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Uncovering the Impact of Interface Discoverability on User Satisfaction and Task Performance: The Case of Enterprise Systems

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Résumé

Les transformations numériques poussent les entreprises à adopter des systèmes d'entreprise basés sur le cloud, reconnus pour leur grande flexibilité et leur haut niveau de personnalisation, afin d'accélérer leurs performances et d'optimiser leur productivité. Cependant, malgré ces capacités de personnalisation, cette transition peut représenter des défis considérables pour les utilisateurs, notamment en raison de la complexité des interfaces. Ce mémoire souligne un facteur clé souvent négligé dans la conception des interfaces : la découvrabilité. Ce concept est la capacité d'un utilisateur à utiliser un système sans formation approfondie. L'objectif principal de cette étude est d'analyser l'impact du niveau de découvrabilité des ERP sur la performance et la satisfaction des utilisateurs débutants. De plus, cette étude examine le lien entre l'attention visuelle, la charge cognitive et les réponses émotionnelles en utilisant une méthodologie de NeuroIS. En étudiant l'interaction des utilisateurs avec trois systèmes ERP de découvrabilité variable, cette étude utilise un design expérimental intra-sujets. L'étude a été réalisée dans un laboratoire avec 86 participants. Les résultats de cette recherche montrent qu'une interface hautement découvrable favorise une navigation efficace en orientant naturellement l'attention visuelle vers les éléments essentiels de la tâche, réduisant les erreurs et améliorant la performance. L'attention visuelle d'un utilisateur facilite la découverte et l'expérience utilisateur, soit la performance et la satisfaction. Cependant, contrairement aux attentes, les réponses émotionnelles et la charge cognitive n'ont pas été des médiateurs significatifs, laissant penser que d'autres facteurs pourraient jouer un rôle dans cette relation. Ce mémoire propose une méthodologie détaillée et reproductible pour faciliter la reproduction d'études similaires par d'autres chercheurs. Les implications pratiques de ces résultats, notamment dans le contexte des transformations numériques, sont examinées, ainsi que les pistes pour des recherches futures.

Mots clés: Découvrabilité • Progiciels de Gestion Intégré • ERP • Interaction Homme-Machine • Expérience Utilisateur • Ergonomie des logiciels • Transformation numérique

Méthodes de recherche: Expérience Utilisateur • Suivi Oculaire • Analyse d'Expression Faciale Automatique • Activité Électrodermale • Pupillométrie

Abstract

Digital transformations are incentivizing companies to adopt cloud-based enterprise systems, which are well-known for their exceptional flexibility and high degree of customization, to enhance performance and optimize productivity. Nevertheless, even with these customization possibilities, users may face significant challenges during this transition, primarily due to the complexity of the interfaces. It highlights a key factor often overlooked in interface design: discoverability. This concept is the ability of a user to operate a system without extensive training. The main objective of this study is to analyze the impact of ERP discoverability levels on the performance and satisfaction of novice users. In addition, this study examines the link between visual attention, cognitive load and emotional responses using a NeuroIS methodology. This study employs a within-subjects experimental design to investigate users' interaction with three ERP systems of varying discoverability. The study was conducted in a laboratory setting with 86 participants. This research shows that a highly discoverable interface promotes efficient navigation by naturally directing visual attention to the essential elements of the task, reducing errors and improving performance. A user's visual attention facilitates discovery and user experience, i.e. performance and satisfaction. However, contrary to expectations, emotional responses and cognitive load were not significant mediators, suggesting that other factors may play a role in this relationship. This thesis proposes a detailed and reproducible methodology to facilitate the replication of similar studies by other researchers. The practical implications of these findings, particularly in the context of digital transformations, are examined, as are avenues for future research.

Keywords: Discoverability • Enterprise Systems • ERP • Human-Computer Interaction • User Experience • Software Ergonomics • Digital Transformation

Research methods: User Experience • Eye tracking • Automatic Facial Expression Analysis • Electrodermal activity • Pupillometry

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"I want to thank me. I want to thank me for believing in me. [...] I want to thank me for having no days off. I want to thank me for never quitting. [...] I want to thank me for being me at all times."

(Fiorentino, 2018)

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To everyone who has been part of this journey, thank you from my heart. You’ve made this year unforgettable.

Introduction

In the 1970s, the Xerox Palo Alto Research Center (PARC) laid the groundwork for modern human-computer interaction. At a time when computers were predominantly reserved for experts and featured complex text-based interfaces, Xerox PARC revolutionized the field with groundbreaking innovations such as the graphical user interface (GUI), the mouse, and built-in ethernet (Dennis, 2023). Their mission was clear: democratize access to digital technologies by creating interfaces that were intuitive and accessible to the general public (Carlson, 2017). One of Xerox PARC's most pioneering contributions was the discovery learning approach. This method emphasized that users could grasp a system’s functionality through exploration, provided the interface was intuitively designed with clear visual cues (Wood, 2001). While "discoverability" had not yet been coined, its principles were central to Xerox PARC's work. For example, the visual signifiers in the Xerox Alto system naturally guided users, eliminating the need for extensive tutorials (Dennis, 2023). These innovations profoundly influenced interface design, shaping the work of companies like Apple and contemporary user experience standards (DeCarlo, 2021).

Apple built upon Xerox PARC's foundation in subsequent decades, mainly by introducing its Human Interface Guidelines in 1986 (Huber, 1986). These guidelines outlined a vision for creating intuitive, user-friendly software, promoting a shift from complex "remember-and-type" systems to accessible "see-and-point" interaction models (Huber, 1986).

At the same time, corporate information systems were evolving along a separate trajectory. Unlike the consumer-facing interfaces influenced by Xerox PARC and Apple, those systems were primarily designed to meet a business's functional and operational needs (McManus, 2024). Usability was frequently regarded as an afterthought, overshadowed by the emphasis on optimizing processes and integrating data across departments. These systems, encompassing early mainframes and specialized business software, were generally designed for technical users, operating under the assumption of extensive training and expertise (McManus, 2024). This emphasis on functionality rather than usability led to significant learning curves for end-users, frequently resulting in inefficiencies and dissatisfaction in the workplace.

In contrast, material requirements planning (MRP), commonly considered the forerunner of enterprise resource planning (ERP), originated in the 1960s to aid businesses in managing manufacturing processes. From its inception and throughout the evolution of ERP systems in the 1990s, functionality consistently outweighed usability (McManus, 2024). Only in the 2010s did ERP providers emphasize user-friendly design and software ergonomics, aligning their strategies with the usability principles advocated decades earlier by Xerox PARC and Apple (McManus, 2024). Not only do companies have to adapt quickly to technological evolutions, but they also have to deal with changes in the enterprise software interface, primarily due to the shift toward cloud-based solutions. According to Gartner, companies increasingly adopt cloud ERP systems because they offer enhanced process automation and analytical capabilities (Leiter et al., 2023). While cloud-based ERP systems offer enhanced process automation and analytical capabilities (Leiter et al., 2023), they also present significant challenges, among others, in user adoption and integration costs, mainly due to the steep learning curve associated with their use. These challenges are exacerbated when systems need more intuitive design, leading to increased reliance on training programs and technical support (Ha & Ahn, 2014).

The widespread adoption of ERP systems across sectors, from agriculture to food services (Carter, 2024), underscores the necessity of ensuring these systems are both accessible and usable, as users from diverse educational and professional backgrounds, use these systems, further highlights the importance of ensuring these systems are both accessible and usable. Moreover, in 2024, the revenue in the Enterprise Resource Planning Software market is anticipated to attain $52.99 billion, with a predicted annual growth rate of 4.26% through 2029 (*Statista*, 2024). Since there is such a widespread number of users, these systems need to be usable, and the design needs to be more user-friendly and discoverable as it enables users to easily perceive possible actions and interact effectively with the interfaces (Norman, 2013).

Suppose the system's interface is not well-designed to consider discoverability, and the users are struggling with discovering how to accomplish their tasks properly. In that case, it can result in missed opportunities for process optimization and cost savings (Moss, 2011). As organizations increasingly depend on digital and video training for employee onboarding, users are expected to learn and proficiently use these platforms autonomously. Without intuitive and discoverable interfaces, this training method may be unproductive, resulting in personnel being perplexed and ill-equipped to utilize the system to its full potential (Gupta et al., 2010).

While current research in human-computer interaction (HCI) and user interface design offers valuable foundational insights, our literature review highlights a significant gap in studies addressing the concept of discoverability in enterprise systems. Most existing research focuses on general usability or isolated interface elements only after fully considering the comprehensive demands of corporate environments or the diverse users interacting with these systems daily (Kaptelinin & Nardi, 2012; Mackamul, 2023). Many of these studies prioritize surface-level aspects, such as navigational simplicity or aesthetic appeal (Fennedy et al., 2022), while overlooking deeper cognitive and emotional processes triggered when users independently explore and interact with system features (Eriksson, 2023). In response to this gap, our study seeks to delve into the critical role of discoverability in cloud-based SaaS enterprise applications. We focus on how users' ability to locate, understand, and effectively utilize system features influences their task performance and overall user experience. By investigating this dimension, we aim to bridge the existing knowledge gap and provide actionable insights for designing enterprise systems that align with the practical needs of organizations and their workforce. For this reason, we have developed the research question below:

To what extent does the level of perceived discoverability of an enterprise system influence task performance and user satisfaction?

Through a within-subjects experimental design utilizing three distinct enterprise systems with varying levels of discoverability, this study addresses the research question by examining how interface discoverability influences user performance and satisfaction. This was achieved by assessing internal experiences, including visual attention, cognitive load, and emotional responses, which were measured using eye tracking, pupillometry, facial analysis, and electrodermal activity.

This thesis provides important theoretical and practical contributions to the study and implementation of discoverability in enterprise systems and digital transitions. Theoretically, it clarifies and harmonizes previous definitions of discoverability by incorporating many levels. Furthermore, this thesis contributes to extending the theoretical frameworks of guided search and affordance theories by highlighting the mediating role of visual attention in the relationship between the level of discoverability of an interface and user satisfaction and performance. Furthermore, the results challenge several of the hypotheses by revealing that cognitive load and emotional responses are not significant mediators, opening the door for future study into alternative factors impacting these interactions.

On a practical level, this work offers actual recommendations for enterprises undergoing digital transformation. It emphasizes the necessity of including discoverability from the start when selecting and designing corporate software products. It supports intuitive design to save integration costs, minimize training requirements, and improve user happiness in the long run. The report also emphasizes the importance of user-centred techniques, such as integrating employees in the system personalization process and aligning systems with their needs, resulting in increased adoption and improved operational efficiency.

An introduction to this thesis and the context of this study were discussed in this chapter. Chapter 2 will extensively present the scientific article summarizing this study's methodology and findings. It addresses the impact of discoverability on one's performance, visual attention, cognitive load, emotions, and satisfaction. It ends by discussing the contributions to the scientific community and the implications for designers and management, and it discusses possible ways for future research. This chapter is a scientific manuscript in preparation to be published in the Journal *Interacting with Computers*. Chapter 3 will present a short managerial article that will propose essential guidelines for management and designers to follow when implementing a new enterprise system to increase employee performance and satisfaction when discovering their new tool. This short managerial article is in preparation to be publish in our industrial partner's magazine, *Deloitte Insights Magazine*. The last chapter, chapter 4, is the conclusion, which summarizes the entire study. Table 1 details the student's contributions to her thesis at Tech3Lab.

Table 1

Student contributions and responsabilities in this thesis

Stage in the process	Contribution
Research Question	Identified gaps in literature to define the research problem and its implications [90%] – Problematic initially conceived by the industrial partner. – Contextualization of the problematic in academic research by the student.
Literature Review	Conducted the relevant search and thorough scan of scientific articles to understand the current body of academic knowledge on discoverability and its impacts on the user. [100%]
Experimental Design	Application to the Research Ethics Board (REB) of HEC Montréal [90%] – Preparation of documentation related to the submission by the student. – Application reviewed by thesis co-supervisors and Tech3Lab operations staff. Development of the experimental protocol and stimuli [80%] – Conception of experiment procedure, questionnaires and instruments by the student. – Stimuli were selected by the industrial partner. – Implementation and customization of the systems were done by a research assistant.
Data Collection	Recruitment of participants for data collection. [20%] – Participants for data collection were recruited by the student and mainly by the Tech3Lab's panel. Laboratory setup [80%] – The student created the protocol and the eye tracker timeline. – Assembly of multi-device data collection instruments with help from Tech3Lab staff (Salima Tazi and Xavier Côté). – Extensive testing and polishing of laboratory set up by the student. Pre-testing and data collection operations management [100%] – The student coordinates and prepares pre-test operations. – Moderation and observation of all user tests by the student. – Technical support and organization of data collection staff by Tech3Lab management. Independent Manipulation Check data collection [100%] – Create the protocol and survey. – The student recruited participants for the data collection.
Statistical Analysis	Conducted the analysis of psychophysiological data [80%] – Extraction and treatment of the data to synchronize all instruments by the Tech3Lab statistician. – Statistical analysis on SAS and R by the student with the help of the Tech3Lab statistician. – Interpretation and presentation of results by the student. Conducted the analysis of the manipulation check [10%] – Extraction and treatment of the data to synchronize all instruments by the student. – Statistical analysis by the Tech3Lab statistician and Théophile
Redaction	Wrote the articles and the present thesis [100%] – Article co-authors and thesis co-supervisors provided comments and corrections.

