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**Découvrabilité des assistants d'IA dans l'expérience bancaire : une étude sur
la perception visuelle**

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À l'attention de : Pierre-Majorique Léger, HEC Montréal

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Projet # : 2025-6411

Titre du projet de recherche : Perception des changements et découvrabilité de l'intelligence artificielle dans les interfaces bancaires

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Résumé

Dans un contexte où les services bancaires numériques intègrent de plus en plus rapidement des fonctionnalités fondées sur l'intelligence artificielle, il devient essentiel de comprendre non seulement pourquoi les utilisateurs adoptent ces innovations, mais d'abord s'ils parviennent réellement à les percevoir. Ce mémoire examine le rôle de la prédisposition à la cécité au changement dans la détection et la reconnaissance consciente d'une nouvelle fonctionnalité d'IA intégrée à une interface bancaire mobile. Plus précisément, il évalue l'influence de cette prédisposition sur la détection visuelle vécue, la reconnaissance consciente du changement et la charge perceptuelle et cognitive. Cette étude utilise une expérimentation intra-sujets menée en laboratoire auprès de 25 participants. Les données recueillies combinent des mesures oculométriques et psychophysiologiques, des échelles perceptuelles ainsi que des mesures de rappel et de reconnaissance du changement. Les résultats indiquent que la prédisposition à la cécité au changement ne semble pas prédire directement la reconnaissance consciente de la nouveauté ni la majorité des indicateurs de détection visuelle. Toutefois, les participants présentant une plus forte prédisposition rapportent une charge perceptuelle plus faible et manifestent un effort cognitif moindre, suggérant un engagement attentionnel réduit face à l'interface. Une relation inattendue émerge également entre certains indicateurs oculométriques et la reconnaissance : une durée de fixation plus élevée n'est pas associée à une meilleure détection consciente du changement, illustrant le décalage potentiel entre exposition visuelle et prise de conscience. Ce mémoire met en lumière l'écart entre voir et remarquer dans les environnements numériques familiers et montre que l'intégration d'une innovation visible ne garantit pas sa perception consciente. Il invite à repenser les stratégies de conception et d'évaluation de la découvrabilité en intégrant les limites attentionnelles et les différences individuelles dans l'analyse de l'expérience utilisateur.

Mots clés : Cécité au changement, découvrabilité, expérience utilisateur, intelligence artificielle, attention visuelle, interfaces bancaires, processus cognitifs, suivi oculaire, détection du changement.

Méthodes de recherche : Expérience utilisateur, étude expérimentale, suivi oculaire, pupillométrie, mesures psychophysiologiques, questionnaires, mesures de rappel et de reconnaissance

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Liste des abréviations

IA – Intelligence artificielle

UX – Expérience utilisateur (User Experience)

HCI – Interaction humain–ordinateur (Human–Computer Interaction)

FinTech – Technologies financières (Financial Technologies)

TOI – Temps passé sur la zone d'intérêt (Time on Interest area)

AOI – Zone d'intérêt en suivi oculaire (Area of Interest)

Avant-propos

Ce mémoire a été réalisé dans le cadre de la maîtrise ès sciences en gestion, concentration expérience utilisateur, à HEC Montréal, et a été validé par l'administration du programme. La direction de recherche a autorisé sa rédaction selon une formule par article scientifique, et l'ensemble des coauteurs associés à ce travail ont donné leur accord quant à leur participation et à la diffusion des résultats. L'article intitulé "When change goes unnoticed: The role of change blindness in detecting new AI functionalities in banking interfaces" a été rédigé en vue d'une soumission au journal *Behaviour & Information Technology*.

L'étude liée à cette recherche a reçu l'approbation du Comité d'éthique de la recherche de HEC Montréal en mars 2025 (dossier 2025-6411) et a été menée en conformité avec les normes éthiques régissant la recherche auprès de participants humains. Toutes les procédures de consentement, de confidentialité et de protection des données ont été appliquées tout au long du projet.

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Chapitre 1 – Introduction

1.1 Contexte de la recherche

Le secteur financier est aujourd'hui au cœur d'une transformation systémique sans précédent. Sous les effets de la numérisation, de la forte montée des technologies financières (désignées sous le terme FinTech, qui correspond à l'application des technologies modernes aux produits et services financiers dans le but d'améliorer les processus de services financiers (Huang et al., 2025; Leong, 2018) et de l'essor de l'utilisation de l'intelligence artificielle (IA), les frontières conventionnelles du domaine financier sont en train de se transformer (Thomas, 2025). En 2025, plus de 78% des internautes dans le monde utilisent désormais au moins un service issu de la technologie financière chaque mois, et ce taux devrait dépasser les 80% d'ici la fin de l'année (Ashcraft, 2025b). On observe que 91% des milléniaux ont recours aux applications FinTech et que, chez la génération Z, 68% d'entre eux utilisent aussi considérablement ce type de service et ont même tendance à le privilégier aux banques traditionnelles (Ashcraft, 2025b). Néanmoins, on constate en même temps que les générations plus âgées ne sont pas en reste lorsqu'il s'agit d'utiliser ces technologies récentes dans le secteur financier. En effet, 42% des baby-boomers sont utilisateurs et l'on observe même une hausse de leur niveau de confiance face à ce type de service (Ashcraft, 2025b). Cela illustre que les FinTechs ne sont plus perçues comme des innovations réservées à une clientèle technophile, mais comme des outils financiers destinés au grand public et désormais intégrés aux pratiques quotidiennes. Ces plateformes : applications bancaires mobiles, portefeuilles électroniques, assistants virtuels ou robots-conseillers ont instauré de nouvelles attentes chez les usagers qui s'attendent maintenant à de l'autonomie, de l'instantanéité et de l'accompagnement proactif (Chauhan et al., 2022; Sharma & Dubey, 2022). Les clients s'attendent maintenant à pouvoir gérer leurs opérations bancaires de façon autonome, sans intermédiaire, tout en bénéficiant d'une exécution instantanée et d'un accès continu aux services. Cette recherche d'efficacité s'accompagne d'un désir d'accompagnement proactif, où les institutions financières anticipent leurs besoins et proposent des conseils personnalisés grâce à l'intelligence artificielle. Ainsi, l'expérience bancaire devient à la fois libre, rapide et intelligente, redéfinissant la relation entre l'utilisateur et son institution (Sindhu, 2025).

Dans cet environnement en constante transformation, les banques « traditionnelles » se retrouvent confrontées à l'obligation d'accélérer leur transformation numérique et ainsi, le déploiement de nouvelles fonctionnalités numériques pour maintenir leur compétitivité et leur pertinence face à l'émergence des technologies financières et aussi pour répondre aux attentes grandissantes exprimées par les utilisateurs (Hakizimana et al., 2023). Cette dynamique s'impose désormais comme une condition de survie dans ce marché qui est dominé par des acteurs agiles, capables d'introduire de nouvelles fonctionnalités en quelques semaines seulement (Siek & Sutanto, 2019). Toutefois, cette course à l'innovation crée un paradoxe. En effet, même si les institutions financières déploient de plus en plus de fonctionnalités, beaucoup peuvent demeurer invisibles, ignorées ou sous-utilisées par les usagers. Ce paradoxe trouve son origine dans la préférence des utilisateurs pour la stabilité et les pratiques familières, renforcée par les efforts cognitifs et pratiques exigés lorsqu'il faut modifier ses habitudes face à l'utilisation d'un service ou d'une fonctionnalité. Cette réticence à changer limite souvent la découverte et l'adoption des nouvelles fonctionnalités (Chan et al., 2022). Avec le temps, cette réticence se transforme en habitudes : les utilisateurs développent des comportements automatiques qui les amènent à se concentrer uniquement sur les fonctions essentielles, limitant ainsi l'exploration et l'utilisation des nouveautés, même lorsque celles-ci sont technologiquement avancées (Alalwan et al., 2017). Ainsi, la performance technologique ne garantit plus l'adoption, car, pour une institution financière, une fonctionnalité non perçue représente non seulement une innovation perdue, mais aussi un investissement inefficace et une occasion manquée de renforcer la relation client (Lee & Chen, 2022).

Face à cette réalité, les institutions financières doivent repenser la manière dont elles conçoivent et introduisent les nouvelles fonctionnalités dans leurs interfaces. La priorité n'est plus seulement de créer des outils performants, mais de s'assurer qu'ils soient visibles, compréhensibles et intégrés dans les parcours utilisateurs. En d'autres termes, la transformation numérique du secteur bancaire ne se mesure pas seulement à la quantité d'innovations livrées, mais à la capacité des utilisateurs à percevoir et s'approprier ces changements.

Parmi les nouvelles fonctionnalités numériques les plus étudiées dans le secteur financier, l'intégration de l'intelligence artificielle (IA) représente un tournant majeur dans la conception et l'usage des services bancaires. L'intelligence artificielle (IA) est généralement définie comme la

capacité d'un système à interpréter correctement des données externes, à en tirer des apprentissages, puis à utiliser ceux-ci pour atteindre un but spécifique par une adaptation flexible (Haenlein & Kaplan, 2019). Elle fait également référence à des machines ou des systèmes capables de simuler des tâches généralement dépendantes de l'intelligence humaine, comme le raisonnement logique, l'apprentissage, la résolution de problème et la prise de décision (Morandín-Ahuerma, 2022). Étant donné le présent contexte, une définition de l'IA dans le secteur bancaire est également nécessaire. Dans ce secteur, l'IA fait référence à l'emploi de système capable d'imiter les processus d'intelligence humaine afin d'automatiser et d'optimiser les opérations bancaires, d'enrichir le service client et d'augmenter l'efficacité, l'efficacité ainsi que la rentabilité de ces organisations (Mehndiratta et al., 2023). L'IA permet aujourd'hui d'automatiser l'analyse des données, la personnalisation des services et la recommandation de produits financiers, tout en redéfinissant la relation entre les institutions et leurs clients.

Dans le domaine des technologies financières, l'IA a principalement été étudiée en ce qui concerne son niveau d'adoption par les utilisateurs. En effet, plusieurs recherches donnent un aperçu de caractéristiques nécessaires ou influençant l'adoption des fonctionnalités ou services issues de l'IA par les usagers. La littérature indique que l'intention d'adopter des services utilisant l'IA est influencée par la confiance, la facilité d'utilisation perçue, l'utilité perçue et les attitudes envers l'intelligence artificielle, tandis que l'adoption effective, elle, est modulée par des facteurs démographiques et psychologiques (Piotrowski & Orzeszko, 2023). D'autres recherches confirment ces idées en montrant que l'adoption des technologies financières s'appuie sur des fondements théoriques issus des modèles d'acceptation technologique, tels que le Technology Acceptance Model (TAM) (Davis, 1989). Ces approches mettent en évidence que la perception de l'utilité, la facilité d'usage et la confiance constituent les principaux leviers de l'intention d'adoption et d'utilisation des nouvelles technologies (Belanche et al., 2019). Des travaux plus récents soulignent toutefois que l'adoption durable de ces fonctionnalités dépend aussi de la qualité de l'expérience utilisateur. La transparence du fonctionnement algorithmique, la personnalisation des recommandations et la convivialité des interfaces favorisent la compréhension et la confiance envers les systèmes d'IA, conditions essentielles pour encourager un usage continu et informé de ces technologies dans les services financiers (Huang et al., 2024). L'adoption de ces technologies repose également sur la qualité du design visuel et interactionnel, qui influence directement la perception et l'engagement des utilisateurs. Des éléments tels qu'un langage conversationnel

naturel ou des caractéristiques anthropomorphiques renforcent la confiance, la présence sociale perçue et la satisfaction, tout en captant davantage l'attention visuelle (Chen et al., 2024; Lee & Chen, 2022). Une conception plus humaine et intuitive favorise ainsi une expérience fluide et engageante, essentielle à l'appropriation des fonctionnalités d'intelligence artificielle dans les services financiers (Chen et al., 2024; Lee & Chen, 2022).

Cependant, malgré les avantages perçus en matière d'efficacité et de personnalisation, les utilisateurs demeurent réticents à adopter pleinement les fonctionnalités d'IA lorsqu'il s'agit de décisions financières complexes ou à fort enjeu. Les recherches montrent que la confiance et la crédibilité perçue restent des conditions déterminantes, les clients accordant encore une préférence marquée aux conseillers humains pour leur dimension empathique et leur orientation client (Northey et al., 2022). L'adoption des technologies d'IA dans la banque apparaît ainsi fortement contextuelle, étant favorisée dans les situations à faible risque et plus hésitante lorsque la relation de confiance et l'engagement émotionnel sont en jeu. (Northey et al., 2022).

Cela dit, la plupart des études portant sur l'adoption des fonctionnalités fondées sur l'intelligence artificielle dans le domaine des technologies financières se concentrent sur des facteurs comportementaux ou attitudeux, tels que la confiance, l'utilité perçue et la satisfaction des utilisateurs, mais négligent les mécanismes perceptifs essentiels qui précèdent ces processus. En effet, en s'appuyant principalement sur des modèles d'acceptation technologique tels que le TAM, plusieurs travaux expliquent l'adoption des services d'IA à partir de facteurs évaluatifs, comme l'utilité perçue, la facilité d'utilisation et les attitudes envers la technologie (Belanche et al., 2019; Piotrowski & Orzeszko, 2023). D'autres études montrent que la transparence des systèmes, la personnalisation des recommandations et la convivialité des interfaces renforcent la compréhension et la confiance des utilisateurs (Huang et al., 2024). Ces approches demeurent toutefois centrées sur l'évaluation consciente des systèmes, sans s'intéresser aux étapes perceptives préalables. Cela met en évidence un important manque dans la littérature, puisque la plupart des recherches partent du principe que les utilisateurs sont déjà conscients de l'existence de ces fonctionnalités d'IA, sans toutefois examiner s'ils les remarquent, les reconnaissent ou les comprennent réellement avant que leur adoption ne soit mesurée. En effet, avant que les utilisateurs puissent évaluer, faire confiance ou adopter une fonctionnalité fondée sur l'intelligence artificielle, ils doivent d'abord remarquer sa présence dans l'interface. Or, une grande partie des interactions

avec les applications bancaires est devenue automatique et inconsciente, les usagers ouvrent l'application, accomplissent une tâche familière, puis la referment sans prêter attention aux nouvelles fonctionnalités. Puisque ces processus relèvent d'un traitement de l'information en grande partie inconscient, il devient essentiel de s'intéresser à la détection réelle et vécue des nouveautés dans l'interface, plutôt qu'à leur perception autoévaluée, souvent mesurée à travers des indicateurs d'attitude ou d'intention d'adoption (Chen et al., 2024).

Pour dépasser cette limite, il apparaît essentiel d'élargir la perspective en s'intéressant non seulement aux raisons qui motivent l'adoption d'une technologie, mais aussi aux processus attentionnels et perceptifs mobilisés dès les premiers contacts avec l'interface numérique. La manière dont les utilisateurs perçoivent, remarquent et reconnaissent une nouvelle fonctionnalité pourrait constituer une étape déterminante du parcours d'adoption. Comprendre ces processus initiaux s'impose pour expliquer pourquoi certaines innovations numériques peuvent échapper à l'attention des utilisateurs, même lorsqu'elles sont intégrées à des interfaces familières et présentent un fort potentiel fonctionnel.

Cette réflexion invite à explorer les mécanismes cognitifs et attentionnels qui précèdent les jugements d'attitude ou de confiance. Elle met en lumière le rôle de la perception visuelle et de la charge attentionnelle dans la détection d'un changement ou d'une nouveauté au sein d'une interface familière. L'attention visuelle est un mécanisme cognitif qui régule l'accès sélectif aux informations visuelles et leur intégration, permettant de concentrer le traitement visuel sur le stimuli pertinent tout en inhibant ceux qui sont non pertinents (Evans et al., 2011). Lorsque l'attention est dirigée vers une tâche précise, les signaux visuels associés à une nouvelle fonctionnalité peuvent ne pas être intégrés consciemment, même s'ils apparaissent dans le champ visuel. Ce phénomène, connu sous le nom de cécité au changement, renvoie à l'incapacité de détecter une modification visuelle dans un environnement familier (Simons & Levin, 1997). Il révèle les limites de l'attention et de la conscience perceptive dans l'expérience utilisateur, rappelant que voir une innovation ne garantit pas nécessairement de la percevoir ni de la reconnaître comme telle. Des travaux empiriques illustrent concrètement les effets de la cécité au changement sur le comportement des utilisateurs. Lors d'interactions sociales en temps réel, un changement majeur d'interlocuteur peut passer inaperçu chez près de la moitié des participants, bien que l'élément modifié soit directement observé, ceux-ci encodant principalement le sens

général de la situation plutôt que les détails visuels spécifiques, ce qui entraîne la poursuite normale de l'échange sans ajustement comportemental (Simons & Levin, 1998). D'autres recherches montrent que les individus surestiment fortement leur capacité à détecter les changements visuels, entretenant une surestimation de leurs capacités perceptives et induisant une baisse de vigilance ainsi qu'une diminution de l'exploration volontaire, les utilisateurs s'attendant à ce que toute nouveauté significative attire spontanément leur attention (Levin et al., 2002). Enfin, des études basées sur l'oculométrie indiquent que les éléments modifiés peuvent être fixés sans être reconnus consciemment, en raison d'un traitement attentionnel superficiel caractérisé par des fixations plus brèves, insuffisantes pour permettre une comparaison visuelle entre les états avant et après changement, ce qui conduit les utilisateurs à poursuivre leurs actions sans intégrer la nouveauté observée dans leur comportement (Chetverikov et al., 2018). Ensemble, ces résultats confirment que la cécité au changement engendre non seulement des limites perceptives, mais également des comportements d'usage qui entravent la détection et la reconnaissance conscientes des innovations dans les interfaces numériques.

