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**Comparing Clickable Demos and FAQ Tools in Digital Banking: A
Study on Effectiveness, Efficiency and Cognitive Load**

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Certificate of Ethical Approval

HEC MONTRÉAL

Comité d'éthique de la recherche

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

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Résumé

La transformation numérique remodèle continuellement la façon dont les consommateurs interagissent avec les services financiers, offrant une commodité sans précédent, mais créant également de nouveaux défis en matière de satisfaction et d'adoption des utilisateurs. Alors que les questions fréquemment posées (FAQ) ont été adoptées comme un outil d'assistance simple et rentable, l'évolution des attentes des utilisateurs favorise désormais des solutions plus interactives telles que les démonstrations cliquables. Cette thèse consiste en un article scientifique intitulé *Comparing Clickable Demos and FAQ Tools in Digital Banking : A Study on Effectiveness, Efficiency and Cognitive Load* et d'un article managérial, *Beyond FAQs : Are Clickable Demos the Right Support Tool in Digital Banking*, tous deux issus de notre recherche. Dans cette étude, nous avons examiné le rôle du niveau d'interaction avec les outils d'assistance et leur impact sur les états émotionnels et cognitifs des utilisateurs, la performance des tâches et la satisfaction perçue. En comparant l'efficacité des démos cliquables à celle des FAQ traditionnelles pour améliorer l'assistance aux utilisateurs au sein des plateformes bancaires numériques, nos résultats suggèrent que les plateformes bancaires numériques devraient adopter une approche holistique et adaptée aux tâches des outils d'assistance numérique, en proposant à la fois des démos cliquables et des FAQ en fonction de la complexité de la tâche.

En s'appuyant sur la théorie de la charge cognitive et la théorie de l'apprentissage multimédia, cette étude contribue aux pratiques de conception pédagogique en comparant les FAQ et les démos cliquables en tant qu'outils d'assistance dans les plateformes bancaires numériques. Une expérience entre sujets a été menée avec 33 participants, recueillant des données via le suivi oculaire, la reconnaissance des expressions faciales, des mesures de l'activité électrodermale et des évaluations questionnaires. Les résultats de l'étude ont montré que les démos cliquables amélioraient les taux de réussite des tâches et les performances des utilisateurs par rapport aux conditions d'absence de soutien, mais qu'elles n'étaient pas significativement plus performantes que les FAQ traditionnelles dans toutes les mesures. Les démos cliquables ont réduit le nombre d'étapes nécessaires à la réalisation de la tâche, mais n'ont pas affecté les états émotionnels et cognitifs des

participants. La complexité de la tâche était un facteur plus important pour l'efficacité de l'outil. Ces observations ont d'importantes implications pour la transformation de la banque numérique, en guidant les praticiens de l'expérience utilisateur et les responsables de la réussite des clients dans la conception de l'assistance aux utilisateurs. Cette étude présente certaines limites, notamment un petit nombre de participants avertis sur le plan technologique

Mots-clés: banque numérique, outils pédagogiques, outils d'assistance, démonstrations cliquables, FAQ, charge cognitive, performance de la tâche, satisfaction de l'utilisateur, suivi des yeux, activité électrodermale.

Méthodes de recherche: Conception entre sujets, analyse de l'expression faciale, mesures de l'activité électrodermale, pupillométrie, observations comportementales et évaluations auto-déclarées.

Abstract

Digital transformation has been reshaping how consumers interact with financial services, offering unprecedented convenience, but also creating new challenges in user satisfaction and adoption. While frequently asked questions (FAQs) have been adopted as a simple and cost-effective support tool, evolving user expectations now favor more interactive solutions like clickable demos. This thesis consists of a scientific article, *Comparing Clickable Demos and FAQ Tools in Digital Banking: A Study on Effectiveness, Efficiency and Cognitive Load* and a managerial article, *Beyond FAQs: Are Clickable Demos the Right Support Tool in Digital Banking?*, both products of our research. In this study, we examined the role of the level of interaction with support tools and their impact on users' emotional and cognitive states, task performance, and perceived satisfaction. By comparing the effectiveness of clickable demos versus traditional FAQs to improve user support within digital banking platforms, our findings suggest that digital banking platforms should adopt a holistic, task-tailored approach to digital support tools, offering both clickable demos and FAQs depending on the task complexity.

By drawing on Cognitive Load Theory and Multimedia Learning Theory, this study contributes to instructional design practices by comparing FAQs and clickable demos as support tools in digital banking platforms. A between-subjects experiment with 33 participants was conducted, collecting data via eye-tracking, facial expression recognition, electrodermal activity measures, and self-reported assessments. The study findings showed that clickable demos improved task success rates and user performance compared to no support conditions but did not significantly outperform traditional FAQs in all measures. Clickable demos reduced the number of steps needed to task completion but did not affect participants' emotional and cognitive states. Task complexity was a more critical factor in the tool's effectiveness. These insights have important implications for digital banking's transformation, guiding user experience practitioners and customer success leads in designing user support. This study had some limitations, which includes a small set of tech-savvy participants.

Keywords: digital banking, instructional tools, support tools, clickable demos, FAQs, cognitive load, task performance, user satisfaction, eye-tracking, electrodermal activity.

Research methods: Between-subjects design, facial expression analysis, electrodermal activity measures, pupillometry, behavioural observations, and self-reported assessments.

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Preface

This thesis was completed as part of my MSc. In User Experience at HEC Montreal. To ensure compliance with the ethical requirements, the research and data collection performed went through ethical review, with an approval granted by the Research Ethics Board at HEC Montreal with a certificated project number 2024-5919 issued on May 9th, 2024.

Chapter 1—a scientific article—was written in preparation and structured to be submitted to *International Journal of Bank Marketing*. All co-authors of this chapter have provided their written consent to be included as part of the thesis (Appendix 2). This article has not been submitted yet.

Chapter 2—a managerial article—has not been submitted to any specific journal or publication. This article was fully written under my authorly.

This study was conducted with the financial aid of the Natural Sciences and Engineering Research Council of Canada (NSERC) and the fiduciary organization Prompt.

I certify to have no affiliations or involvement with any organization and have no financial or non-financial interest in the matter, research or production of this document.

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When I started conceptualizing this thesis, and the research itself, I thought it would be almost impossible to put together all these pages, but it was possible. I'm very thankful to Prof. Camille Grange for helping me understand this journey and how to approach it creatively and methodologically.

This research was done with the collaboration and support of many institutions that worked together to make UX research possible, special thanks to BNC, for trusting and funding this research. That makes possible the progress on user experience research in pro of a more accessible and inclusive digital world.

Finally, I want to thank my family. I would not be here without all the support of my parents, who had always nurtured me with the idea of pursuing intellectual challenges and develop my interest in design, research and technology, I'm the luckiest son ever. Finally, the biggest thanks to Gaby, my beloved wife, who decided to leap with me, moving to Montreal and providing me with all the emotional support through this journey. Thank you!

Introduction

Context and Background

Digital transformation has emerged as a critical factor for organizations across various sectors in recent years, as it enables them to remain competitive and adaptable in rapidly evolving markets (Vial, 2019), and the banking sector is no exception (Carbó-Valverde et al., 2024). As consumers increasingly shift towards digital platforms for everyday transactions, banks are in constant search of providing seamless, user-friendly digital services that can meet the demands of modern, tech-savvy customers. However, despite the current adoption of digital banking platforms, many users still face challenges when navigating complex or new features and functionalities, leading to a significant need for effective customer support solutions (Chheda et al., 2023). Nevertheless, customer education and guidance is crucial for successful digital adoption, as users need to be confident and comfortable with these digital tools to ensure high and continuous engagement and satisfaction (Carbó-Valverde et al., 2024).

Although systems should be intuitive enough to be used without additional documentation, sometimes supplementary guidance is essential (Kendrick, 2020). To address this challenge, digital banking platforms have implemented various instructional and support tools, such as frequent asked questions (FAQs) as well as more interactive solutions like clickable demos. FAQs provide users with a list of common questions, usually offering information to help resolve issues without the need for direct interaction. In contrast, clickable demos are interactive guides that allow users to navigate through a feature step by step. For example, a clickable demo might simulate the money transfer process by guiding the users through a series of mock screens that resemble the actual app, highlighting each button they need to click to show exactly what to expect.

Research Problem

Along the years, there has been some studies on the implementation of instructional digital tools that provide support (Damani et al., 2020; Davis & Wiedenbeck, 1998; Grossman et al., 2009; Palmiter & Elkerton, 1991). Similarly, other studies suggest that well-designed multimedia instructional tools, such as clickable demos, can improve user engagement by offering a more hands-on, guided experience (Clark & Mayer, 2016; Mayer & Moreno, 2003). However, we have not identified studies that directly compare the effectiveness of traditional FAQs versus clickable demos within the context of digital banking platforms.

Despite the potential advantages of clickable demos, FAQs continue to be prevalent in many digital platforms due to their simplicity and cost-effectiveness. However, the specific impact of both clickable demos and FAQs on user satisfaction, task performance, and cognitive and emotional states within digital banking platforms remains underexplored. Comparing FAQs and clickable demos is therefore valuable because not only are two of the most adopted tools (Chheda et al., 2023), but each of them impacts user guidance differently from a cost-efficiency point of view. Filling this gap is essential for improving customer support strategies and ensuring users can interact with digital banking features effectively, leading to enhanced user experiences and, ultimately greater customer retention.

Purpose and Objective

The primary purpose of this research is to conduct a comparative analysis of clickable demos and FAQs as support tools within digital banking platforms. By focusing on their impact on users' emotional and cognitive states, task performance, and perceived satisfaction, this study aims to identify which tool is more effective in enhancing user experiences when learning how to use a feature in the digital banking context. For the objectives of this study, a feature is defined as a distinct functionality or service offered within the digital banking platform, which the user needs to interact with. The central research question leading this study is: *To what extent are clickable demos more or less effective compared to traditional FAQ tools when users learn to use a feature in digital*

banking platforms? This study seeks to answer this question by examining key variables such as perceived task complexity, support tool interaction level, and emotional and cognitive responses during task completion.

Significance of the Study

This research is significant for several reasons. With foundations in the Cognitive Load Theory and the Multimedia Learning Theory which have been well-explored in both digital and traditional educational settings (Mayer & Moreno, 2003; Plass & Kalyuga, 2019; Sweller, 1988), it contributes to the instructional design knowledge by directly comparing the effects of FAQs versus clickable demos as support tools in digital banking platforms. Cognitive Load Theory has been well-explored in both digital and traditional educational settings. Still, there is limited research on its application to digital banking interfaces, where users often must learn complex processes for high-importance tasks quickly and efficiently. Similarly, studies on the Multimedia Learning Theory, suggests that interactive tools like clickable demos can facilitate deeper cognitive processing (Mayer & Moreno, 2003), this study fills a gap in the literature by applying the theory while comparing both support tools in the already mentioned context.

On the managerial and industry side, the findings of this study have important implications for digital banking undergoing digital transformation. The insights from this study can guide user experience practitioners and customer success leads in designing and implementing user-centric support strategies for digital platforms, ultimately driving higher rates of digital adoption and customer retention. These findings can also be applied to other industries, providing a framework for evaluating and improving instructional and support tools in various digital platforms.