Chapter 2
Hidden in Plain Sight: Unraveling How Discoverability Shapes one's experience in Enterprise Systems[1]

Andrada Toma, Pierre-Majorique Léger, Théophile Demazure, Alexander Karran, Thaddé Rolon-Mérette, Shang-Lin Chen, Constantinos K. Coursaris, Sylvain Sénécal

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Abstract: In the modern corporate world, where employees juggle multiple applications, the efficient use of digital systems is becoming a central issue. Yet many of these systems lack designs tailored for novice or occasional users, creating barriers to adoption. This laboratory study examines the concept of discoverability, defined as the ease with which users can identify and access a system's functionalities, and its impact on user performance and satisfaction. Using a within-subject experimental design, 86 participants interacted with three enterprise resource planning systems characterized by varying levels of discoverability. A combination of self-reported psychometric scales and physiological measures, including eye-tracking and pupillometry, was employed to capture user experiences. The findings reveal that systems with high levels of discoverability significantly enhance performance and satisfaction. Visual attention partially mediates this relationship, directing users to critical interface elements, while cognitive load and emotional responses showed no significant mediating effects. By integrating physiological and psychometric data, this research provides actionable insights for designing more intuitive and effective enterprise systems, underscoring the critical role of discoverability in increasing user experience and performance.

Keywords: User Experience • Eye tracking • Automatic Facial Analysis • Electrodermal activity • Pupillometry

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[1] This article is in preparation to be published in the Journal *Interacting with Computers*.

2.1 Introduction

The landscape of enterprise software is rapidly evolving, with cloud-based solutions becoming a dominant force in driving organizational change. Enterprise systems are at the forefront of this transformation, recognized for their capacity to automate business processes and provide enhanced analytical capabilities. These systems are increasingly being adopted as businesses seek greater efficiency and scalability, encouraged by vendors phasing out support for outdated on-premises systems (Fan et al., 2015; Leiter et al., 2023). They are critical in reducing information fragmentation and improving operational efficiency across diverse industries, such as agriculture and hospitals. By integrating diverse business functions, these systems are instrumental in lowering information fragmentation and improving organizational efficiency across various sectors, including agriculture, hospitality, and beyond (Baluch, 2023).

However, despite these advancements, many enterprise systems implementations fail to deliver their full potential due to challenges in user experience and system adoption (Al-Okaily et al., 2021; Ha & Ahn, 2014). The complexity of these systems, mainly when multiple platforms are used across different departments, often results in increased learning curves and a more cumbersome user experience (Eriksson, 2023; Shaji George, 2024). This can decrease productivity and employee dissatisfaction, undermining the system's effectiveness (Wüllerich & Dobhan, 2021).

To truly harness the benefits of those cloud-based enterprise systems, it is essential that employees not only familiarize themselves with these platforms but also achieve a level of mastery that enables them to perform tasks efficiently (Al-Okaily et al., 2021). A positive user experience is crucial, not only for improving employee performance, but also for reducing operational costs. As highlighted in recent research, such as the 2022 Gartner Digital Worker Survey, which surveyed over 4,800 participants globally, proficiency in digital tools is key to driving productivity, enhancing autonomy and satisfaction (Natarajan & Paulman, 2023). This emphasized the importance of the ease with which users can locate and use system features without extensive training, in other words, discoverability, as a critical factor in ensuring user satisfaction and maximizing the performance of enterprise systems.

When system interfaces are not designed with the user in mind, users struggle to complete tasks efficiently, resulting in lost potential for process improvement and company cost savings (Moss, 2011; Norman, 2013). Furthermore, discoverability is critical to the effectiveness of training programs, primarily as firms rely more on digital and video-based training methods for employee onboarding. Without intuitive interfaces, such training tactics are rendered worthless, leaving users perplexed and unable to fully utilize the system's capabilities (Eriksson, 2023).

Although research in Human-Computer Interaction (HCI) and user interface design has produced fundamental insights, it often overlooks the specific challenges of discoverability within corporate systems. Much of the focus has been on general usability aspects like navigational ease or visual appeal, neglecting the more nuanced cognitive and emotional experiences users encounter when exploring and utilizing features in enterprise systems (Wüllerich & Dobhan, 2021). This gap in research invites a closer examination of discoverability, especially concerning enterprise systems that play a vital role in everyday business operations.

Our research addresses the issue by exploring the significance of discoverability in cloud-based software-as-a-service (SaaS) business applications. We strive to comprehend how a system's discoverability, or a user's capacity to identify and understand its features readily, impacts task performance and overall satisfaction with the system. Specifically, our research question is:

To what extent does the level of perceived discoverability of an enterprise system influence task performance and user satisfaction?

Our study addresses this research question using the NeuroIS approach (Dimoka et al., 2011), which integrates cognitive neuroscience methods and theories into information systems research, and grounded in theories such as the guided search, and cognitive load theories, we examine how these constructs mediate the relationship between interface discoverability and user performance and satisfaction. Utilizing physiological measures like eye-tracking to assess visual attention and pupillometry to gauge cognitive load enables us to directly access the mental and emotional processes that drive human-computer interactions. By implementing these principles, we enhance our comprehension of mediators such as visual attention and emotional responses, illuminating discoverability's impact on user performance and satisfaction.

To address this issue, we performed a laboratory experiment examining the relationships between discoverability, task performance, and user satisfaction. This research adds to the growing knowledge regarding the usability of business systems. We investigated the mediating relationships among discoverability, performance, and satisfaction, considering human factors like visual attention, cognitive load, and emotional response in enterprise software applications. As a result, we gathered data through physiological metrics, such as eye-tracking for assessing visual attention, pupillometry for measuring cognitive load, facial analysis, and electrodermal activity to capture users' emotional responses. We also utilized psychometric scales to measure user satisfaction.

The findings suggest that higher discoverability significantly enhances user performance and satisfaction. Visual attention also plays a crucial role, proving to be a partial mediator between discoverability, performance, and satisfaction. However, the mediating effects of cognitive load and emotional responses were not statistically significant. These results contribute to the scientific community by highlighting the importance of visual attention as a mechanism by which discoverability influences user performance. Our findings underscore the necessity of creating easily navigable interfaces to enhance operational efficiency and user satisfaction, thereby increasing the value of enterprise systems.

We begin by reviewing the relevant literature and identifying the research gap. This review is followed by a presentation of the theoretical framework and hypotheses. Next, the methodology section outlines the experimental design and measures. The results are then presented, accompanied by a detailed discussion of their implications. Finally, the article concludes with a summary of key findings and suggestions for future research.

2.2 Literature Review

2.2.1 Discoverability

Discoverability is crucial in designing an interface for a system because it dictates how easily people can perceive and understand an object or system's possible actions and functions. When discoverability is successfully implemented in the design, users can determine what actions are possible, where and how to perform them, and what the results of those actions will be, leading to a seamless and positive user experience (Norman, 2013). With good discoverability, users feel understood and satisfied, leading them to make errors, abandon tasks, and develop negative perceptions of the design (Norman, 2013). This is particularly problematic for complex devices or systems, which often require manuals or instructions that can further impede the user's experience (Norman, 2013).

Gibson's (2015) affordance theory postulates that the environment offers inherent action possibilities or “affordances” to individuals. According to Gibson (2015), affordances are directly perceptible by individuals; in other words, they can understand what actions an object or the environment allows them to take without explicit instructions or prior knowledge. That said, using the lens of affordance theory to understand the construct of discoverability, we need to start by understanding the relationship between the action possibilities of the object or system and the cues the user perceives. Discoverability then depends on the user's ability to perceive these affordances. For example, a button affords pressing, or a door affords opening. Norman (2013) has criticized this simplification of affordances in design, especially in interfaces. So, he expands on the subject by introducing the concept of “signifiers” to address the limitations of Gibson's (2015) theory of affordances and talk about discoverability in design. According to Norman (2013), signifiers are perceptible signals of what can be done - they specify how users discover these possibilities, these “affordances,” and communicate where the answer should be to the user. Effective use of signifiers ensures discoverability and that feedback is well communicated and intangible (Norman, 2013).

One central area of research is the discoverability of interactions in systems. Highlighting that discoverability is a recurring issue in interactive designs, with users frequently needing help understanding the commands offered in a new system. Researchers look at ways to enhance discoverability, emphasizing how effective design can significantly increase user engagement and happiness with those systems (Kirschthaler et al., 2020). Similarly, other research calls for a greater emphasis on discoverability in interactive systems, arguing that its value should be better integrated into research agendas to improve user interfaces. This is consistent with the findings of Mckelvey and Hunt (2019), who suggest that discoverability is an essential component in how applications and platforms encourage user interaction with their features while focusing on content providers and audience discovery.

In addition to interaction discoverability, identifying new features is an integral part of the notion. It offers a unified command selection mechanism that improves command discoverability on touch-based devices, implying that a well-designed interface can result in more efficient user interactions (Fennedy et al., 2022). This is supplemented by the work of, who investigate the discoverability of hidden widgets in mobile interfaces, demonstrating that creative interaction designs can give users faster access to instructions, improving the system's overall usefulness (Pong & Malacria, 2019).

Discoverability, as a construct, remains vague, and there needs to be more specific research focusing on simplifying feature discovery or enhancing the discoverability of existing features within these systems. Not only is research about discoverability within complex enterprise systems rare, but in general, research about the construct of discoverability referenced explicitly is scarce (Mackamul, 2023). Trying to find a clear definition of the construct was challenging since the literature revealed a need for a universally agreed-upon definition, leading to a spectrum of interpretations and applications of the term Definitions of discoverability vary, with some emphasizing it as an inherent characteristic of the interface (Kirschthaler et al., 2020; Mackamul, 2023; Moss, 2011; Srinivasan et al., 2019), while others consider it a user-specific skill (Cardello, 2014; Eriksson, 2023; Furqan et al., 2017; Goguey et al., 2018; Hosio et al., 2013; Mackamul, 2023; McKelvey & Hunt, 2019; Norman, 2013) or relate it to the task that facilitates discovery within the interface (Fennedy et al., 2022); we have compiled the definitions found in Table 2. We have decided to adhere to the following definition as it is at the user's level.

"The ability for users to perceive and comprehend a system, function or input method as such when encountering it for the first time despite a lack of previous awareness or knowledge. This may be through intentional effort or serendipitously." (Mackamul, 2023, p.11)

Table 2

Summary of the definitions of the construct "Discoverability"

Level	Definition	Reference
Interface	It is discussed as the quality of an interface that allows users to easily find and understand how to use its functionality.	Moss, 2011
	Interaction discoverability concerns whether users can identify and comprehend interaction and input methods when they encounter them without instruction or guidance.	Mackamul, 2023
	Discoverability: the ability for users to find and execute features through a user interface	Kirschthaler et al., 2020
	Discoverability, in this context, entails (1) awareness — making users aware of the operations that can be performed using speech; and (2) understanding — educating users on how requests should be phrased so the system can interpret them correctly	Srinivasan et al., 2019
User	When we interact with a product, we must figure out how to work it. This means discovering what it does, how it works, and what operations are possible: discoverability. Discoverability results from the appropriate application of five fundamental psychological concepts covered in the following few chapters: affordances, signifiers, constraints, mappings, and feedback. However, there is a sixth principle, perhaps the most important of all: the system's conceptual model. It is the conceptual model that provides true understanding. So, I now turn to these fundamental principles, starting with affordances, signifiers, mappings, and feedback, then moving to conceptual models.	Norman, 2013, p.10
	System discoverability is focused on whether potential users notice the overall system and recognize it as something they can interact with.	Mackamul, 2023
	Feature discoverability covers the user's ability to discover features or functionality they were previously unaware of while using a system.	Mackamul, 2023
	New content or functionality that [the users] were not aware of previously	Cardello, 2014
	A dynamic, personalized process influenced by platform interfaces, user interactions, and algorithms	Mckelvey & Hunt, 2019
	Discoverability is a means to achieve learnability	Furquan et al, 2017
	The ability for users to perceive and comprehend a system, function or input method as such when encountering it for the first time despite a lack of previous awareness or knowledge. This may be through intentional effort or serendipitously.	Mackamul, 2023
	The ability of users to find and learn about new features or functions within a system without being overwhelmed or frustrated.	Ericksson, 2023
	There is easy discoverability for novices, support for a smooth transition from novice to expert behaviour, a high-performance ceiling for experts, and fluid switching between text selection modes.	Goguey et al., 2018
	How users discover a feature	Hosio et al., 2013
Task	How effectively do users discover the existence and functionality through their interaction with specific tasks within the software.	Fennedy et al., 2022
	It is possible to determine what actions are feasible and what the device's current state is.	Norman, 2013, p.72

2.2.2 Visual Attention

Visual attention is the process by which individuals selectively focus on specific information in their environment, enabling them to prioritize relevant details while filtering out distractions (Matzen et al., 2016). Eye-tracking studies in HCI research provide evidence that users' eye movements are influenced by both bottom-up (stimulus-driven) and top-down (goal-oriented) features when interacting with scenes (Hollingworth & Bahle, 2019).

Wolfe’s guided search theory (1994) explains this process by highlighting the interaction between bottom-up and top-down features and how those two are combined to guide attention. Bottom-up features are stimulus-driven and refer to visual properties like color, contrast, and brightness that instantly draw attention due to their prominence in the visual field (Wolfe, 1994). Top-down features, on the other hand, are goal-oriented and use the viewer's cognitive intents, past knowledge, and expectations to direct attention to relevant parts (Wolfe, 1994). Moreover, the theory distinguishes between the preattentive, during which the visual system processes basic visual features in parallel across the visual field, and attentive stages of visual processing, during which the visual system processes more complex operations (Wolfe, 1994). This theory has been used in many fields such as psychology, HCI, IS and neuroscience because it provides a framework for understanding how users interact with digital interfaces. It explains how users direct their visual attention when traversing complicated system interfaces, assessing which items are easily visible and which may be neglected. It emphasizes the importance of top-down processes, in which user expectations and prior knowledge influence their attention throughout a visual search task (Wolfe, 1994). Top-down guidance in IS enables designers to align interface layouts with users' mental models, making key features more straightforward to locate and interact with (Davids et al., 2015). This theory allows for a foundation to interpret how visual elements such as menus, buttons, and icons affect metrics of visual attention and therefore user experience and performance.

2.2.3 Cognitive Load

Cognitive load is the mental strain on a person's system during task execution. Working memory, which stores and processes information, is limited (Chen & Epps, 2014; Davids et al., 2015; Hossain & Elkins, 2018). It increases with task demands, which may reduce performance if working memory capacity is exceeded (Krejtz et al., 2018; Szulewski et al., 2015).