1.2 Question de recherche et objectifs

C'est dans cette perspective de compréhension des mécanismes perceptifs qui freinent la perception et l'utilisation des innovations numériques que cette étude tente de répondre à la question suivante :

Dans quelle mesure la prédisposition à la cécité au changement empêche-t-elle l'utilisateur de détecter une nouvelle fonctionnalité dans une interface ?

En abordant cette question dans le contexte précis des applications bancaires, cette étude vise à contribuer aux modèles classiques d'adoption centrés sur les intentions ou les attitudes, en apportant une contribution visant à approfondir la compréhension des premiers moments de l'interaction entre l'utilisateur et la nouveauté technologique, c'est-à-dire à la manière dont celle-ci est perçue et identifiée dès le premier contact. Elle cherche ainsi à mieux comprendre pourquoi certaines innovations numériques, pourtant utiles et bien conçues, passent inaperçues auprès des utilisateurs. Plus précisément, l'étude examine dans quelle mesure la prédisposition à la cécité au

changement, soit la tendance à ne pas remarquer des modifications visuelles dans un environnement familier, influence trois dimensions clés de l'expérience utilisateur :

- La détection visuelle vécue du changement;
- La reconnaissance consciente de la nouvelle fonctionnalité;
- La perception de la charge cognitive et perceptuelle associée à la tâche présentant la nouvelle fonctionnalité.

Afin d'examiner empiriquement ces dimensions et d'en mesurer les effets dans une situation d'interaction réelle, une étude expérimentale a été conçue. L'étude présentée dans ce mémoire est une expérimentation intra-sujets menée auprès de 25 participants âgés de 19 à 65 ans réalisant deux tâches de transfert Interac : l'une sur une interface standard et l'autre intégrant une nouveauté : un assistant financier basé sur l'intelligence artificielle. Les tests ont été effectués en laboratoire, à l'aide de mesures oculométriques, psychophysiologiques et auto-rapportées permettant d'analyser l'attention visuelle, la reconnaissance du changement, ainsi que la charge cognitive perçue. Ce protocole a permis de relier les processus cognitifs de détection du changement à la capacité des utilisateurs de remarquer et d'intégrer de nouvelles fonctionnalités dans des contextes d'interaction réalistes.

1.3 Chapitres du mémoire

Ce mémoire est structuré selon un format par articles. Après le chapitre d'introduction, le chapitre 2 est consacré à l'article scientifique présentant l'étude empirique, rédigé selon les normes d'une publication académique pour un journal. L'article scientifique explore de manière détaillée le phénomène étudié en passant par la description de l'étude, sa méthodologie, ses résultats et leurs implications théoriques et pratiques.

Le chapitre 3 (conclusion) revient sur la question de recherche, synthétise les principaux résultats à la lumière de la littérature, et les traduit en recommandations concrètes pour la recherche et la pratique. Il présente également les enseignements tirés, les choix méthodologiques et leurs limites, ainsi que des pistes précises pour de futures études. Enfin, il conclut sur les contributions globales du mémoire et leur pertinence dans le contexte actuel de la transformation numérique bancaire.

L'article scientifique est rédigé dans l'objectif d'être publié dans le journal *Behaviour & Information Technology*.

Ce mémoire a été réalisé au sein du Tech3Lab dans un contexte de collaboration impliquant plusieurs intervenants à différentes étapes du projet. Le **Tableau 1** présente ma contribution intellectuelle personnelle pour chacun des aspects du mémoire. Conformément aux normes du laboratoire, une contribution minimale globale de 50 % est attendue de la part de l'étudiant. Les dimensions pour lesquelles ma contribution dépasse ce seuil reflètent un rôle de leadership et une responsabilité principale dans la réalisation de la phase concernée.

Tableau 1 – Contribution personnelle aux étapes du projet de recherche

Étapes du processus	Contribution
Question de recherche	Identification des lacunes dans la littérature afin de définir le problème de recherche et ses implications [90 %] - Problématique initialement formulée par le partenaire industriel. - Contextualisation de cette problématique dans la recherche académique par l'étudiante.
Revue de la littérature	Réalisation d'une recherche approfondie et d'une analyse rigoureuse des articles scientifiques afin de comprendre l'état actuel des connaissances académiques sur la découvrabilité et ses effets sur l'utilisateur. [100 %]
Design expérimental	Development of the experimental protocol and stimuli [70%] - Conception du protocole expérimental. - Les stimuli ont été sélectionnés par le partenaire industriel.
Collecte des données	Recrutement des participants pour la collecte de données. [30 %] - Les participants pour la collecte de données ont été recrutés par une firme externe
	Mise en place du laboratoire [80 %] - L'étudiante a conçu le protocole et une partie du questionnaire final - Assemblage des instruments de collecte de données avec l'aide du personnel du Tech3Lab (Salima Tazi, Xavier Côté et Élise Imbeault). - Nombreux tests et ajustements du dispositif expérimental effectués par l'étudiante.
	Prétests et gestion des opérations de collecte de données [100 %] - L'étudiante a coordonné et préparé les opérations de prétest. - L'étudiante a assuré la modération et l'observation de l'ensemble des tests utilisateurs. - Le soutien technique et l'organisation du personnel de collecte de données ont été assurés par l'équipe de gestion du Tech3Lab.

Analyse des données	Analyse des données psychophysiologiques et qualitatives [80 %] - Extraction et traitement des données pour la synchronisation des instruments réalisés par le statisticien du Tech3Lab. - Analyses statistiques effectuées sur SAS et R par l'étudiante, avec l'aide du statisticien du Tech3Lab au besoin. - Analyses qualitatives effectuées sur Optimal Workshop par l'étudiante. - Interprétation et présentation des résultats effectuées par l'étudiante. - Création des graphiques.
	Analyse de la vérification de la manipulation [50 %] - Extraction et traitement des données pour la synchronisation des instruments réalisés par l'étudiante. - Analyses statistiques revalidées par le statisticien du Tech3Lab.
Conformité éthique	Préparation des documents requis pour l'approbation éthique [80%] - Formulaire d'information, consentement, démarches.
Rédaction du mémoire	Rédaction de l'article scientifique et du présent mémoire [100 %] - Les codirecteurs de recherche ont fourni des commentaires et des corrections.

Chapitre 2 – Article scientifique

When change goes unnoticed: The role of change blindness in detecting new AI functionalities in banking interfaces

Sarah-Bianca Mbonimpa, Pierre-Majorique Léger, Constantinos K. Coursaris

Abstract

The rapid integration of AI-powered functionality into mobile banking interfaces raises questions about whether users actually notice these new functionalities during routine interactions. This study investigates how individual predisposition to change blindness influences users' ability to detect and recognize an AI assistant embedded in a familiar banking interface. A within-subject experiment was conducted with 25 clients of a financial institution. Participants first completed a flicker task to obtain three indicators of their change blindness propensity, then performed two realistic Interac transfer tasks on the bank's mobile interface: one without and one with an AI assistant. Eye-tracking data (fixation count, fixation duration, time on page, K coefficient and pupil dilation), perceived perceptual load and post-task recall and recognition measures were collected. Overall, very few participants noticed the interface change, and change blindness propensity showed no significant effect on recognition or most visual detection metrics, with only time on page presenting a marginal trend. Fixation count and fixation duration were also weakly related to recognition, but in an unexpected direction, as spending more time looking at the interface did not increase recognition. By contrast, participants with a stronger predisposition to change blindness reported lower perceptual load and showed smaller pupil dilation, suggesting lower cognitive engagement or effort. These findings highlight a gap between visual exposure and conscious awareness in mobile banking use, showing that the presence of an AI feature is not sufficient for users to detect it. Users may process the interface visually without becoming consciously aware of changes, underscoring the ongoing challenge of ensuring new AI functionalities are noticeable in routine banking use.

2.1 Introduction

The financial sector is undergoing rapid transformation as financial technology companies (FinTechs), major technology firms, and payment providers use generative AI to blur traditional industry boundaries and redefine the way financial services generate and deliver value to users (Thomas, 2025). More than 78% of internet users worldwide now use FinTech services each month, with adoption among millennials exceeding 90%. As a result, platforms such as mobile banking apps, and online payment systems have established new expectations for personalization, user autonomy, and proactive financial guidance (Ashcraft, 2025b). In this evolving ecosystem, traditional banks have little choice but to accelerate their own AI transformation to remain competitive and relevant. Today, most consumers are comfortable with AI being integrated into their financial lives and often prefer not to visit bank branches, as many services can now be managed directly through mobile devices. TD Bank reports that 89% are comfortable adopting new technology, and nearly half believe it can provide trustworthy financial advice (Ashcraft, 2025a). This emphasizes the importance for banking institutions to continue developing new functionalities, like AI-powered functionalities, not only to better address users' financial needs and demands by guiding them toward appropriate products and services but also to remain competitive in a rapidly digitalizing financial market. In practice, these emerging AI features represent an effort to integrate guidance and personalization directly into the mobile banking experience. As users increasingly rely on digital platforms for financial clarity and reassurance, banks are investing in tools capable of supplementing human expertise, supporting everyday decisions, and proactively surfacing relevant financial opportunities (Hakizimana et al., 2023). This shift has led to a new generation of digital services in which AI is expected not only to enhance efficiency, but also to improve the quality of financial decision-making.

As banks increasingly integrate AI into digital financial services, robo-advisors have become a clear example of how these technologies are reshaping financial guidance. As they provide personalized recommendations and structured decision support while preserving users' autonomy, they have emerged as a key subject of research aimed at understanding how individuals evaluate, trust, and adopt AI-driven functionalities. Following this interest, previous studies have mainly examined how these tools are adopted in the FinTech context. Prior research indicates that the intention to adopt robo-advisory services is influenced by trust, perceived ease of use, usefulness,

and attitudes toward AI, while actual adoption is further shaped by demographic and psychological characteristics (Piotrowski & Orzeszko, 2023). Other studies emphasized that banks view robo-advisors as a competitive advantage, with usability, risk perception, and social norms emerging as key determinants of acceptance (Belanche et al., 2019). More recent contributions highlight the role of AI-enabled robo-advisors, demonstrating that transparency, personalization, and user-friendly design are essential to building trust and sustaining continued use (Huang et al., 2024). Research also suggests that anthropomorphic design cues can also enhance perceptions of trust and social presence, while guiding user attention (Chen et al., 2024). Nevertheless, even if robo-advisors can provide efficient advice, evidence shows that consumers continue to prefer humans in high involvement financial decisions (Northey et al., 2022).

However, previous research in this area assumes that users actually notice these AI features when they appear in the interface. This is a major issue. If users do not see a new functionality, they cannot evaluate it, trust it, or adopt it. In practice, this means that banks may develop helpful tools that users never realize are available. When a feature goes unnoticed, its benefits are lost, and the feature cannot meaningfully support the user or enhance their experience. Surprisingly, this first step of simply noticing a feature is rarely considered in existing studies, even though it determines whether an innovation becomes part of the user experience or remains invisible in the interface. Taken together, these observations point to a gap between how adoption is typically conceptualized in research and how users actually encounter new functionalities in real interfaces. While the absence of detection highlighted above has often been treated as an implicit issue, it suggests that perceptual processes and behaviours may play a central role in determining whether a new functionality can even enter the user experience. Rather than assuming that technologies are always consciously noticed prior to evaluation, these findings invite closer attention to the conditions under which visual changes are detected, processed, and recognized.

Despite these insights, most existing studies approach adoption from a behavioural or attitudinal perspective, overlooking the perceptual mechanisms that precede the processes. Before users can evaluate, trust, or adopt an AI-driven functionality, they must notice its presence in the interface. However, much of users' interaction with banking applications has become automatic and unconscious: they open the app, complete a familiar task, and pay little attention to new features.

This creates a critical challenge for designers, particularly in financial services, where the effectiveness of new functionalities depends on their visibility. Understanding this limitation requires shifting the focus from why users choose to adopt technologies to how they visually and cognitively encounter them in the first place. In other words, adoption does not begin with evaluation or intention; it begins with perception. Exploring this perceptual stage is essential to explain why certain digital innovations remain unnoticed despite their potential usefulness. One potential explanation for this phenomenon lies in change blindness, defined as the failure to detect visual changes in a scene even when they occur within our field of view (Simons & Levin, 1997). It reveals the limits of visual attention and awareness, showing that even noticeable interface modifications can go unseen when users' focus is directed elsewhere.

Research also shows that change blindness is not experienced in the same way by everyone. Although it is a universal perceptual limitation, individuals differ in how prone they are to it. This trait component, often referred to as change blindness propensity, reflects relatively stable differences in attentional control, working memory capacity, and the strength of visual representations (Anderman et al., 2019; Bergmann, 2016). Some people form more precise visual comparisons and shift their attention more flexibly, which makes them less likely to miss a change. Others rely more on habits, maintain a narrower attentional focus, or form weaker visual representations, which makes them more susceptible to change blindness. These individual differences help explain why not all users are equally likely to notice new AI elements in an interface. Factors such as attention, working-memory capacity, interface familiarity, expectations about what is likely to change, and confidence in navigating digital systems all influence how users process visual information (Anderman et al., 2019; Simons & Ambinder, 2005; (Uke) Karacan et al., 2010). Some users naturally scan screens more broadly and are more sensitive to subtle updates, while others perform routine tasks with minimal conscious attention. As a result, the discoverability of new AI features may vary widely across users, making it essential to investigate how predisposition to change blindness affects feature detection in real banking contexts (Chetverikov et al., 2018; Solomon et al., 2025).

Yet, little research has examined the cognitive and perceptual factors that influence whether users detect and engage with such innovations, leaving a gap in understanding how technologies are

discovered in practice. Since previous research has shown that users may fail to detect newly introduced AI functionality in an interface in the first place, the present study examines the underlying reasons for this failure. In other words, changes may go unnoticed, but the question remains why. The goal of this research is to determine whether individual differences linked to change blindness propensity can help explain this situation. That is precisely what this study set out to examine, not only whether users notice a new functionality, but also why they do or do not, by investigating this process through the lens of individual differences in change blindness propensity, as reflected in the following research question: “To what extent does predisposition to change blindness prevent users from detecting a new AI functionality in an interface?” Together, these questions clarify both the general perceptual challenge posed by the new functionality and the individual factors that may influence detection.

To address these issues, we conducted a within-subject experiment in which participants completed two Interac transfer tasks, one with and one without an AI assistant, while eye-tracking metrics, recall measures, and self-reported data on cognitive and perceptual load were collected. Unlike traditional lab paradigms, this study examines change blindness in a real banking interface, making the findings directly relevant to usability and adoption.

Overall, the study is based on an experiment involving the detection of newly introduced AI functionality by users with varying levels of change blindness propensity. The findings of this study indicate that individuals with a stronger predisposition to change blindness were significantly less likely to consciously recognize the integration of the AI assistant, even though eye-tracking data revealed clear visual processing of the change. This divergence highlights the gap between unconscious attention and reported awareness in applied digital contexts.

The rest of this article first reviews the literature on change blindness and AI in financial technologies, then describes the experimental design and methods. It next presents the results from eye-tracking, recall, and self-reported measures, followed by a discussion of their theoretical and practical implications. The article ends with recommendations for future research.

2.2 Literature Review and Hypothesis Development

2.2.1 Change blindness

Change blindness refers to the surprising failure to notice large visual changes in a scene, even when those changes would normally be easy to detect. In several studies involving change blindness scenarios, 50% of observers fail to notice basic changes (Simons & Ambinder, 2005). Given those types of situation failures of change detection, we must question the assumption that we have a detailed representation of our visual world. That is why many articles articulate that this phenomenon does not come from deficits in the visual system itself but rather reflects the limits of attention and visual awareness, which determine what elements of the environment are processed, maintained, and compared over time (Simons & Levin, 1997). This shows that visual perception is not a continuous or complete record of what we see. It is more of a selective process influenced by attention, expectations, and cognitive effort (Ellis, 2012).

Several complementary explanations have been proposed to account for why observers often miss substantial visual changes. One widely accepted explanation is the limited capacity or sparse visual representation. This suggests that people retain only a limited portion of visual information at a time, and that most details fade quickly unless they are noticed and attended to. In other words, only details that receive focused attention will be retained (Simons & Levin, 1997; Simons & Rensink, 2005). There is also the attention-based idea, which builds on this perspective by emphasizing that focused attention is essential for detecting change, as even obvious changes can go unnoticed in its absence (Rensink, 2002). Predictive-processing models extend these explanations by proposing that change blindness manifests when the brain fails to update its internal predictions about the visual world in response to new sensory input, leading to a false sense of visual stability (Anderman et al., 2019). Other frameworks emphasize the joint contribution of visual working memory, iconic memory, and attentional allocation, showing that these systems must interact effectively for a change to reach conscious awareness (Martin et al., 2023; Wright et al., 2024).