Theoretical Framework

This study is based on two primary theoretical frameworks: Cognitive Load Theory (CLT) and Multimedia Learning Theory (MLT). These theoretical frameworks provide a base ground for understanding how digital instructional tools can enhance user experiences in digital banking by optimizing cognitive workload during task completion.

Cognitive Load Theory (Sweller, 1988) is fundamental in designing instructional tools that manage mental demands quoted to the users. The theory emphasizes that the cognitive load is formed by intrinsic, extraneous and germane types. Intrinsic load frames the inherent complexity of the material, extraneous load is influenced by how the material is presented, and the germane load refers to the cognitive resources dedicated to process the material (Sweller, 1988). Prior studies suggest that instructional tools which effectively manage cognitive load can significantly improve task outcomes. By reducing extraneous load and enhancing germane mental processing, users should be better prepared to navigate and interact with complex digital tasks without feeling overwhelmed (Mayer & Chandler, 2001).

MLT complements CLT by focusing on how multimedia elements and user interaction can improve the learning experience. According to Mayer & Moreno (2003), tools that distribute information across different modalities and provide an interactive approach, like clickable demos, which integrate text, images, and user interaction, can better align with users' learning preferences and facilitate deeper engagement than traditional FAQs.

The integration of both CLT and MLT provides an initial foundation for analyzing how instructional tools impact user experience in digital banking. Digital banking tasks can benefit from instructional designs that reduce cognitive load and enhance task performance (Indriasari et al., 2022). The frameworks also address the importance of considering user interaction levels. High interaction levels, as seen in clickable demos, encourage active engagement, which can lead to improved task performance and satisfaction by reducing cognitive effort. These insights from cognitive and multimedia learning theories help explain why different instructional tools like FAQs or clickable demos might vary in their effectiveness.

Lastly, this study considers the Power Law of Practice (Newell & Rosenbloom, 1981), which explains that people get better and faster at a task the more they do it. This happens because with practice, our brain finds easier and quicker ways to handle a task. This concept is useful when we look at the nuances of different levels of interaction between FAQs and clickable demos in digital banking platforms.

Methodological Approach

In this study a confirmatory research design was used to assess the comparative effectiveness of support tools, specifically clickable demos versus FAQs, within a digital banking platform. A between-subjects experimental approach was used, allowing a systematic comparison of user experiences across different support conditions, including a control condition with no support tool available. This methodological approach ensures that the study could control for variables and measure the impact of each tool on users' cognitive and emotional states, task performance and perceived satisfaction.

We recruited 33 participants, each randomly assigned to one of three conditions per task: clickable demo, FAQ, or no-support. Random assignment of the task was critical to reduce any potential biases. The experiment was conducted under laboratory-controlled conditions where the participants were tasked with completing specific tasks in the banking platform prototype after going through the support tool experience. These tasks were selected to range in complexity, allowing the study to assess how each instructional tool performed under different levels of task difficulty. The experiment design also considered the task order by randomizing the sequence in which the task was presented to prevent learning effects.

A mixed-method approach was utilized to collect comprehensive data on user performance and experience. Quantitative measures included psychophysiological tools like eye-tracking technology, facial expression analysis, and electrodermal activity sensors, which provided objective insights into users' cognitive load and emotional responses during task completion (Skiendziel et al., 2019). Additionally, self-reported questionnaires were administered to the participants before and after the tasks to gather data on participants' perceived task difficulty, satisfaction, and effort. The data collected were analyzed using a combination of linear and logistic regression models to examine the effects of the instructional tools on task performance, cognitive load, and emotional responses. Given the mixed types of data, appropriate statistical models were selected to handle the specific characteristics of each dataset.

Scope and Limitations

This research focused specifically on investigating the effectiveness of clickable demos and FAQs in digital banking platforms. While offering valuable insights, some limitations need to be addressed. First, a relatively small and specific sample of tech-savvy participants from Québec may limit the generalizability of the findings as it may not fully represent a broader set of user demographics. Additionally, the controlled lab environment, though ideal for internal validity and precise measurement may not replicate real-world conditions where users interact with digital banking tools under everyday distractions and multitasking. Similarly, the usage of a limited prototype rather than a production ready platform may carry some challenges for external validity. Future research should consider a more diverse participant sample and explore these instructional tools in more naturalistic settings to obtain a deeper understanding of their practical effectiveness and achieve higher external validity. Despite these limitations, the study provides a solid foundation for understanding how digital instructional and support tools can be optimized to enhance user experience and task performance on digital banking contexts.

Thesis Structure

An introduction to this paper and the context of this research were discussed in this introductory section. Following, Chapter 1 contains the scientific article, written in preparation and structured to be submitted to *International Journal of Bank Marketing*. This article summarizes the core research and the experimental method and its findings. It addresses the comparison between clickable demos and FAQs and their impact on the user emotional and cognitive states as well as their effectiveness and efficiency within the digital banking context. Chapter 2 presents a managerial article which highlights the implications of our study findings for practitioners within the banking industry as well as customer success leads and user experience practitioners. Finally, the closing section of this paper is a conclusion that summarizes the entire study and provides a take on future studies.

Personal Contribution

This thesis was conducted in close collaboration with my thesis co-directors and other members of the Tech3Lab HEC Montréal (Canada). Table 1 provides an overview of my contributions across different stages of the study. As per the collaboration standards set, the concepts where the student contribution exceeds 50%, should be considered lead or own by the student.

Table 1.1: Personal contribution (Part 1).

Step in the process	Contribution
Research Question	Definition of the research problem based on literature gap. [65%] - Problem statement and mandate proposed by the industrial partner. - Problem adaptation towards academic research done by the student. - Formulation of the research question done collaboratively with the thesis co-directors' guidance.
Literature Review	Research and understanding of the current knowledge referent to Cognitive Load Theory and Multimedia Learning Theory within the digital banking context done by the student. [100%]
Experimental Design	Definition and implementation of the experimental design. [40%] - Conception of the experiment procedure mainly conducted by the Tech3Lab team. - Experimental protocol conceived by the Tech3Lab team.
Stimuli	Definition and development of the experimental stimuli. [20%] - The stimuli were developed by the industrial partner under review and task suggestions from the student and the Tech3Lab team.
Questionnaires	Definition and development of research questionnaires. [45%] - In collaboration with the Tech3Lab team and under supervision of co-directors.
Ethics	Application to the Research Ethics Board (REB) of HEC Montréal. [70%] - Documentation preparation done by the student. - Supervision, review and submission done by Tech3Lab operations team and thesis co-directors.
Pretest	Preparation and conduction of pretest and rehearsals. [45%] - Pre-test recruitment and preparation done in collaboration with Jia Zheng - Pre-test setup and supervision by the Tech3Lab team
Recruitment	Recruitment for the study sample. [25%] - Screening questionnaires done in collaboration with Tech3Lab team and Jia Zheng. - Recruitment and participants management done through the Tech3Lab panel.

Table 2.2: Personal contribution (Part 2).

Step in the process	Contribution
Data collection	Data collection and laboratory setup. [45%] <ul style="list-style-type: none">- Laboratory setup performed by Tech3Lab team- User testing observation and behavioural data collection in collaboration with Jia Zheng and the Tech3Lab team.- Post-test interviews by the Tech3Lab team.- Data processing by the Tech3Lab team.
Statistical Analysis	Analysis for psychophysiological and behavioural data. [80%] <ul style="list-style-type: none">- Extraction and treatment of raw data by the Tech3Lab team.- Data clean and preparation by the Tech3Lab team and statistics staff (Shang-Lin Chen).- Programming of statistical analysis on SAS 9 by the student with collaboration and supervision of the statistics staff (Shang-Lin Chen).- Results interpretation and presentation by the student.
Writing	Writing of both scientific and managerial articles. [100%] <ul style="list-style-type: none">- Thesis co-supervisors and co-directors provided comments and corrections.

Comparing Clickable Demos and FAQ Tools in Digital Banking: A Study on Effectiveness, Efficiency and Cognitive Load

Juan Francisco Monroy Guevara, Sylvain Sénécal, Ruxandra M. Luca

Abstract

Purpose: While clickable demos have potential advantages, FAQs remain prevalent due to their simplicity and cost-effectiveness. However, the specific impact of both tools on user satisfaction, task performance, and cognitive and emotional states within digital banking platforms has not been fully explored in previous research. This paper addresses this gap by comparing the effectiveness of clickable demos versus traditional Frequently Asked Questions (FAQs) in this context.

Design/methodology/approach: The study used a confirmatory research approach with a between-subjects experiment involving 33 participants. Data was collected using eye-tracking technology, facial expression recognition, and electrodermal activity measures, combined with self-reported measures of task performance, emotional states, and satisfaction.

Findings: The results revealed that clickable demos improve task success rate and performance in comparison to the conditions where participants received no support, but they did not show an advantage over traditional FAQ in all measures. The higher level of interaction made clickable demos more effective in reducing the number of steps needed to task completion but did not have an impact on participant emotional and cognitive states. Task complexity played a more critical role in determining the tools' effectiveness.

Research limitations/implications: The study's findings were limited by the small sample size and the specific demographic of tech-savvy participants. Future research should explore the impact of other moderating factors such as motivation and familiarity with digital banking platforms.

Practical implications: The findings suggest that banks should consider a more holistic approach and task tailored solution to digital support tools. Digital banks should provide both clickable demos and FAQs depending on the complexity of the tasks. Customer support strategies would be greatly benefited by implementing user-centric design that minimizes cognitive load when helping the users to solve problems or learn how to use new features or products.

Originality/value: This paper contributes to both theoretical understanding and practical applications in user experience by building on current research around Cognitive Load and Multimedia Theories in the context of digital banking, offering new insights for improving customer education and support in the industry's digital transformation.

Keywords: digital banking, instructional tools, clickable demos, FAQs, cognitive load, task performance, user satisfaction, eye-tracking, electrodermal activity.

Paper type: Research paper

1.1 Introduction

In recent years, digital transformation has become one of the most critical objectives in many industries, as it enables them to remaining competitive and adaptable in the rapidly evolving markets, and the banking industry is no exception, with customers' highly inconsistent digital adoption being one of the biggest challenges (Chheda et al., 2023). Customer education plays a crucial role in successfully adopting digital banking features; as banks introduce innovative features and new digital experiences, they must ensure that customers are correctly informed and comfortable using these technologies. In addition, customer perception and satisfaction are significantly influenced by how well banks communicate the benefits and how to use those functionalities (Carbó-Valverde et al., 2024). To address this, banks can drive awareness of new digital offerings or features with marketing and communications, such as “how-to” videos on their websites and mobile apps (Chheda et al., 2023).

Ideally, systems should be intuitive enough to use without additional documentation; however, there are instances where supplementary guidance and documentation are essential (Kendrick, 2020). This has become a significant challenge for instructional designers since meaningful learning can require many essential cognitive processes, such as active engagement with the material, critical thinking to analyze and evaluate the information, and applying knowledge to real-world scenarios (Paas et al., 2010). Therefore, since the user's cognitive resources are limited, guidance and documentation should be designed in ways that minimize any unnecessary cognitive overload and focus on the user's task (Mayer & Moreno, 2003). This phenomenon encompasses not only the direct comparison in learning and problem-solving effectiveness but also the potential psychological impact, primarily focusing on the working memory load experienced by users when interacting with clickable demos versus utilizing traditional Frequently Asked Questions (FAQs) when learning or solving problems independently (Paas & Sweller, 2014).