Specifically, task complexity, perceptual demands, user proficiency, and interface design affect cognitive load. Interactive interfaces with intuitive design, unique signifiers, and structured information reduce cognitive burden, allowing users to focus on essential tasks (Krejtz et al., 2018; Norman, 2013).

Measuring cognitive load is crucial for building intuitive interfaces in IS and HCI. Interface designers can reduce cognitive load and improve usability and learning by minimizing extraneous elements and directing users through coherent task flows (Chen & Epps, 2014; Davids et al., 2015; Mitre-Hernandez et al., 2021). Physiological tests like pupillometry measure cognitive stress. The task-evoked pupillary response measures pupil size to indicate temporary cognitive stress during a task. Increased pupil dilation is often inferred as increased cognitive strain, providing a real-time metric of mental burden that can help evaluate interface design results. These measures help researchers and designers improve interface components to better suit users' cognitive abilities, improving interaction efficiency (Chen & Epps, 2014; Krejtz et al., 2018; Szulewski et al., 2015).

2.2.4 Emotions

Emotions involve complex interactions between physiological, cognitive, and behavioural elements, distinguished by intensity, short duration, and specific causes (Tidikis et al., 2017). Unlike broader concepts like "affect" or "mood," emotions involve active appraisals and have clear cognitive impacts. Emotions are shaped by two key dimensions: *valence*, which represents the positive or negative quality of an experience, and *arousal*, the intensity or physiological activation (Barry et al., 2005; Tidikis et al., 2017). High arousal is marked by excitement or agitation, while low arousal is associated with calmness and relaxation.

Studies reveal a link between system use and user emotions, as affective states like anxiety and enjoyment directly influence user engagement (Éthier et al., 2008). Understanding how emotions arise during user interactions enables researchers and designers to create positive, engaging environments that foster desired behaviours (Deng & Poole, 2010). Additionally, interface design, primarily through visual aesthetics, can evoke positive emotions, enhancing cognitive processing and learning outcomes (Dong, 2010).

2.2.5 Gap

Despite growing recognition of discoverability's importance, research has focused on simpler systems such as mobile apps or software developed with a user-centric approach (Kirschthaler et al., 2020; Pong & Malacria, 2019). For instance, mobile apps are typically designed for specific, narrowly defined tasks and are often developed with minimalistic, user-friendly interfaces since they are tailored for one defined user group (Pong & Malacria, 2019). In contrast, enterprise systems are platforms that integrate various business processes within a single interface, often used by diverse user groups. Hence, they require users to navigate through interconnected modules, making them more complex and increasing the importance of discoverability (Ibrahim et al., 2023). More studies need to be done on enterprise systems, especially cloud-based SaaS platforms, which limits understanding of how discoverability affects user performance in complex systems. Additionally, definitions of discoverability vary, with some focusing on interfaces and others on user tasks, complicating comparisons.

2.3 Theoretical Development

2.3.1 Theoretical Foundation

The theory of guided visual search (Wolfe, 1994) is at the heart of this study, helping us to explain how users direct their visual attention when interacting with complex interfaces. He argues that visual processes rely on bottom-up and top-down mechanisms. In the realm of visual search within enterprise systems, characterized by complex, feature-laden interfaces or minimalistic layouts concealing functionality behind a hamburger menu, examining visual search is crucial for understanding how users swiftly and effectively identify features.

Interface design provides visible affordances or signifiers in systems characterized by high discoverability, as Norman (2013) described. These affordances direct users' attention to essential functionalities, minimizing excessive exploration and cognitive load and enhancing performance and satisfaction. The idea of affordances consequently bolsters the theory of guided visual search, elucidating that distinct affordances and effective signifiers enable users to comprehend instantly how to engage with a system, irrespective of prior expertise or explicit instructions (Hollingworth & Bahle, 2019; Poole & Ball, 2006).

Cognitive load theory (Sweller, 2011) aligns with this line of thought by elucidating how discoverability affects users' cognitive load during their initial engagement with an enterprise system interface. In enterprise systems with poorly designed or complex interfaces, users must allocate considerable attention to navigation and functionality discovery, engaging in exploration rather than exploitation, which elevates extrinsic cognitive load and diminishes performance and satisfaction (Eriksson, 2023). Enhancing the discoverability of these interfaces diminishes cognitive burden, enabling users to focus entirely on their work, hence enhancing task performance and elevating user happiness through a seamless, frustration-free experience (Eriksson, 2023; Fennedy et al., 2022; Goguey et al., 2018; Mackamul, 2023; Moss, 2011).

Additionally, emotional responses significantly influence consumers' assessment of systems. Pleasant feelings, such as satisfaction and enjoyment, emerge when users engage with systems that alleviate the cognitive burden and facilitate task completion effortlessly (Éthier et al., 2006, 2008). Well-designed interfaces with high discoverability can enhance user performance and elevate overall happiness, enabling improved system acceptance and adoption.

The model of information systems success proposed by DeLone and McLean (Petter et al., 2008) underscores that system quality, especially regarding usability and discoverability, directly affects user satisfaction and indirectly impacts performance. A system with enhanced discoverability diminishes cognitive burden by streamlining visual search, enhances users' emotional responses, and results in a more gratifying experience. Consequently, discoverability is a crucial element connecting system quality to user pleasure and performance.

In enterprise environments, where cloud-based SaaS systems are becoming increasingly prevalent, it is crucial to understand how discoverability influences critical outcomes such as user satisfaction, performance, and visual attention. An effectively designed system interface can successfully be navigated by users through its functionalities, minimizing trial-and-error behaviours and the resultant cognitive burden that could hinder performance and satisfaction (Eriksson, 2023; Fennedy et al., 2022; Goguey et al., 2018; Norman, 2013). Based on Guided Search Theory (Wolfe, 1994), discoverability is a crucial element that boosts users' capacity to find pertinent elements, elevating their entire experience. Systems with enhanced discoverability enable users to engage more efficiently, resulting in more efficient task completion and increased pleasure through improved visual attention.

2.3.2 Hypothesis Development

Building on this theoretical foundation, we establish hypotheses regarding the mediating roles of visual attention, cognitive load, emotional reactions, and effects of the level of discoverability on performance and satisfaction as seen in Figure 1.

System discoverability, characterized by the ease with which users may recognize and comprehend the functionalities of an interface without prior instruction, is essential for performance and user satisfaction in enterprise settings (Mackamul, 2023). High discoverability enables users to explore the system efficiently, swiftly locate essential tools and functionalities, and complete their activities with increased ease (Norman, 2013). This enhances their pleasure with the interface since users experience fewer challenges and impediments (Norman, 2013). Consequently, enhanced discoverability results in superior user performance, expedited and more precise task completion (Goguey et al., 2018), and a more favourable user experience (Eriksson, 2023). In cloud-based enterprise systems, characterized by complex and multifunctional interfaces, users' capacity to identify and utilize pertinent functionalities directly influences their performance and satisfaction. Increased satisfaction and reduced frustration with the platform correlate with enhanced productivity (Davids et al., 2015). Prior research in HCI indicates that well-crafted interfaces featuring distinct visual signifiers enhance navigation efficiency and overall user satisfaction (Davids et al., 2015; Mackamul, 2023).

In systems characterized by high discoverability, users are instinctively directed to the most pertinent aspects (Norman, 2013), minimizing the time required to locate essential functionalities (Moss, 2011). Visual signifiers in effectively designed interfaces direct users' attention to the critical components, enhancing their navigational efficiency (Poole & Ball, 2006). High discoverability channels users' visual focus towards pertinent system features, minimizing cognitive distraction and enhancing navigation efficiency. Consequently, visual attention emerges as a crucial way discoverability affects user performance.

Visual attention is crucial for cognitive processes during discoverability. When visual attention is successfully focused on pertinent parts of an interface, users may traverse and interact with the system more efficiently, enhancing task completion performance and diminishing cognitive load. Furthermore, this concentrated attention enhances user satisfaction by reducing aggravation related to locating functionalities and maneuvering through intricate interfaces (Joseph & Murugesh, 2020). Research indicates that interfaces that enhance visual attention improve user experience and superior performance in corporate systems (Guo et al., 2016). Thus, adequately focused visual attention allows users to engage with the system more seamlessly and effectively, enhancing their enjoyment and performance.

H1a: *Focused visual attention mediates the positive effect of the high level of discoverability on task performance.*

H1b: *Focused visual attention mediates the positive effect of the high level of discoverability on user satisfaction.*

Cognitive load theory (Sweller, 2011) posits that the mental effort necessary for task execution can be categorized into intrinsic cognitive load, associated with the activity itself, and extrinsic cognitive load, linked to the presentation or organization of information. In enterprise systems, an interface with strong discoverability diminishes extrinsic cognitive burdens by enhancing information accessibility and lowering user-perceived complexity. When discoverability is elevated, users expend less effort locating functionalities or comprehending system interactions, reducing their cognitive load (Davids et al., 2015; Eriksson, 2023). Consequently, discoverability is a crucial element that directly impacts users' cognitive load. Alleviating this burden allows users to concentrate their cognitive resources on task completion instead of navigating and seeking features, hence enhancing performance and fostering a more gratifying experience.

Cognitive load mediates the relationship between discoverability and user results. Reducing cognitive load enhances user efficiency in task execution, improving outcomes (Hossain & Elkins, 2018). Reduced cognitive load enables users to concentrate their mental resources on their task performance, leading to increased precision and time efficiency (Le Meur & Chevet, 2010; Mitre-Hernandez et al., 2021). Simultaneously, reduced cognitive load enhances the user experience, as users are potentially less overwhelmed and have greater ease in their interactions with the system, elevating their pleasure (Chen & Epps, 2014). Prior studies indicate that systems designed to reduce cognitive load enhance performance and user happiness, enabling users to complete activities without incurring significant mental weariness (Sevcenko et al., 2023). Consequently, less cognitive load enhances user experience and improves performance.

H2a: *Reduced cognitive load mediates the positive effect of high level of discoverability on task performance.*

H2b: *Reduced cognitive load mediates the positive effect of high level of discoverability on user experience.*

User interactions with a system might potentially impact their emotional responses. In highly discoverable interfaces, users can locate and use the necessary functionality without frustration or uncertainty, leading to positive emotions such as satisfaction, pleasure, and a sense of accomplishment (Sears & Jacko, 2009). These positive emotional responses improve the user experience, as emotions are a key factor in interface evaluation (Deng & Poole, 2010). When users complete tasks successfully and stress-free, they feel more satisfied and confident, which boosts both user satisfaction and performance. Discoverability enhances users' engagement and productivity by minimizing negative emotions like frustration and fostering positive feelings like contentment. Thus, we posit that emotional responses mediate the relationship between discoverability and user outcomes, promoting smoother interactions and greater task efficiency.

H3a: *Positive emotional responses mediate the positive effect of the high level of discoverability on task performance.*

H3b: *Positive emotional responses mediate the positive effect of the high level of discoverability on user experience.*

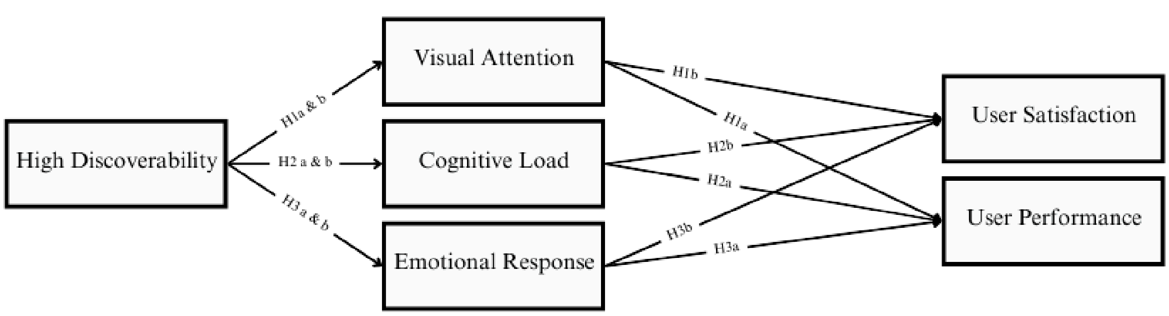

Figure 1. Research Model

2.4 Methods

2.4.1 Experimental Design

This research employed a within-subjects experimental design as illustrated in Figure 2, where participants were randomly assigned to interact with two out of three enterprise systems. The core manipulation of the experiment revolved around the specific system provided to participants for completing the assigned task. To maintain consistency across conditions, the task was identical for all systems, enabling isolation and examination of the impact of discoverability on user performance and experience. Participants were presented with a realistic workplace scenario, assuming the role of an employee tasked with completing a job-related activity. Specifically, they were instructed to create a vertical bar graph summarizing the distribution of the company's clients across different industry sectors. This setup aimed to replicate a typical work environment, encouraging participants to engage with the systems as they would in their daily professional tasks. Although three enterprise systems were tested in the study, each participant only interacted with two of them. This method was used to minimize cognitive fatigue and keep participants engaged throughout the study. The distribution of systems was counterbalanced across participants to guarantee that each system was examined equally while avoiding order effects.