Still, today, debate continues regarding what change blindness reveals about the nature and richness of our visual representations. Some researchers argue that internal representations are

extremely limited or even absent, implying that people rely on the external world as a kind of visual memory store (Simons & Levin, 1997). Others propose that these representations are present but fragile or inaccessible : observers may encode both pre and post change information but fail to compare effectively or retrieve them in time (Simons et al., 2002; Varakin & Levin, 2006). Taken together, these findings highlight that change blindness emerges from the interaction of attention, memory and consciousness. It challenges the traditional assumption that humans maintain a detailed and stable representation of their surroundings, revealing instead that visual awareness is highly selective, with a limited capacity and continuously updated based on where attention is directed at each moment (Rensink, 2002; Simons & Levin, 1997).

2.2.2 Link between Change Blindness and the UX field

Research shows that user experience (UX), where digital interfaces often update, animate, or reorganize visual elements, is directly related to change blindness phenomenon. Since every interface modification constitutes a visual change, the same cognitive limitations that produce change blindness in natural scenes can impair a user's ability to notice new or updated features in digital interactions. Studies on web interfaces have shown that even when users intentionally search for changes, significant modifications to layout or content often go unnoticed, thus demonstrating again that UX environments are subject to the same perceptual limitations observed in natural change blindness scenes (Steffner & Schenkman, 2012). When an interface is modified, the user must perceive the visual change in order to recognize that something has been updated, yet this is not guaranteed. In UX contexts, adding, removing, or altering interface elements is not inherently sufficient for users to notice that a change has occurred, since the visual system may fail to register the transition between previous and current states of the interface. Understanding how and when such changes go unnoticed helps designers anticipate which modifications will be perceptible and which may be overlooked. This principle applies directly to UX, where knowledge of human perceptual limits is essential for ensuring that interface updates are seen and for improving the overall digital experience of users (Martin et al., 2023).

A growing body of UX and HCI research provides direct evidence that the phenomenon of change blindness occurs during real interface use. Studies on mobile devices show that users often fail to notice new icons, updated notifications or modified menu items when these changes happen

alongside other visual activities or during common interactions, such as scrolling or switching views (Davies & Beeharee, 2012). Research on proximity-aware and adaptive mobile interfaces finds similar results: when interface elements update gradually or while the device is being moved, users miss a significant proportion of these changes because the visual transient that signals the modification is weak or absent (Brock et al., 2018). Web-based flicker studies also reveal that changes to layout or content can remain unnoticed, especially in dense or visually complex pages where competing stimuli draw attention away from the modified area (Steffner & Schenkman, 2012). Together, these findings show that change blindness is a reliable phenomenon within UX contexts and that interface updates are not always perceived, even when they are relevant to the user's task.

2.2.3 Change blindness propensity

Change blindness propensity refers to how likely an individual is to experience change blindness. It emphasizes stable individual differences rather than the phenomenon itself. In other words, it captures stable individual differences rather than momentary, task-dependent effects. While change blindness describes a general failure to notice visual changes, propensity helps explain why some people are more susceptible than others. This susceptibility is linked to the strength and stability of visual representations, attentional control, and working-memory capacity (Andermane et al., 2019; Bergmann, 2016). Variations in how individuals allocate and redirect attention within a scene also contribute to these differences, as those who maintain a narrower or less adaptable attentional focus are more likely to miss changes due to inefficient distribution of cognitive resources (Ellis, 2012). Furthermore, contextual and cognitive factors, such as familiarity with the visual environment or expectations about what is likely to change, can shape attentional deployment, making some individuals consistently more prone to change blindness than others (Ellis, 2012).

In addition to cognitive capacity, metacognitive judgments also contribute to individual differences in change blindness. People who accurately estimate their own ability to notice changes tend to detect them more quickly, even when the changes are subtle (Barnas & Ward, 2022). However, it is worth noting that while individuals can predict which tasks will be easier or harder, they generally overestimate their overall ability to detect changes, a bias known as change blindness

blindness (Barnas & Ward, 2022). Personal experience further shapes these judgments, as individuals who previously failed to detect changes tend to underestimate both their own and others' ability to do so (Ortega et al., 2021). Moreover, social and contextual factors influence change blindness, with individuals being more likely to miss visual changes when interacting with out-group members or when their attention is guided by strong expectations about what should remain constant in a scene (Saeed et al., 2024; Simons & Levin, 1997). Together, these findings indicate that change blindness propensity emerges from a complex interaction between perceptual capacity, attentional strategies, and situational relevance. Understanding these variations helps explain why some individuals systematically fail to notice meaningful changes in their environment, particularly when attention is overloaded or narrowly focused.

2.2.4 Link between Change Blindness propensity and the UX and field

The insight talked about in the previous paragraph highlights that individual susceptibility to missing visual changes extends to interface settings, where updates and redesigns often happen without drawing attention to the moment of the change, contrary to usual change blindness studies in natural settings. In digital environments, users must compare the current state of an interface with their memory of their prior memory of it, and individual differences in the precision of these representations influence whether updates are noticed at all. Studies in online and digital contexts show that factors such as expectation, familiarity, and attentional guidance strongly affect detection, leading some users to consistently overlook modifications during routine interactions (Saeed et al., 2024).

Linking individual change-blindness propensity to UX involves recognizing that users differ in how much visual information they encode, how their attention is distributed, and how strongly their expectations shape what they believe they will see. These differences reflect the same attentional constraints that make some individuals more prone to overlooking changes, including biases in judging their own visual awareness and tendencies to rely on stable assumptions about interface structure (Johansson et al., 2008; Varakin et al., 2004). In the context of interface use, this means that detecting an update depends not only on the visual change itself but also on the user's habits, attentional focus, and the strength of the mental representation formed before the

modification. For UX design, this implies that interfaces should not assume that users notice every change.

Change-blindness propensity has often been studied through its underlying attentional mechanisms, and similar mechanisms appear in UX and HCI research, even when these studies do not explicitly use the term change blindness. Many of these works examine situations in which users fail to notice updates for reasons that differ across individuals, such as limited encoding, weak comparison processes, or strong expectations about stability. For example, people vary widely in how many details they retain across successive views, meaning that an interface update may go unnoticed simply because the earlier state was not encoded precisely enough to support comparison (Bergmann, 2016). Research also shows that claims of implicit change detection are controversial, as many effects attributed to unconscious processing can instead be explained by explicit mechanisms such as low-confidence reporting or partial awareness, emphasizing that unnoticed changes often stem from limits in attention and memory rather than implicit detection (Mitroff et al., 2002). Work examining mismatches between expected and actual outcomes during continuous interactions shows that users may fail to register that something has changed when the interaction flow feels seamless, a pattern that closely aligns with the kinds of unnoticed changes observed in change blindness (Johansson et al., 2008). Together, these studies reveal meaningful individual differences in how visual information is encoded, compared, and confirmed across moments, helping explain why interface updates may go unnoticed even when they are visually present and relevant to the user's task.

2.2.5 Change blindness propensity effect on visual and perceived change detection

Individuals with a strong predisposition to change blindness tend to show a reduced ability to consciously recognize changes in visual scenes. People with weaker or less stable visual representations often fail to form accurate comparisons between pre- and post-change images, resulting in lower change recognition accuracy. In these cases, visual information may be processed but not consciously integrated, meaning that changes occur “in plain sight” without being recognized. This relationship suggests that people who are more prone to change blindness are also less capable of consciously identifying visual updates, which aligns with the hypothesis that a strong predisposition to change blindness decreases the user's change recognition ability.

A similar pattern can be observed in visual change detection, the earlier perceptual stage of noticing that a change has occurred before consciously identifying it. Individual differences in working memory, attentional control, and certain personality traits have been found to predict how quickly and accurately people detect visual changes, indicating that an individual's success in detecting visual changes is reliably predicted by their inherent mental abilities and temperament. Individuals with stronger attentional control and more stable cognitive resources tend to detect changes more efficiently, while those with higher anxiety or cognitive load are more likely to miss them. Although age-related declines in attentional capacity have been documented, the relative consistency of detection performance within individuals over time suggests that change blindness propensity represents a stable cognitive trait (Bergmann, 2016). Altogether, these findings support the idea that a strong predisposition to change blindness reduces visual change detection ability, as limited attentional and memory resources prevent visual updates from reaching conscious awareness.

Taken together, these findings indicate that individual differences in change blindness propensity influence both the conscious recognition of visual updates and the earlier perceptual ability to detect that a change has occurred. We therefore posit the following hypotheses:

H1: A strong predisposition to change blindness decreases the user's change recognition ability.

H2: A strong predisposition to change blindness decreases the user's visual change detection ability.

2.2.6 Visual change detection capacity and perceived change detection

While the two previous hypotheses describe the direct effects of change blindness propensity on both change recognition and visual change detection abilities, the present hypothesis examines whether visual change detection ability could act as a mediating factor, partly explaining how change blindness propensity influences the perceived recognition of changes. It is expected that a high visual change detection ability increases a person's capacity to recognize changes, since both

processes rely on similar cognitive mechanisms. These include the strength and stability of visual working memory and the efficient use of attention (Andermane et al., 2019). People who can quickly notice changes tend to form stronger and more stable visual representations, which allows them to accurately recognize what has changed (Andermane et al., 2019). Computational models support this link: accurate encoding and maintenance of visual information improve detection and, in turn, recognition (Johnson et al., 2009), while both abilities rely on shared mechanisms of attention and memory precision (McAnally & Martin, 2016).

Eye-tracking research further supports this connection. Fixation count and fixation duration are well-established indicators of attentional engagement during change detection; higher values on both measures predict successful detection and stronger encoding of visual details (Nikolaev et al., 2011; (Uke) Karacan et al., 2010; Zelinsky, 2001). Similarly, total viewing time, often measured as time on page (TOI), has been shown to increase before successful detections, reflecting deeper visual processing (Uke) Karacan et al., 2010). Finally, the coefficient K, which quantifies the balance between ambient (exploratory) and focal (detail-oriented) attention, predicts detection accuracy: higher (positive) K values are associated with better performance, as they indicate the more deliberate, focal attention required for detail-oriented processing (Krejtz et al., 2016). Although some studies suggest partial independence between detection and recognition (Tversky, 1974), findings from realistic visual environments indicate that stable and meaningful visual representations strengthen both (Uke) Karacan et al., 2010). Overall, the evidence supports the hypothesis that a high visual change detection ability increases the user's change recognition ability.

Taken together, the evidence suggests that visual change detection plays a direct role in supporting accurate change recognition. We therefore posit the following hypothesis:

H3: A high visual change detection ability increases the user's change recognition ability.

2.2.7 Change blindness propensity on perceived and lived cognitive load

Individuals who are more prone to change blindness often experience their visual environment as less demanding, suggesting a link between susceptibility to change blindness and lower perceived

perceptual load. Perceptual load refers to the amount of visual information competing for attention at any given moment, shaping how efficiently people process and interpret visual scenes (Lavie & Tsai, 1994). When the perceptual load is high, attentional resources become concentrated on task-relevant elements, leaving fewer available for unattended information and increasing the likelihood of missing visual changes (Lavie, Beck, & Konstantinou, 2014). In these conditions, observers may fixate directly on changing objects yet fail to consciously perceive them, indicating that awareness depends more on attentional capacity than on gaze position (Greene et al., 2017). Other research shows that visual awareness decreases as perceptual and task demands rise, since attention is quickly depleted under high load (Matias et al., 2022). Conversely, those with a strong predisposition to change blindness may process fewer visual details overall, which makes the visual environment seem less complex and therefore reduces perceived perceptual load (Murphy & Murphy, 2018).

A similar tendency can be observed with cognitive load, as individuals with a higher predisposition to change blindness appear to engage less mental effort when processing visual information. Cognitive load refers to the amount of mental effort imposed on working memory when processing and comparing visual information. It increases as task complexity and information demands rise, which can overload working memory and limit the ability to notice or retain visual changes (Sweller, 2024). People who invest greater cognitive effort tend to show stronger engagement and improved detection of visual changes, often reflected in physiological markers such as pupil dilation and gaze behaviour (Duchowski et al., 2018; Floyd & Wichary, 2023). Larger pupil dilation and broader gaze patterns signal greater mental effort, whereas smaller pupil responses and limited exploration suggest reduced engagement and weaker detection performance (Wang & Duff, 2016). When attention and working memory resources are not fully mobilized, visual encoding becomes shallower and less effective, which may explain why individuals prone to change blindness experience lower cognitive effort during visually demanding tasks. These findings, indicate that individuals with a stronger predisposition to change blindness tend to experience lower perceptual and cognitive load when processing visual information. We therefore posit the following hypothesis:

H4: A strong predisposition to change blindness decreases the user's perceived perceptual load.

H5: A strong predisposition to change blindness decreases the user's experienced cognitive load.

The full set of hypotheses formulated in this section, along with their expected directional effects, is summarized in **Table 2**. This table provides an overview of the five hypotheses tested in the study and indicates the expected direction of each relationship. Together, these hypotheses are integrated into the research model shown in **Figure 1**, which provides an overview of the conceptual framework guiding this study.

Table 2 – Summary of Hypotheses and Expected Effects

Hypothesis	Description	Expected effect
H1	A strong predisposition to change blindness decreases the user's change recognition ability	Negative
H2	A strong predisposition to change blindness decreases the user's visual change detection ability	Negative
H3	A high visual change detection ability increases the user's change recognition ability	Positive
H4	A strong predisposition to change blindness decreases the user's perceived perceptual load	Negative
H5	A strong predisposition to change blindness decreases the user's experienced cognitive load	Negative

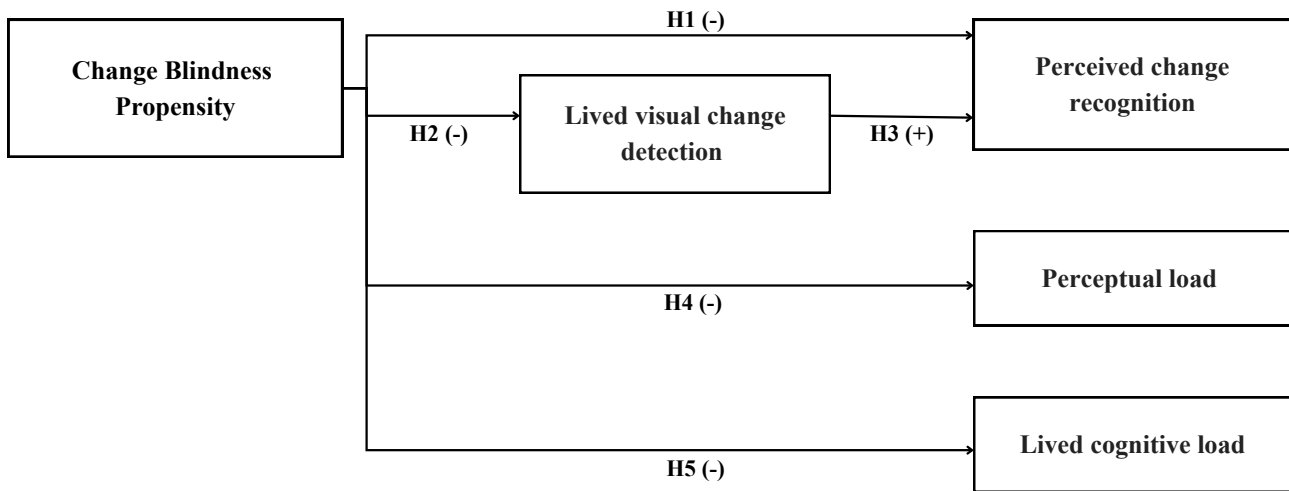


Figure 1 – Research model

2.3 Methodology

The present study adopted an experimental methodology to examine how change blindness propensity influences users' ability to detect and recognize visual updates within a mobile banking interface. Because the research questions focus on causal relationships between individual cognitive characteristics and behavioural responses, an experimental design provides the necessary control to isolate these effects. This approach allows for the manipulation of specific interface elements, such as the presence or absence of the AI assistant, while keeping all other conditions constant. As a result, differences in detection and recognition performance can be attributed to the variables of interest. In addition, the use of eye tracking and controlled task sequences makes it possible to measure perceptual and attentional processes that cannot be reliably captured through self-report alone. Overall, an experimental approach is the most appropriate method for testing the study's hypotheses and for understanding how cognitive predispositions shape users' interaction with evolving digital interfaces.

