013; Matthews et al., 2015). These findings highlight that emotional strain is a core component of user experience in complex systems, reflecting a direct response to demanding task structures rather than a mere by-product of poor performance. In contrast, H5b was not supported, as positive emotional response did not significantly predict better performance. Although positive affect can enhance cognitive flexibility in open-ended or creative tasks, it is not strongly linked to improved accuracy in structured, rule-based environments (Fredrickson, 2001; Ashby et al., 1999). In ERP workflows, where precision, sequence adherence, and attentional control dominate, positive emotions appear less central to task execution than cognitive load or frustration. This pattern clarifies the limits of emotional influence in operational digital tasks: negative affect can hinder performance, but positive affect alone is insufficient to generate measurable performance gains. This outcome is therefore unexpected in highly structured, rule-based environments such as ERP workflows, where performance depends mainly on attentional control and working-memory capacity than on cognitive flexibility (Sweller, 2011; Wickens, 2008). Complex, sequential tasks leave limited room for the broader and more flexible thinking often associated with positive affect (Fredrickson, 2001). In this context, positive emotions may improve how users feel about the task without necessarily improving their speed or accuracy.

To deepen the understanding of how users cope with demanding ERP tasks, this study tested whether visual search propensity moderated the effects of task complexity on emotional, cognitive, and behavioral outcomes. The results indicate that visual search propensity exerts a subtle but meaningful influence: rather than directly enhancing performance, it shapes users' ability to manage the cognitive and affective demands created by complex workflows. The following sections detail how visual search propensity moderates the effects of task complexity on frustration, cognitive load, visual search behavior, emotional response, and performance.

The moderation analyses for frustration supported H6a. Inhibitory control did not significantly alter the effect of task complexity on frustration, indicating that filtering irrelevant stimuli offers little protection against the emotional strain of demanding ERP tasks. In contrast, goal-oriented visual exploration buffered the impact of complexity. Users with stronger goal-directed search abilities reported less frustration as demands increased, reflecting the value of efficiently locating task-relevant cues. In contrast, weaker visual processing heightened frustration under high complexity, likely due to more frequent search failures and uncertainty.

Parallel analyses on cognitive load revealed complementary patterns, supporting H6b. Inhibitory control showed a non-significant trend whereby weaker inhibitory control was associated with higher cognitive load under complex conditions, suggesting that difficulty suppressing irrelevant fixations may increase the attentional effort required to stay on task (Sodhi et al., 2002). Visual processing showed a clearer effect: users with weaker feature-detection abilities reported higher cognitive load, indicating that difficulty identifying relevant interface elements adds memory and attentional demands during execution. In contrast, goal-oriented visual exploration did not significantly moderate cognitive load, suggesting that even efficient searchers cannot fully offset the mental demands imposed by complex ERP workflows.

No moderating effects of visual search propensity were found on gaze behavior, and H6c was therefore not supported. Although some coefficients aligned with expectations, such as slightly larger saccades or marginally faster completion times among users with stronger goal-oriented visual exploration, these effects were small and non-significant. This is consistent with research showing that real-time gaze behavior is shaped primarily by interface structure and moment-to-moment task demands rather than by stable attentional traits (Kastrati et al., 2021;

Goldberg & Kotval, 1999). In highly structured ERP workflows, users must visually follow prescribed sequences, leaving limited flexibility for dispositional differences to substantially alter gaze patterns. Still, the trends suggest subtle tendencies. Weaker visual processing corresponded to longer completion times and higher frustration, whereas stronger goal-oriented visual exploration aligned with slightly faster performance.

No moderating effects were found on emotional responses, and H6d was therefore not supported. While users with stronger goal-oriented visual exploration or visual processing showed slightly more stable affective patterns, these tendencies were weak and inconsistent. This pattern is theoretically coherent with prior research showing that emotional responses in task environments are primarily driven by perceived workload, uncertainty, and task difficulty rather than by stable perceptual-attentional traits (Sweller, 2011; Matthews et al., 2015). In structured ERP workflows, emotional strain tends to emerge directly from cognitive overload and performance pressure. Contextual factors such as interface feedback, error messages, and task interruptions may further shape affective reactions, limiting the moderating influence of individual visual search propensity. Still, the small trends suggest that weaker visual processing or less efficient goal-oriented visual exploration could contribute to greater emotional strain during particularly demanding moments.