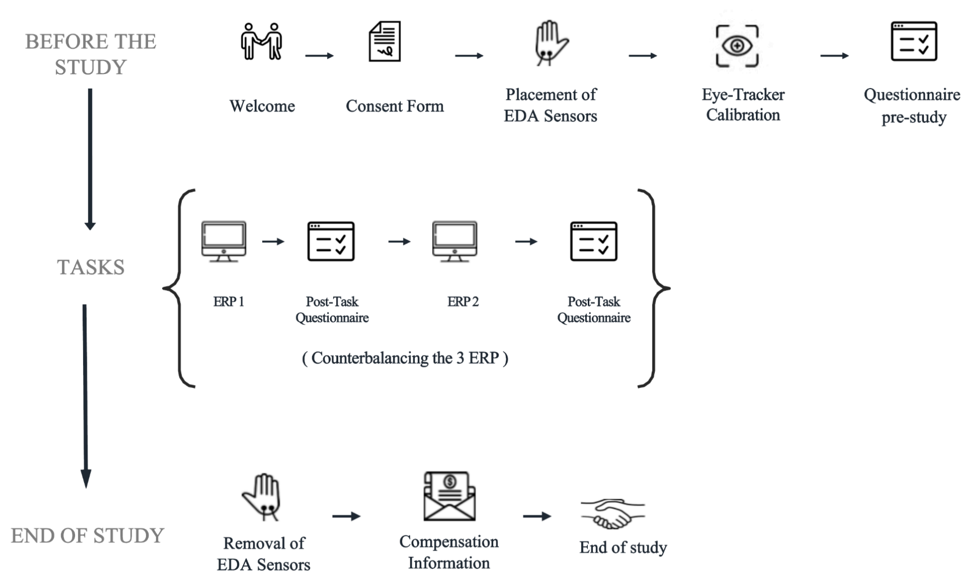

Figure 2. Experimental Design

2.4.1.1 Stimuli Design

To manipulate the level of discoverability, we selected three enterprise resource planning systems (ERPs) that varied in their design, layout, and interactive elements. Each ERP offered a different level of discoverability. This variability was intentionally incorporated to observe how users discovered how to navigate the system to complete the task. The three ERPs differed in interface layout and visual design, but we also chose three ERPs at different maturity states.

ERP 1 had the most densely packed interface, with minimal signifiers and affordances present. The interface was cluttered, with most navigation elements hidden under the hamburger menu. Users had to manually explore the system, which could have significantly increased the cognitive load and the overall complexity of task completion. The lack of clear signifiers made it difficult for users to identify available actions, which could have led to frustration. ERP 1 is the youngest of the three, launched in the last few years.

ERP 2's interface had a more complex design and fewer explicit cues than System A. While signifiers were present, they were not as intuitive as in System A, requiring users to rely more on trial and error to navigate the interface. The layout of System B was denser, with multiple menu options and subcategories that were not immediately visible, which might have increased the cognitive effort required to locate specific functionalities, which required a more exploratory behaviour. ERP 2 is a business system that small and medium-sized enterprises almost always use.

ERP 3's design was clean and intuitive and highly perceived as discoverable with clearly visible signifiers and well-placed affordances that immediately communicated possible actions to users. Key features, such as the navigation bar, buttons, and interactive elements, were aligned with common user expectations, making it easy for users to find and use necessary tools without significant cognitive effort. This system's visual cues minimized users' need to explore or experiment to accomplish tasks. ERP 3 is an enterprise system ubiquitous on the market and used only by large companies.

2.4.1.2 Manipulation Check

To validate the variability in system discoverability, we conducted an independent manipulation check with a panel of nine experts specializing in customer relationship management and ERP systems (2 female; age M=30, SD=7.7). All participants had extensive experience in enterprise systems and specialized expertise in IT or IS, ensuring a robust evaluation of the systems. During the assessment, the experts were introduced to the construct of discoverability, including a precise definition and examples to ground their understanding. They were guided through the task for each system, observing how functionalities and features were accessed and utilized. Afterward, they were asked to rank the three systems based on their perception of discoverability, reflecting the ease with which users could identify and navigate system functionalities. This expert-based manipulation check was critical in confirming the intended variability in discoverability across the three systems, providing a reliable foundation for the main study. Their insights validated the experimental design and underscored the construct's practical relevance in real-world enterprise system environments.

2.4.2 Participants

We recruited a sample of 86 participants for this study via the HEC Montreal panel. The study involved a diverse group of participants, with an average age of 26. Among them were 38 females and 48 males, creating a balance that allowed for a comprehensive exploration of the findings. Each participant received a compensation of $20. The inclusion criteria were as follows: 18 years old and over, fluent in French, with no skin diseases or sensitivities, and no astigmatism. The exclusion criteria concerned people who had already worked with ERPs and CRMs. This study was approved by the Research Ethics Board (REB) of our institution (certificate #2024-5933).

2.4.3 Procedure

Before the participants arrived, the researcher launched the required software and configured data recording and synchronization tools. Profiles for each participant were created using a standard naming convention. Upon arrival, participants were instructed to store personal items in secure lockers, silence their phones, and discard chewing gum. They were offered a restroom break before reading and signing the Qualtrics consent form on an iPad. The moderator addressed any questions participants had. The physiological equipment setup began with cleaning the participants' non-dominant hands before attaching EDA sensors with adhesive. A compression glove was applied to stabilize the sensors. The Biopac hardware was activated, and data quality was confirmed. Eye tracker calibration followed the moderator's recorded demographic information. Participants tracked a moving dot on the screen to ensure accurate calibration, maintaining a 65 cm distance from the monitor. Once calibration was complete, the moderator launched Observer XT, synchronizing it with AcqKnowledge and MediaRecorder 6. A 53-second video displaying white squares was shown to establish an emotional baseline.

The study used a Latin square design to present two of three systems in randomized order. Participants received instructions via Qualtrics and a printed guide to help them remember their tasks. The moderator began screen recording in Tobii Pro Lab, opened the assigned system in a private Chrome window, and gave participants 5 minutes to complete each task. The moderator recorded observations on task flow and completion. After each task, participants completed a post-task questionnaire. All recordings were saved at the study's conclusion under the appropriate naming convention. The researcher removed the physiological sensors, cleaned the attachment sites, and facilitated the participants' compensation process. Participants were thanked and escorted out of the lab.

2.4.4 Instruments and Measures

Emotional valence was measured using FaceReader 9.1 (Noldus, Wageningen, Netherlands), an automated facial expression analysis software. Valence was presented as a continuous variable ranging from -1 (negative, unpleasant emotions) to +1 (positive, pleasant emotions) at intervals of 1/10th of a second (Loijens & Krips, 2021). Widely regarded as a reliable tool for identifying basic emotions, this software has been extensively applied in studies on digital interfaces (Lewinski et al., 2014). Sessions were recorded via MediaRecorder 6 (Noldus, Wageningen, Netherlands) using a high-definition camera to supplement the facial expression analysis.

Arousal was assessed using electrodermal activity (EDA), recorded through BIOPAC's MP-150 system (BIOPAC, Goleta, USA) and analyzed with AcqKnowledge software (BIOPAC, Goleta, USA). EDA sensors were attached to participants' non-dominant hands, stabilized with medical tape and a compression glove to ensure accurate, continuous measurements throughout the session. The phasic EDA measure provided reliable insights into arousal levels, ranging from calm to highly aroused states (Maia & Furtado, 2016).

Eye movements and pupil diameter were captured using a Tobii Pro Nano eye tracker (60Hz, Tobii AB, Stockholm, Sweden) mounted on the monitor. Participants were seated 65 cm away to ensure standardized conditions across sessions. The raw data was processed with Tobii Pro Lab (Tobii AB, Stockholm, Sweden), which classified eye movements into distinct types for analysis (Zammarchi et al., 2021). A dual-monitor moderation setup was employed, with one screen mirroring the participants' display and the other managing the eye-tracking software for real-time monitoring.

Synchronization of psychophysiological data was achieved using an indirect approach (Courtemanche et al., 2018) that employed the SyncBox and The Observer XT 11 solution (Noldus Information Technology BV, Wageningen, Netherlands). Periodic signals were sent to all data collection tools to harmonize recordings into a unified timeline (Zimmerman et al., 2008). This synchronization was further refined during post-processing using the Cobalt Photobooth solution (Léger et al., 2019).

To measure user satisfaction, we utilized two psychometric scales. The Computer System Usability Questionnaire (CSUQ;Lewis,1995) initially included 19 items rated on a 7-point Likert scale (1 = "strongly disagree," 7 = "strongly agree"). To align with the project's industrial partner's requirements, the overall satisfaction item was removed, and the Customer Satisfaction Score (CSAT;Farris et al., 2010) was incorporated instead. The remaining 18 CSUQ items, which assess system usefulness ($\alpha = .96$), information quality ($\alpha = .91$), and interface quality ($\alpha = .91$), were retained without modification. These dimensions provided a robust framework for assessing user satisfaction. See Annexe A for the complete scale items.

Task performance was measured by systematically documenting all potential workflows required to complete the assigned tasks across the three systems. Each workflow was divided into distinct steps, with multiple pathways identified for each system. The "number of steps" represented the sequential actions completed by participants while navigating the system, reflecting the system's intuitive design and the participants' ability to discover and utilize features effectively. This metric served as a valid indicator of system discoverability. To ensure comparability, workflows were divided into three significant phases of task completion. This structured approach highlighted differences in discoverability by capturing variability in task performance across systems. A greater number of completed steps signified deeper exploration and understanding of the system. Each step represented progress toward the task objective, underscoring the system's discoverability. This consistent and transparent framework aligned the "number of steps" measure with the study's objectives, providing a robust foundation for evaluating task performance and interface usability.

2.4.5 Data Analysis

We employed advanced statistical techniques using R and SAS software to address the research hypotheses, ensuring a robust and comprehensive analysis. A repeated measures causal mediation analysis was conducted in R using bootstrapping methods within the mediation package (Tingley et al., 2014). This allowed us to estimate confidence intervals for the indirect effects of the independent variable on the dependent variables through mediators such as visual attention, cognitive load, and emotional responses. Furthermore, we utilized a linear mixed-effects model, implemented with the lme4 package in R (Version 4.1.0) to analyze the nested structure of repeated measures collected from participants (Bates et al., 2015). Random intercepts were included to account for inter-individual variability

SAS (Version 4.3) was used for hypothesis testing and descriptive analyses. Descriptive statistics, such as means, standard deviations, and counts, were calculated for all variables across the three ERP systems to summarize the data comprehensively. Linear regression models were then employed to examine direct relationships between system discoverability and user outcomes, including performance and satisfaction, and associations between mediators such as fixation count and pupil size and these dependent variables. This step was essential to identify the intermediary pathways that influence user outcomes.

In predicting task performance, cumulative logistic regressions were performed to analyze ordinal and non-linear data, such as fixation and saccade counts. Log transformations were applied for skewed variables, such as electrodermal activity to stabilize variance and meet normality assumptions required for regression analysis. To ensure the validity of all statistical models, residual and diagnostic plots were systematically reviewed, and multicollinearity checks confirmed that independent variables were not overly correlated. Additionally, random intercepts were incorporated to address the hierarchical nature of the data, capturing variability at the participant level.

The explanatory power, R^2, was calculated with R^2m representing the marginal R^2 which is the variance explained solely by the fixed factors (HR, flow, and clutch), and R^2c representing the conditional R^2c which is the variance explained by both fixed and random factors (Nakagawa and Schielzeth, 2013).

2.5 Results

2.5.1 Manipulation check

Before the commencement of the study, a manipulation check was conducted to ensure the validity of the experimental conditions. To evaluate the discoverability of each system, an ANOVA was employed, focusing on the ranking provided by the experts. A system with high discoverability was expected to rank higher, reflecting its ease of use, interface quality, and overall utility (Cardello, 2014; Mackamul, 2023; Moss, 2011). As illustrated in Figure 2, the analysis did not reveal a statistically significant difference (p=.36) among the systems. Despite the lack of significance, there is a noticeable, albeit slight, variation in discoverability levels across the systems.

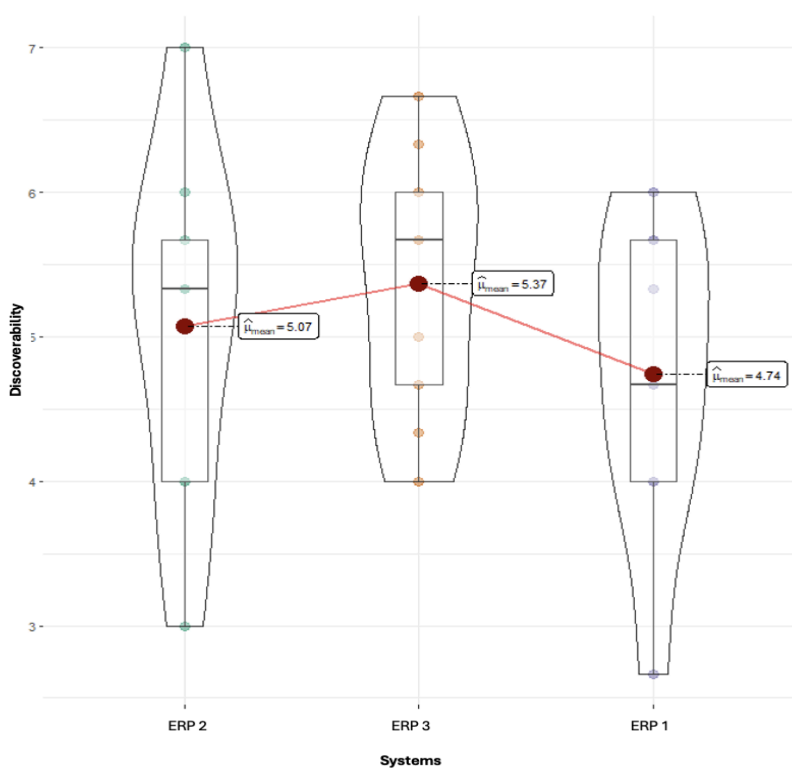

Figure 3. Discoverability Ranking According to Experts

2.5.2 Descriptive statistics

Table 3 shows the descriptive statistics for all measured variables in the three ERP systems. It measures user satisfaction, task performance, cognitive load, emotional responses, visual attention, and the system's means and standard deviations. In addition, the table includes the number of data points (n) gathered for each variable.