2.3.1 Participants

The sample consisted of 26 current members of the banking institution (12 females, aged 19-65 years with a mean age of 40.31, $SD=13.38$), recruited through an external firm to take part in the study. All participants were, to varying degrees, familiar with the banking institution's mobile platform. We conducted this study in accordance with the ethics committee's regulations after receiving its formal approval (2025-6411). In addition, every participant signed an informed consent form during the recruitment phase and prior to the start of the study, they were all allowed to quit the experiment at any time with compensation. Data from one participant were excluded because the stimuli central to the study were not functional during their session, making meaningful comparisons with the other participant's data impossible. Thus, the data of 25 participants were used. Every participant received a compensation of \$125, administered by the recruitment firm.

2.3.2 Experimental design

The experimental design was developed to directly test how users respond to a controlled change within a mobile banking interface. Because the goal of the study was to examine how participants detect and interpret a specific visual modification, the design needed to clearly isolate the manipulated element while minimizing the effects of individual variability. A within-subject approach was therefore appropriate, as it ensures that every participant is exposed to all conditions, allowing direct comparison of their performance across interface versions. This structure increases the internal validity of the study and improves the accuracy of conclusions regarding the effect of the manipulated factor.

A preliminary experimental paradigm and three banking tasks were used, although the third banking task was not relevant to the present analysis. The two banking tasks involved Interac transfers, which functioned as cover tasks. Although presented as the participants' primary activity, their primary purpose was to expose participants to two versions of the banking interface in order to assess whether they detected a visual change between them. The manipulated factor was the presence versus absence of the AI assistant, which constituted the experimental condition. In the first version of the interface (T1), the AI assistant was absent, whereas in the second version

(T2), the AI assistant was present. This manipulation represents the independent variable, and each participant experienced both conditions in randomized order to control order effects.

To ensure clarity and alignment with the research model, the manipulated factor was defined with two distinct levels:

T1 – Interface without the AI assistant

T2 – Interface with the AI assistant.

No other elements of the interface changed between conditions. This strict control ensures that any variation in users' detection or recognition of change can be attributed solely to the presence of the AI assistant. By embedding this manipulation within realistic banking tasks, the study maintains ecological validity while preserving experimental control.

The randomization of task orders helped counterbalance potential learning, fatigue, or expectation effects that could influence participants' responses. Presenting both versions of the interface to each participant also allowed the calculation of difference scores, which reflect the user's sensitivity to the change introduced between T1 and T2. Finally, a visual representation of the two versions is provided in **Figure 3** to clearly illustrate the manipulated factor and the structure of the within-subject design.

2.3.3 Experimental paradigm

As previously mentioned in the experimental design section, we used the flicker task as an experimental paradigm to measure an individual's propensity for change blindness. In this task, as shown in **Figure 2**, participants were shown two versions of a visual scene (such as photographic or images) that alternate rapidly, with a brief blank screen or mask inserted between each version. The two visual scenes differ by a single change (e.g., an object appears, disappears, alters or a colour change), and the participants are instructed to detect what has changed. The brief blank or mask disrupts automatic change detection, making even large changes surprisingly difficult to notice without focused attention. In this study, we used three types of measures; performance, average alternations (which stands for the number of flickers) and flicker score. Performance in the flicker task refers to the observer's efficiency in detecting a change between the two alternating

scenes (Favieri et al., 2024). This score is primarily measured by the time taken to respond and the correctness of the change identification (Favieri et al., 2024). The average alternation is a direct measurement of detection time (Marchetti et al., 2006). In the flicker task, two images alternate repeatedly, separated by a blank screen. The number of flickers corresponds to the number of cycles, or transitions between the original and modified visual scene, required for a participant to identify the change. In general, participants who detect the change more quickly require fewer flickers (Marchetti et al., 2006). Lastly, the flicker score uses both previous scores. It reflects participants' performance, measured through the number of flickers needed or the time taken to identify the change (Favieri et al., 2024). These metrics effectively quantify the degree of change blindness experienced by the observer.

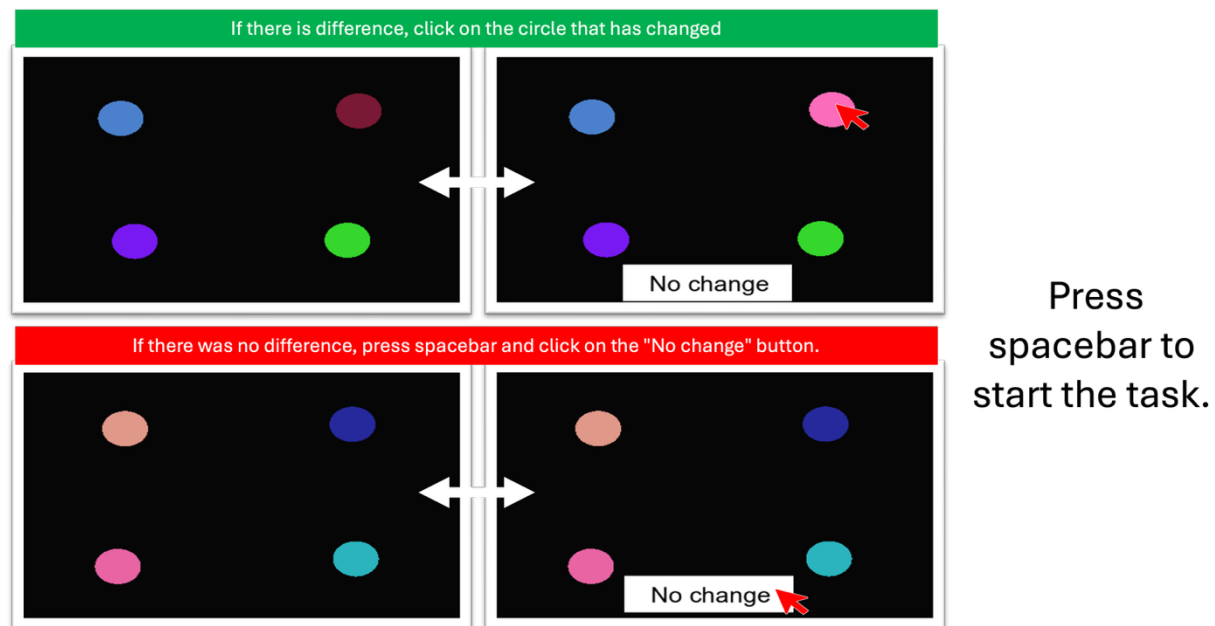


Figure 2 – Visual representation of the flicker task

2.3.4 Experimental Stimuli

The experimental stimuli consisted of two closely similar versions of the banking institution's Interac transfer interface created by the banking institution using Figma. The first version (T1) presented the interface without the AI assistant, while the second version (T2) presented the actual

version currently available to the bank's clients, which included the assistant. Thus, the only difference between the two interfaces was the presence or absence of the assistant in the lower part of the interface, with all other visual and functional features of the interface remained constant (see **Figure 3**). The manipulated area of interest (AOI) corresponded specifically to the interface elements modified between T1 and T2, which all participants viewed under identical conditions. These stimuli allowed us to isolate the effect of the AI assistant on participants' attention and change detection capacity.

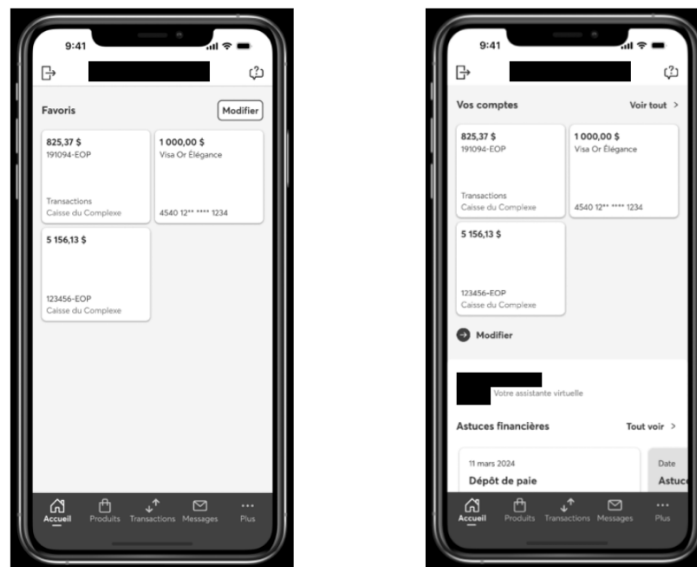


Figure 3 - Mobile banking interface without and with the presence of the AI assistant

2.3.5 Instrumentation, Equipment and Lab Setup

The stimuli were presented on a computer monitor (23.8 inches, resolution 1920 x 1080) simulating an iPhone mobile interface. The interfaces were displayed through the Figma web platform, ensuring accurate reproduction of the mobile layout on a larger screen. All participants viewed the stimuli under identical conditions in a controlled laboratory environment. Eye movements and pupil dilatation were recorded using Tobii Pro Fusion eye tracker (Stockholm, Sweden) with a sampling rate of 60Hz, which was placed at the bottom of the monitor. We use the Tobii Pro Lab software to then process the data. Participants were needed to be seated approximately 65 cm from the monitor to ensure we obtain the best eye tracking data. Alongside these instruments, the Qualtrics platform (Provo, United States, 2024) was used to deliver the

study's questionnaires. This system enabled the administration of demographic items and several rating scales, and it supported the collection of various self-reported measures required for the study. The following figures illustrate the layout of the laboratory, which was divided into two separate areas to allow real-time observation of participants without disrupting their experience. **Figure 4** depicts the workspace used by the research team, while **Figure 5** shows the participant station equipped with the recording devices.

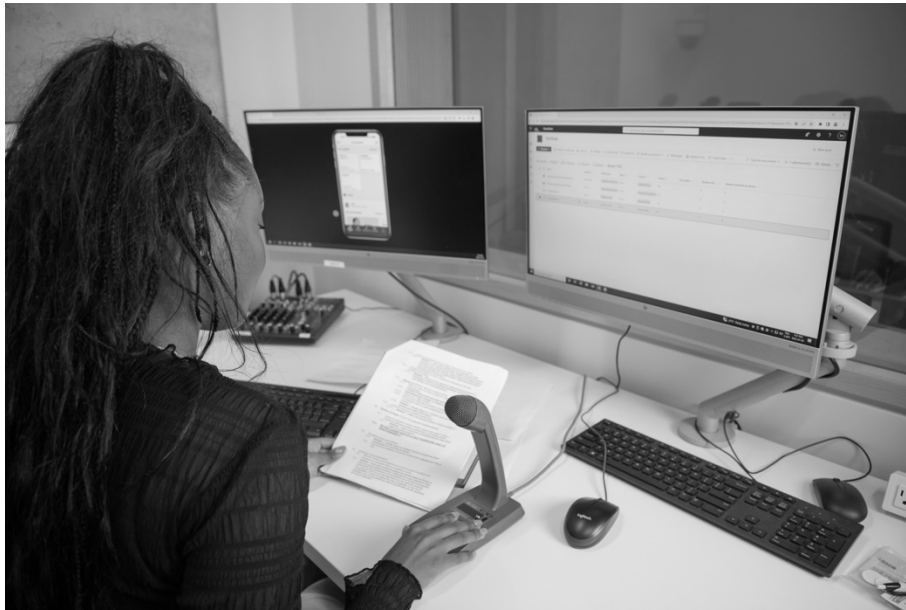


Figure 4 - Laboratory room from the moderator's perspective

Note: This is where the research team (moderator and technical assistant) is located.



Figure 5 - Participant station and experimental setup

Note: The participants could not see the research team positioned behind the one-way mirror.

2.3.6 Measures

During the experiment, eye movements and pupil size were recorded at 60Hz for each participant. Areas of interest (AOIs) were defined as the lower part of the interface (where the change was made; see Appendix D) for each Interac transfer to isolate the elements manipulated element between conditions, namely the presence or absence of the AI assistant in the page. Eye-tracking metrics that were extracted from Tobii included fixation count, fixation duration, time of interest spent on the page (TOI), K coefficient and pupil dilation for each AOI. Perceived measures were also collected, including recall and recognition questions as well as the VISAWI-positive scale to assess perceptual load. The following sections describe each measure in greater detail.

Change blindness propensity was measured using the Flicker paradigm (Andermane et al., 2019), which provided three individual predisposition score: the overall performance, the flicker score and the average alternations. Each score ranged from 0 to 1, with values closer to 0 indicating a stronger predisposition to change blindness and values closer to 1 indicating a weaker predisposition to change blindness. It is important to mention that all dependent variables in the study were computed as difference scores ($T2-T1$), obtained by subtracting the values obtained

during the first transfer task without the AI assistant (T1) from those obtained during the second transfer task with the AI assistant (T2).

Visual change detection was measured using fixation count difference, fixation duration difference, time of interest (TOI) difference and the K coefficient difference. We suppose that a higher fixation count, fixation duration and K coefficient difference, paired with a lower time of interest difference (Cheng, 2016; Krejtz et al., 2016; (Uke) Karacan et al., 2010; Wals & Wichary, 2023) were interpreted as indicators that a participant visually detected a change in the interface.

Besides, perceived change detection was assessed through recall and recognition questions (Appendix C). However, due to a lack of variance in one of the recognition items, only the recall and the other recognition question were analyzed.: “Did you notice any differences in the interfaces of the previous tasks?” and “Is this interface different from the one you usually use on your phone?” Responses were coded binary with 0 when the participant did not correctly recall the interface change and 1 when they did.

Pupil dilation differences served as an indicator of cognitive load, with greater dilation reflecting higher levels of cognitive effort (Duchowski et al., 2018). Perceived perceptual load difference was measured using the VISAWI-Positive questionnaire (Perrig et al., 2023). Example items included “The layout is easy to grasp” and “Everything goes together on the site” (see Appendix A). Responses were collected on a 7-point Likert scale ranging from 1 (strongly agree) to 7 (strongly disagree). The operationalization of all study variables is summarized in **Table 3**.

Table 3 – Summary of the measures used for each variable in the study

Variable	Measure(s)	Description
Change Blindness propensity	• Flicker task: ○ Performance ○ Flicker score ○ Average alternations	Individual behavioural indices of change detection ability, where lower detection performance and flicker scores (0 to 1), as well as higher alternation counts, indicate greater susceptibility to change blindness.

Lived visual change detection	• Fixation duration • Fixation count • Time of interest (TOI) • K coefficient	Eye-tracking indicators of attentional allocation and visual processing related to change detection. Eye-tracking indicators of individual visual change detection. Higher fixation count, fixation duration, and K coefficient values, together with lower TOI values indicate greater sensitivity to interface changes. Negative K values reflect ambient attention, positive values focal attention, and values near zero a balance between both.
Perceived change recognition	• Recall question: Recalling a difference between the two interfaces showed during the tasks • Recognition question: Recognition of the current interface as theirs	Self-reported indicators of conscious recognition of interface changes based on recall of visual differences and recognition of the interface variant experienced, with responses coded binarily (0 = did not recall or recognize the change, 1 = did recall or recognize the change).
Perceptual load	• VISAWI positive	Self-reported measure of perceived visual workload; since VisAWI-Pos is composed of positively worded items, higher scores reflect more favourable visual perception and lower perceptual load, whereas lower scores indicate higher perceptual load during task performance.
Cognitive load	• Pupil dilatation	Physiological indicator of cognitive effort, with greater pupil dilatation reflecting higher cognitive load during task execution.

2.3.7 Procedure

Before the experiment, the participant was asked to complete the consent form. We then proceeded to collect demographic questions. Once all information was gathered, the moderator explained the goals and steps of the study to the participants. The next step consisted of calibrating the eye tracker in Tobii. Participants completed a nine-point calibration, which required attentively following a white dot moving across the screen. Following calibration, the recording of the experiment was started before proceeding with the baseline. Immediately after the baseline, participants completed a short questionnaire including sociodemographic questions and other measures that were not relevant to the present study (see Appendix E). Participants first completed the experimental paradigm (flicker task). Once this was completed, they performed the two Interac transfer tasks, each followed by the VISAWI positive scale (see Appendix A). After both transfer tasks were completed, participants were asked the recall and recognition questions. During the experiment, participants were instructed to remain as still as possible with a straight back while maintaining a comfortable position. Each participant was asked to adjust the screen position to them. Participants were also asked not to place their hands on their face to ensure consistent eye-tracking data. They were permitted to ask questions at any point during the experiment. The **Figure 6** following visually presents the manipulation of the factors (the interface with and without the presence of the AI functionality) introduced by the order of the Interac transfer task.