The emergence of new media technologies and tools designed to enhance customer success has led to a significant evolution in customer support methodologies, such as the development of clickable demos (Bitner et al., 2002). Clickable demos are interactive guides that offer step-by-step navigation, allowing users to explore new features, learn tasks or solve problems directly within the interface by clicking through series of prompts and instructions. In contrast, FAQs are traditional support tools that provide users with a list of common questions and answers, offering information to help resolve issues without the need of direct interaction.

The increasing digitalisation of the banking industry—reflected in an 11% increase in daily active users between 2021 and 2022—highlights the need for improved customer success strategies, with FAQs emerging as a popular solution to address recurring user queries (Chheda et al., 2023). Yet, as users' expectations evolve, tools like clickable demos are becoming popular for offering a more interactive approach to customer support. While interest in clickable demos is growing, FAQs low cost maintenance and adoption has kept them on customer support teams' radars (Farrell, 2014).

This research aimed to evaluate the relative effectiveness of clickable demos compared to traditional FAQ tools within digital banking platforms. It specifically focused on their impact on users' emotional and cognitive states during problem-solving, task performance, and perceived satisfaction. The research provided insights to digital banks that help them develop support strategies that maximize customer satisfaction while optimizing resources allocation. Even though cognitive load theories, instructional design, and the impact of different media tools on cognitive load have been well-studied (e.g., Chandler & Sweller, 1991; Mayer & Chandler, 2001; Mayer & Moreno, 2003; Sweller et al., 2019), there is a notable lack of studies comparing the effects of FAQs versus clickable walkthroughs on users' emotional and cognitive states and task performance. In addition, while broad research exists in instructional design, there is insufficient focus on the specific niche of digital banking platforms. Evaluating FAQs and clickable demos is worthwhile not only because they are among the most widely adopted support tools (Chheda et al., 2023), but also because they offer distinct advantages in how they guide users and differ in terms of cost-effectiveness. This gap in research is particularly significant given the rapid adoption of digital banking solutions and their increasing base of customers and users (Carbó-Valverde et al., 2024; Chheda et al., 2023).

Our study contributes to the theory by showing that in digital banking, perceived task difficulty moderates the relationship between interactivity and cognitive load, specifically when comparing FAQs versus clickable demos. Grounded in Cognitive Load Theory (Sweller, 1988) and Multimedia Learning Theory (Mayer & Chandler, 2001), this research examined the impact of clickable demos and FAQs on users' emotional states, cognitive load, and task performance. The findings highlight the context-dependent nature of instructional tools, showing how different levels of interactivity affect cognitive and emotional states, ultimately affecting performance, perceived satisfaction and perceived effort. By integrating these theoretical frameworks, the study fills existing gaps in the literature, providing a comparative analysis of these instructional methods while pointing their broader implications for platform design, customer success strategies, and user experience in digital banking platforms. The central question guiding this research is: "To what extent are clickable demos, compared to traditional FAQ tools, more or less effective when learning to use a feature in digital banking platforms?"

This study collected data using eye-tracking technology, facial emotions, and phasic electrodermal activity while participants completed tasks involving both instructional tools. The findings of this research make two main theoretical contributions. First, by showing that emotional and cognitive states were not significantly different between clickable walkthroughs and FAQs, our results contribute to the literature on instructional tools by challenging the assumption that more interactive formats inherently lead to better emotional and cognitive outcomes (Mayer & Chandler, 2001). This suggests that task complexity maybe a more influential factor, rather than the tool itself. Second, our findings highlighted the context-dependent nature of the instructional tool effectiveness, contributing to the broader understanding of how digital support mechanisms should be tailored to specific tasks, particularly in high-stakes environments such as digital banking platforms.

This paper is structured as follows: First, we outline the theoretical frameworks focusing on cognitive load theory and multimedia learning. Second, we present the research model and key hypotheses. Then, we describe the methodology and findings of the study. Last, we discuss implications and provide recommendations for digital banking platforms.

1.2 Theoretical frameworks

1.2.1 Cognitive Load Theory and Its Relevance to Instructional Design

Since its formulation, the Cognitive Load Theory (CLT) proposed by Sweller (1988), has been a key framework in instructional design that focuses on the management of cognitive resources to optimize the learning and problem-solving process. Cognitive Load Theory divides the cognitive load into 3 types: intrinsic, extraneous and germane, each playing a specific role in how people process information. Intrinsic load frames the inherent complexity of the material, extraneous load is influenced by how the material is presented, and the germane load refers to the cognitive resources dedicated to process the material (Sweller, 1988). A study by Chandler and Sweller (1991) have shown that reducing the

extraneous cognitive load through effective instructional design can significantly improve the learning and problem-solving process.

Over the years, CLT has evolved to acknowledge the relation between cognition, emotional states, and user satisfaction (Plass & Kalyuga, 2019). It has been observed that cognitive load not only affects the efficiency of learning but also influences users' emotional responses and overall satisfaction with the learning experience (Um et al., 2012). High levels of cognitive load, particularly extraneous load, can lead to negative emotional states (Paas et al., 2003). In contrast, when instructional design effectively manages and balances cognitive load, it can promote positive emotions and increase satisfaction levels (Plass & Kaplan, 2016). Recent research emphasizes that the principles of CLT, extend beyond traditional learning to digital platforms, highlighting new dimensions of extraneous load induced by digital interactions. For instance, Skulmowski & Xu, (2022) have discussed how modern digital learning environments and digital platforms that include interactive media, present challenges to CLT by sometimes inducing extraneous cognitive load while still promoting learning outcomes by fostering deeper engagement. This theory guides the current study on how different instructional tools like clickable demos and FAQs impact users' cognitive load when interacting with digital platforms and how it might impact their performance, emotional states, and perceived satisfaction.

1.2.2 Multimedia Learning and User Interaction

Mayer and Moreno (2003) explored how multimedia tools could be designed to align with the Cognitive Load Theory and its principles to improve learning efficiency. Their research points to how well-structured multimedia tools could reduce cognitive overload by distributing information across different senses (Mayer & Moreno, 2003). Furthermore, interactive multimedia elements, such as clickable demos, lead users into deeper cognitive processing and better learning outcomes (Clark & Mayer, 2016). This interactivity could potentially reduce extraneous cognitive load by aligning the instructional material with the user's individual needs and preferences, therefore improving performance and satisfaction. On the other hand, FAQs, act as modular

segments that can be consumed independently. According to the segmenting principle, breaking information into smaller manageable parts helps learners better process and retain it (Mayer, 2020).

This is relevant to this study, as it evaluates the effectiveness of interactive clickable demos versus static FAQs on users' performance when interacting with digital banking platforms. By leveraging multimedia learning principles, clickable demos in comparison to FAQs, may enhance users' understanding and retention of information, potentially leading to better task performance and increased satisfaction.

1.2.3 Power Law of Practice

Based on Newell and Rosenbloom's (1981) work, the Power Law of Practice explains that the more a user performs a task, they get better and faster on it. The user's brain finds easier and quicker ways to handle the task in question (Newell & Rosenbloom, 1981). This idea is particularly useful when we look at FAQs and clickable demos in digital banking. FAQs are helpful, but they require users to figure out steps in their own, especially if they're not accompanied with visual representations of the feature. In contrast, clickable demos guide users step by step, letting them practice and learn by doing. This, in conjunction with the Multimedia Learning Theory, and the levels of interactivity of the clickable demos versus static FAQs, could potentially lead to a better task performance as well.

1.3 Model Development and Hypotheses

The proposed research model integrates both theoretical frameworks, linking the type of instructional tool—clickable demos versus FAQs—to emotional states, cognitive load and task performance within the digital banking domain. Research findings suggest that the level of interaction of the instructional tool, influences both emotional and cognitive states, which at the same time affect performance and perceived effort (Moreno & Mayer, 2007). The moderating role of task complexity, which taxes the intrinsic cognitive load, is also investigated, providing a comprehensive framework for understanding the

comparison of between both instructional tools' effectiveness in digital contexts (Sweller, 1988).

The proposed research model (see Figure 1) considers the relationships between various constructs that influence performance, perceived effort and perceived satisfaction. The model for this study suggests that the type of instructional tool, defined by its level of interaction, affects arousal, valence and cognitive load. This model also introduces the perceived task difficulty, as a moderating factor also affecting the arousal, valence and cognitive load. In turn, the model suggests that arousal, valence, and cognitive load impact performance and perceived effort, which collectively contribute to perceived satisfaction.

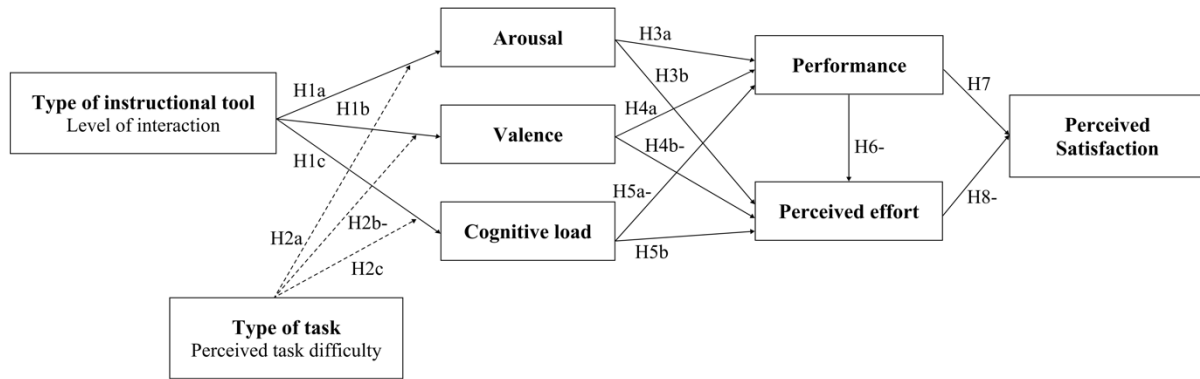


Figure 1: Research model.

1.3.1 Interaction Levels of Instructional Tool and Their Impact on Emotional and Cognitive States

According to Shneiderman & Plaisant (2004), clickable demos offer a higher level of interactivity than FAQs, allowing users to engage directly with content. This hands-on approach supports more effective task comprehension compared to passive information formats. Prior research also indicates that reducing extraneous cognitive load through effective instructional design promotes positive emotional responses by reducing frustration and unnecessary cognitive effort (Sweller et al., 2011). Furthermore, varying

levels of interaction in the instructional tool affect users' emotional states particularly in terms of arousal, valence, and cognitive load. (Mayer & Moreno, 2003). Arousal refers to the degree of physiological and psychological activation or alertness, while valence describes the level of positivity or negativity of an emotional response (Russell, 1980). Higher levels of interactivity with the support tool can rise arousal levels because users engage more deeply, leading to increase alertness and engagement (Norman, 2004). Similarly, a higher level of interaction with the support tool is shown to enhance positive valence by making the user experience more engaging and enjoyable (Or-Bach, 2013). Finally, according to CLT as the level of interaction in the support tool increases, so does cognitive load, because interactive elements require users to process more information simultaneously (Paas & Sweller, 2014). That said, we propose the following:

H1a. As the level of interaction with the instructional tool increases, the level of arousal increases.