Table 3
Summary of Descriptive Statistics

Variable	ERP 1		ERP 2		ERP 3	
	n	*M ± SD*	n	*M ± SD*	n	*M ± SD*
CSAT	59	2.68 ± 1.44	58	3.88 ± 1.72	56	4.70 ± 1.64
CSUQ	59	2.76 ± 1.15	58	3.81 ± 1.28	56	4.55 ± 1.46
Number of steps	60	0.90 ± 0.99	60	1.55 ± 0.77	57	2.49 ± 0.78
Pupil Mean	58	0.01 ± 0.05	58	-0.3 ± 0.05	56	0.04 ± 0.78
Valence Mean	57	-0.10 ± 0.16	58	-0.9 ± 0.15	56	-0.10 ± 0.15
EDA Mean	56	0.23 ± 0.31	54	0.21 ± 0.33	52	0.14 ± 0.13
K Coefficient Mean	58	0.07 ± 0.17	58	0.11 ± 0.19	56	0.07 ± 0.16
Average Fixation Duration	60	288.53 ± 36.79	59	303.92 ± 37.85	58	306.78 ± 39.65
Fixations Count	59	815.47 ± 132.04	58	705.45 ± 203.50	58	440.98 ± 240.28
Saccades Count	60	726.28 ± 131.05	59	639.90 ± 183.83	58	396.97 ± 220.22
Average Saccade Amplitude	60	3.89 ± 0.53	59	3.99 ± 0.51	58	3.93 ± 0.64

2.5.3 Hypothesis testing

Since our hypotheses focused on mediation analysis, we first examined the direct effects to determine if significant results were present. In order to ensure that our study had appropriate statistical power to identify significant effects, we ran an a priori power analysis using G*Power 3.1 (Faul et al., 2009). Based on a linear multiple regression model with four predictors, a medium effect size ($f^2 = 0.15$), an alpha level of 0.05, and a statistical power of 0.95, the study revealed a required minimum sample size of 129 participants. Given our final sample size of 86 people, our study was slightly underpowered, which may have altered the detection of certain effects, particularly in the mediation analysis. However, the observed power remained strong enough to detect moderate to significant effects in the direct correlations between discoverability, visual attention, and performance measures. Only after confirming significant direct effects did we proceed with the mediation analysis. Table 4 presents the direct effects of ERP discoverability levels on the variables measured, as illustrated in Figure 4. Table 5 highlights the direct effects of the mediators on the dependent variables, also depicted in Figure 4. Finally,

Table 6 outlines the indirect effects, focusing solely on variables that demonstrated significant results in the direct effects analysis.

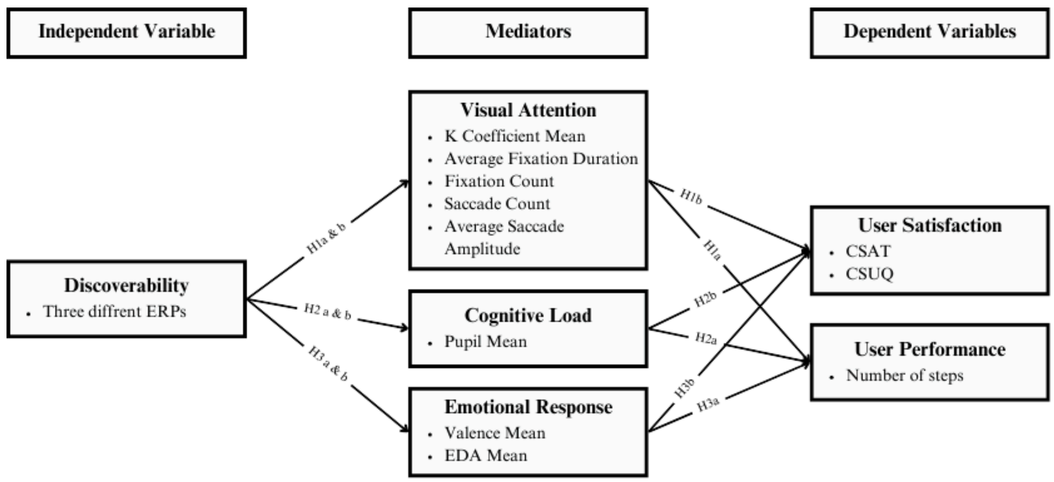

Figure 4. Constructs and Measures Overview

2.5.3.1 Visual Attention

A series of linear regressions were conducted to evaluate the direct effects of discoverability on the visual attention measures depicted in Figure 4. The results, summarized in Table 4, reveal significant differences between groups in the number of user saccades during the task as direct effects. The pairwise comparison revealed that ERP 1 produced significantly more saccades than ERP 3 ($\beta = 319.93$, $t(89) = 9.98$, $p<.0001$) and ERP 2 ($\beta = 245.66$, $t(89) = 7.68$, $p<.0001$). Additionally, ERP 2 prompted more saccades than ERP 3 ($\beta = 74.28$, $t(89) = 2.34$, $p=.0218$). Specifically, there were more saccades for ERP 1 ($M = 726.28$, $SD = 131.05$) than ERP 2 ($M = 639.90$, $SD = 183.83$, $p=.01$) and than ERP 3 ($M = 396.97$, $SD = 220.22$, $p<.001$), and ERP 2 had more saccades than ERP 3 ($p<.001$).

Similarly, as shown in Table 4, a significant difference was observed across groups in the number of user fixations. Pairwise comparisons further indicated that ERP 1 produced significantly more fixations than ERP 3 ($\beta=365.87$, $t(88)=10.38$, $p<.0001$) and ERP 2 ($\beta=98.32$, $t(88)=2.79$, $p=.006$). ERP 2 also resulted in more fixations compared to ERP 3 ($\beta=267.56$, $t(88)=7.60$, $p<.0001$). Specifically, ERP 1 ($M = 815.47$, $SD = 132.04$) had more fixations than ERP 2 ($M=705.45$, $SD =203.50$, $p=.003$) and ERP 3 ($M=440.98$, $SD =240.28$, $p<.001$). ERP 2 had more fixations than ERP 3 ($p<.001$). However, no significant differences were found across groups in the mean fixation duration. Additionally, analyses of the k coefficient and average saccade amplitude showed no significant differences between the groups.

H1a: Mediation of visual attention on performance

A cumulative logistic regression was conducted to evaluate the direct effects of visual attention measures—namely, average fixation duration, fixation count, saccade count, k coefficient, and saccade amplitude—on task performance, measured by the number of steps accomplished. As presented in Table 5, only fixation count (β=0.0055, $t(86)$=6.04, p<.001) and saccade count (β=0.0060, $t(87)$=6.05, p<.001) demonstrated significant differences, indicating their direct influence on task performance. Conversely, no significant direct effects were found for average fixation duration (p=.876), k coefficient (p=.260), or average saccade amplitude (p=.257).

Subsequently, a mediation analysis was performed to assess the indirect effects of visual attention measures. As shown in Table 6, the analysis revealed a highly significant causal mediation effect of fixation count and saccade count, indicating their role as partial mediators between the varying levels of discoverability and the number of steps accomplished. The analysis revealed significant average causal mediation effects (ACME) for both fixation count and saccade count across all pairwise system comparisons. Specifically, fixation count mediated 36.2% of the total effect for ERP 3 vs. ERP 2 (*ACME*=-0.329, p<.001), 17.4% for ERP 2 vs. ERP 1 (*ACME*=-0.126, p=.003), and 28.1% for ERP 3 vs. ERP 1 (*ACME*=-0.457, p<.001). Similarly, saccade count mediated 36.1% of the total effect for ERP 3 vs. ERP 2 (*ACME*=-0.336, p<.001), 14.9% for ERP 2 vs. ERP 1 (*ACME*=-0.105, p=.013), and 27.7% for ERP 3 vs. ERP 1 (ACME=-0.443, p<.001). Finally, in order to quantify the strength of these mediations, we also examined the fit of the model. For task performance, the model's explanatory power was substantial, with R^2c = 0.54, and R^2m 0.42 for fixation count (AIC = 453.56, BIC = 472.51). Similarly, for the saccade count, the model explained R^2c = p.54 of the total variance, and R^2m = 0.43 of the variance under fixed effects (AIC = 456.13, BIC = 457.15). Hypothesis H1a is supported.

H1b: Mediation of visual attention on satisfaction

A linear regression was used to examine the direct effects between the visual metrics of the average fixation duration, the fixation count, the saccade count, the k coefficient means and the saccade amplitude and the satisfaction, measured by the psychometric measure of the CSAT. As shown in Table 5, fixation count (β=-0.0042, $t(84)$=-9.08, p<.001) and saccade count (β=-0.0045, $t(85)$=-8.64, p<.001) were the only metrics with significant direct effects on CSAT scores. Average fixation duration (p=.713), k coefficient mean (p=.809), and average saccade amplitude (p=.678) did not show any significant relationships with satisfaction.

A linear regression was used to examine the direct effects between the same visual metrics and the satisfaction, measured by CSUQ scores. As shown in Table 5, only the fixation count (β=-0.0036, $t(84)$=-9.6, p<.001) and the saccade count (β=-0.0037, $t(85)$=-8.94, p<.001) again demonstrated significant direct effects, whereas average fixation duration (p=.894), k coefficient mean (p=.65), and saccade amplitude (p=.62) remained non-significant.

As shown in Table 6, the mediation analysis showed a highly significant causal mediation effect of fixation and saccades as a partial mediator between the different levels of discoverability and psychometrics measures used to measure the user's satisfaction. For the indirect effects on the CSAT scores, the mediation analysis showed that the fixation count mediated 43.8% of the total effect for ERP 3 vs. ERP 2 (*ACME*=-0.692, p<.001), 9.4% for ERP 2 vs. ERP 1 (*ACME*=-0.2829, p=.013), and 27.6% for ERP 3 vs. ERP 1 (*ACME*=-0.976, p<.001). Saccade count also showed significant mediation effects, accounting for 54.4% of the total effect for ERP 3 vs. ERP 2 (*ACME*=-0.8579, p<.001), 6.3% for ERP 2 vs. ERP 1 (*ACME*=-0.292, p=.008), and 34.2% for ERP 3 vs. ERP 1 (*ACME*=-1.134, p<.001). Similarly, the mediation analysis conducted on the CSUQ scores showed that the fixation count mediated 36.2% of the total effect for ERP 3 vs. ERP 2 (*ACME*=-0.9138, p<.001), 11.2% for ERP 2 vs. ERP 1 (*ACME*=-0.377, p=.001), and 40% for ERP 3 vs. ERP 1 (*ACME*=-1.284, p<.001). Saccade count also demonstrated significant mediation effects, accounting for 54.6% of the total effect for ERP 3 vs. ERP 2 (*ACME*=-0.8579, p<.001), 11.2% for ERP 2 vs. ERP 1 (*ACME*=-0.292, p=.008), and 34.2% for ERP 3 vs. ERP 1 (*ACME*=-1.134, p<.001). Finally, in order to quantify the strength of these mediations, we examined the fit of the model. First, for CSAT, the model's explanatory power was moderate, with R^2c = 0.45, and R^2m = 0.36 for the number of fixations (AIC = 637.98, BIC = 656.80). Similarly, for the number of saccades, the model explained R^2c = 0.43 of the total variance, and $R^2m = 0.35$ for the variance under fixed effects (AIC = 646.71, BIC = 665.60). For the CSUQ, the number of fixations explained $R^2c = 0.60$ of the total variance, and $R^2m = 0.38$ of the variance under fixed effects (AIC = 562.51, BIC = 581.32). Similarly, the number of saccades explains $R^2c = 0.58$ of the total variance, and $R^2m = 0.37$ of the variance under fixed effects (AIC = 571.52, BIC = 590.41). Hypothesis H1b is supported.

Table 4

Pairwise comparisons of Key Metrics across Three Systems

Variables	ERP 2 vs ERP 3			ERP 2 vs ERP 1			ERP 3 vs ERP 1		
	b ± SD	*CI**	*p*	b ± SD	*CI**	*p*	B ± SD	*CI**	*p*
CSAT	-0.98 ± 0.35	[-1.55, -0.09]	.004	1.11 ± 0.34	[0.48, 1.92]	<.001	2.09 ± 0.35	[1.29, 2.75]	<.001
CSUQ	-0.93 ± 0.24	[-1.35, -0.28]	<.001	1.04 ± 0.24	[0.53, 1.58]	<.001	1.97 ± 0.24	[1.33, 2.40]	<.001
Number of steps	2.31 ± 0.44	[1.43, 3.19]	<.001	-1.84 ± 0.42	[1.01, 2.68]	<.001	-4.15 ± 0.57	[3.02, 5.29]	<.001
Pupil Size Mean	-0.08 ± 0.02	[-0.09, -0.04]	.999	-0.05 ± 0.01	[-0.06, -0.01]	<.001	0.03 ± 0.01	[0.004, 0.05]	.997
Average Fixation Duration	-0.001 ± 5.44	[-13.80, 11.55]	.585	13.44 ± 5.39	[0.79, 25.97]	.988	13.44 ± 5.5	[1.71, 27.29]	.990
Valence Mean	0.004 ± 0.01	[-0.02, 0.03]	.5	-0.0002 ± 0.01	[-0.03, 0.03]	.5	-0.004 ± 0.01	[-0.03, 0.03]	.5
EDA Mean	0.02 ± -.21	[-0.37, 0.63|	.5	-0.05 ± 0.21	[-0.62, 0.37]	.5	-0.07 ± 0.21	[-0.75, 0.25]	.669
Saccades Count	253.06 ± 36.04	[167.61, 323.71]	<.001	-42.42 ± 35.73	[-151.87, 3.32]	.01	-295.48 ± 36.57	[-398.14, -241.72]	<.001
Fixations Count	280.07 ± 40.24	[181.6, 353.52]	<.001	-60.69 ± 40.24	[-184.19, 12.44]	.003	-340.76 ± 40.83	[451.93, -279.82]	<.001
K coefficient Mean	0.08 ± 0.041	[-0.03, 0.13]	.794	0.07 ± 0.040	[-0.03, 1.13]	.205	-0.007 ± 0.04	[-0.08, 0.08]	.520
Average Saccade Amplitude	0.03 ± 0.08	[-0.16, 0.23]	.5	0.08 ± 0.08	[-0.12, 0.27]	.5	0.04 ± 0.08	[-0.15, 0.24]	.5

Notes. CI*: [lower, upper]

2.5.3.2 Cognitive Load

A linear regression was used to examine the direct effect of the system difference on users' average pupil size. As shown in Table 4, there is a significant difference between ERP 2 (M = -0.3, SD = 0.05) and ERP 1(M =0.01, SD = 0.05, p<.001) the systems when compared, but there was not a statistically significant difference between ERP 2 (M = -0.3, SD = 0.05) and ERP 3 (M =0.04, SD = 0.78, p=.999), and ERP 3 (M=0.04, SD = 0.78) and ERP 1(M =0.01, SD = 0.05, p=.997). Pairwise comparisons revealed that the significant effect was driven by ERP 1 having significantly smaller pupil sizes than ERP 2 (β=-0.037, $t(87)$=-3.78, p<.001). In contrast, ERP 2 and ERP 3, as well as ERP 3 and ERP 1, did not differ significantly (p=.999 and p=.997, respectively).