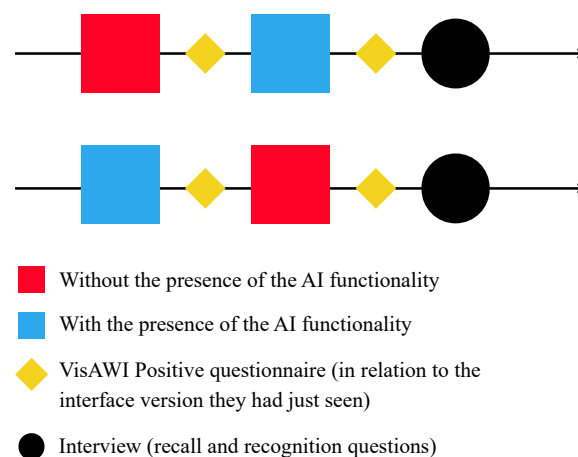


Figure 6 – Order of the tasks (manipulation of the factors)

We measured change blindness propensity, using the Flicker paradigm (Andermane et al., 2019), which provided three individual predisposition score: the overall performance, the flicker score and the average alternations. Each score ranged from 0 to 1, with values closer to 0 indicating a stronger predisposition to change blindness and values closer to 1 indicating a weaker predisposition to change blindness. It is important to mention that all dependent variables in the study were calculated as difference scores, derived by subtracting the values obtained during the first transfer task without the AI assistant (T1) from those obtained during the second transfer task with the AI assistant ($T2 - T1 = \text{difference score}$). Visual change detection was measured using fixation count difference, fixation duration difference, time of interest (TOI) difference and the K coefficient difference. We suppose that a higher fixation count, fixation duration and K coefficient difference, paired with a lower time of interest difference (Cheng, 2016.; Krejtz et al., 2016; (Uke) Karacan et al., 2010; Wals & Wichary, 2023) would indicate that a participant visually detected a change in the interface.

Besides, perceived change detection was measured using recall and recognition questions (see Appendix B). However, due to the absence of variation in one of the recognition questions, only the recall and the other recognition question were analyzed.: “Did you notice any differences in the interfaces of the previous tasks?” and “Is this interface different from the one you usually use on your phone?” Responses were coded as 0 when the participant did not correctly recall the interface change and 1 when they did. Pupil dilation differences served as an indicator of cognitive load, with greater dilation reflecting higher levels of cognitive load (Duchowski et al., 2018). Perceived perceptual load difference was assessed using the VISAWI positive questionnaire (Perrig et al., 2024). Example items include ‘The layout is easy to grasp’ and ‘Everything goes together on the site’ (Appendix A). Responses were collected on a 7-point Likert scale ranging from 1 (strongly agree) to 7 (strongly disagree).

2.3.8 Data analysis

To test our hypotheses, a series of regression models were conducted depending on the nature of the dependent variable. More precisely, logistic regressions were used to examine the relationship between change blindness propensity and recognition (H1), as well as between visual change detection and recognition performance (H3). Furthermore, linear regressions were conducted to assess the association between change blindness propensity and visual change detection (H2).

However, because fixation count differences represent count-based data, a negative binomial regression was employed for this indicator of visual change detection (H2a4 to H2a6). Finally, linear regressions were also applied to examine the relationship between change blindness propensity and both perceptual load and cognitive load (H4 and H5). An alpha level of .05 was used for all the statistical tests.

In addition to this conventional threshold, results approaching significance ($p < .10$) were reported and interpreted as marginal trends rather than definitive effects, in line with the exploratory nature of the present study. In exploratory research contexts, p-values near .10 are commonly used to identify emerging trends that may reflect potentially meaningful relationships worthy of further investigation, particularly in early-stage or underpowered studies (Rubin, 2017; Vidgen & Yasseri, 2016). Using a more flexible threshold helps limit the risk of missing potentially meaningful effects, as long as such findings are interpreted cautiously and not treated as definitive conclusions (Colquhoun, 2014).

2.4 Results

2.4.1 Descriptive statistics

Descriptive statistics were conducted to provide an overview of performance across the main variables. They will be presented separately according to participants' responses to Recall (detection of the IA assistant between the transfers) and Recognition (recognition of the AI assistant in their current mobile app).

For Recall, only three participants reported noticing differences between the two interfaces, compared to twenty-two who did not. As shown in **Table 4**, which presents the descriptive statistics for eye-tracking and cognitive indicators according to participants' recall of the interface change, mean performance scores on the Flicker task were comparable between groups ($M = 0.83$, $SD = 0.17$ vs. $M = 0.81$, $SD = 0.18$). Differences in visual change detection metrics indicated higher fixation counts and longer fixation durations among participants who detected the change ($M = 4.00$, $SD = 5.66$; $M = 93.67$, $SD = 76.54$), contrary to those who did not ($M = 3.00$, $SD = 4.29$; $M = 75.77$, $SD = 106.20$). Time spent on the area of interest also tended to differ between groups, with participants who noticed the change spending less time on the interface with the AI assistant

($M = -6337.50$, $SD = 47.38$) compared to those who did not ($M = 2434.42$, $SD = 7880.52$). Differences in pupil size, perceptual load, and saccadic coefficient (K) were minimal across groups. Since only three participants detected the change, Recall was excluded from inferential statistical analyses due to insufficient variance, as meaningful conclusions could not be drawn from such a small number of participants.

Table 4 - Descriptive statistics of eye-tracking and cognitive measures in Recall

Variables	Yes (n=3)		No (n=22)	
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Performance	0.83	0.17	0.81	0.18
Fixation count (difference)	4.00	5.66	3.00	4.29
Fixation duration (difference)	93.67	76.54	75.77	106.20
Time spent on the area of interest (difference)	-6337.50	47.38	2434.42	7880.52
Coefficient K (difference)	-0.08	0.09	0.03	0.22
Pupil size (difference)	-0.05	0.03	0.02	0.09
Perceptual load (difference)	-0.07	0.12	-0.09	0.47

For Recognition, sixteen participants correctly recognized the current banking interface, while nine did not. Again, performance scores were similar between groups ($M = 0.83$, $SD = 0.17$ vs. $M = 0.77$, $SD = 0.20$). Participants who recognized the interface showed fewer fixations ($M = 1.57$, $SD = 2.68$) and shorter fixation durations ($M = 46.63$, $SD = 101.13$) than those who did not ($M = 5.44$, $SD = 5.32$; $M = 133.56$, $SD = 80.38$). Patterns for the time of interest, pupil size, and perceptual load were less consistent, with small overall mean differences between groups. **Table 5** presents the descriptive statistics for eye-tracking and cognitive indicators according to participants' recognition of the interface.

Table 5 - Descriptive statistics of eye-tracking and cognitive measures in Recognition

Variables	Yes (n=16)		No (n=9)	
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Performance	0.83	0.17	0.77	0.20
Fixation count (difference)	1.57	2.68	5.44	5.32

Fixation duration (difference)	46.63	101.13	133.56	80.38
Time spent on the area of interest (difference)	1552.77	8007.22	1674.13	8346.31
Coefficient K (difference)	0.04	0.24	-0.03	0.13
Pupil size (difference)	0.01	0.10	0.00	0.06
Perceptual load (difference)	-0.04	0.39	-0.18	0.54

2.4.2 Correlation between variables

To examine the relationships between the study variables, a correlation matrix presented in Table 6, was computed (see Table 6). The table presents relationship between the main variables included in the study, including indicators of change blindness propensity, eye-tracking measures of visual change detection, perceptual load, and change recognition.

Overall, most correlations between the variables were weak to moderate. Significant relationships were observed between the indicators of change blindness propensity. Performance was positively correlated with flicker score ($r = .61$, $p < .01$), while flicker score was strongly negatively correlated with the average number of alternations ($r = -.74$, $p < .001$).

Some significant associations were also observed among eye-tracking measures. As expected, fixation count was positively correlated with fixation duration ($r = .47$, $p < .05$) and time spent on the area of interest ($r = .54$, $p < .05$), as these measures all reflect aspects of visual attention to the interface. In addition, change recognition was negatively correlated with fixation count ($r = -.45$, $p < .05$) and fixation duration ($r = -.42$, $p < .05$). Perceptual load was positively correlated with time spent on the area of interest ($r = .42$, $p < .05$).

Table 6 - Correlations Among Study Variables

<i>Variable</i>	<i>M</i>	<i>SD</i>	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Performance	0.81	0.18	-									
2. Flicker score	0.25	0.09	0.61**	-								
3. Avg. alternations	3.46	1.05	-0.06	-0.74***	-							
4. Fixation count (difference)	3.09	4.27	-0.27	-0.18	0.03	-						
5. Fixation duration (difference)	77.92	101.78	0.02	0.03	0.01	0.47*	-					
6. Time spent on the area of interest (difference)	1599	7928	-0.29	-0.23	-0.01	0.54*	0.29	-				
7. Coefficient K (difference)	0.01	0.21	0.05	0.25	-0.24	-0.33	0.04	-0.13	-			
9. Recognition	0.64	0.49	0.18	0.16	-0.15	-0.45*	-0.42*	-0.01	0.15	-		
10. Perceptual load (difference)	-0.09	0.44	-0.37	-0.36	0.09	0.33	0.02	0.42*	-0.38	0.15	-	
11. Pupil size (difference)	0.01	0.09	0.01	0.28	-0.32	0.23	0.34	0.41	0.13	0.06	0.23	-

Note. M= Mean, SD= Standard Deviation, Note. * = $p < .05$, ** = $p < .01$, *** $p < .001$

2.4.3 Effect of Change Blindness on Change Recognition Performance (H1)

The hypothesis suggested a relationship between predisposition to change blindness and users' change recognition ability, predicting that a higher change blindness propensity would reduce recognition performance. We conducted logistic regressions to examine the influence of change blindness propensity metrics on perceived change detection (Recognition). The analysis indicated that the performance level did not significantly predict the likelihood of correctly recognizing and correctly recalling the interface [$\beta = 2.13$, SE B = 2.41, $t(df) = 0.88$, 95% CI = [-2.86, 7.12], $p = 0.39$]. Similarly, additional logistic regressions showed no significant effect on the flicker score [$\beta = 4.17$, SE B = 5.15, $t(df) = 0.81$, 95% CI = [-6.49, 14.83], $p = 0.43$], or for average alternations time [$\beta = -0.30$, SE B = 0.40, $t(df) = -0.76$, 95% CI = [-1.14, 0.53], $p = 0.46$], on the probability of recognizing the correct mobile banking interface. Therefore, the results do not support this hypothesis.

2.4.4 Relationship Between Change Blindness and Visual Change Detection indicators (H2)

This hypothesis suggested a relationship between predisposition to change blindness and users' visual change detection ability, predicting that higher change blindness propensity would be associated with lower visual detection performance. Linear regressions were conducted to examine the effect of change blindness propensity metrics on visual change detection metrics. Out of the

12 tests conducted, only the effect of performance on the time of interest difference ($p = .10$) was of marginal significance, indicating a possible tendency for participants with lower flicker task performance (reflecting stronger change blindness predisposition) to show less visual attention. Thus, across all other models, performance levels, flicker score, and average alternations were not significant predictors of fixation duration difference, time of interest difference, or K coefficient difference. Therefore, the results do not support this hypothesis. All results of the regression analyses examining the relationship between change blindness propensity indicators and visual change detection metrics are presented in **Table 7**.

Table 7 - Regression Analyses Examining the Effect of Change Blindness Metrics on Visual Change Detection Indicators

Effect	<i>Estimate</i>	<i>Standard Error</i>	<i>t Value</i>	<i>p</i>	<i>IC 95%</i>
Performance (Fixation duration difference) *	8.85	119.47	0.07	0.47	[-238.28, 255.99]
Performance (Fixation count difference)	-1.18	1.09	-1.08	0.29	[-3.48, 1.12]
Performance (Time of Interest difference) *	-13818.00	10355.00	-1.33	0.10	[-35491.00, 7855.91]
Performance (K coefficient difference) *	0.06	0.24	0.26	0.40	[-0.44, 0.57]
Flicker Score (Fixation duration difference) *	34.53	239.28	0.14	0.44	[-460.46, 529.51]
Flicker Score (Fixation count difference)	-1.09	2.69	-0.40	0.35	[-6.74, 4.57]
Flicker Score (Time of Interest difference) *	-20210.00	19606.00	-1.03	0.16	[-61246.00, 20826.00]
Flicker score (K coefficient difference) *	0.59	0.47	1.24	0.11	[-0.29, 1.57]
Average alternations (Fixation duration difference)	1.02	20.17	0.05	0.96	[-40.60, 42.65]
Average alternations (Fixation count difference) *	-0.04	0.17	-0.26	0.40	[-0.40, 0.31]
Average alternations (Time of Interest difference)	-92.11	1763.65	-0.05	0.96	[-3783.48, 3599.25]
Average alternations (K coefficient difference) *	-0.05	0.04	-1.21	0.12	[-0.13, 0.03]

Note: * indicates that the direction of the coefficient was consistent with the hypothesis

2.4.5 Impact of Visual Change Detection on Change Recognition Performance (H3)

The hypothesis suggested a relationship between visual change detection ability and users' change recognition ability, predicting that stronger visual detection performance would enhance recognition accuracy. Logistic regression analyses indicated that fixation duration difference [$\beta = -0.01$, SE B= 0.01, $t(df) = -1.94$, 95% CI = [-0.02, 0.00], $p = 0.06$] and fixation count difference

$[\beta = -0.28, SE B = 0.15, t(df) = -1.92, 95\% CI = [-0.59, 0.02], p = 0.07]$ were marginally significant predictors of recognition, suggesting that higher fixation durations or counts were associated with a lower probability of correctly recognizing the presence of the AI assistant in the mobile banking app (see **Figure 7**). By contrast, neither time spent on the area of interest, $[\beta = -2.03E-6, SE B = 0.00, t(df) = -0.03, 95\% CI = [-0.00, 0.00], p = 0.97]$, nor the K coefficient $[\beta = 1.62, SE B = 2.14, t(df) = 0.76, 95\% CI = [-2.81, 6.05], p = 0.46]$, significantly predicted recognition. Therefore, the results do not support this hypothesis, as the observed relationships contradict the predicted effect.

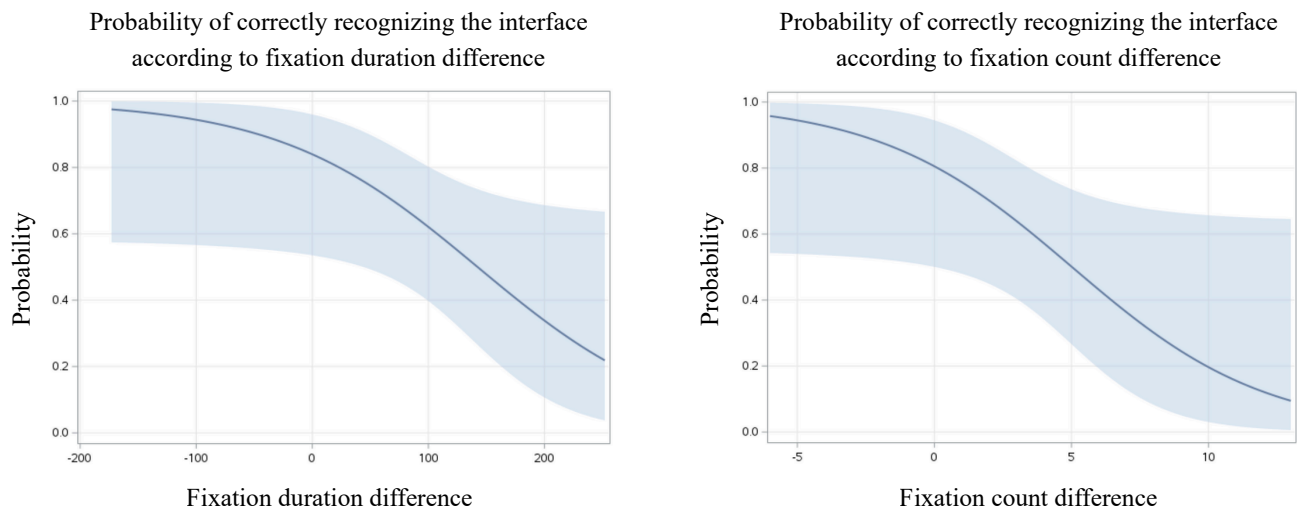


Figure 7 - Interaction effects of fixation duration difference and fixation count difference on the probability of correctly recognizing and recalling the current mobile banking interface

2.4.6 Influence of Change Blindness on Perceptual Load (H4)

The hypothesis suggested a relationship between predisposition to change blindness and perceived perceptual load, predicting that higher change blindness propensity would be associated with lower perceived load. Results revealed marginally significant negative associations between performance and perceptual load $[\beta = -0.93, SE B = -0.48, t(df) = -1.91, 95\% CI = [-1.93, 0.07], p = 0.03]$ and between flicker score and perceptual load $[\beta = -1.79, SE B = 0.97, t(df) = -1.84, 95\% CI = [-3.81, 0.23], p = 0.04]$. As shown in **Figure 8**, these results are aligned with expectations, suggesting that as performance increases (change blindness predisposition decreases), perceptual load scores decrease. Therefore, participants reported higher visual load, since the questionnaire was positive. This suggests that participants with stronger change blindness propensity tended to

experience lower visual load during the task. No significant effect was observed for average alternations [$\beta = 0.04$, $SE\ B = 0.09$, $t(df) = 0.44$, $95\%\ CI = [-1.14, 0.22]$, $p = 0.33$]. Therefore, these results partially support this hypothesis, as they indicate a marginal trend consistent with the hypothesized relationship, suggesting that lower predisposition to change blindness may be associated with higher perceived visual load.