No moderating effect was found on performance, and H6e was therefore not supported. Although individuals with stronger goal-oriented visual exploration or visual processing performed slightly better overall, these differences did not alter how task complexity affected success rates or task completion times. This pattern is theoretically coherent with research showing that performance in structured ERP workflows depends mainly on intrinsic task demands, working-memory load, sequential steps, and error sensitivity, rather than on stable attentional traits (Paas & van Merriënboer, 2020; Sweller, 2011). In such environments, increases in complexity constrain performance for all users, regardless of individual attentional traits (Wickens, 2008). Prior work similarly indicates that visual search ability predicts baseline efficiency but does not buffer against performance declines caused by higher task complexity (Wolfe, 2021). These findings suggest that while visual search proficiency supports overall task execution, it does not fundamentally change how complexity impacts objective performance outcomes in tightly structured ERP tasks.

Complementing the moderation analyses, additional models assessed whether user's propensity for visual search directly predicted ERP performance. The results showed that baseline visual search accuracy, measured independently of task complexity, was a consistent predictor of task success. Participants with higher accuracy in goal-oriented visual exploration and visual processing performed ERP tasks more successfully, indicating that individuals who more effectively identify and prioritize relevant visual elements tend to manage complex workflows more efficiently. These findings suggest that visual search proficiency operates not only as a potential moderator but also as a stable individual predictor of performance across all complexity levels. This highlights that inherent perceptual–cognitive abilities contribute meaningfully to users' capacity to complete structured ERP tasks, alongside the cognitive and emotional mechanisms examined in the main analyses.

Taken together, the results show that visual search propensity mainly shapes users' emotional and cognitive responses to task complexity. Goal-oriented visual exploration reduced frustration, while weaker visual processing consistently predicted greater frustration and higher cognitive load. Inhibitory control had little influence, and none of the visual search dimensions altered gaze behavior or performance, which were driven largely by intrinsic task demands. Yet, complementary analyses indicate that visual search proficiency itself, especially accuracy in goal-oriented visual exploration and visual processing, also predicts better performance across all complexity levels. Thus, visual search functions both as a factor that modulates users' cognitive–emotional experience and as a stable individual ability supporting effective task execution.

2.6.2 Theoretical contributions

This study advances theoretical understanding in HCI and Information Systems (IS) by integrating cognitive, emotional, and perceptual mechanisms into a unified explanation of how users manage complex ERP tasks. Rather than treating performance solely as a function of task characteristics or interface design, the findings highlight the central role of users' cognitive and affective states, as well as their underlying perceptual abilities.

First, the results extend Cognitive Load Theory (Sweller, 2011; Paas & van Merriënboer, 2020) by showing that cognitive load in complex digital environments is jointly shaped by task complexity and emotional strain. Frustration emerged as a key affective mechanism through which complexity impairs performance, demonstrating that emotional regulation is integral to managing

mental workload. This supports a more integrated cognitive–affective model in which task demands, cognitive resources, and emotional responses interact dynamically to influence user performance.

Second, the study contributes to visual search theory (Wolfe, 2021) by demonstrating its explanatory value in applied ERP contexts. Measures of goal-oriented visual exploration and visual processing, typically assessed in controlled laboratory paradigms, predicted performance in real-world-like tasks. This positions visual search proficiency as a stable individual trait that shapes how effectively users extract relevant information, regulate attention, and navigate visually dense workflows. The findings help bridge basic visual cognition research with applied system use, showing that perceptual efficiency has meaningful implications for performance in complex operational environments.

Third, the study clarifies the selective role of visual search propensity in shaping users' responses to complexity. While these abilities did not moderate performance outcomes or gaze behavior, domains largely constrained by intrinsic task structure, they significantly influenced frustration and cognitive load. This distinction advances theory by illustrating that perceptual skills do not uniformly affect all levels of interaction; instead, they predominantly shape users' emotional and cognitive experience of complexity, rather than their moment-to-moment execution.