H2a: Mediation of cognitive load on performance

A cumulative logistic regression was used to examine the direct effect of the pupil mean and the number of steps accomplished in the tasks. As shown in Table 5, the effect was not significant (β=-5.75, $t(86)=-2.36$, $p=.990$). Due to the lack of significance in the direct effect of both relationships, a mediation analysis was not conducted. Hypothesis H2a is not supported.

H2b: Mediation of cognitive load on satisfaction

Two linear regressions were conducted to examine the direct effect of the pupil mean on user satisfaction, measured by the psychometric scores of CSAT and CSUQ. For CSAT, the regression analysis showed no significant effect of the pupil mean on satisfaction (β=0.54, $t(83)=0.23$, $p=.591$). Similarly, for CSUQ, the regression analysis also revealed no significant effect (β=0.74, $t(83)=0.39$, $p=.652$). Due to the lack of significant direct effects, a mediation analysis was not performed. Hypothesis H2b is not supported.

Table 5

Pairwise comparisons of Psychophysiological and Behavioral Metrics

Variables	CSAT			CSUQ			Number of steps		
	b ± SD	*CI**	*p*	b ± SD	*CI**	*p*	b ± SD	*CI**	*p*
Pupil Mean	0.54 ± 2.35	[-4.14, 5.22]	.590	0.74 ± 1.90	[-3.04, 4.53]	.651	-5.75 ± 2.44	[-10.59, -0.91]	.990
Average Fixation Duration	0.002 ± 0.004	[0.005, 0.009]	.713	0..004 ± 0.003	[-0.002, 0.01]	.894	-0.004 ± 0.003	[-0.01, -0.002]	.876
Valence Mean	-1.29 ± 0.94	[-3.15, 0.57]	.915	-1.29 ± 0.94	[-2.98, 0.13]	.964	2.06 ± 0.92	[-0.23, 3.89]	.986
EDA Mean	0.001 ± 0.12	[-0.23, 0.23]	.490	0.06 ± 0.10	[-0.13, 0.26]	.254	0.10 ± 0.10	[-0.11, 0.31]	.833
Saccades Count	-0.005 ± 0.001	[-0.005, -0.003]	<.001	-0.004 ± 0.000	[-0.004, -0.003]	<.001	0.006 ± 0.001	[0.004, 0.008]	<.001
Fixations Count	-0.004 ± 0.001	[-0.005, -0.003]	<.001	-0.004 ± 0.000	[-0.004, -0.003]	<.001	0.006 ± 0.001	[0.004, 0.007]	<.001
K coefficient Mean	-0.68 ± 0.77	[-2.23, 0.86]	.809	-0.25 ± 0.64	[-1.52, 1.02]	.653	-0.50 ± 0.77	[-2.03, 1.03]	.260
Average Saccade Amplitude	0.11 ± 0.25	[-0.37, 0.60]	.678	0.06 ± 0.21	[-0.35, 0.47]	.617	-0.23 ± 0.25	[-0.72, 0.27]	.257

Notes. CI*: [lower, upper]

2.5.3.3 Emotional Response

A linear regression was used to examine the direct effect of the various levels of discoverability on the valence mean. As shown in Table 4, there is no significant difference across groups. Pairwise comparisons using the one-tail p-values revealed no significant differences between ERP 2 and ERP 3 (*p*=.5), ERP 2 and ERP 1(*p*=.5), or ERP 3 and ERP 1 (*p*=.5). For the electrodermal activity, a log transformation was performed to stabilize variance and make the data more normally distributed. Then, a linear regression was used to examine the data. As shown in Table 4, there is no significant difference across groups. Pairwise comparisons using one-tail p-values also revealed no significant differences between ERP 2 and ERP 3 (*p*=.5), ERP 2 and ERP 1 (*p*=.5), or ERP 3 and ERP 1 (*p*=.669).

H3a: Mediation of emotional response on performance

A cumulative logistic regression was conducted to examine the direct effect of valence mean on the number of steps accomplished in the tasks. As shown in Table 5, there was no significant effect (β=2.06, *t*(85)=2.24, *p*=.986). Similarly, a cumulative logistic regression was conducted to examine the direct effect of the electrodermal activity (EDA) mean, measured as log-transformed phasic activity, on the number of steps accomplished. The analysis also revealed no significant effect (β=0.102, *t*(80)=0.97, *p*=.833). Due to the lack of significant direct effects for both valence mean and EDA, a mediation analysis was not conducted. Hypothesis H3a is not supported.

H3b: Mediation of emotional response on satisfaction

Two linear regressions were conducted to examine the direct effects of valence mean and electrodermal activity (EDA) mean on user satisfaction, as measured by CSAT and CSUQ scores. As shown in Table 5, for CSAT, neither valence mean (β=-1.29, *t*(82)=-1.38, *p*=.915) nor log-transformed EDA mean (β=0.00067, *t*(77)=0.01, *p*=.490) had a significant effect on satisfaction. Similarly, for CSUQ, neither valence mean (β=-1.42, *t*(82)=-1.82, *p*=.964) nor log-transformed EDA mean (β=0.0644, *t*(77)=0.66, *p*.254) demonstrated significant effects. Due to the lack of significant direct effects for both valence mean and EDA mean on satisfaction, a mediation analysis was not conducted. Hypothesis H3b is not supported.

Table 6

Summary of the mediation analysis

	Mediator	Fixation Count		Saccade Count	
IV	**DV**	*b [CI]*	*p*	*b [CI]*	*p*
ERP 2 vs ERP 3	**CSAT**	1.07 [0.57, 3.06]	< .0001	1.03 [0.54, 2.84]	< .0001
	CSUQ	0.306 [0.11, 0.6]	< .0001	0.79 [0.44, 1.7]	< .0001
	Number of steps	0.36 [0.17, 0.62]	< .0001	0.36 [0.18, 0.63]	< .0001
ERP 2 vs ERP 1	**CSAT**	0.31 [0.11, 0.6]	0.001	0.24 [0.06, 0.51]	0.008
	CSUQ	0.26 [0.09, 0.46]	0.002	0.19 [0.05, 0.39]	0.013
	Number of steps	0.17 [0.05, 0.37]	0.003	0.15 [0.03, 0.34]	0.013
ERP 3 vs ERP 1	**CSAT**	0.63 [0.4, 0.95]	< .0001	0.56 [0.34, 0.84]	< .0001
	CSUQ	0.51 [0.33, 0.74]	< .0001	0.46 [0.28, 0.68]	< .0001
	Number of steps	0.28 [0.14, 0.45]	< .0001	0.28 [0.13, 0.43]	< .0001

Note. Sample size between 157 and 177; simulations 2000

The results reveal that, despite the mediators not exhibiting full mediation effects, discoverability demonstrated a significant direct effect on both user performance and satisfaction. A cumulative regression analysis was used to examine the direct effect of different levels of discoverbility on performance measured by the number of steps. As shown in Table 4, the number of steps accomplished by users is a significant predictor of system discoverability across groups. Specifically, pairwise comparisons revealed that ERP 2 resulted in significantly fewer steps completed compared to ERP 3 (β=2.31, $t(87)$=5.24, p<.0001), and ERP 1 required significantly more steps than both ERP 2 (β=1.84, $t(87)$=4.39, p<.0001) and ERP 3 (β=4.15, $t(87)$=7.26, p<.0001). A linear regression was performed to measure the direct effect of the different systems on the user's satisfaction, which was assessed using the psychometric measure of the CSAT and the CSUQ. Pairwise comparisons indicated that satisfaction scores of the CSAT were significantly higher for ERP 3 compared to ERP 2 (β=0.82, $t(85)$=2.75, p=.0037), for ERP 1 compared to ERP 3 (β=2.02, $t(85)$=6.79, p<.0001), and for ERP 1 compared to ERP 2 (β=1.20, $t(85)$=4.07, p<.0001). Pairwise comparisons revealed that satisfaction CSUQ scores were significantly higher for ERP 3 compared to ERP 2 (β=0.81, $t(85)$=3.71, p=.0002), for ERP 1 compared to ERP 3 (β=1.87, $t(85)$=8.52, p<.0001), and for ERP 1 compared to ERP 2 (β=1.05, $t(85)$=4.88, p<.0001). As shown in Table 4, there is a significant difference across groups regarding satisfaction. Table 7 summarizes the main findings for each hypothesis tested in the study.

Table 7

Summary of main findings

Hypothesis		Finding
H1a	Focused visual attention mediates the positive effect of the high level of discoverability on task performance.	Supported
H1b	Focused visual attention mediates the positive effect of the high level of discoverability on user satisfaction.	Supported
H2a	Reduced cognitive load mediates the positive effect of high level of discoverability on task performance.	Not supported
H2b	Reduced cognitive load mediates the positive effect of high level of discoverability on user experience.	Not supported
H3a	Positive emotional responses mediate the positive effect of the high level of discoverability on task performance.	Not supported
H3b	Positive emotional responses mediate the positive effect of the high level of discoverability on user experience.	Not supported

2.6 Discussion

We aimed to examine how enterprise systems' discoverability influences user satisfaction and performance by exploring how visual attention, cognitive load, and emotions influence and mediate these relationships. Indeed, the results confirm that discoverability significantly impacts user satisfaction and performance. Still, the findings point to nuances in its differentiated impact according to the variables examined.

Firstly, our results show that the discoverability of systems significantly influences user performance. The system with the best discoverability enabled users to progress further through their task workflow, defined here as the sequence of logical steps required to complete a given task, and complete more steps, indicating improved performance. Designed to offer good discoverability, the system helped participants reduce navigation errors by enabling them to find their way more intuitively, thus minimizing unnecessary or incorrect actions that could hamper their performance. Moreover, this result aligns with the literature, which emphasizes that an easy-to-use, intuitive navigation interface promotes users' autonomy, reducing their dependence on technical assistance to accomplish their tasks. These findings corroborate previous research demonstrating that discoverability improves performance in user interfaces, particularly in contexts where users have to perform complex tasks (Mackamul, 2023; McKelvey & Hunt, 2019).

About the indirect impact of discoverability on user satisfaction, the results also indicate a significant effect. Better discoverability thus contributes to a smoother user experience, increasing satisfaction and reducing frustrations associated with finding features and information. By reducing sources of frustration, users can navigate more easily, find functionalities more quickly, and therefore experience less discomfort, which improves their overall perception of the interface. In addition, an intuitive interface makes the system easier to understand and use, giving users a sense of control and mastery. Good discoverability reduces the need for support or additional training, which empowers users and contributes to a more satisfying experience, as they can complete their tasks without interruption. This finding aligns with existing research, which shows that discoverability is a key driver of satisfaction, as it reduces the effort required to navigate the interface (Mackamul, 2023; Norman, 2013).

Increased satisfaction can also encourage user loyalty to the company, as satisfied users are more likely to use the interface continuously and fully adopt its functionalities. This satisfaction can also contribute to better employee retention: high-performing, autonomous and satisfied employees have less reason to look for another job, as they feel in control and valued (Yadav & Vihari, 2023). Moreover, a competent and motivated employee tends to exceed expectations, directly benefiting the company. Indeed, this increases profitability, as the company limits the costs associated with hiring and training a new employee and benefits from a committed and productive workforce (Gheidar & ShamiZanjani, 2020).

The hypotheses concerning visual attention, H1a and H1b, are supported; visual attention acts as a partial mediator between discoverability variability and user performance and satisfaction. In other words, visual attention influences the relationship between these variables. Thus, an interface with high discoverability guides the user's attention to relevant elements and intuitively facilitates navigation to necessary options and information without unnecessarily prolonging the visual path. This result aligns with the literature on discoverability and affordance theory (Norman, 2013), according to which affordances enable users to instinctively understand what can be done in the interface through signifiers without explicit instructions (Norman, 2013). This underlines the importance of compelling visual elements in capturing attention and enhancing the discoverability of the platform. By incorporating clear visual elements, the interface reduces unnecessary visual exploration, minimizing the dispersion of attention on non-essential elements.

This result is consistent with the Guided Search Theory (Wolfe, 1994), which proposes that well-placed visual cues help guide attention to key elements. This theory postulates that visual attention is directed by an interplay between bottom-up processes (based on stimulus characteristics) and top-down processes (based on user expectations). In other words, the visual elements of an interface actively guide users' attention, both by what they spontaneously perceive and actively seek.

Bottom-up processes are triggered by salient or attractive visual signifiers, such as brightly coloured buttons, icons or highlighted titles (Guo et al., 2016). These elements act as affordances or visual “leads,” automatically attracting attention without the user needing to search actively. In this way, a well-designed interface with high discoverability highlights essential elements so that they stand out naturally (Joseph & Murugesh, 2020). For example, a high-contrast main action button immediately grabs attention, allowing users to intuitively know where to click based on their experience and expectations. The top-down process, on the other hand, is based on the user's expectations and prior experience. It enables users to anticipate where to find certain functionalities and to process visual information more quickly. The interaction between these two processes optimizes navigation and visual search efficiency in a well-designed interface (Matzen et al., 2016). Visual attention is effectively directed when critical visual elements are prominent (bottom-up) and placed in expected locations (top-down). Discoverability plays a key role in facilitating this synergy, as a system with good discoverability enables users to rely on visual cues and expectations to navigate effectively, reducing cognitive load and improving performance and satisfaction.