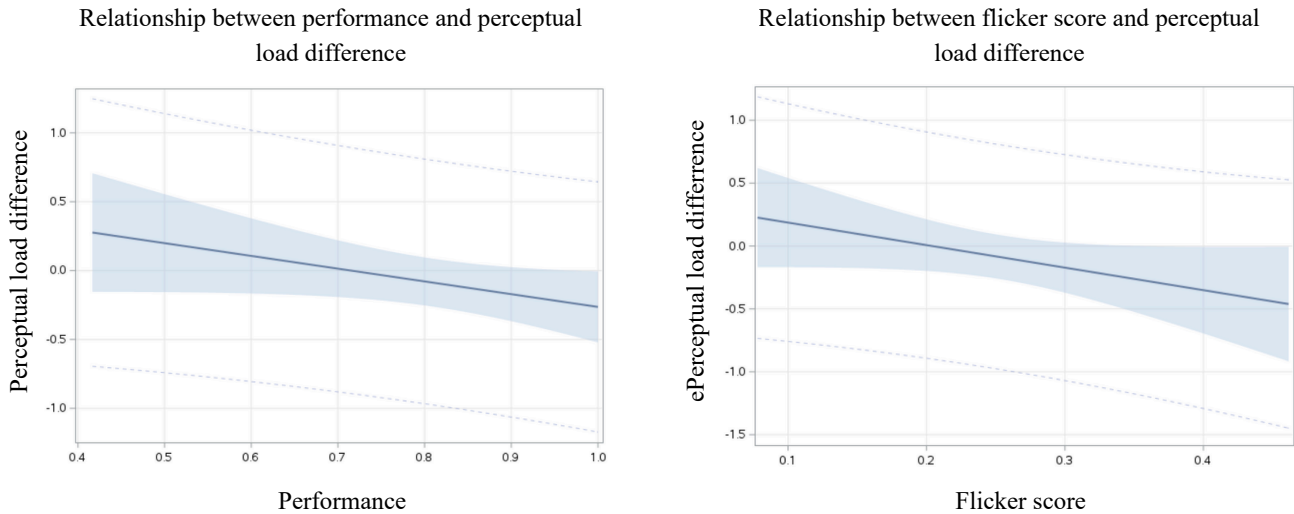


Figure 8 - Interaction effects of performance difference and flicker score on perceptual load

2.4.7 Effect of Change Blindness on Cognitive Load (H5)

The hypothesis suggested a relationship between predisposition to change blindness and users experienced cognitive load, predicting that higher change blindness propensity would be associated with lower cognitive load. Linear regressions were also conducted to assess the effect of change blindness indicators on cognitive load, measured via pupil dilation. Results indicated no significant effect between performance and pupil size [$\beta = 0.00$, $SE\ B = 0.10$, $t(df) = -0.04$, $95\%\ CI = [-0.17, 0.18]$, $p = 0.49$]. By contrast, the flicker score showed a positive effect that was marginally significant [$\beta = 0.28$, $SE\ B = 0.20$, $t(df) = 1.41$, $95\%\ CI = [-0.13, 0.68]$, $p = 0.09$], while average alternations showed a marginally significant negative effect [$\beta = -0.03$, $SE\ B = 0.02$, $t(df) = -1.60$, $95\%\ CI = [-0.06, 0.01]$, $p = 0.06$]. As shown in **Figure 9**, these results suggest that a lower predisposition to change blindness exhibited a trend toward greater pupil dilation, reflecting higher cognitive load. In contrary, higher average alternations (indicative of a stronger predisposition to change blindness) were associated with reduced pupil dilation, suggesting lower cognitive load.

Therefore, the results reveal marginal trends consistent with the hypothesized relationship, suggesting that lower predisposition to change blindness may be associated with greater pupil dilation and therefore higher cognitive load. Accordingly, the hypothesis is considered partially supported based on exploratory trends

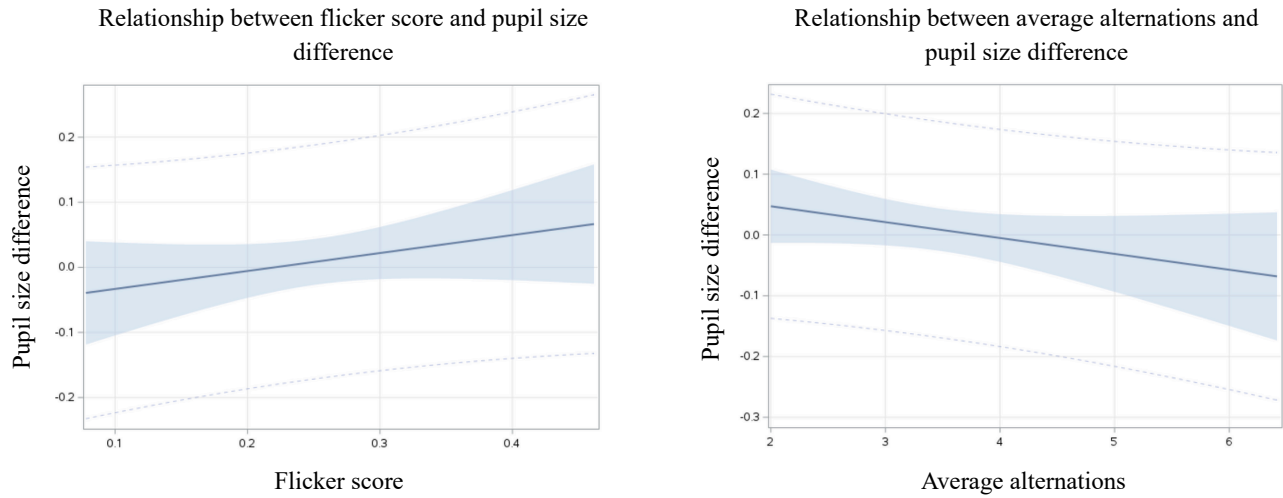


Figure 9 - Interaction effects of flicker score and average alternations on pupil size difference

Overall, the analyses indicate limited direct support for the hypothesized relationships between change blindness propensity, visual detection, and conscious recognition of the AI assistant. No significant effects were observed between change blindness propensity and recognition performance (H1), nor between change blindness propensity and most eye-tracking indicators of visual detection (H2), with only one marginal trend observed for time of interest. Similarly, the expected positive relationship between lived visual detection and recognition (H3) was not supported, although marginal effects emerged for fixation duration and fixation counts, suggesting that higher levels of visual exploration were associated with lower recognition accuracy. In contrast, change blindness propensity showed marginal associations with perceptual load (H4), with lower predisposition corresponding to higher perceived visual load, and with cognitive load (H5), where lower predisposition tended to be associated with greater pupil dilation. Taken together, these results indicate that associations between change blindness propensity and users' subjective experience showed more observable trends than those observed for objective visual detection or conscious recognition outcomes. **Table 8** summarizes the statistical results for each

hypothesis tested in the study, while **Figure 10** summarizes the regression results and indicate which hypotheses were supported or not.

Table 8 – Validity test results

Hypothesis	From	To	Path Coeff.	t-Value	p-Value	Status
1	Change Blindness propensity	Perceived change detection				
	Performance	Recognition	2.13	0.88	0.39	Not supported
	Flicker Score	Recognition	4.17	0.81	0.43	Not supported
	Average alternations	Recognition	-0.31	-0.76	0.46	Not supported
2	Change Blindness propensity	Lived change detection				
	Performance	Fixation duration difference	8.85	0.07	0.47	Not supported
	Flicker Score	Fixation duration difference	34.52	0.14	0.44	Not supported
	Average alternations	Fixation duration difference	1.02	0.05	0.96	Not supported
	Performance	Fixation count difference	-1.18	-1.08	0.29	Not supported
	Flicker Score	Fixation count difference	-1.08	-0.40	0.35	Not supported
	Average alternations	Fixation count difference	-0.04	-0.26	0.40	Not supported
	Performance	Time of Interest difference	-13818	-1.33	0.10	Not supported
	Flicker Score	Time of Interest difference	-20210	-1.03	0.16	Not supported
	Average alternations	Time of Interest difference	-92.11	-0.05	0.96	Not supported
	Performance	K coefficient difference	0.06	0.26	0.40	Not supported
	Flicker Score	K coefficient difference	0.59	1.24	0.11	Not supported
	Average alternations	K coefficient difference	-0.05	1.21	0.12	Not supported
3	Lived change detection	Perceived change detection				
	Fixation duration difference	Recognition	-0.01	-1.94	0.06	Not supported*
	Fixation count difference	Recognition	-0.28	-1.92	0.07	Not supported*
	Time of interest difference	Recognition	-2.03E-6	-0.03	0.97	Not supported
	K coefficient difference	Recognition	1.61	0.76	0.46	Not supported
4	Change Blindness propensity	Perceptual load				
	Performance	Perceptual load difference	-0.93	-1.91	0.03	Supported
	Flicker Score	Perceptual load difference	-1.79	-1.84	0.04	Supported
	Average alternations	Perceptual load difference	0.04	0.44	0.33	Not supported
5	Change Blindness propensity	Cognitive load				
	Performance	Pupil size difference	0.00	0.04	0.49	Not supported
	Flicker Score	Pupil size difference	0.28	1.41	0.09	Partially supported (marginal trend)

Average alternations	Pupil size difference	-0.03	-1.60	0.06	Partially supported (marginal trend)
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Note: * indicates that the results are significative, but inconsistent with hypothesis.

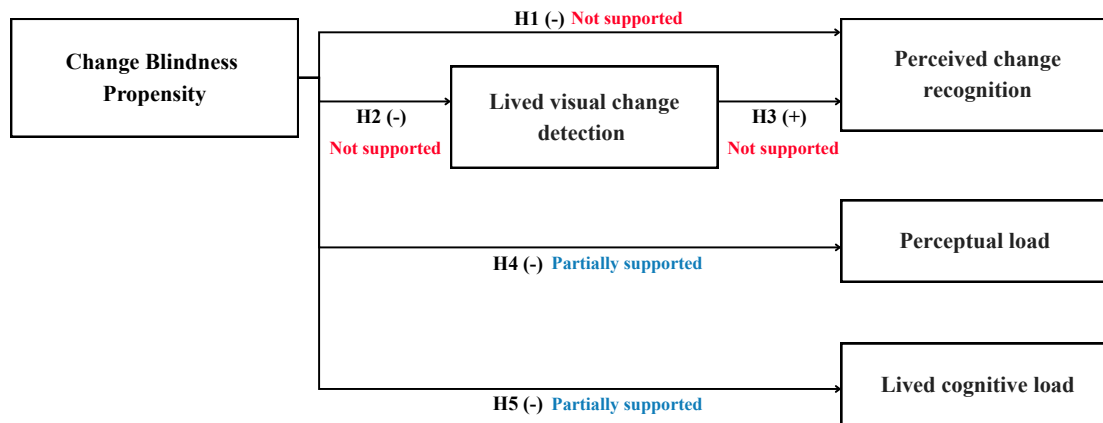


Figure 10 – Summary of tested hypotheses and results

2.5 Discussion

2.5.1 Context

Digital interfaces evolve rapidly, yet users often fail to notice meaningful changes such as new features or design updates. This lack of awareness can undermine both usability and adoption, especially when changes occur within familiar environments, like online banking platforms. To address this issue, the present study asked: to what extent does predisposition to change blindness prevent users from detecting a new functionality in an interface? We proceeded to investigate how individual predisposition to change blindness influences users' ability to detect and recognize a new AI-based functionality integrated within a familiar banking interface. The objective was to understand how cognitive and attentional mechanisms, like selective attention or perceptual load, affect users' capacity to notice and later recognize a meaningful interface update during their

interaction with the interface. Eye-tracking, pupil dilation, perceptual load questionnaire and post-task recognition measures were combined to capture both visual and conscious indicators of change detection. Grounded in attention-based and limited capacity perspectives, which posit that humans can only process a small amount of visual information at a time and that conscious awareness depends on where attention is directed (Rensink, 2002; Simons & Levin, 1997). It was also examined using Perceptual Load Theory, which proposes that awareness of visual stimuli decreases as task complexity and attentional demands increase (Lavie & Tsal, 1994). By combining these frameworks, the study extends change blindness research beyond controlled laboratory paradigms to a real world UX context, where unnoticed changes have direct implications for technology adoption.

2.5.2 Findings

First, our results showed no significant effect between change blindness propensity and change recognition ability. In fact, none of the indicators of change blindness propensity, seemed to show a tendency to increase or decrease the recognition ability. Thus, the absence of a significant relationship between change blindness propensity and conscious recognition in the present study is consistent with prior evidence showing that failure to detect a visual change does not necessarily imply a failure to encode or retain a representation of the original scene. This experimental research found that recognition accuracy was comparable for participants who successfully detected a change and those who did not notice the change. Both groups recognized the changed stimulus more frequently than would be expected by chance, suggesting that even observers who missed the change often represented sufficient detail to select the correct pre-change stimulus from an array of distractors, which showed that the predisposition to change blindness did not demonstrate a clear or consistent effect in the context of recognizing interface changes (Simons et al., 2002). Additional evidence supports this interpretation. Studies show that participants who failed to notice a change were equally able to recognize changed items compared to those who detected the change, demonstrating comparable recognition accuracy across groups (Angelone et al., 2003). Similarly, observers monitoring and responding to objects exhibited high rates of change blindness while still performing well on recognition tests for those same objects, indicating that visual details were encoded even when the change itself went unnoticed (Jensen, 2015). Together, these results

suggest that missed detections seem more likely due to a failure to compare successive visual representations rather than a failure to encode object information in the first place.

Although change blindness propensity did not significantly predict recognition performance, the present study nevertheless revealed a limited yet measurable influence on visual detection metrics. Among the indicators of gaze behaviour, only the time of interest has shown a marginal trend with change blindness performance. Participants with stronger predisposition to change blindness (lower performance scores) tended to spend less time attending to key interface elements, particularly the area displaying the AI assistant and nearby textual or graphical prompts intended to draw attention to the new feature during the transfer task, suggesting a possible reduction in visual engagement and attentional allocation. These findings are consistent with prior studies showing that time spent on relevant areas reflects the depth of attentional processing during change detection (Nikolaev et al., 2011; Zelinsky, 2001). However, the overall non-significant associations across most eye-tracking measures suggest that while predisposition to change blindness may constrain awareness, its direct impact on raw visual scanning behaviour may depend on contextual salience and user motivation. Additional evidence supports this pattern by showing that common gaze metrics are often poor predictors of successful change detection (Andermane et al., 2019; Chetverikov et al., 2018; Nikolaev et al., 2011). Although fixation locations and eye movements tend to differ relative to the region of change, neither saccade amplitudes nor fixation durations around target areas consistently predict whether a change will ultimately be detected, indicating that looking longer or more often does not guarantee awareness (Nikolaev et al., 2011). Instead, detection success has been linked to the alignment between physiological indicators of attentional engagement and eye movements, suggesting that conscious detection depends on whether overt gaze is accompanied by genuine attentional processing rather than on visual scanning behaviour alone (Nikolaev et al., 2011). These findings reinforce the present results, suggesting that differences in visual detection cannot be completely explained by differences in gaze behaviour or predisposition to change blindness alone.

To further explore this relationship at a more specific level, additional analyses examined the direct association between fixation-based measures and recognition performance. A marginally significant trend was observed between fixation-based measures and recognition performance. Participants who spent more time fixating on the interface tended to perform worse on recognition,

suggesting that prolonged visual engagement did not necessarily facilitate awareness. This pattern is consistent with research on visual search strategies showing that inefficient or struggling search behaviour is often characterized by fewer fixations of longer duration; whereas more effective search is marked by many brief fixations, reflecting rapid comparison and decision processes rather than prolonged inspection (Zelinsky, 2001). Longer fixation durations may therefore signal difficulty in resolving visual comparisons rather than deeper or more successful encoding of visual information, supporting the interpretation that increased gaze engagement can reflect impaired processing rather than enhanced detection performance (Zelinsky, 2001).

Those results contrast with other work showing that increased fixation duration on the changing object is often associated with improved encoding and comparison processes, as longer fixations can support deeper processing of visual details and facilitate conscious awareness of the change (Andermane et al., 2019). One study found a high correlation between participants' explicit verbal reports of detecting a change and their eye fixations. Specifically, the average fixation durations on changing objects were longer for the participants who reported that they had recognized the change. This suggests that longer fixation durations on the changing objects provided them with awareness of that specific change ((Uke) Karacan et al., 2010). This study also suggests that familiarity with an environment increases visual attention to deviations from normal interface states, with experienced users fixating longer on changed elements than less familiar users, suggesting that knowledge of the expected layout can enhance the detection of updates ((Uke) Karacan et al., 2010). In terms of attentional processing, successful change detection is typically associated with a focal mode of attention, characterized by longer fixations and shorter saccades that support detailed inspection and visual comparison, whereas detection failures are more often linked to an ambient mode marked by shorter fixations and shallower processing of visual information (Krejtz et al., 2016). These findings indicate that sufficient fixation duration is necessary to allow the focal attention required for encoding and comparing visual representations, reinforcing the view that conscious detection depends not on gaze alone but on the quality of attentional engagement directed toward the changing element (Chetverikov et al., 2018). Taken together, this discrepancy highlights that visual metrics such as fixation duration can reflect different underlying processes depending on how attention is allocated during a task, and that their meaning depends on the operationalization and context of measurement rather than providing a straightforward indicator of successful change detection.