Finally, the study offers a methodological contribution by demonstrating that laboratory-based perceptual–cognitive tasks can meaningfully predict behavior in complex ERP environments. This supports the use of controlled paradigms to capture stable individual differences that matter for real-world system use, complementing traditional usability metrics. By empirically linking laboratory measures to applied performance outcomes, the study contributes to a more rigorous experimental foundation for research on human–system interaction in complex information environments.

2.6.3 Managerial Implications

The results of this study have direct implications for organizations engaged in ERP-driven digital transformation. Although participants completed a vicarious training module, an approach widely used in ERP deployments for its scalability and efficiency (Yi & Davis, 2003; Gupta & Huber, 2010) they still experienced high levels of cognitive load, frustration, and performance

difficulties during complex workflows. This reinforces prior evidence that procedural, observation-based training does not adequately prepare users for the cognitive and emotional realities of ERP complexity (Besson & Rowe, 2012; Seddon et al., 2010). Organizations must therefore rethink ERP training as a capability-building initiative rather than a simple transfer of procedural knowledge. From a managerial perspective, this implies reallocating resources from short, efficiency-driven training formats toward structured learning pathways that explicitly develop cognitive and attentional skills required for complex system interaction. Failure to do so may result in persistent productivity losses, higher support costs, and reduced return on ERP investments (Vial, 2019; Ceschi et al., 2017).

A first implication concerns the need to strengthen cognitive readiness. Because complex ERP workflows impose high demands on working memory and attentional control, training should be designed to help users manage cognitive load rather than merely memorize steps. Approaches such as segmented microlearning, progressive exposure to complexity, and just-in-time reminders are consistent with Cognitive Load Theory (Sweller, 2011; Paas & van Merriënboer, 2020) and research showing that managing mental workload improves technology learning outcomes (Ceschi et al., 2017). For example, instead of presenting complete transactional workflows at once, training modules could isolate high-load decision points and progressively increase complexity as users gain mastery. Instructional design research grounded in Cognitive Load Theory shows that segmentation and progressive task exposure improve learning efficiency and reduce overload in complex systems (Sweller, 2011; Paas & van Merriënboer, 2020). Such approaches help users consolidate working-memory resources before confronting full workflow complexity (Kalyuga, 2011). These methods help mitigate the overload created by having to retain instructions observed during vicarious learning while executing demanding sequences.

A second implication is the incorporation of perceptual–attentional training into ERP onboarding. The study shows that users with weaker visual processing or less efficient goal-oriented visual exploration experience higher cognitive load and frustration. This aligns with research indicating that perceptual discrimination and goal-directed scanning can be strengthened through training and attentional guidance (Rayner, 2009; Krejtz et al., 2018). Organizations can support these abilities directly in training by teaching users how to identify task-relevant cues, limit visual search inefficiencies, and structure their attention in dense interfaces. Embedding these

principles within broader change management initiatives may also reduce resistance to ERP adoption. Studies in IS show that user resistance often stems from perceived difficulty and loss of control during system transitions (Besson & Rowe, 2012; Seddon et al., 2010). Supporting users' cognitive readiness can therefore improve perceived usability and facilitate smoother digital transformation processes (Vial, 2019). At the system level, interface optimizations such as reducing clutter, structuring visual hierarchies, and adding salient cues are supported by HCI literature as effective strategies for reducing workload and errors (Wickens, 2008; Tullis & Albert, 2013).