H1b. As the level of interaction with the instructional tool increases, the level of valence increases.

H1c. As the level of interaction with the instructional tool increases, the level of cognitive load increases.

1.3.2 Perceived Task Difficulty and Its Impact on Emotional and Cognitive States

High task difficulty can increase intrinsic cognitive load, elevating arousal and leading to negative emotional valence, while effective instructional design that meets user expectations can reduce cognitive demand and promote positive emotional responses (Paas & Sweller, 2014). Therefore, we hypothesize that perceived task difficulty moderates the relationship between the level of interaction with instructional tools and users' cognitive and emotional states. This proposition leads us to the following hypotheses:

H2a. Perceived task difficulty moderates the relationship between the level of interaction with the instructional tool and user arousal, such that the relationship becomes stronger as perceived task difficulty increases. As the level of interaction with the instructional increases, user arousal increases. Higher levels of perceived task difficulty amplify the user arousal by demanding more attention and engagement.

H2b. Perceived task difficulty moderates the relationship between the level of interaction with the instructional tool and user valence, such that the relationship becomes stronger as perceived task difficulty increases. As the level of interaction with the instructional increases, user valence increases. Higher levels of perceived task difficulty diminish the user valence.

H2c. Perceived task difficulty moderates the relationship between the level of interaction with the instructional tool and user cognitive load, such that the relationship becomes stronger as perceived task difficulty increases. As the level of interaction with the instructional increases, user cognitive load increases. Higher levels of perceived task difficulty amplify the user cognitive load by demanding more attention and engagement.

1.3.3 Cognitive and Emotional States and Their Impact in User's Performance

Understanding the effects of emotional and cognitive states on user performance is essential in the context of instructional design and digital banking platforms. Emotional states, particularly arousal and valence, can significantly influence cognitive processes and learning outcomes (Um et al., 2012). Additionally, cognitive load remains as a critical factor; whereas excessive cognitive load, especially extraneous load, can diminish user's performance (Paas et al., 2003; Sweller, 1988). Based on the theoretical framework, the following hypotheses were proposed:

H3a. As the user arousal increases, the performance increases.

H4a. As the user valence increases, the performance increases.

H5a. As the user cognitive load increases, the performance decreases.

1.3.4 Cognitive and Emotional States and Their Impact on User Perceived Effort

Prior research describes how interactive elements, such as clickable demos, provide familiarity and active engagement, leading to deeper cognitive processing than static support tools like FAQs (Clark & Mayer, 2016). In addition, emotional states triggered by interactive tools can affect cognitive effort, influencing users' perceived effort and satisfaction (Pekrun, 2006). The punctual hypotheses are:

H3b. As the user arousal increases, the perceived effort increases.

H4b. As the user valence increases, the perceived effort decreases.

H5b. As the user cognitive load increases, the perceived effort increases.

1.3.5 User's Performance and Its impact in Perceived Effort and Satisfaction

Previous studies findings showed that as performance improves, users report lower perceived effort, constantly associated with higher satisfaction (Hart & Staveland, 1988). Similarly, Jakob Nielsen's (1993) principles in usability suggest that when users can complete tasks more efficiently, they experience greater satisfaction and lower cognitive strain. Similarly, as task performance improves, perceived effort decreases because users expend less mental and physical energy to achieve their goals, making the interaction feel easier and more manageable (Hart & Staveland, 1988; Nielsen, 1993). These statements lead to the following hypotheses:

H6. As the user performance increases, the perceived effort decreases.

H7. As the user performance increases, the satisfaction increases.

H8. As the user perceived effort increases, the satisfaction decreases.

1.4 Research Methodology

1.4.1 Experimental Design

A controlled laboratory experiment was conducted to test the hypotheses, and a between-subject design was used. Participants were randomly assigned to one of three conditions, consisting of the same seven tasks with a different combination of support tools assigned to each task, which included clickable demo, FAQ, or control condition where no support tool was provided. The order of the tasks presented to the participants were counterbalanced to minimize any potential learning effect.

The interaction provided by the support tool was manipulated through three conditions: control, low and high. In the control condition, participants did not receive a support tool. In the low interaction condition, participants received a FAQ as support tool, while in the high interaction condition, they received a clickable demo as support tool.

These conditions were chosen to reflect varying levels of interactivity, as Mayer's Multimedia Learning theory suggests that tools promoting active engagement, like clickable demos, enhance cognitive processing and user retention (Mayer & Moreno, 2003). In contrast, FAQs offer a more passive guidance, while the control group allowed for a baseline comparison. Below, the details on stimuli and their roles in the experimental setup:

Clickable Demos: Participants with assigned tasks in this condition interacted with interactive guided demos available in the production environment on the partner's website. These demos consisted of walkthroughs prompting the user to click on specific areas of the embedded bank platform user interface. Following a pulsating hint, the users could navigate through the necessary steps to complete the bank operations assigned in the experiment tasks.

FAQ: Participants with assigned tasks in this condition were provided with text-based instructions from the Frequently Asked Questions (FAQ) section of the partner's website. These instructions described the necessary steps to complete each of the bank operations related to the study tasks.

1.4.2 Participants

Eligible participants were 18 years or older and did not have prior experience with the partner's bank digital platform. To guarantee high-quality data, the study employed eye-tracking technology, therefore, the participants must not have visual impairments and were not prone to epileptic conditions.

The sample included 16 women and 17 men, (Age $M = 29.30$, $SD = 10.66$) The participants' ages ranged from 19 to 64 years old. Data collection took place between May 13th and June 3rd, 2024. Participants were compensated \$30 CAD by Interact transfer for one and a half hours.

While the study was conducted among a relatively small sample, the usage of eye-tracking technology has demonstrated how detailed gaze data provides valuable insights into cognitive processes. The precision and richness of eye-tracking data can compensate for a smaller sample (Duchowski, 2007). Similarly, electrodermal activity (EDA) measures provide fine-grained insights into emotional arousal and cognitive processes (Boucsein, 2012) Due to the sensitivity of EDA to subtle changes in arousal, studies can often use smaller samples while still getting reliable data.

1.4.3 Procedure

Upon arrival, the research assistant asked the participants to leave their personal effects in a designated area. Once in the observation room, the moderator introduced himself/herself and explained the expected duration of the study, as well as a quick overview of the data collection tools and the number of tasks to be performed. Also, the total amount of the compensation to be rewarded to the participant was explained. After that, the participant was presented with the consent form and asked to read and sign it if they agreed. Once the consent form was signed, the moderator asked confirmatory and demographic questions.

Each observation room required two computers with a single screen. On computer No.1, the Tobii Pro Lab software was executed (Danderyd, Sweden). This computer controlled both the timeline of the experiment as well as the Tobii Pro Fusion eye tracker. On computer No. 2, the Cobalt Capture software (HEC Montréal, Montreal, Canada) was used to both record and synchronize both participants' screens and webcam. The moderator always used a microphone to communicate with the participant from the observation room.

For data collection tools, the moderator installed the EDA sensors in the participant's non-dominant hand and verified the signal performance. With the sensors in place, the moderator proceeded to verify the participant's right position in relation to the camera and the eye tracker (65 cm from the screen). Once the participant has the sensors installed and with the participant positioned at the proper distance from the screen, the moderator starts the eye tracker calibration.

During the study, each participant was presented with seven tasks: *T1 managing personal information*, *T2 registering for direct deposit*, *T3 registration for Interac automatic deposit*, *T4 adding a travel notice*, *T5 managing notifications*, *T6 adding a recipient and transfer money via Interact*, and *T7 adding and paying a bill*. These tasks were selected as a representative sample of commonly used tasks, balancing both long, complex tasks and shorter ones. Before starting the tasks, the participant started with a self-perceived task difficulty questionnaire where the participants self-reported how difficult they think each task will be. After completing the first questionnaire, the participants completed the seven designated tasks. The task orders were randomly assigned, and each participant was randomly assigned to one of the three conditions.

Each task consisted of two phases. First, the participant had to complete either a clickable demo or a FAQ article, representing the ideal step-by-step process for completing the task in the bank platform. If the participant was assigned to the control condition on the task, this first phase would not be presented.

For the second phase of the tasks, the participants had to complete the tasks using a Figma clickable prototype of the bank platform. Each task had to be completed in under 5

minutes. For each task, the research team captured the behavioral measures for time on task, success rate, and number of steps to task completion. During the experiment, additionally 2 scales were administered via Qualtrics (Provo, UT, n.d.) to measure the perceived level of effort and perceived satisfaction. Perceived satisfaction and perceived effort were each evaluated with three-item Likert-based 7-point scales (Kim & Son, 2009; Wang & Benbasat, 2009), administered after each task (Appendix 2). Finally, perceived emotional valence and perceived arousal were measured after each task using single-item affective sliders (Betella & Verschure, 2016).

At the end of the experiment, the research assistant went into the observation room and provided the participants with a compensation form so they could fill out their payment details. Then, the research assistant removed the sensors and accompanied the participants to exit the experimental room.

1.4.4 Measures

The specific measures used to collect the data for this study consist of both psychophysiological and self-reported assessments, as well as observed behavioral data. Below is a detailed description of each measure:

Emotional valence (Psychophysiological): Emotional Valence was measured using the facial expression recognition tool FaceReader 9 developed by Noldus Information Technology BV (Wageningen, the Netherlands). The process to determine the facial expressions used by Noldus consists in three steps: 1) Finding the face position within an image by using a face-finding algorithm, 2) Artificial face modeling, which describes the location of 468 key points in the face, and 3) Face classification, where a trained deep artificial neural network recognizes patterns in the face and then classifies facial expressions (Noldus Information Technology BV, 2024). This tool was used by the study to assess facial expressions and infer emotional valence (Skiendziel et al., 2019).

Emotional Arousal (Psychophysiological): Emotional Arousal was measured by placing two sensors in the participant's non-dominant hand to capture and send their average

phasic electrodermal activity (EDA) (Léger et al., 2019) via the Cobalt Bluebox (HEC Montréal, Montréal, Canada). EDA is a physiological measure that reflects changes in the electrical conductance of the skin, which varies with moisture level due to eccrine sweat gland activity. The relationship between EDA and emotional states is well established; increases in EDA are typically associated with heightened emotional arousal, regardless of the valence of the emotion (positive or negative) (Kosonogov et al., 2017).

Perceived Arousal (Self-reported): Participants self-reported their perceived arousal levels using an affective slider, a one-item scale going from 0 to 100, designed to capture subjective emotional arousal (Betella & Verschure, 2016).

Perceived Valence (Self-reported): Similar to perceived arousal, participants self-reported their perceived valence levels using the affective slider with a scale going from 0 to 100, designed to capture their subjective emotional valence (Betella & Verschure, 2016).