Perceptual and cognitive load analyses provided additional insight into this phenomenon. As hypothesized, higher predisposition to change blindness showed marginal associations with lower perceived visual load, as participants with stronger change blindness tendencies reported the interface as less demanding. This pattern suggests that those who notice more details, hence have a lower predisposition to change blindness, may perceive the interface as visually denser, consistent with Load Theory's argument that perceptual awareness depends on the extent of attentional engagement (Lavie et al., 2014). Similarly, results for cognitive load showed a marginally significant effect in the predicted direction: participants with lower predisposition to change blindness (i.e., better change detection ability) displayed greater pupil dilation, reflecting increased cognitive effort (Duchowski et al., 2018). This pattern suggests that higher engagement of working-memory resources supports change detection, while users who invest less cognitive effort remain unaware of visual updates even when fixating upon them (Sweller, 2024).

Taken together, these results suggest that users' ability to detect and consciously recognize changes within digital banking interfaces depends on a complex balance between attention, effort, and visual salience. While participants with stronger change blindness tendencies visually processed the interface, their reduced cognitive and perceptual engagement may have limited the transition from visual detection to conscious recognition. This gap between looking and noticing reinforces the need to consider perceptual mechanisms, rather than only behavioural intentions, when studying the adoption of new AI-based functionalities in real-world interfaces. Furthermore, this pattern suggests that the effects of change blindness may extend beyond a single first exposure. Repeated interactions with familiar interfaces may continue to favour routine task completion, thereby limiting attentional resources available for detecting interface updates. Consequently, even when changes are encountered multiple times, they may remain insufficiently processed to reach conscious recognition.

2.5.3 Implications

This study contributes to the theoretical understanding of change blindness by suggesting that failures to notice visual updates arise from an imbalance between attention, working memory, and cognitive engagement, rather than from purely perceptual limitations. By situating the phenomenon within a real digital banking interface, the findings extend attention-based and limited-capacity accounts (Simons & Levin, 1997; Rensink, 2002) beyond controlled visual

paradigms to applied contexts where user goals and habits influence awareness. The results also bridge perceptual load theory (Lavie & Tsai, 1994) and cognitive load theory (Sweller, 2024), suggesting that the detection of change depends on the degree of attentional investment and mental effort mobilized by the user. These findings position change blindness propensity as a possible stable cognitive trait that moderates how attention and memory interact during visual information processing.

From a design and management perspective, the findings underline that users may look at new interface elements without consciously perceiving them, especially when these are introduced into familiar environments. For organizations integrating AI-driven functionalities, this implies that visibility alone may not guarantee awareness or adoption. Designers should, therefore, use salient visual cues, such as animation, contrast, or contextual highlights, to draw focused attention toward new features while maintaining cognitive balance. Additionally, guided discovery strategies and short onboarding sequences can help ensure that changes are consciously registered, thereby improving usability, trust, and acceptance of new digital services.

Methodologically, this study demonstrates the value of combining psychophysiological and behavioural data to study attention and awareness in realistic digital environments. By integrating eye-tracking, pupil dilation, questionnaires and recognition measures, the research provides a richer view of how users allocate cognitive resources during interaction. Unlike traditional flicker task paradigms, this mixed method approach captures both overt visual behaviour and underlying cognitive load within an authentic task setting. This contributes to methodological approaches in UX research by offering a framework for studying perceptual awareness under ecologically valid conditions.

2.6 Conclusion

2.6.1 Limitations and future research

This study was designed as an exploratory investigation aimed at examining change blindness within a realistic mobile banking interface, a context that has rarely been examined in prior research. Given the novelty of this research setting and the demands of laboratory eye-tracking experimentation, a moderate sample size was selected as a practical choice to identify initial trends in users' visual attention, recognition, and cognitive load. This sample size was sufficient for

exploratory analyses but limited the statistical power needed to detect smaller effects or potential moderating relationships, such as those involving interface familiarity or perceptual load. Future studies should, therefore, include larger and more diverse samples to allow for stronger statistical testing and more detailed analyses of individual differences and user subgroups.

A second methodological choice involved the use of recall measures to assess conscious change recognition. While this approach was appropriate for examining differences between visual detection and conscious reports of the change, the very low number of participants who reported noticing the change reduced variance in this measure and prevented meaningful inferential analyses. This imbalance limited variance in the recall measure and limited inferential analyses. Future research should increase sample size or task repetitions and incorporate additional recall or recognition measures to ensure sufficient response variability.

Finally, the experiment was conducted using a desktop simulation of the mobile banking interface. This setup was necessary to ensure experimental control and reliable eye-tracking data collection. However, it does not fully replicate natural mobile use conditions, such as touch interaction, handheld device use, or everyday multitasking. These factors may influence attention and perceptual processing. Future studies should therefore aim to replicate this research in mobile device contexts to improve ecological validity and examine how closer real-world usage contexts shape change detection and awareness.

2.6.2 Summary and Implications

This study examined how individual predisposition to change blindness influences users' ability to detect and recognize new functionalities within a familiar digital banking interface. By integrating behavioural and psychophysiological data, the research provided a detailed view of how attentional focus, working memory, and perceptual load shape users' awareness of interface changes. The findings revealed that users with stronger change blindness tendencies often visually processed but failed to consciously recognize the new AI-based feature, underscoring the gap between perception and awareness in applied digital contexts. These results extend existing attention and load theories to real world UX environments and highlight change blindness propensity functions as a stable individual trait that shapes both cognitive effort and perceptual engagement.

Beyond confirming the presence of change blindness in a real-world UX context, this study makes a theoretical contribution by demonstrating a dissociation between visual exposure and conscious recognition. The absence of strong relationships between gaze metrics, change-blindness propensity, and explicit recognition emphasizes that seeing is not sufficient for noticing. This reinforces contemporary models proposing that failures of change awareness stem primarily from limitations in attentional integration and comparison processes rather than from failures of visual encoding. By extending these mechanisms into applied interface environments, the findings strengthen the argument that perceptual limitations actively shape technology adoption outcomes, even when interface changes are visually available.

Looking ahead, this research opens new perspectives for both cognitive and design sciences. Future studies could further explore the interaction between change blindness propensity and other underlying cognitive mechanisms, such as memory processes and cognitive scripts, to better understand their role in change detection within complex interfaces. Additional research should also examine how design cues, task goals, or adaptive AI interfaces can mitigate change blindness and promote awareness in dynamic digital environments. Finally, conducting studies with larger samples would allow testing of potential moderating effects and increase the robustness of findings. As interfaces continue to evolve toward greater automation and personalization, understanding how users allocate and sustain attention will be crucial for fostering trust, engagement, and effective human–AI collaboration.

From a practical perspective, the results highlight the importance of designing explicitly for change awareness rather than relying on passive visibility. Simply adding new AI features to familiar interfaces may not be sufficient to ensure user discovery or adoption. Designers should, therefore, prioritize salient change cues, guided onboarding interactions, or dynamic highlighting techniques that actively attract focal attention and support comparison processes. Without such support, valuable functionalities risk remaining cognitively invisible to users, limiting their real-world impact.

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Chapitre 3 - Conclusion

3.1 Rappel de la question de recherche et des objectifs

Cette étude visait à répondre à la question de recherche suivante : « Dans quelle mesure la prédisposition à la cécité au changement empêche-t-elle l'utilisateur de détecter une nouvelle fonctionnalité dans une interface ? » Plus précisément, l'étude cherchait à évaluer l'effet de cette prédisposition sur la détection visuelle vécue (nombre de fixations, durée de fixation, temps passé sur la page et coefficient K) et la reconnaissance consciente (reconnaitre l'interface présentant la nouvelle fonctionnalité comme la version actuelle de leur application bancaire) d'une nouvelle fonctionnalité intégrée à une application bancaire mobile. L'objectif était également d'examiner dans quelle mesure la détection visuelle influence la reconnaissance, c'est-à-dire à quel point l'engagement visuel est déterminant ou contribue de la capacité de rappel d'une nouvelle fonctionnalité. Enfin, l'étude explorait le lien entre la prédisposition à la cécité au changement, la charge perceptuelle perçue et la charge cognitive vécue (dilatation de la pupille), afin de mieux comprendre comment les ressources attentionnelles pourraient moduler la perception du changement en contexte d'usage numérique.

3.2 Synthèse des résultats principaux

Les résultats montrent qu'une forte prédisposition à la cécité au changement ne prédit pas directement la détection visuelle du changement ni la reconnaissance d'une nouvelle fonctionnalité. Autrement dit, les individus plus enclins à ne pas remarquer des changements visuels ne présentent pas de différences significatives dans leurs comportements oculaires ni dans leur capacité à se souvenir de la fonctionnalité dans leur propre application bancaire. Ces observations suggèrent que la cécité au changement ne se manifeste pas nécessairement par un déficit de traitement visuel mesurable, mais plutôt par une limite dans la transition entre la perception et la conscience.

Les résultats mettent en évidence des différences révélatrices dans la manière dont les utilisateurs portent attention à l'interface. Les personnes présentant une forte prédisposition à la cécité au

changement ont eu tendance à accorder moins longtemps de temps sur les zones d'intérêts de l'interface (la nouvelle fonctionnalité) et à percevoir l'interface comme moins visuellement exigeante. Ce profil témoigne d'une exploration plus automatique ou superficielle, possiblement guidée par l'habitude plutôt que par une réelle analyse visuelle, traduisant une faible mobilisation des ressources attentionnelles et limitant ainsi la probabilité de remarquer les nouveautés.

De façon plus inattendue, les analyses de reconnaissance révèlent qu'un plus grand nombre ou une plus longue durée de fixations ne garantit pas la détection consciente du changement. En effet, les résultats montrent qu'un plus grand nombre ou une plus longue durée de fixations ne se traduisent pas nécessairement par une meilleure reconnaissance du changement. Les participants les plus affectés par la cécité au changement pouvaient regarder la nouveauté sans la remarquer, probablement parce que leur attention était guidée par des schémas d'usage familiers et non par la recherche d'éléments nouveaux. À l'inverse, les utilisateurs moins sujets à la cécité au changement ont manifesté un engagement attentionnel plus soutenu et ont jugé l'interface plus chargée visuellement, signe qu'ils investissent davantage d'effort cognitif pour traiter l'information. Une charge perceptuelle plus élevée semble donc favoriser une sensibilité accrue aux changements, même subtils, présents dans l'interface.

En somme, une forte prédisposition à la cécité au changement semble associée à un engagement attentionnel plus limité, d'une sous-estimation de la complexité visuelle et d'une transformation moins efficace de la perception en conscience, illustrant la frontière fragile entre voir et remarquer dans les environnements numériques familiers. Cependant, la perception d'une nouvelle fonctionnalité ne dépend pas uniquement de la vision, mais d'un ensemble de processus cognitifs et attentionnels qui déterminent si une information perçue parvient ou non au niveau de la conscience.

3.3 Contribution théorique et pratique

Ce mémoire contribue à la littérature sur la perception visuelle et l'expérience utilisateur en transposant les fondements de la cécité au changement, généralement étudiée en contexte expérimental contrôlé, à un environnement numérique, soit une interface bancaire mobile. D'un point de vue théorique, il maintient les travaux de Simons et Levin (1997) en démontrant que la

cécité au changement résulte des limites conjointes de l'attention, de la mémoire visuelle et de la conscience. Il montre aussi que ce phénomène peut survenir même face à des modifications évidentes lorsque l'attention de l'utilisateur est dirigée ailleurs. Comme l'a soutenu Rensink (2002), la perception visuelle ne consiste pas en une représentation complète et stable du monde, mais plutôt en une construction dynamique mise à jour en fonction de ce qui attire l'attention à un moment précis. Ce mémoire étend ces fondements à un contexte d'usage réel, montrant que cette limite cognitive se manifeste également dans des environnements numériques familiers, où l'attention est fortement guidée par les habitudes de navigation. Cette démarche permet ainsi de situer la cécité au changement dans le champ de l'expérience utilisateur, en reliant les modèles attentionnels issus de la psychologie cognitive à la question de la découvrabilité technologique.

Les résultats empiriques confirment également les observations de Simons et Ambinder (2005) selon lesquelles la détection du changement repose sur la manière dont l'attention est distribuée entre les éléments pertinents et non pertinents, plutôt que sur la quantité d'information disponible. Ce mémoire met en évidence que les individus ayant une forte prédisposition à la cécité au changement adoptent une exploration visuelle plus automatique et routinière, guidée par des schémas d'usage familiers, traduisant une moindre mobilisation des ressources cognitives. À l'inverse, les utilisateurs qui manifestent une charge perceptuelle et cognitive plus élevée sont plus enclins à détecter la nouveauté, ce qui soutient la Load Theory selon laquelle le niveau d'engagement attentionnel conditionne la profondeur du traitement conscient (Lavie, 2006; Lavie & Tsal, 1994). Ces résultats enrichissent donc les modèles existants en positionnant la prédisposition à la cécité au changement comme un trait cognitif stable, influençant la manière dont l'attention et la mémoire interagissent pour permettre ou non la reconnaissance consciente d'un changement dans un environnement numérique.

Du point de vue de la pratique UX, cette recherche met en évidence plusieurs pistes concrètes applicables à la conception et à l'évaluation des interfaces numériques. D'abord, elle rappelle qu'une nouveauté bien intégrée visuellement ne garantit pas sa perception consciente : les utilisateurs peuvent la regarder sans la remarquer, leur attention étant principalement dirigée par leurs objectifs de tâche et leurs habitudes d'usage (Simons & Levin, 1997). En mobilisant les enseignements de Rensink et al. (1997), selon lesquels la perception du changement n'émerge que lorsque l'attention est dirigée vers la région concernée, ce mémoire soutient l'idée que la

découvrabilité d'une innovation repose sur la synchronisation entre l'apparition du changement et le moment où l'attention de l'utilisateur est disponible. Ces résultats peuvent se traduire en plusieurs recommandations opérationnelles pour la pratique UX. Lors de l'introduction de nouvelles fonctionnalités, il est pertinent de soutenir activement l'attention de l'utilisateur par des signaux discrets mais intentionnels, tels que des micro-animations ciblées, des changements temporaires de contraste ou de légers indicateurs visuels contextuels apparaissant au moment opportun de la tâche. Ces interventions doivent rester limitées dans le temps afin de favoriser la prise de conscience sans perturber l'expérience globale.

Dans la même logique, il pourrait également être recommandé d'introduire les nouveautés à des moments où l'attention de l'utilisateur est le plus disponible, par exemple lors d'un écran de confirmation, lors d'un premier accès à une fonctionnalité ou à la suite d'une action significative, plutôt que durant des phases d'utilisation routinières dominées par les automatismes. Ce positionnement temporel favoriserait une meilleure mobilisation de l'attention et augmenterait les chances que la nouveauté perçue soit reconnue consciemment par l'utilisateur.

Ces constats invitent aussi les concepteurs et chercheurs en expérience utilisateur à revoir certaines pratiques méthodologiques. Dans un premier temps, la cécité au changement pourrait être prise en compte lors de la planification des tests utilisateurs. Au même titre que l'âge, la familiarité ou l'expérience technologique, la prédisposition à la cécité au changement représente une variable individuelle influençant la perception des nouveautés. Dans un second temps, cette étude illustre la valeur ajoutée d'enrichir les méthodes d'évaluation de l'expérience utilisateur. En effet, l'association de mesures objectives et subjectives, telles que le suivi oculaire, la dilatation pupillaire et les mesures de reconnaissance, offre une approche plus complète pour évaluer la découvrabilité d'une fonctionnalité que les tests d'utilisabilité classiques, centrés sur la performance ou la satisfaction qui peinent à détecter les cas de non-perception d'une fonctionnalité. Ces indicateurs permettent d'aller au-delà des simples mesures déclaratives, en révélant la différence entre ce qui est vu et ce qui est réellement remarqué et permettrait de mieux comprendre les raisons pour lesquelles certaines innovations échappent à la conscience de l'utilisateur.

Tous ces résultats pourraient guider les concepteurs, chercheurs et institutions financières vers une conception davantage centrée sur l'attention et la perception réelle. En intégrant les limites cognitives des utilisateurs dès la conception, il devient possible d'améliorer la découvrabilité, la compréhension et la confiance envers les fonctionnalités d'intelligence artificielle, tout en renforçant la transparence et l'efficacité globale des interfaces numériques.