A third implication relates to the use of simulation- and scenario-based practice. Because vicarious training does not expose users to the cognitive and emotional pressures of real ERP tasks, organizations should provide training environments that reproduce the complexity and uncertainty of authentic workflows. Prior research shows that simulation-based learning improves performance under complexity by allowing individuals to develop adaptive expertise and regulate emotional responses (Carroll & Rosson, 2007). Graduated practice scenarios can therefore help users build the resilience needed for ERP adoption. This is particularly important in operational contexts where errors may carry financial, compliance, or reputational consequences. Simulation-based learning has been shown to improve performance under complexity by allowing users to practice decision-making under realistic cognitive load and emotional pressure (Salas et al., 2008; Carroll & Rosson, 2007). Such exposure helps develop adaptive expertise before live deployment in enterprise systems. Additionally, the predictive value of goal-oriented visual exploration accuracy and visual processing highlights the potential of light cognitive profiling in training programs. Brief perceptual-cognitive assessments, commonly used in training science (Makransky & Petersen, 2019; Clark et al., 2006) could help identify users who may require additional support or slower pacing. This approach is not about screening but about tailoring training to individual needs, in line with evidence that adaptive training improves learning outcomes in complex systems (Kalyuga, 2011). However, such perceptual-cognitive assessments should be implemented transparently and ethically, ensuring that they are used to provide developmental support rather than to exclude users. Research on adaptive training emphasizes that tailoring instruction to individual cognitive profiles improves outcomes while maintaining fairness when framed as supportive interventions (Kalyuga, 2011; Makransky & Petersen, 2019).

Furthermore, since performance was largely driven by intrinsic task complexity rather than attentional traits, organizations should examine and simplify highly complex workflows. Reducing redundant fields, consolidating steps, and minimizing interface clutter aligns with literature showing that structural simplification reduces cognitive load and improves human–system performance (Wickens, 2008; Tarafdar et al., 2019). Training alone cannot compensate for unnecessarily complex processes. Managers should therefore conduct workflow audits to identify steps that generate disproportionate cognitive load without adding business value. Human–system performance research shows that structural simplification, reduction of unnecessary interface elements, and clearer visual hierarchies significantly reduce workload and improve task efficiency (Wickens, 2008; Tullis & Albert, 2013). Addressing structural complexity is critical, as training alone cannot compensate for poorly designed processes (Tarafdar et al., 2019).

Taken together, these implications underscore that ERP adoption depends on preparing users to manage the cognitive, emotional, and attentional demands inherent to complex digital work. Strengthening cognitive readiness (Ceschi et al., 2017), supporting perceptual efficiency (Rayner, 2009), and providing adaptive, simulation-based learning (Salas et al., 2008) will help organizations reduce frustration, enhance performance, and improve long-term system effectiveness. In the broader context of digital transformation, such interventions represent not only a human-centered investment but a strategic mechanism for building organizational capability and resilience (Vial, 2019; Haffke et al., 2016). Ultimately, ERP success depends not only on technical implementation but also on developing human capabilities aligned with system complexity. Digital transformation research highlights that sustainable performance gains arise when technological change is accompanied by organizational learning and capability development (Vial, 2019; Haffke et al., 2016). Integrating cognitive principles into training, interface design, and process governance therefore represents a strategic lever for improving long-term ERP effectiveness.

Limitations & Future Work

This study provides meaningful insights into how task complexity and individual visual search propensity influence user performance in ERP systems. To properly situate the scope of these findings, it is necessary to clarify the boundaries set by the methodological choices, as well as the broader limitations that constrain how the results may be generalized.

First, the experimental scope was intentionally delimited to three ERP tasks aligned with the visual search paradigms, inhibitory control, goal-oriented visual exploration, and visual processing. These boundaries were established to ensure a controlled comparison between participants' baseline visual-cognitive profiles and their behaviour in the ERP environment. This focused design enabled a precise examination of specific cognitive mechanisms, but it also narrows the generalizability of the results. Real-world ERP workflows often involve interdependent steps, parallel goals, and context-dependent decision-making that extend beyond

the controlled task structures used in this study. Future research could expand the task repertoire to include more complex, realistic, and multi-stage ERP activities to capture a fuller range of complexity challenges.

A second limitation concerns the geographic scope of the study. Data were collected within a single regional context, which restricted the diversity of participants typically found in large-scale ERP deployments. Although this allowed for controlled recruitment and consistent testing conditions, it does not capture the broader variation in digital infrastructure, training practices, or organizational exposure to ERP systems observed across different regions. Such factors can meaningfully influence how users experience task complexity and engage with visual search demands. Future research should therefore include participants from multiple geographic contexts to examine whether institutional and environmental conditions moderate cognitive, emotional, and performance outcomes in ERP tasks.