Cognitive Load (Psychophysiological): Cognitive Load was measured through pupillometry by observing and measuring pupil dilation using Tobii's eye-tracking technology (TobiiAB, 2023). This effect indicates that as cognitive load increases, so does pupil diameter, making it a well-known index for measuring cognitive effort across various tasks and context (Pfleging et al., 2016). This study used the eye tracking software Tobii Pro Lab, developed by Tobii AB (Danderyd, Sweden).

Perceived Task Difficulty (Self-reported): Participants reported the difficulty of tasks using a one-item 7-point Likert scale (1 = Very easy, 7 = Very difficult) from The Perceived Difficulty Assessment Questionnaire (Ribeiro & Yarnal, 2010).

Perceived Satisfaction (Self-reported): Satisfaction was measured using a 3-item 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree) (Kim & Son, 2009).

Perceived Effort (Self-reported): The perceived effort was also assessed through a 3-item 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree) (Wang & Benbasat, 2009).

Performance (Behavioral Observed): User performance was measured through time on task, task success, and steps to task completion. Time on task was continuously recorded in seconds to capture the time required to complete each task. Task success was documented as a binary variable, with 1 indicating success and 0 indicating failure. Additionally, steps to task completion were tracked by recording the number of interactions participants performed within the prototype to complete each task, which was then compared to a benchmarked baseline of steps for performance evaluation.

1.4.5 Apparatus

The experiment for this study ran on one desktop machine with a single screen (Appendix 3). One C922 Pro Stream webcam from Logitech International S.A. (Lausanne, Switzerland) was placed in front of the user at the top of the screen, and the video recorded from this camera was processed to be used with the FaceReader software. The second Logitech webcam was placed just to the left of the monitor, and it was used to capture the pre-and post-test interviews. This setup used one Tobii Pro Fusion eye tracker developed by Tobii AB (Danderyd, Sweden) at the bottom of the screen. The setup required the participant to be comfortably seated 65 cm from the screen. One hanging microphone placed on the room's ceiling and one speaker located on the desktop were used as communication methods between the experimental room and the observation room. Finally, both the Cobalt Blue Box and the Syncbox (HEC Montréal, Montréal, Canada) were placed next to the non-dominant hand of the participants.

1.5 Statistical Analysis

Using SAS Studio 9.04.01 (SAS Institute Inc., Cary, NC, USA), we ran a series of statistical tests to evaluate the different hypotheses of the study. During the analysis, various tests were employed depending on the nature of each hypothesis and the type of data involved. More details on how the different tests were selected follows.

For time on task and EDA-arousal, due to the skewed distribution of the data we implemented logarithmic transformation to achieve a more normal distribution that allowed us to run a linear regression analysis (Osborne, 2010). Furthermore, once the data was transformed, it helped us to enhance the validity and predictive power of our regression model.

For perceived satisfaction and perceived effort which were measured in a Likert scale with values from 1 to 7, we calculated the median, and then split the data values into high and low categories. The median for effort was 1.5, which allowed us to classify values above this as high effort, and for satisfaction, it was 6.5, for which values above it were categorized as high satisfaction. Using a median split simplified our analysis by converting continuous data into categorical variables, allowing a clearer examination of relationships in a binary framework (MacCallum et al., 2002), ultimately it helped us to highlight key patterns relevant to our hypotheses.

Due to the normal distribution of the independent variables, we performed a set of linear regressions to evaluate the effects of support type on arousal, valence, and cognitive load, as well as the effect of the interaction between support type and pre-task perceived difficulty. Additionally, we assessed the influence of arousal, valence and cognitive load on time on task. Given that each participant performed the same seven tasks, resulting in repeated measures, we employed linear mixed-effects models to handle the non-independence of observations (Barr et al., 2013). Specifically, we included random intercepts for participants and for tasks, so we could account for both variabilities (Baayen et al., 2008). Additionally, Bonferroni adjustments were applied to the tests to correct p-values when multiple pairwise comparisons and reduce Type I errors (Holm, 1979).

Given the binary nature of the success variable and the exponential distribution of the effort and satisfaction data, we employed logistic regressions with random intercepts (Hosmer & Lameshow, 2000). We used these models to compare the effects of arousal and valence on success as well as to assess the impact of arousal, valence, and cognitive load on time on task, number of steps to task completion, and success on perceived effort and satisfaction.

Finally, because the number of steps to task completion is discrete count type of data, we used Negative Binomial regression models with random intercepts to evaluate the effects of arousal, valence, and cognitive load in this outcome (Hilbe, 2011). The Negative Binomial model is more suitable for over dispersed count data, and the usage of random intercepts accounted for the repeated measures within participants (Barr et al., 2013).

1.6 Results

1.6.1 Descriptive Statistics

Independent Variable Means Across Different Support Tools

Table 2 presents the means for the independent variables across the three support tool conditions –no support tool, clickable demo, and FAQs– during the participants’ interaction with the digital banking platform. Participants exposed to the clickable demo condition reported the highest levels of self-reported arousal ($M = 63.25$, $SD = 18.28$) and self-reported valence ($M = 65.75$, $SD = 20.67$), indicating higher energy and more positive emotional response. The exposure to this condition also resulted in the highest physiological arousal, measured by electrodermal activity ($M = .30$, $SD = 1.00$). However, for the physiological valence results both clickable demo condition ($M = -.11$, $SD = .21$) and FAQs ($M = -.11$, $SD = .16$) were very similar. Regarding the cognitive state of the participants, FAQs revealed the lower cognitive load ($M = .03$, $SD = .17$) suggesting that FAQs condition was less taxing in the cognitive workload for the participants.

In terms of task efficiency, the clickable demo condition presented the shortest average time on task ($M = 32.63$, $SD = 43.67$) while the FAQs showed in average the lower number of steps ($M = 7.37$, $SD = 3.48$). For effectiveness, the clickable demo revealed the highest success rate ($M = .97$, $SD = .16$).

Finally clickable demo condition shows to lowest perceived effort ($M = 2.00$, $SD = 1.49$) and the highest perceived satisfaction ($M = 5.97$, $SD = 1.45$), suggesting a higher user engagement with this type of support tool. Overall, the clickable demo appeared to

provide the most favorable results across several user experience measures, suggesting its potential as an effective and efficient support tool.

Table 3: *Independent variable means across different support tool conditions.*

Independent variable	No support tool		Clickable demo		FAQs	
	M	SD	M	SD	M	SD
Self-reported arousal	61.43	21.17	63.25	18.28	58.17	20.13
Self-reported valence	61.31	22.20	65.75	20.67	63.32	21.29
EDA-Arousal	.24	.78	.30	1.00	.14	.29
Valence	-.13	.17	-.11	.21	-.11	.16
Cognitive load	.05	.15	.05	.20	.03	.17
No. of Steps	9.86	8.24	7.70	3.97	7.37	3.48
Time on task	62.10	65.60	32.63	43.67	47.05	57.89
Success	.83	.38	.97	.16	.93	.25
Perceived effort	2.32	1.77	2.00	1.49	2.07	1.47
Perceived satisfaction	5.74	1.64	5.97	1.45	5.86	1.45

Perceived Task Difficulty Before and After Task Completion

Figure 2 illustrates the perceived task difficulty before and after task completion across the seven tasks presented to the participants. The data reveals a general trend where the perceived task difficulty decreases. Overall, the analysis suggests that tasks T3, T4, and T5 are perceived as the most difficult both before and after task completion.

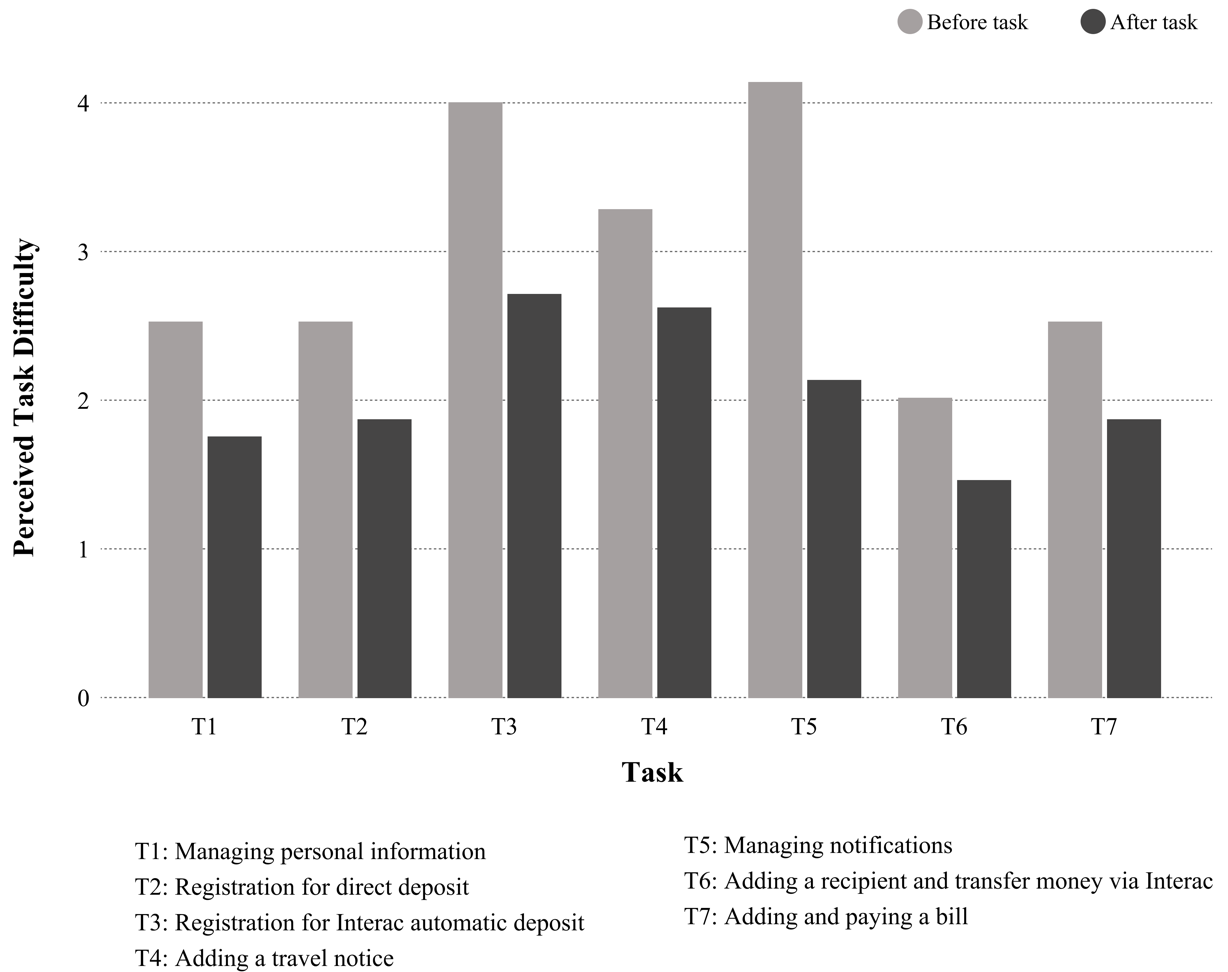


Figure 2: Means for perceived task difficulty before and after task completion.