3.4 Limites de l'étude et recommandations futures

L'étude présentée dans ce mémoire comporte certaines limites, particulièrement en ce qui concerne la taille de l'échantillon et le contexte expérimental. Cette recherche ayant été conçue comme une étude exploratoire visant à examiner la cécité au changement dans un contexte d'interface bancaire réaliste encore peu étudié, les choix méthodologiques ont privilégié la faisabilité expérimentale. D'abord, la participation de vingt-cinq individus limite la portée statistique des analyses et la généralisation des résultats. Ce nombre de participants représentait le minimum nécessaire pour mener des tests en laboratoire permettant de dégager des tendances initiales. Une taille d'échantillon plus importante aurait permis de tester si des variables comme la familiarité jouaient un rôle modérateur. Ensuite, la faible variation observée dans les réponses de reconnaissance a restreint l'interprétation de certains résultats, notamment ceux liés à la détection consciente du changement. Cette faible variabilité découle en partie du nombre restreint de participants ayant explicitement rapporté le changement. Un échantillon plus large aurait probablement permis d'obtenir une plus grande variabilité dans les réponses et de mieux saisir les différences individuelles dans la perception du changement.

Quant au contexte expérimental, l'étude a été menée sur un environnement simulant une application bancaire mobile, mais présentée sur un écran d'ordinateur en laboratoire. Cette configuration était nécessaire afin de garantir un contrôle précis des conditions expérimentales et la fiabilité des mesures oculométriques. Cette configuration, bien qu'elle assure un meilleur contrôle des variables, s'éloigne légèrement des conditions réelles d'utilisation, où les interactions tactiles, les interruptions et le contexte mobile peuvent influencer l'attention et la détection du changement. De futures recherches pourraient reproduire le protocole sur des appareils mobiles afin d'évaluer comment les contraintes contextuelles et motrices affectent la perception des nouveautés dans un usage quotidien.

Pour prolonger ce travail, plusieurs pistes de recherche intéressantes peuvent être envisagées. Une première consisterait à comparer l'efficacité de différentes stratégies de design visant à mieux capter l'attention et à réduire la cécité au changement. De futurs travaux pourraient, par exemple, tester de manière expérimentale l'effet de micro-animations, de variations de contraste dans le temps, de signaux auditifs discrets ou encore de messages contextuels dynamiques sur la détection consciente des nouveautés dans des interfaces bancaires ou transactionnelles. Ces recherches permettraient de dépasser une approche essentiellement descriptive du phénomène pour identifier des solutions pratiques de conception favorisant la découvrabilité.

Une deuxième piste porterait sur la personnalisation des mécanismes de visibilité. En s'appuyant sur les différences individuelles mises en lumière dans le présent mémoire, de nouvelles études pourraient explorer comment adapter la présentation des nouvelles fonctionnalités en fonction du profil attentionnel des utilisateurs, de leur degré de familiarité avec la plateforme ou de leurs habitudes de navigation. Une telle approche ouvrirait la voie à des interfaces capables de moduler automatiquement la visibilité des nouveautés, afin de soutenir la prise de conscience des changements sans alourdir ni perturber l'expérience utilisateur.

Une troisième avenue concernerait l'étude longitudinale de la perception du changement. Une recherche future pourrait suivre les mêmes utilisateurs à travers plusieurs mises à jour successives d'une application afin d'examiner comment la répétition des changements, l'habituation ou la consolidation des scripts cognitifs influencent l'apparition ou, au contraire, la diminution de la cécité au changement au fil du temps. Ce type de dispositif permettrait également d'approfondir le lien entre l'attention, la confiance envers les systèmes d'intelligence artificielle et l'appropriation progressive des nouvelles fonctionnalités.

Enfin, les travaux présentés dans ce mémoire pourraient être étendus à d'autres domaines que le secteur bancaire afin de tester la portée des mécanismes observés. Des contextes tels que la santé numérique, les services gouvernementaux ou les environnements professionnels constituent des terrains particulièrement pertinents, où la non-détection d'une fonctionnalité peut avoir des conséquences concrètes. Explorer ces milieux permettrait de mieux comprendre comment les

dynamiques entre attention, perception et adoption technologique se manifestent dans des situations à enjeux élevés.

Une prochaine étape immédiate pourrait consister à examiner l'évolution de la perception du changement à travers des expositions répétées à une même nouveauté, en continuité avec l'idée selon laquelle les effets de la cécité au changement pourraient se prolonger au-delà d'une première exposition. Un protocole similaire à celui du présent mémoire pourrait être reconduit en multipliant les tâches successives afin d'analyser si la cécité au changement persiste, diminue ou se transforme avec la familiarisation progressive à l'interface. Cette approche permettrait d'étudier la dynamique temporelle de la transition entre perception visuelle et reconnaissance consciente.

3.5 Conclusion générale

En conclusion, cette étude met en évidence que la prédisposition à la cécité au changement, bien qu'elle ne détermine pas directement la reconnaissance consciente ni la détection visuelle d'une nouveauté, influence la manière dont les utilisateurs mobilisent leur attention et leurs ressources cognitives lors de leur interaction avec une interface. Ces résultats montrent que la perception du changement ne dépend pas seulement du regard, mais d'un équilibre entre attention, charge perceptuelle et engagement cognitif. En ce sens, la cécité au changement constitue un cadre d'analyse intéressant pour comprendre pourquoi certaines innovations, pourtant visibles, échappent encore à la conscience des utilisateurs.

Sur le plan appliqué, cette recherche souligne l'importance de concevoir des interfaces qui tiennent compte des limites attentionnelles des utilisateurs. Elle souligne l'importance d'introduire des mécanismes favorisant la découvrabilité sans alourdir l'expérience, notamment en tenant compte des contextes réels d'utilisation où l'attention de l'utilisateur est partagée. En intégrant ces considérations dans les démarches de recherche et de design, les concepteurs peuvent mieux soutenir la transition entre la perception et la compréhension, favorisant ainsi une adoption plus naturelle des nouvelles fonctionnalités. Plus largement, cette recherche s'inscrit dans un contexte où les interfaces numériques évoluent rapidement sous l'effet de l'automatisation et de l'intégration croissante de l'intelligence artificielle. À mesure que les plateformes bancaires, médicales ou même gouvernementales se complexifient, la capacité des utilisateurs à percevoir et

intégrer de nouvelles fonctionnalités devient essentielle pour assurer une expérience numérique de qualité. En mettant en évidence les mécanismes perceptuels qui limitent la conscience du changement, ce mémoire souligne que l'innovation technologique n'est pleinement efficace que si elle reste perceptible et compréhensible pour les utilisateurs.

Enfin, cette recherche soulève plus largement une réflexion sur l'écart croissant entre les investissements importants réalisés par les institutions financières dans les technologies d'intelligence artificielle et leur usage réel par les clients. Elle invite également à remettre en question la pertinence et le véritable besoin de certaines fonctionnalités d'IA dans le contexte bancaire du point de vue des usagers. Une fonctionnalité peut être techniquement performante et stratégiquement justifiée sans pour autant produire de valeur si elle demeure invisible, mal comprise ou peu alignée sur les attentes réelles des utilisateurs. Ces résultats invitent ainsi à reconsidérer la notion même d'utilité en contexte bancaire : une innovation ne peut être considérée utile que si elle est non seulement fonctionnelle, mais également perçue, comprise et adoptée par les usagers. L'enjeu immédiat pour les organisations ne réside donc pas uniquement dans le développement de nouvelles capacités technologiques, mais dans la conception d'expériences qui permettent à ces innovations d'émerger concrètement dans la conscience des utilisateurs.

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Annexes

Annexe A - Échelle de mesure pour la charge perceptuelle perçue (échelle positive)

VisAWI-Positive_T1



Veuillez donner votre **niveau d'accord** avec les énoncés suivants par rapport à l'interface AccèsD.

	1 - Fortement en désaccord	2	3	4 - Neutre	5	6	7 - Fortement en accord
La mise en page semble épurée.	☐	☐	☐	☐	☐	☐	☐
La mise en page est facile à comprendre.	☐	☐	☐	☐	☐	☐	☐
La mise en page semble bien structurée.	☐	☐	☐	☐	☐	☐	☐
L'application paraît uniforme.	☐	☐	☐	☐	☐	☐	☐
Tout va ensemble sur l'application.	☐	☐	☐	☐	☐	☐	☐

Annexe B - Questions de l'entrevue suivant le bloc de tâches de virement

Type	Questions	Code
Rappel	Avez-vous remarqué s'il y avait des différences sur les interfaces des tâches précédentes ? Si oui, lesquelles ?	0 = Ne se souvient pas d'avoir vu une différence 1 = Se souvient d'avoir vu une différence
Reconnaissance	Voici les interfaces des tâches précédentes. Remarquez-vous des différences dans l'interface ?	0 = Ne remarque pas la différence 1 = Remarque la différence
Reconnaissance	Voici l'interface de la dernière tâche (avec astuces). Est-ce que cette interface est différente de l'interface que vous utilisez sur votre téléphone ?	0 = Interface différente 1 = Même interface

Annexe C - Instructions des tâches de virement

T1_Instructions

Tâche A

Vous allez maintenant procéder à un **virement interac** à l'aide de l'**application AccèsD** de Desjardins. Utilisez l'application se trouvant sur l'ordinateur pour effectuer le virement.

- Le virement doit être fait au contact **Flavie Bélanger**.
- La question de sécurité et le mot de passe s'ajoutent automatiquement, mais vous devez cliquer dans le champ pour qu'elle s'affiche.
- Le montant est de **100\$** et se fait à partir du compte **23456-EOP** (le premier).

Veillez indiquer à haute voix au modérateur lorsque vous êtes prêt(e) à débiter la tâche.

T2_Instructions

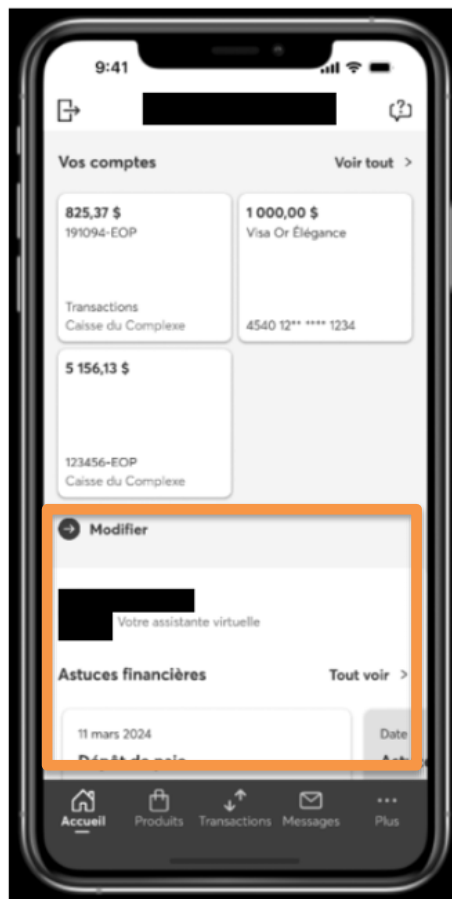
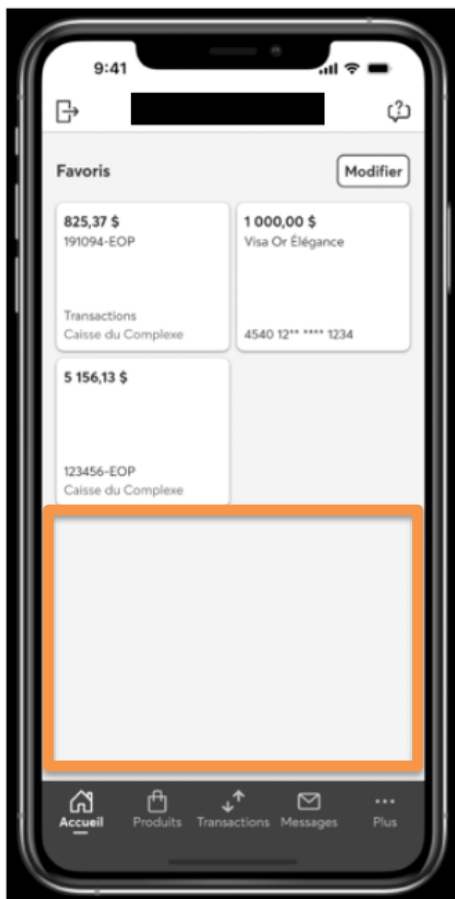
Tâche B

Vous allez procéder à un **virement interac** à l'aide de l'**application AccèsD** de Desjardins. Utilisez l'application se trouvant sur l'ordinateur pour effectuer le virement.

- Le virement doit être fait au contact **Flavie Bélanger**.
- La question de sécurité et le mot de passe s'ajoutent automatiquement, mais vous devez cliquer dans le champ pour qu'elle s'affiche.
- Le montant est de **100\$** et se fait à partir du compte **23456-EOP** (le premier).

Veillez indiquer à haute voix au modérateur lorsque vous êtes prêt(e) à débiter la tâche.

Annexe D - Délimitation visuelle des AOI (zones d'intérêt)



Annexe E – Questionnaires pré-tâche

Occupation



Quel énoncé décrit le mieux votre occupation actuelle ?

- ☐ Employé (Temps plein)
- ☐ Employé (Temps partiel)
- ☐ Étudiant
- ☐ En recherche d'emploi
- ☐ À la retraite
- ☐ Autre

Saut de page

Activité



Quel est votre domaine d'activité principal ?

- ☐ Administration et gestion
- ☐ Commerce et vente
- ☐ Informatique et technologies
- ☐ Santé et services sociaux
- ☐ Éducation et formation
- ☐ Ingénierie et sciences
- ☐ Arts et culture
- ☐ Transport et logistique
- ☐ Industrie et fabrication
- ☐ Autre, Précisez

Éducation



Quel est le plus haut niveau d'étude que vous avez terminé ?

- ☐ Secondaire
- ☐ CEGEP
- ☐ 1er Cycle Universitaire
- ☐ 2ème Cycle Universitaire
- ☐ 3ème Cycle Universitaire
- ☐ Autre, Précisez

Saut de page

Frequence_AccesD



En moyenne, dans une semaine, combien de fois utilisez-vous les services bancaires numériques de Desjardins (AccèsD) ?

- ☐ Jamais
- ☐ 1 seule fois par semaine
- ☐ Entre 2 et 5 fois par semaine
- ☐ 1 fois par jour
- ☐ Plusieurs fois par jour

Autonomie_Financiere



Veuillez donner votre **niveau d'accord** avec les énoncés suivants.

	1 - Fortement en Désaccord	2	3	4 - Neutre	5	6	7 - Fortement en Accord
Il est difficile de respecter mon plan de dépenses lorsque des dépenses imprévues surviennent.	☐	☐	☐	☐	☐	☐	☐
Il est difficile de progresser dans la réalisation de mes objectifs financiers.	☐	☐	☐	☐	☐	☐	☐
Lorsque des dépenses imprévues surviennent, je dois généralement utiliser du crédit.	☐	☐	☐	☐	☐	☐	☐
Lorsque je suis confronté à un problème financier, j'ai du mal à trouver une solution.	☐	☐	☐	☐	☐	☐	☐
Je manque de confiance en ma capacité à gérer mes finances.	☐	☐	☐	☐	☐	☐	☐
Je crains de manquer d'argent à la retraite.	☐	☐	☐	☐	☐	☐	☐

Familiarité



Veuillez donner votre **niveau d'accord** avec les énoncés suivants.

	1 - Fortement en Désaccord	2	3	4 - Neutre	5	6	7 - Fortement en Accord
Je suis familier/ère avec les applications mobiles bancaire.	☐	☐	☐	☐	☐	☐	☐
Je suis familier/ère avec l'utilisation d'applications mobiles bancaires pour gérer mes finances.	☐	☐	☐	☐	☐	☐	☐
Je suis familier/ère avec Desjardins.	☐	☐	☐	☐	☐	☐	☐
Je suis familier/ère avec AccèsD.	☐	☐	☐	☐	☐	☐	☐
Je suis familier/ère avec l'utilisation des conseils de AccèsD.	☐	☐	☐	☐	☐	☐	☐

Aspects_marque_PRE



À quel point chacun de ses éléments influencent votre lien avec Desjardins :

	1 - Aucune influence	2	3	4 - Neutre	5	6	7 - Grande influence
Les produits offerts par Desjardins (produits bancaires, produits d'épargne, produits d'assurance, etc.)	☐	☐	☐	☐	☐	☐	☐
Les conseils fournis par Desjardins via un conseiller	☐	☐	☐	☐	☐	☐	☐
Les conseils fournis par Desjardins via leur site internet ou leur application mobile (Alvie et les astuces, outils d'aide à la décision, etc.)	☐	☐	☐	☐	☐	☐	☐
Les services en ligne (site internet, application mobile, etc.)	☐	☐	☐	☐	☐	☐	☐
Le principe de la coopérative financière (vie démocratique, ristourne, part sociale, etc.)	☐	☐	☐	☐	☐	☐	☐

Déclaration de l'utilisation de l'intelligence artificielle

Dans le cadre de la rédaction de ce mémoire, l'autrice a utilisé des outils d'intelligence artificielle à des fins d'assistance rédactionnelle, notamment pour la correction grammaticale, la reformulation de certaines phrases et l'amélioration de la clarté du texte. Aucune contribution de fond, conceptuelle, méthodologique ou analytique n'a été générée par cet outil. L'autrice a procédé à une révision critique complète de l'ensemble du texte et demeure pleinement responsable de son contenu.