The results also show a significant relationship between the number of fixations and satisfaction, with a higher number associated with increased satisfaction (Guo et al., 2016). However, many fixations may indicate a less efficient search, as the user must examine several areas to find the desired information (Poole & Ball, 2006). This highlights the trade-off between satisfaction and efficiency: a highly satisfactory interface may encourage users to explore further, but it may also lengthen search time. Similarly, the number of saccades showed significant differences, indicating increased visual scanning when discoverability was high (Poole & Ball, 2006). This reflects active visual search behaviour where users scan the interface more extensively, probably to check multiple options or information quickly.

In contrast, saccade amplitudes showed no significant difference. A wider saccade amplitude is generally associated with detecting more significant visual signals, attracting attention from a distance (Poole & Ball, 2006). In this case, participants' proximity to the screen could explain the lack of a significant difference. Users are less likely to make large saccades with a reduced interface size, as the visual search space is restricted.

By mediating the impact of discoverability on performance, visual attention enables users to quickly locate the information and actions they need to accomplish their tasks, thus improving their efficiency. An interface that effectively guides attention reduces navigation errors, as users find the required elements more precisely and avoid incorrect actions. This increases their performance as they complete their tasks more successfully. By focusing users' attention on essential elements, the interface also reduces the cognitive load associated with information retrieval, freeing up mental resources for the task. In other words, the interface is not limited to mere technical support but plays an active role in users' performance by facilitating their attentional processes.

Concerning the mediation of visual attention on satisfaction, an interface with good discoverability enables users to find what is relevant quickly, thus reducing frustration linked to difficult navigation or hidden elements. Users appreciate the interface more and perceive their experience as less demanding and stressful. A well-designed interface promotes smooth, intuitive navigation, helping users to understand the interface better and feel more autonomous, as they can complete their tasks more quickly and efficiently. The mediation of visual attention shows that users are more satisfied with a system that meets their visual expectations and makes essential information easily accessible (Matzen et al., 2016). When attention is well directed, satisfaction naturally increases, as users do not feel as if they are “struggling” to accomplish their tasks. These results indicate that designers should prioritize discoverability in interface design, optimizing visual elements to guide attention. This improves performance and user satisfaction, as they feel supported and valued in their interaction with the system.

Although the results show a significant effect of discoverability on improved performance and satisfaction, it has no significant direct impact on cognitive load. Although improved discoverability facilitates navigation, it does not necessarily alleviate the cognitive complexity perceived by users when accomplishing tasks. Average fixation time, often associated with information retrieval difficulty (Poole & Ball, 2006), was not significantly affected by variations in system discoverability. This suggests that, although users navigate more efficiently, they must mobilize cognitive resources to interpret or process task-specific information, irrespective of interface accessibility. Cognitive load, therefore, is influenced by other factors, notably the intrinsic complexity of tasks or the nature of the content to be processed, rather than by discoverability alone. High-discoverability interfaces facilitate navigation but do not necessarily reduce the tasks' complexity. Similarly, measuring cognitive load by pupil size did not reveal any significant difference. This could indicate that, even with high discoverability, users expend sustained mental effort to accomplish complex tasks, as this effort is more related to information processing than localization.

The fact that cognitive load does not mediate between discoverability, performance and satisfaction suggests that, even if users find features more efficiently, more than this is needed to reduce mental effort to influence their performance or satisfaction directly. This indicates that in this particular context, satisfaction and performance are influenced more by other elements, such as visual attention, than by cognitive load itself. In complex enterprise systems, cognitive load can remain high even with good discoverability, as users must process multiple pieces of information and make complex decisions. Consequently, while discoverability improves navigation and efficiency, it does not necessarily reduce the mental load associated with strategic or complex tasks.

In a work environment or a controlled laboratory setting, as in this study, users may adopt a relatively neutral emotional posture when interacting with ERP systems. They perceive this interaction as a professional task rather than an engaging or entertaining experience. Therefore, this context limits the impact of discoverability on emotional responses, such as arousal or valence (positive or negative emotions). So, even with improved discoverability of the interface, this does not generate notable changes in valence or arousal among users, who do not feel a strong emotional commitment to this type of interaction. Users are often more focused on processing information and completing tasks, which only sometimes mobilize emotional responses. Electrodermal (EDA) and FaceReader, while effective in measuring emotions in emotionally intense contexts, may also be less sensitive to subtle emotional changes in work environments where emotions remain relatively stable and neutral.

Theoretical contributions

This study contributes to the literature by clarifying and harmonizing existing definitions of discoverability in information systems, thus offering a more nuanced understanding of the concept. Indeed, discoverability has been defined in many ways, according to different levels of analysis: the interface, the user and the task. At the interface level, the concept of discoverability encompasses the ability of users to determine possible actions and the device's current state

(Norman, 2013). From this perspective, discoverability is linked to the visibility of functionalities and the system's recognition as a set of potential interactions (Mackamul, 2023). Researchers have also highlighted the dynamic nature of discoverability, influenced by the platform's interactions with the user and its algorithms (McKelvey & Hunt, 2019). At the user level, discoverability is seen as a means of achieving better learning ability (Furqan et al., 2017) and as an ability to understand an input system or method without the need for explicit guidance (Mackamul, 2023). According to this approach, discoverability is based on users' ability to grasp new functions without experiencing frustration or cognitive overload, thanks to a well-designed interface (Eriksson, 2023). It is also associated with the quality of an interface that enables users to easily find and understand how to use its functionalities (Moss, 2011). Finally, discoverability facilitates the transition from novice to expert behaviour at the task level while enabling smooth navigation between selection modes (Goguey et al., 2018). This dimension highlights the importance of discoverability in allowing the users to understand and execute operations autonomously and efficiently, particularly in complex task contexts.

Cleaning up definitions enriches the conceptual framework of discoverability, highlighting the diversity of levels to which it can be applied. By integrating these different perspectives, our study contributes to a more coherent and precise application of discoverability in ERP systems, enabling a better understanding of user-system interactions in a business context.

Managerial implications

The results of this study highlight the crucial importance of integrating discoverability into enterprise systems from the earliest stages of selection and customization. Intuitive interfaces increase productivity and employee satisfaction while reducing training costs and incorporating new technologies (Furqan et al., 2017). These findings give managers strong arguments for investing in user-centred design approaches to develop and customize enterprise systems that better meet employees' specific needs while aligning them with the organization's strategic objectives. By actively involving employees in the design and customization process, companies can create interfaces tailored to their expectations, strengthening their commitment (Follini, 2017; Tams, 2019).

In addition, the study emphasizes the importance of anticipating training needs based on the discoverability level of the selected systems. Highly discoverable systems require less intensive training and technical support, lowering implementation costs. Conversely, less intuitive systems often require more significant investment in repeated training and ongoing technical support, slowing operational efficiency and decreasing return on investment. By directing users to the key elements of the interface, intuitive and highly discoverable systems reduce the attentional load, enabling employees to focus on their core tasks (Eriksson, 2023). This simplification improves performance, reduces frustration, and delivers a smoother user experience.

Finally, this research highlights the strategic value of investing in highly-discoverable systems during the early stages of a digital transformation process. Companies can ensure a smoother digital transition by optimizing internal processes with systems that intuitively direct users' visual attention and minimize errors (Petter et al., 2008). This helps them maintain a competitive edge in an ever-changing technological environment and maximizes organizational efficiency while improving user satisfaction and performance.

2.7 Limitations & Future Work

Although this study has provided relevant results concerning the role of discoverability in ERP systems, certain limitations must be considered to contextualize these results better and open up perspectives for future research.

Firstly, regarding the measurement of cognitive load by pupillometry, the validity of this measure could have been improved by integrating ambient light control in the experimental room. Indeed, variations in brightness can influence pupil size measurements, making the data less reliable. In the future, it would be essential to add a control variable for light to increase the validity of this measurement, which aligns with experimental standards in NeuroIS.

Furthermore, although we sought to strengthen the ecological validity of the study by using three ERP systems widely available on the market, the laboratory experimental setting needs to be revised. This controlled setting, which minimizes distractions and allows participants to concentrate fully on their tasks, differs significantly from the reality of professional environments. In real-life settings, users are often confronted with unexpected interruptions, time constraints and more complex interactions, which could influence their performance and satisfaction with ERP systems. Thus, future research could include studies conducted directly in professional environments to reflect these dynamics better.

Finally, the generalizability of the results is limited by the profile of the participants, who were novice users. This reduces the scope of conclusions for experienced employees with different expectations and behaviours. For example, an employee with 30 years of experience on an old ERP system might find it more challenging to adapt to a new platform, requiring certain habits to be “unlearned,” unlike a younger employee familiar with various technologies. To increase the external validity and generalizability of the results, future research could include a more diversified sample, considering age, experience and degree of familiarity with ERP systems. Such diversification would capture various behaviours and reactions to discoverability, offering a more comprehensive and nuanced view of user challenges and needs in work environments.

2.8 Conclusion

In conclusion, this study provides strong empirical support for the fundamental role of discoverability in improving performance and user satisfaction in enterprise systems. By demonstrating that high levels of discoverability lead to better performance results and that users are more satisfied when using the platform, our findings thus underline the importance of prioritizing user-centred design in enterprise software development. Furthermore, it confirms that discoverability is broader than the visibility of functionality. It fundamentally shapes the user experience, enabling employees to navigate systems intuitively and perform their tasks more efficiently by highlighting visual attention as a key mediator between discoverability and user outcomes. Well-designed interfaces direct users' gaze to relevant elements, facilitating fluid interaction. In contrast, the anticipated roles of cognitive load and emotional response proved less marked, suggesting that these factors are less influential in professional contexts where emotional engagement is generally neutral.

Theoretically, this study enriches the academic conversation around the discoverability construct by clarifying and harmonizing existing definitions of discoverability in information systems. This work of “cleaning up” definitions helps to situate discoverability as a multidimensional concept applicable at the interface, user, and task levels, thus enriching the academic understanding of this concept. Regarding practical implications, our results provide concrete avenues for designers and managers, particularly in digital transformation. Focusing on discoverability in interfaces reduces integration time, minimizes training needs, and increases employee satisfaction, contributing to higher productivity and lower turnover. In short, companies that invest in highly discoverable systems can benefit from more autonomous and confident employees, promoting better adoption of digital tools and, ultimately, greater organizational efficiency.

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Chapter 3
The Power of Discoverability: How Visual Attention Influences Employees' Performance and Satisfaction[2]

Our study highlights that highly discoverable enterprise systems aid in digital transitions, streamline processes, and boost employee satisfaction. We offer practical recommendations for managers on selecting and customizing systems, stressing user-centred design to maximize ROI.

3.1 Introduction

The enterprise software market is undergoing a metamorphosis as companies increasingly adopt cloud-based enterprise systems, not only because of improved automation and analytics abilities but also due to vendor-imposed deadlines for onsite support and the more general trend toward cloud-based systems' adoption (Leiter et al., 2023). While the transition to new technologies presents challenges, a critical factor that must be addressed is the discoverability of these enterprise systems. Discoverability, or the ease with which users can identify and use a system's functionalities without extensive training, is vital to optimizing employee training and productivity. In a period of rapid change, it becomes crucial to consider the impact that system discoverability will have on employees' learning curve. Systems that are difficult to grasp not only slow down initial productivity but also increase the need for repeated training, integration time and gradual adoption (Sykes et al., 2014). These hidden costs can weigh heavily on a company's resources, affecting user satisfaction and performance (Al-Okaily et al., 2021). Against this backdrop, this article examines the relationship between an enterprise system's level of discoverability and its effects on task performance and user satisfaction. The research question guiding this reflection is:

To what extent does an enterprise system's discoverability level influence task performance and user satisfaction?

Therefore, this article provides practical recommendations for managers and industry professionals to anticipate digital transformation challenges better. By emphasizing the effects of discoverability on operational efficiency, we seek to guide enterprise systems implementation

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strategies and enhance the allocation of necessary resources. Through a thorough understanding of these issues, companies can reduce training costs, promote a smoother transition and, ultimately, increase the satisfaction and performance of their teams in an ever-changing technological environment.

3.2 The Study

This study is based on an approach that combines usability tests, physiological measures of visual attention, and psychometric assessments to analyze the impact of different levels of discoverability on user productivity and satisfaction. For our manipulation, we selected three widely used systems based on an expert evaluation, which assessed their discoverability. Three enterprise systems, using platforms already on the market, were chosen to introduce discoverability variance and strengthen the ecological validity of the study. The first system is a legacy enterprise solution widely used by large companies, recognized for its stability and lasting market presence. The second enterprise is a more recent platform adopted mainly by small and medium-sized enterprises (SMEs), with a shorter market life than the first system. Finally, the third enterprise is a newcomer, a modern solution with recent development and implementation. For the study, we recruited 86 participants via the laboratory panel. Attentional measures were collected using an eye tracker to analyze eye movements and cognitive load. In addition, we assessed participants' emotional valence and the intensity of their emotional reactions when interacting with the systems with physiological instruments.

3.2.1 The Results

The results of our study underline the importance of integrating discoverability into the choice and customization of enterprise systems, particularly during periods of digital transformation. Indeed, they show that enterprise systems with high discoverability reduce the need for intensive training, as there is a reduction in navigation errors, an increase in performance, and higher user satisfaction, all of which are critical factors for successful deployment in a crucial period of digital transformation. As mentioned earlier, enterprise systems with high discoverability allow users to navigate intuitively, which reduces navigation errors since the interface has affordances and signifiers that will enable users to use their past experiences and be visually guided by signifiers to get where they want to go, engaging them in an exploitation mode. In other words, this ease of navigation and use translates into increased user satisfaction, as there are no barriers to overcome or blockages preventing them from completing their task. Moreover, highly discoverable interfaces naturally focus users' attention on the essential elements, thus limiting attentional load. By minimizing visual confusion and simplifying navigation, these interfaces enable users to focus their attentional resources on core tasks, increasing productivity and efficiency. In other words, systems requiring more significant attentional effort will generally require longer integration times, higher training costs, and additional user support. Users will find it harder to get used to them and perform well, as the platforms will only allow them to take necessary paths. They will potentially be less inclined to want to use them, as the system will create confusion and dissatisfaction. In other words, our results show that favouring enterprise systems with high discoverability contributes to a smoother digital transition by improving user efficiency and satisfaction while alleviating users' attentional resources.