Task Performance Means Across Different Support Conditions

The analysis shows that the clickable demo support condition provides the highest and most consistent success rates across almost all tasks (see Figure 3). In contrast, both FAQ and no support conditions results in more variability and lower success rates, with the no support condition performing the lowest, particularly in tasks T3 and T4 which are part of the task perceived as the most difficult ones.

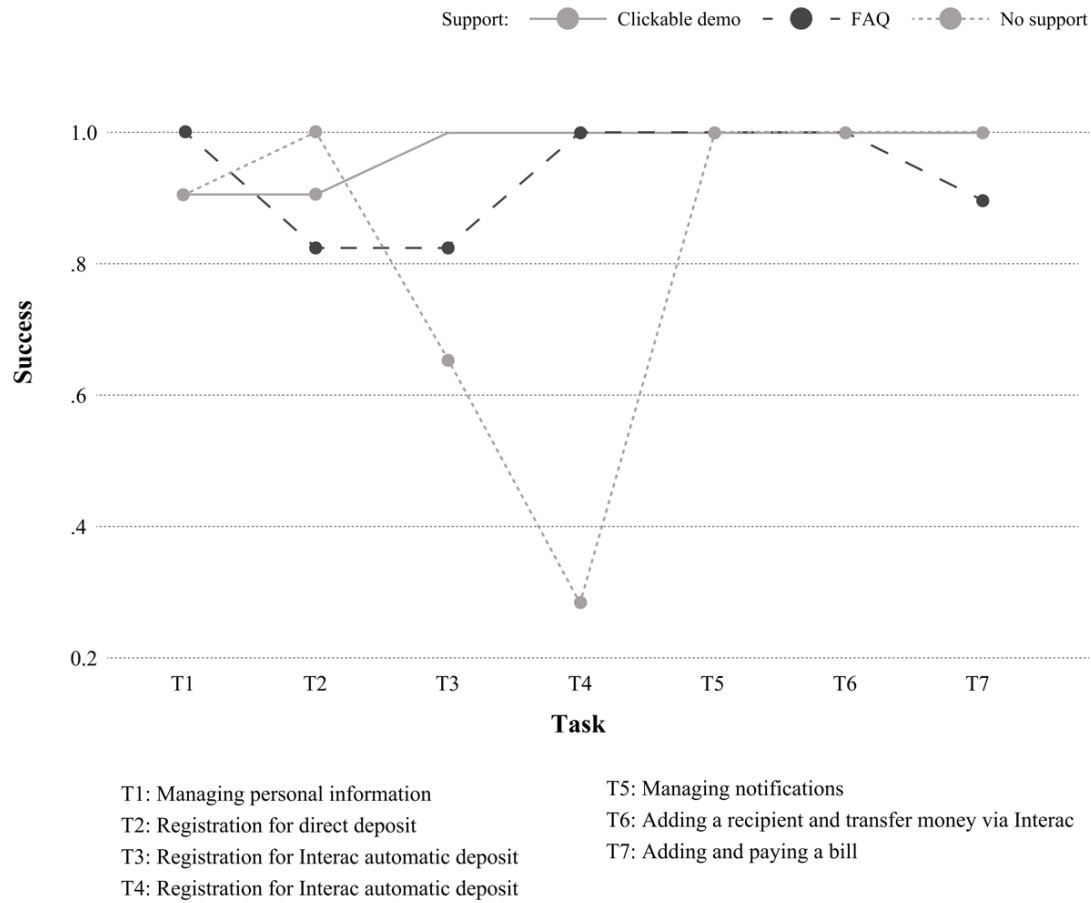


Figure 3: Means for task success across different support conditions.

A logistic regression was performed to evaluate the differences in task success across the three support conditions (see Table 3). The comparison between the no support (C) and clickable demo (D) conditions indicated a significant difference in success rates, [$t(2,193) = -2.61, p = .01$] suggesting that the clickable demo condition significantly improves task success compared to having no support. In the comparison between the no support (C) and FAQ (F) conditions, the analysis reaches a marginal statistical significance, [$t(2,193) = -1.940, p = .05$] indicating a trend where FAQ might be more effective than having no support. Finally, the comparison between clickable demo (D) and FAQ (F) conditions did not suggest a significant difference [$t(2,193) = 1.12, p = .13$].

Table 4: Pairwise comparison analysis of task success across different support conditions.

Measure	Paired conditions		Estimate	SE	df	t	p
Success	C	D	-2.03	.78	193	-2.61	.01*
Success	C	F	-1.08	.55	193	-1.94	.05*
Success	D	F	.96	.85	193	1.12	.13

Note: p values are 1-tailed.

Number of Steps Means by Task Across Different Support Tools

When analysing the number of steps for task completion across different support conditions, overall, the result indicates that the no support condition generally requires the highest number of steps for task completion, particularly for task T4, where the mean number of steps rises significantly. In contrast, the clickable demo and FAQ conditions show the lower number of steps depending on the task (see Figure 4).

To evaluate the differences in number of steps for task completion across the three support conditions a Negative Binomial regression was conducted (see Table 4). The comparison between the no support (C) and clickable demo (D) conditions indicated a significant difference in success rates, [$t(2,194) = 2.39, p = .02$] suggesting that the clickable demo condition significantly reduces the number of steps for task completion in comparison to having no support. When comparing the no support (C) and FAQ (F) conditions, the analysis reaches a statistical significance [$t(2,194) = 2.80, p = .01$], indicating that FAQ are more effective than having no support. Lastly, the comparison between clickable demo (D) and FAQ (F) conditions did not suggest a significant difference [$t(2,194) = 0.42, p = .66$]

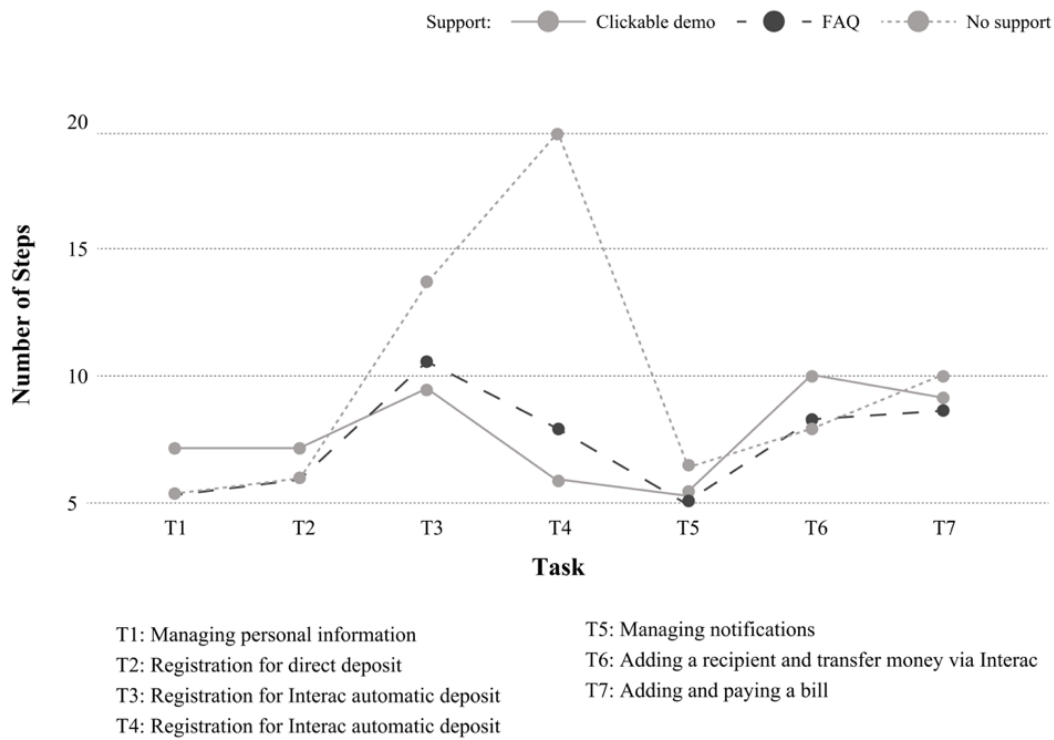


Figure 4: Means of number of steps for task completion across different support conditions.

Table 5: Pairwise comparison analysis of number of steps across different support conditions.

Measure	Paired conditions		Estimate	SE	df	t	p
Number of steps	C	D	.25	.10	194	2.39	.02*
Number of steps	C	F	.29	.10	194	2.80	.01*
Number of steps	D	F	.04	.11	194	0.42	.66

Note: p values are 1-tailed.

1.6.2 Hypothesis Testing

Effect of Support Conditions on User Emotional and Cognitive States

In the study research model, H1a, H1b, and H1c, proposed that higher levels of interaction with the support tool, lead to increased user arousal (H1a), user valence (H1b), and user cognitive load (H1c). To test these hypotheses, we conducted linear regression analyses to examine the effects of the three support tool conditions on participants' emotional and cognitive states. The Pairwise comparison analysis indicated a statistically significant difference in user self-reported arousal between clickable demo (D) and FAQ (F) conditions [$t(2,196) = 2.31, p = .03$]. However, no other comparisons for user arousal, user valence, or user cognitive load reached statistical significance (see Table 5). These findings provide partial support for Hypothesis H1a, as increased interaction led to higher user self-reported arousal, but they do not support Hypothesis H1b or H1c, as no significant effects were observed for user valence and user cognitive load.

Effect of the Interaction Between Perceived Task Difficulty and Support Conditions on Emotional and Cognitive States

We hypothesized that perceived task difficulty would moderate the effects of support tool interaction level on user emotional and cognitive states, strengthening its impact on user arousal (H2a), reducing user valence as perceived task difficulty increases (H2b), and amplifying user cognitive load (H2c).

Linear regression analyses revealed significant interaction effects for self-reported user valence [$F(2,193) = 2.78, p = .03$] and psychophysiological measured valence, [$F(2,151) = 2.47, p = .04$], indicating that, in support of H2b, perceived task difficulty moderates the relationship between the support tool interaction level and user valence. In contrast, no significant effects were found for user arousal or user cognitive load (see Table 6). Thus, H2a and H2c are not supported.

Table 6: Pairwise comparison analysis of emotional and cognitive states across different support conditions.

Measure	Paired conditions		Estimate	SE	df	t	p
<i>Self-reported Emotional States</i>							
Self-reported Arousal	C	D	-2.40	2.56	196	-0.94	.17
Self-reported Arousal	C	F	3.51	2.56	196	1.37	.83
Self-reported Arousal	D	F	5.91	2.56	196	2.31	.03*
Self-reported Valence	C	D	-5.52	3.13	196	-1.76	.12
Self-reported Valence	C	F	-2.48	3.13	196	-.79	.33
Self-reported Valence	D	F	3.04	3.13	196	.97	.33
<i>Emotional States</i>							
EDA - Arousal	C	D	.44	.30	138	1.46	.81
EDA - Arousal	C	F	-.03	.30	138	-.01	.46
EDA - Arousal	D	F	-.47	.30	138	-1.55	.81
Valence	C	D	-.03	.02	154	-1.62	.16
Valence	C	F	-.02	.02	154	-.98	.33
Valence	D	F	.01	.02	154	.65	.33
<i>Cognitive State</i>							
Pupil Dilation	C	D	-.01	.02	148	.73	.29
Pupil Dilation	C	F	.02	.02	148	1.06	.71
Pupil Dilation	D	F	.03	.02	148	1.79	.11

Note: p values are 1-tailed.