A further boundary concerns the distribution of visual search proficiency in the sample. Participants tended to perform well across the visual search paradigms, yielding a relatively homogeneous cognitive profile. This limited variability reduces the ability to detect moderating effects of visual search propensity on performance. Future work would benefit from recruiting participants with a broader range of attentional and perceptual abilities, or from using pre-screening to deliberately vary cognitive profiles.

An additional limitation concerns occasional technical issues encountered during data collection. Due to intermittent recording interruptions in the eye-tracking system, some gaze data segments were not successfully captured. Although data quality checks were conducted and incomplete recordings were excluded from analysis, these technical disruptions reduced the overall volume of usable data and may have limited statistical power in certain analyses. Future studies should incorporate redundancy protocols, extended calibration procedures, or backup recording systems to minimize data loss and strengthen measurement reliability.

Additionally, although the laboratory setting allowed for tight control over confounding variables, it differs substantially from real-world ERP use. Professional environments introduce interruptions, multitasking, time pressure, and collaborative workflows that affect cognitive load and search behaviour in ways that a controlled experiment cannot fully reproduce. Field-based or

hybrid study designs, would provide a richer and more ecologically valid understanding of how users manage complexity in practice.

Finally, the use of time limits for each ERP task, while necessary to standardize experimental conditions, constrained participants' opportunity to explore alternative strategies or fully adapt to interface complexity. Time pressure may have amplified cognitive load and reduced variability in search behaviour, potentially limiting the detection of more nuanced strategic adjustments. Future research could allow flexible task durations or incorporate longer interaction windows to examine how visual search strategies evolve over extended engagement with complex ERP workflows.

In sum, these boundaries and limitations outline several avenues for future research. Broadening task diversity, recruiting more heterogeneous user groups, and moving toward more naturalistic study environments would deepen our understanding of how users cope with ERP complexity across contexts. Such extensions would also strengthen the practical relevance of this research for designing ERP systems that are cognitively accessible, operationally sustainable, and better aligned with the realities of organizational work.

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Conclusion

Ce mémoire avait pour objectif d'examiner dans quelle mesure les différences individuelles dans les stratégies de recherche visuelle influencent la manière dont les utilisateurs composent avec la complexité des tâches dans un environnement ERP, et ce, après une formation fondée sur l'apprentissage vicariant. En mobilisant une approche expérimentale multimodale reposant sur des mesures oculométriques, comportementales et affectives, l'étude a permis d'observer directement les mécanismes attentionnels et cognitifs engagés lors de l'exécution de tâches organisationnelles dans un système d'entreprise. Cette perspective fine, encore largement absente de la littérature ERP, offre un éclairage empirique nouveau sur les facteurs micro-cognitifs qui conditionnent la performance des utilisateurs et leur expérience dans les environnements numériques complexes.

Les résultats montrent que la complexité des tâches exerce un effet clair sur la charge cognitive, la frustration et, ultimement, sur la performance. De plus, la propension à la recherche visuelle, soit la capacité à orienter l'attention vers les éléments pertinents et à traiter rapidement les caractéristiques visuelles de l'interface, se manifeste par des parcours oculaires plus ciblés et un filtrage plus efficace de l'information. Ces stratégies aident les utilisateurs à réduire la charge cognitive et la frustration associées aux tâches complexes. Bien que la propension à déployer ces stratégies ne modère pas systématiquement la relation entre la complexité des tâches et la performance, les analyses complémentaires révèlent que l'exactitude des utilisateurs au niveau des

tâches dans les paradigmes de recherche visuelle constitue un prédicteur significatif de la performance, toutes conditions confondues. Ce constat confirme l'importance des différences individuelles dans les capacités perceptives et attentionnelles, souvent sous-estimées dans la recherche sur les ERP.

Sur le plan théorique, l'étude contribue à combler un écart important dans la littérature en intégrant les concepts de complexité des tâches, de charge cognitive et de stratégies de recherche visuelle dans un même modèle empirique. Elle ouvre également la voie à une compréhension plus nuancée de la place qu'occupent les mécanismes perceptifs dans l'utilisation des systèmes d'entreprise, un aspect crucial pour l'ergonomie cognitive et l'expérience utilisateur, mais peu documenté jusqu'ici. Sur le plan pratique, les résultats soulignent l'importance d'adapter les stratégies de formation, notamment en intégrant des principes issus de l'apprentissage vicariant, et de concevoir des interfaces ERP plus sensibles aux contraintes cognitives réelles des utilisateurs. Ces recommandations répondent directement aux défis actuels de transformation numérique, où la performance des outils repose autant sur la technologie que sur la capacité des employés à en maîtriser la complexité.