3.3 Best Practices & Recommendations

Based on our findings, we offer several practical recommendations to help large and small companies overcome the everyday challenges of implementing enterprise systems, focusing on improving discoverability and user experience.

3.3.1 Choosing a high-discoverability system from the start

As we have seen in the study and the current literature, a highly discoverable interface emphasizes the essential elements. It helps the user be more visually apparent and concentrate on completing tasks without exploring the interface (Eriksson, 2023). Opting for an enterprise system with high discoverability from the outset is a crucial strategy for minimizing integration obstacles and reducing training costs. An intuitive system makes it easier for users to familiarize themselves with and master its use quickly while limiting errors and maintaining high satisfaction (Petter et al., 2008). Indeed, a well-designed interface, with clear signifiers and affordances, guides users effectively, helping them to accomplish their tasks autonomously and reducing their need for ongoing technical assistance (Norman, 2013). By integrating intuitive systems right from the selection phase, companies can accelerate the learning curve and limit repetitive training sessions, thus improving their operational efficiency.

3.3.2 Anticipating training needs according to the level of discoverability of the chosen system

When implementing new enterprise systems, it is essential to assess the system's level of discoverability to anticipate user training needs. Systems with low discoverability often require intensive training sessions and enhanced technical support, while systems with high discoverability can be integrated more seamlessly and require less training (Furqan et al., 2017). This anticipation enables companies to plan appropriate resources and reduce integration costs, facilitating faster, more efficient adoption (Phelan, 2014).

3.3.3 Integrating users into the customization process for user-centered design

Involving users from the earliest stages of system customization and design is an essential best practice for developing interfaces that meet employees' needs. Their active participation in co-creation workshops strengthens their sense of ownership and commitment, fostering faster and longer-lasting adoption of new technology in the organization (Follini, 2017; Tams, 2019). User-centred customization enhances the user experience and maximizes return on investment by reducing training time and increasing employee productivity. By integrating user feedback, companies can design intuitive interfaces that facilitate day-to-day work and improve overall satisfaction.

3.4 Conclusion

In conclusion, our study strongly indicates that prioritizing discoverability from the design stage of enterprise systems is essential for achieving successful digital transformation. This approach not only enhances user experience but also drives overall performance. It unequivocally demonstrates the critical importance of discoverability in designing enterprise systems, especially during digital transformation. An intuitive interface minimizes errors, enhances user satisfaction, and optimizes performance, significantly reducing the need for extensive training and technical support (Furqan et al., 2017). In the long run, selecting a system that prioritizes improved discoverability streamlines internal processes, elevates organizational efficiency, and maximizes return on investment.

Moreover, our findings emphasize the undeniable value of user-centered design. Engaging employees from the customization phase ensures the creation of interfaces perfectly tailored to their needs, facilitating quicker and more effective adoption of new tools (Tams, 2019). Ultimately, organizations must proactively renew their tools and processes to stay competitive and meet increasing performance demands.

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Conclusion

The main research objectives of this thesis were: (1) to analyze the impact of discoverability of enterprise systems on user performance and satisfaction, (2) to explain through which human factors discoverability influences user performance and satisfaction, (3) to untangle and clarify definitions of the discoverability construct, and (4) to provide practical recommendations to support companies during digital transformations. To achieve these objectives, an experimental study was carried out, supplemented by a manipulation check with an independent group of ERP experts, to validate the discoverability variance of the platforms tested. The main study integrated psychophysiological measures (visual attention, cognitive load, and emotional responses) to assess user-system interactions thoroughly. This final section of the thesis will summarize the main results obtained and then explore the theoretical and practical contributions in depth before discussing limitations and suggesting avenues for future research.

4.1 Main Findings

The results of this study, presented in this thesis, help to answer the main research question. In addition, the results either support or do not support the hypotheses, and Table 7 provides a complete summary of the main findings.

Table 7
Summary of main findings

Hypothesis		Finding
H1a	Focused visual attention mediates the positive effect of the high level of discoverability on task performance.	Supported
H1b	Focused visual attention mediates the positive effect of the high level of discoverability on user satisfaction.	Supported
H2a	Reduced cognitive load mediates the positive effect of high level of discoverability on task performance.	Not supported
H2b	Reduced cognitive load mediates the positive effect of high level of discoverability on user experience.	Not supported
H3a	Positive emotional responses mediate the positive effect of the high level of discoverability on task performance.	Not supported
H3b	Positive emotional responses mediate the positive effect of the high level of discoverability on user experience.	Not supported

As illustrated in Table 7 above, the variance in the level of discoverability, i.e. a high level of discoverability, directly affects user performance and satisfaction. In other words, ERP systems with higher discoverability enable users to navigate more intuitively, thus facilitating task completion and improving performance and satisfaction.

Visual attention was the only mediator partially involved in this relationship (H1a & H1b), suggesting that other factors could also play a role in influencing discoverability on user outcomes, given that cognitive load (H2a & H2b) and emotional responses (H3a & H3b) did not mediate this relationship. This indicates that the effect of discoverability on performance and satisfaction is direct but not modulated by these intervening variables. The partial role of visual attention as a mediator reinforces the importance of visual cues in interface interaction, emphasizing that practical visual elements are essential to guide the user. In contrast, hypotheses concerning cognitive load and emotional responses were not significantly supported, suggesting that these aspects may be influenced by external factors not considered in this study.

4.2 Theoretical Contributions

This study makes a significant contribution to the literature on discoverability in the field of information systems by clarifying and harmonizing definitions already existing in the scientific literature. Indeed, the concept has often been defined in different ways. Our study has enabled us to “clean up” these definitions by organizing them according to three levels of analysis: interface, user, and task, thus facilitating the application of the concept in various contexts.

At the interface level, discoverability encompasses users' ability to identify possible actions and understand the system's state (Norman, 2013). Similarly, the construct is closely linked to the visibility of functionality and recognition of the system as a set of potential interactions (Mackamul, 2022). This level of analysis highlights the importance of visual signifiers and affordances in guiding the user (Norman, 2013).

At the user level, discoverability is a learning skill that enables users to understand a feature or system without explicit instructions (Eriksson, 2023). Indeed, discoverability is based on users' ability to understand new functionality without experiencing cognitive overload, thanks to well-designed interfaces (Moss, 2011). Thus, our study enriches this perspective by illustrating how an intuitive interface facilitates the transition of novice users to expert behaviour since they can perform better.

Finally, discoverability helps users navigate fluidly between different operations at the task level, particularly in complex tasks requiring an in-depth understanding of functionalities (Goguey et al., 2018). This dimension highlights the importance of a well-designed interface that supports the user in autonomously executing tasks, thereby reducing errors and increasing performance.

Furthermore, our study highlights the role of visual attention as a partial mediator between discoverability, performance and user satisfaction. Drawing on Guided Search Theory, we demonstrated that well-positioned visual cues in an interface effectively direct users' attention to essential elements, thereby enhancing the user experience while facilitating task completion.

4.3 Practical Implications

The results of this study have enabled us to offer crucial practical recommendations for companies in times of digital transformation. They highlight the importance of discoverability in selecting, designing, and implementing ERP systems. These implications are aimed at managers and practitioners to guide them in optimizing their processes to maximize their return on investment.

The first recommendation concerns the initial choice of an ERP system. Our results show that an intuitive interface with clear affordances and well-designed signifiers enables users to navigate more easily and adapt quickly to the new platform. It significantly reduces navigation errors, increasing user performance and overall satisfaction (Norman, 2013). Indeed, ERPs offering a high level of discoverability considerably facilitate the digital transition by reducing the costs associated with integration and training (Furqan et al., 2017; Phelan, 2014). Opting for intuitive systems right from the selection phase reduces operational costs associated with ongoing training and accelerates employee adoption of the new tools. In other words, a well-designed system helps minimize the learning curve and promotes better performance from the very first interactions.

When implementing new ERP systems, it is essential to assess the level of discoverability of the chosen systems to plan training needs appropriately. The results of our study show that systems with low discoverability often require intensive training sessions and increased technical support, as users find it more challenging to complete their tasks compared to those using more intuitive systems. This lack of discoverability leads to higher implementation costs and delays in return on investment (Phelan, 2014). Therefore, integrating this assessment early in planning is crucial to anticipate user learning challenges and develop appropriate training programs. For example, less discoverable systems may require additional training modules, ongoing support and long-term learning resources. By taking these needs into account from the outset, companies can reduce the negative impact of these extra costs and ensure a smoother transition to new technologies.

Another key implication from our findings is the importance of involving users from the earliest ERP customization and design stages. Adopting a user-centred design approach is a best practice that maximizes system efficiency and usability. Companies can develop interfaces that meet employees' specific needs by including end-users in co-creation and design thinking workshops, increasing their sense of belonging and commitment (Tams, 2019). A personalized interface, adapted to users' expectations, promotes better appropriation of tools, reduces the need for additional training and limits navigation errors. This collaborative approach also makes it possible to identify and eliminate potential obstacles in the early stages of the project, minimizing resistance to change and accelerating the adoption of the new system. In other words, user-centered design enhances the user experience and helps maximize return on investment by increasing employee productivity and efficiency.

4.4 Limitations and Future Research

Several limitations need to be considered when interpreting this study's results to contextualize them better and guide future research. Firstly, about the measurement of cognitive load via pupillometry, the validity of this measure could have been strengthened by strict control of the ambient light conditions in the experimental room. Variations in brightness can influence pupil size and bias the data collected. In the future, it would be essential to integrate a light control device or perform specific calibrations to guarantee homogeneous conditions throughout the experiment. This would improve data reliability and validity.

In addition, although ecological validity was enhanced by using three ERP systems already available on the market, the study was carried out in the laboratory, limiting its representativeness under natural working conditions. Indeed, in a controlled environment, participants are often more focused, less prone to distractions and have limited time to complete their tasks. This differs from professional contexts, where unexpected interruptions, time constraints and multitasking are commonplace and can affect user performance and interaction with the system. These differences can affect not only users' performance but also their long-term satisfaction with ERP systems. Future studies could be conducted directly in natural work environments to improve ecological validity, offering a better representation of employee challenges and a more nuanced perspective on user-system interaction.

Furthermore, the generalizability of the results is limited by the profile of the participants, composed of novice users recruited through the laboratory panel. This sample homogeneity limits the scope of conclusions for more experienced employees, who may have different expectations and behaviours. For example, an employee with 30 years of experience with an old ERP system might find adaptation to a new platform more complex, requiring an “unlearning” of previous habits, unlike a younger employee who is more flexible and familiar with different technologies. To increase the external validity and generalizability of the results, future research could include a more diverse sample comprising participants of various ages, levels of experience and degrees of familiarity with ERP systems. This diversification would capture a broader range of behaviours and reactions to system discoverability, offering a more comprehensive and nuanced view of the challenges and needs of diverse users in the workplace. In addition, future research could look at comparing behaviours and interactions between users of different levels of experience with systems and comparing the transition from an enterprise system to someone just entering the workforce and someone with a few decades' experience with the same system. It could reveal practical implications for a company's digital transformation and system renewal.

Finally, future research could also explore the impact of discoverability in different contexts, such as collaborative environments or multi-application systems, where users simultaneously navigate between several pieces of software. A longitudinal approach could also provide a better understanding of how discoverability influences user performance and satisfaction over an extended period by observing the evolution of their learning and adaptation to new ERP systems.

Moving forward, the results of this research and the methodology employed should be extended to other contexts and environments. The current research on discoverability focuses mainly on simpler systems, such as mobile applications, or isolated interface elements, leaving a significant gap in understanding its impact on information systems. Our study provides a solid foundation by examining ERP systems but is limited to controlled laboratory conditions and novice users. Extending this research to real-world business environments, where users face interruptions, time constraints and multitasking, could provide a richer and more ecologically valid understanding of discoverability in action.

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Annexe

Annexe A

Table 8

Items for Psychometric Measures

Construct name	Acronym	Measure type	Description	Source Reference
Perceived satisfaction	CSAT	Self-reported	1 item: CSAT_i: Êtes-vous satisfait,e du système utilisé ?	Farris, P, W,, Bendle, N,, Pfeifer, P,, & Reibstein, D, (2010), Marketing Metrics: The Definitive Guide to Measuring Marketing Performance, Pearson Education,
Perceived satisfaction	CSUQ	Self-Reported	18 items: CSUQ_i - Overall, I am satisfied with how easy it is to use this system, CSUQ_ii - It is simple to use this system, CSUQ_iii - I can effectively complete my work using this system, CSUQ_iv - I am able to complete my work quickly using this system, CSUQ_v - I am able to efficiently complete my work using this system, CSUQ_vi - I feel comfortable using this system, CSUQ_vii - It was easy to learn to use this system, CSUQ_viii - I believe I became productive quickly using this system, CSUQ_ix- The system gives error messages that clearly tell me how to fix problems, CSUQ_x - Whenever I make a mistake using the system, I recover easily and quickly, CSUQ_xi - The information (such as on-line help, on-screen messages, and other documentation) provided with this system is clear, CSUQ_xii - It is easy to find the information I need, CSUQ_xiii - The information provided by the system is easy to understand, CSUQ_xiv - The information is effective in helping me complete my work, CSUQ_xv- The organization of information on the system screens is clear, CSUQ_xvi - The interface of this system is pleasant, CSUQ_xvii - I like using the interface of this system, CSUQ_xviii - This system has all the functions and capabilities I expect it to have,	Lewis, J, R, (1995), IBM Computer Usability Satisfaction Questionnaires: Psychometric Evaluation and Instructions for Use, Internationa l Journal of Human‐ Computer Interaction, 7(1), 57-78,