Table 7: Fixed effects analysis of emotional and cognitive states across the interaction between the task perceived difficulty and different support conditions.

Measure	Effect (Interaction)	Num DF	Den DF	F Value	Pr > F	<i>p</i>
<i>Self-reported Emotional States</i>						
Self-reported Arousal	P. Difficulty * Support	2	193	1.47	.23	.12
Self-reported Valence	P. Difficulty * Support	2	193	2.78	.06	.03*
<i>Emotional States</i>						
EDA-Arousal	P. Difficulty * Support	2	135	0.72	.49	.24
Valence	P. Difficulty * Support	2	151	2.47	.09	.04*
<i>Cognitive State</i>						
Pupil Dilation	P. Difficulty * Support	2	145	.36	.70	.35

Note: *p* values are 1-tailed.

Effect of User Emotional and Cognitive States on Task Performance

Hypothesis H3a proposed that as user arousal increases, user performance would also increase. To test this, we conducted a series of linear regression analyses to examine the fixed effects of both self-reported user arousal and physiological measured arousal on time on task, number of steps, and task success. The results shown in Table 7 indicated that, at a $\alpha = .05$ level, none of the reported effects were statistically significant, providing no support for H3a.

Table 8: Fixed effects of emotional arousal level on task performance.

Measure	Effect	Estimate	SE	df	t	p
Time on Task	EDA - Arousal	-.01	.03	138	.19	.42
Time on Task	Self-reported Arousal	.01	.00	154	2.09	.98
Number of steps	EDA - Arousal	.01	.02	139	.35	.64
Number of steps	Self-reported Arousal	.00	.00	195	.16	.56
Success	EDA - Arousal	-.03	.10	139	-.26	.60
Success	Self-reported Arousal	0	.01	194	-.33	.63

Note: p values are 1-tailed.

We proposed in Hypothesis H4a that as the user emotional valence increases, user performance would also increase. We conducted linear regression analyses to study the fixed effect of user emotional valence, both self-reported and psychophysiological measured, on time task, number of steps to task completion, and success. The results shown in Table 8, revealed a significant negative effects of self-reported user valence on time on task [$t(154) = -6.30, p < .0001$] and on the number of steps to task completion [$t(195) = -6.38, p < .0001$], indicating a higher valence was associated with shorter task completion times and fewer steps. Additionally, self-reported user emotional valence positively impacted task success [$t(194) = 4.99, p < .0001$]. No statistically significant effects were found for the effect of psychophysiological valence on time on task, number of steps, or task success rate. Thus, H4a is partially supported.

Table 9: Fixed effects of user emotional valence on task performance.

Measure	Effect	Estimate	SE	df	t	p
Time on Task	Valence	-.12	.42	154	-.29	.39
Time on Task	Self-reported Valence	-.02	0	154	-6.30	<.0001*
Number of steps	Valence	.29	.27	155	1.09	.64
Number of steps	Self-reported Valence	-.01	0	195	-6.38	<.0001*
Success	Valence	-.92	1.63	155	-.57	.60
Success	Self-reported Valence	.08	.02	194	4.99	<.0001*

Note: p values are 1-tailed.

Based in the research model, H5a proposed that as user cognitive load increases, user performance would decrease. To test the hypothesis, we conducted linear regression analyses to examine the effects of user cognitive load, measured by pupil dilation, on task performance. However, as shown in Table 9, the results revealed no statistically significant effects. Therefore, we do not find support for H5a.

Table 10: Fixed effects of user cognitive load on task performance.

Measure	Effect	Estimate	SE	df	t	p
Time on Task	Pupil Dilation	-.32	.45	148	-.72	.76
Time on Task	Pupil Dilation	-.75	.28	149	-2.68	1.00
Number of steps	Pupil Dilation	-.21	1.59	149	-.13	.45

Note: p values are 1-tailed.

Effect of User Emotional and Cognitive States on Task Perceived Effort

Regarding the effects of user emotional and cognitive states on the user perceived effort, we hypothesized that increased user arousal leads to higher perceived effort (H3b), increased user emotional valence leads to lower perceived effort (H4b), and increased user cognitive load also leads to higher perceived effort (H5b). We used logistic regressions to test these hypotheses.

The analysis of the fixed effects of user emotional and cognitive states on task perceived effort revealed two significant results (see Table 10). Physiological measured user arousal levels had a statistically significant effect on user perceived effort [$t(139) = 2.73, p = .003$], which indicates that the higher the arousal level, the higher the task perceived effort. Additionally, self-reported user emotional valence showed significant negative effect on task perceived effort [$t(197) = -5.81, p < .0001$], suggesting that the higher self-reported valence levels are associated with lower perceived effort. Other effects were not statistically significant at a $\alpha = .05$ level. These findings partially support H3b and H4b, while H5b was not supported.

Effect of Task Performance on User Perceived Effort

According to the research model, we hypothesized that as user task performance increases, user effort decreases (H6). To test this hypothesis, we used logistic regression analysis. The fixed effects analysis of task performance on user perceived effort revealed significant results across all measures (see Table 11). Time on task showed a significant effect on perceived effort, [$t(154) = 4.96, p < .0001$], indicating that increased time on task is associated with higher perceived effort. The number of steps for task completion, also presented a significant effect on perceived effort, [$t(195) = 4.27, p < .0001$], suggesting that the more steps required to complete the task the higher the effort is perceived. Lastly, success had a significant negative effect on perceived effort, [$t(194) = -3.44, p = .0003$], indicating that higher success on task is associated with lower perceived effort. These results support H6.

Table 11: Fixed effects of emotional and cognitive states on task perceived effort.

Measure	Effect	Estimate	SE	df	t	p
	Arousal					
Perceived Effort	EDA - Arousal	.25	.09	139	2.73	.003*
Perceived Effort	Self-reported Arousal	.01	.01	197	.75	.23
	Valence					
Perceived Effort	Valence	-.89	1.24	155	-.71	.24
Perceived Effort	Self-reported Valence	-.1	.01	197	-5.8	<.0001*
	Cognitive Load					
Perceived Effort	Pupil Dilation	-2.66	1.41	149	-1.89	.97

Note: p values are 1-tailed.

Table 12: Fixed effects of task performance on task perceived effort.

Measure	Effect	Estimate	SE	df	t	p
Perceived Effort	Time on Task	1.43	.29	154	4.96	<.0001*
Perceived Effort	Number of Steps	.24	.06	195	4.27	<.0001*
Perceived Effort	Success	-3.76	1.09	194	-3.44	.0003*

Note: p values are 1-tailed.

Effect of User Performance on User perceived Satisfaction

We hypothesized that as user performance increases, user perceived satisfaction increases (H7). To test this hypothesis, we conducted logistic regressions to examine the effects of time on task, number of steps and success rate on user perceived satisfaction.

Table 12 shows the fixed effects of task performance on use perceived satisfaction, showing significant results across the different measures. The analysis indicated that time on task has a significant negative effect on perceived satisfaction, [$t(154) = -4.01, p < .0001$], suggesting that the higher the time on task, the lower the perceived satisfaction was reported. Similarly, the number of steps had a significant negative effect on perceived satisfaction, [$t(195) = -3.23, p = .0007$], indicating that the higher the number of steps for task completion, the lower the satisfaction. Finally, success had a significant effect on perceived satisfaction, [$t(194) = 3.42, p = .0004$], showing that the higher the success on task, the higher the perceived satisfaction. These findings support H7, demonstrating that increased user performance positively impacts user perceived satisfaction.

Table 13: Fixed effects of task performance on user perceived satisfaction.

Measure	Effect	Estimate	SE	df	t	p
Perceived Satisfaction	Time on Task	-1.26	.31	154	-4.01	<.0001*
Perceived Satisfaction	Number of Steps	-.15	.05	195	-3.23	.0007*
Perceived Satisfaction	Success	3.29	.96	194	3.42	.0004*

Note: p values are 1-tailed.

Effect of User Perceived Effort on User Perceived Satisfaction

Finally, H8 hypothesized the increase of user perceived satisfaction as user perceived effort increases. We test this hypothesis with a logistic regression. The results suggest a significant negative effect, [$t(1197) = -4.43, p < .0001$], indicating a strong correlation between increased perceived effort and decreased perceived satisfaction (See Table 13). Therefore, H8 is supported.

Table 14: Fixed effects of user perceived effort on user perceived satisfaction.

Measure	Effect	Estimate	SE	df	t	p
Perceived Satisfaction	Perceived Effort	-.81	.18	197	-4.43	<.0001*

Note: p values are 1-tailed.

Hypotheses Results Summary

The following table (Table 14) presents a summary of the hypotheses results. On it, we report the results for each of them as partially supported, not supported or supported, based on the tests described above in the Hypothesis Testing section.

Table 15.1: Hypotheses result summary (Part 1).

H No.	Hypothesis	Result
H1a	As the level of interaction with the instructional tool increases, the level of arousal increases.	Partially supported
H1b	As the level of interaction with the instructional tool increases, the level of valence increases.	Not supported

Table 14.2: Hypotheses result summary (Part 2).

H No.	Hypothesis	Result
H1c	<i>As the level of interaction with the instructional tool increases, the level of cognitive load increases.</i>	Not supported
H2a	<i>As the level of interaction with the instructional tool increases, user arousal increases. Higher levels of perceived task difficulty amplify the user arousal.</i>	Not supported
H2b	<i>As the level of interaction with the instructional tool increases, user valence increases. Higher levels of perceived task difficulty diminish the user valence.</i>	Supported
H2c	<i>As the level of interaction with the instructional tool increases, user cognitive load increases. Higher levels of perceived task difficulty amplify the user cognitive load.</i>	Not supported
H3a	<i>As the user arousal increases, the performance increases.</i>	Not supported
H4a	<i>As the user valence increases, the performance increases.</i>	Partially supported
H5a	<i>As the user cognitive load increases, the performance decreases.</i>	Not supported
H3b	<i>As the user arousal increases, the perceived effort increases.</i>	Partially supported
H4b	<i>As the user valence increases, the perceived effort decreases.</i>	Partially supported
H5b	<i>As the user cognitive load increases, the perceived effort increases.</i>	Not supported
H6	<i>As the user performance increases, the perceived effort decreases.</i>	Supported
H7	<i>As the user performance increases, the perceived satisfaction increases.</i>	Supported
H8	<i>As the user perceived effort increases, the perceived satisfaction decreases.</i>	Supported

1.7 Discussion

The findings reveal significant insights about the comparative effectiveness and impact on cognitive and emotional states of clickable demos and FAQ tools in digital banking platforms. We hypothesized that the level of interaction with the instructional tool—clickable demo versus FAQ—would influence the users’ emotional states and cognitive load and as a result their task performance, perceived effort, and satisfaction. However, the results suggested a more nuanced picture. When evaluating the impact of the support tool interaction level the results did not lead to significant effects on the emotional nor the cognitive states of the users as it was hypothesized. The significant impact of self-reported valence on task performance and perceived effort in conjunction with the strong correlation between perceived effort and satisfaction, highlights the significant impact of the perceived effort and performance on the perceived task satisfaction.