L'étude comporte néanmoins certaines limites. La nature contrôlée du laboratoire, la distribution relativement homogène des profils cognitifs et la portée géographique restreinte limitent la généralisation des résultats. Les tâches expérimentales, bien que représentatives de workflows ERP, ne reflètent qu'un sous-ensemble des défis rencontrés dans les environnements professionnels, où les interruptions, la collaboration et les contraintes temporelles modulent fortement les comportements attentionnels. Ces limites suggèrent plusieurs avenues pour les travaux futurs. Il serait possible d'élargir la diversité des participants, d'analyser des environnements plus naturalistes, d'accroître la variété des tâches, ou encore d'examiner les interactions entre recherche visuelle, expertise métier et stress organisationnel.

Enfin, ce mémoire apporte une contribution originale à la compréhension des facteurs humains qui influencent la performance dans les ERP. En démontrant que les stratégies de recherche visuelle façonnent la manière dont les utilisateurs naviguent des interfaces complexes, il rappelle que toute transformation numérique repose d'abord sur les capacités cognitives et attentionnelles des utilisateurs finaux. La technologie ne crée de valeur que si elle est comprise, maîtrisée et intégrée par ceux qui l'utilisent au quotidien. Ces résultats invitent ainsi chercheurs et

praticiens à concevoir des systèmes et, surtout, des approches de formation qui reconnaissent la diversité des profils attentionnels et perceptifs. En adaptant les apprentissages et le soutien offert aux utilisateurs, les organisations renforcent l'efficacité, l'adoption et la durabilité de leurs initiatives numériques. Replacer l'utilisateur final au centre des projets et adapter la formation à ses besoins apparaît dès lors comme une condition essentielle à la réussite des transformations numériques.

Annexe

Annexe A

Table 10

Items for Psychometric Measures

Construct name	Acronym	Measure type	Description	Source Reference
Task Complexity	TCI	Self-Reported	<i>To what extent do you agree with the following statement: (7-pt scale)</i> 3 items: TCI_INF: The task involved processing a large amount of information. TCI_AMBG: The task contained ambiguous or unclear information. TCI_GUID: The task provided insufficient guidance.	Braarud, P. Ø. (2001). "Subjective Task Complexity and Subjective Workload: Criterion Validity for Complex Team Tasks." <i>International Journal of Cognitive Ergonomics</i> .
Perceived Frustration	TLX_FRU	Self-Reported	<i>To what extent do you agree with the following statement: (Percentage slider: 0 = low and 100= high)</i> 1 item: TLX_FRU: How insecure, discouraged, irritated, stressed, and annoyed were you?	Hart, S. G., & Staveland, L. E. (1988). "Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research." <i>Human mental workload</i> .
Perceived Cognitive Load	TLX_MD	Self-Reported	<i>To what extent do you agree with the following statement: (Percentage slider: 0 = low and 100= high)</i> 1 item: TLX_MD: How mentally demanding was the task?	Hart, S. G., & Staveland, L. E. (1988). "Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research." <i>Human mental workload</i> .

Annexe B

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this thesis, the author used ChatGPT strictly as a support tool for limited tasks such as grammar refinement, stylistic adjustments, and occasional translation. All content generated with the assistance of this tool was carefully reviewed, corrected, and integrated only when it met the academic standards required for this work. The author takes full responsibility for the accuracy, coherence, and originality of the final written document.

Declaration of generative AI and AI-assisted technologies in the research process

Perplexity.AI was used as an auxiliary tool to help locate relevant scientific articles at the early stage of the research process. The tool was never used to replace critical reading or analytical work. Each reference identified through this service was systematically verified by consulting the original academic sources, which were read in full before being cited or used in the analysis. The author reviewed, validated, and edited all information derived from these tools and assumes full responsibility for the integrity and reliability of the research presented in this thesis.