When analyzing the relationship between perceived task difficulty and success rates across different conditions (no support tool, clickable demos, or FAQs), it is notable that tasks perceived as complex showed a higher increase in success rates as the level of interaction with the support tool’s level of interaction increased. This suggests that the impact of the support tool’s level of interaction may be more significant for complex tasks compared to those perceived as less complex.

1.7.1 Theoretical Implications

Our study contributes to the theory by highlighting that in the context of digital banking, task perceived difficulty moderates the relationship between interactivity and cognitive load, and more specifically by comparing two already adopted support tools like FAQs and clickable demos. In this study, we found that the effects of the interaction levels with the instructional tools on the user cognitive load are highly context-dependent, particularly in digital banking, where task difficulty may vary considerably. Recent applications of Cognitive Load Theory (Sweller, 1988) assume that increased interactivity generally improves task performance by facilitating deeper cognitive engagement (Mayer

& Moreno, 2003; Sutcliffe & Hart, 2017). The results suggest that intrinsic cognitive load –the inherent perceived complexity of banking tasks– plays a fundamental role that interactivity by itself cannot mitigate. This finding aligns with the study conducted by (Rodrigues et al., 2016; Skulmowski & Xu, 2022), which observed that task specificity and user expectations significantly influence the effectiveness of instructional design.

Our findings also add to a more nuanced understanding of how the levels of interaction with instructional tools affect user emotion and cognitive states. Different to the expectations, the clickable demo support tool did not significantly enhance positive emotional states compared to FAQs. The deviation from the Multimedia Learning Theory that highlights the emotional advantages of interactive learning (Mayer & Chandler, 2001), indicates that in high-stakes environments such as digital banking, the task perceived complexity could lessen the emotional advantages of the interactivity levels of the support tool. Previous studies have recognized that high extraneous cognitive load can lead to negative emotional responses (Paas et al., 2003), but our findings suggest that even well-designed interactive support tools like clickable demos may not always alleviate emotional burdens in complex digital tasks.

Finally, by addressing the moderating effect of task difficulty, our research extended the applicability of Cognitive Load Theory to domains where tasks vary in difficulty, such as digital banking platforms. Our analysis shows that for tasks perceived as more difficult, the increased interactivity provided by clickable demos contributed to higher task efficiency and effectiveness.

1.7.2 Managerial Implications

From a managerial perspective, the findings of this study provide actionable insights for improving customer support and user experiences not only in digital banking platforms but potentially in other industries going through digital transformation processes. The study's results suggested that while the benefits of providing appropriate customer support tools in digital banking are well understood (Chheda et al., 2023), the benefits of

clickable demos over traditional FAQs have not been explored. Our results suggested that clickable demos are indeed more effective than offering no support tools at all; however, their advantages compared to traditional FAQs are less significant than we anticipated. This finding implies, that UX practitioners, customer success managers and service designers should not assume that more interactive support tools will automatically lead to better task performance. Instead, a more strategic approach that considers different layers of the task like its perceived difficulty and context might be essential. For instance, in scenarios where users are likely to encounter complex or unfamiliar tasks, providing multiple support options, including both clickable demos and FAQs may be more effective than in simple scenarios. Additionally, understanding the role of perceived effort and its strong correlation with user satisfaction can guide the development of support tools that prioritize efficiency and ease of use on specific and painful flows. This approach can lead to higher customer satisfaction in a highly competitive digital banking market.

1.7.4 Limitations and Future Research Directions

While this study offers valuable insights, it also has limitations that should be acknowledge. The sample size was relatively small, presenting a potential limitation. Although the precision and richness of eye-tracking and EDA data can compensate for smaller samples (Boucsein, 2012; Duchowski, 2007).

Another limitation was the format where the platform was presented. The study was conducted within the boundaries of a Figma prototype that ensured the user flows and experiences were as similar as possible to the real platform. Additionally, because it was a prototype, it removed any potential bias related to actual bank accounts. However, a clickable prototype may carry some safeguards and directed user paths within its interaction, which might influence the reported user performance.

Finally, while the study examined the impact of perceived task difficulty as a moderating variable, other potential moderators, such as user motivations, prior experiences with similar tools (familiarity) were not considered.

Given the previously mentioned limitations, future research could expand the sample in size and to include a more diverse population both in terms of demographics and digital proficiency. It could be valuable to explore whether the findings apply to users with lower levels of digital literacy. Similarly, future studies should consider testing the platform in a sandbox environment where user interactions and flow can be more freely explored by the participants. In addition, future research could incorporate more other variables like user motivations and prior experience to get a more comprehensive understanding of the factors that influence the effectiveness of support tools in digital banking platforms.

1.8 Conclusion

The purpose of this study was to evaluate the effectiveness of clickable demos against traditional FAQ tools in digital banking platforms. It was motivated by the critical need to enhance customer education and support in the way the industry engages with digital transformation. Furthermore, by exploring how these instructional tools impact the emotional and cognitive states of users, task performance, and perceived satisfaction, the research sought to address a significant gap in the literature and contribute to a deeper understanding of user support mechanisms in digital banking. The research found that while clickable demos improved task success rates and performance, their advantages over FAQs were not consistently significant across all measures, particularly regarding user emotional and cognitive states, suggesting that factors like task complexity play a more important role in the equation. These results indicate that the effectiveness of instructional tools like clickable demos is highly context-dependent, pointing the importance of a tailored approach that considers specific tasks and users' context.

As the banking industry continues evolving, there is an opportunity to optimize digital support tools by integrating user-centric design principles that address the diverse learning needs of customers when they are learning certain features or products. This study opens the door to future research in support tools, considering more contextual variables and possible incorporating new technologies in the comparison, like AI-assisted support tools and any new technologies used by customer success teams in their quest to enhance user satisfaction and adoption of the constantly evolving modern digital banking platforms.

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Beyond FAQs: Are Clickable Demos the Right Support Tool in Digital Banking?

Support Tools and Digital Banking Platforms

Digital transformation has fundamentally reshaped how consumers interact with financial services, delivering unprecedented convenience in managing their finances ⁽¹⁾. However, the rapid shift to digital platforms can present challenges in user satisfaction and adoption, as customers may need support to fully understand and navigate these constantly evolving platforms seamlessly ⁽²⁾. Traditionally, to address these needs, digital banking platforms have relied on frequently asked questions (FAQs), valued for their implementation simplicity and cost-effectiveness. Yet, as users' expectations evolve, tools like clickable demos are becoming popular for offering a more interactive approach to customer support.

While clickable demos are growing in interest, they are typically more expensive, require substantial implementation time, and demand ongoing maintenance as platforms evolve. Given these factors, UX practitioners, customer support leads, and product managers may wonder to what extent clickable demos, compared to FAQs, are more effective in supporting users on digital banking platforms.

A Comparative Study Approach

To investigate this question, we conducted a study using a research approach where participants were randomly assigned into separate groups to experience different types of support tools, clickable demos, FAQs, or no-support, for each task. A sample of 33 participants was randomly assigned to one of these groups, allowing for a comparison of how each tool influenced cognitive load—the amount of mental effort required to process information—, emotional responses, and task performances as they completed tasks of varying complexity on a digital banking platform. The study was conducted in a controlled laboratory setting. Data collection included advanced tools like eye-tracking technology and electrodermal activity sensors paired with pre- and post-task surveys to capture objective and self-reported metrics.

Context Shapes the Effectiveness of Support Tools

The research findings revealed how these tools perform under different conditions, for example, showing when clickable demos are evidently more helpful and, on the other hand, when FAQs are sufficient to achieve the user's goal. Furthermore, the study showed how these choices affect users' performance and emotional and cognitive states.

Clickable demos significantly improved task success rates and efficiency compared to no-support conditions, primarily by reducing the steps needed to complete tasks. However, the added value of clickable demos over FAQs depended on task complexity, with more straightforward tasks showing no notable difference. This suggests that even though clickable demos can improve users' performance for complex, multi-step tasks, FAQs may be sufficient for more straightforward tasks.

Contrary to initial expectations, clickable demos did not significantly lower cognitive load compared to FAQs, nor did they affect emotional responses. These results indicate that task complexity influences cognitive and emotional demands more than the choice of support tool. For digital banking platforms, this points out the importance of aligning tool selection with task complexity; interactive support tools may be unnecessary and potentially an implementation overkill for simple or routine tasks.

Perceived task difficulty influences support tool effectiveness, whether it was a clickable demo or FAQs. For complex tasks, clickable demos provided higher success rates and fewer errors, helping to reduce perceived effort and, as a result, increasing users' satisfaction. In contrast, for simpler tasks, FAQs provided quick, accessible help that met user needs without added complexity.

Adapting Support Strategies According to Task Complexity

In digital banking, support tools shouldn't be one-size-fits-all. A more context-driven approach promotes a smoother, more efficient experience, reducing frustration and meeting diverse user needs with targeted adaptable support strategies.

For complex and non-recurrent tasks, clickable demos are more beneficial. These tools can simulate the user's journey, offering prompts and visual cues that make it easier to understand how to proceed. Digital banking platforms should invest in these interactive support tool formats. For example, if a new feature requires multiple steps, providing a clickable demo can help users navigate it with less perceived effort, leading to a highly satisfactory customer experience. On the other hand, tasks that may be more familiar to users and that may represent more straightforward journeys can be effectively supported with FAQs. For UX practitioners, it is essential to understand the customer journey and select the correct support tool for it so that they can keep the balance between budget and optimal user experience as a platform.

Focusing on reducing perceived effort: The study revealed a high correlation between task-perceived effort and user satisfaction. Users who complete their tasks with minimal perceived effort are more likely to feel optimistic about the overall experience. Support tools should aim to minimize the steps needed to complete tasks and provide a straightforward and intuitive experience. For example, reducing the number of clicks, simplifying instructions, and ensuring that information and support are easy to find can all contribute to a more seamless user experience. Not only should the platform be intuitive and user-friendly, but also the support tool provided.

Selecting the Right Tool is a Win-Win

The findings from this research provide important insights into using instructional tools in digital banking. UX designers, customer success teams and product managers should carefully evaluate when to implement each tool, considering variables like task complexity, user familiarity and perceived effort. Understanding their users and their journeys, is a key first step in the instructional design for digital banking support tools. A well-informed support strategy can help digital banks save resources by not overproducing interactive content where it isn't necessary, while still providing robust support for complex features and processes.

Furthermore, the lack of significant differences in cognitive load between tools suggests that simply making a tool more interactive doesn't automatically make it more effective

and easier to use. With that in mind, designers should focus on reducing unnecessary mental effort users expend to navigate and understand the system, including its support tools. This can be achieved through clear design, logical navigation and well-organized content, whether in a clickable demo or FAQ format ⁽³⁾.

When choosing the right support tool, either clickable demos, FAQs, or any other, we are not only enhancing engagement and retention from a business perspective but also ensuring accessibility and inclusivity for all users. In an increasingly complex digital world, banking platforms have a responsibility to serve both tech-savvy and novice customers by providing seamless, intuitive and empowering experiences.

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Conclusion

As digital transformation reshapes the banking industry, understanding how users interact with digital support tools has become vital, mainly when offering a user-centric experience that seeks to achieve high customer success standards. This thesis explored the effectiveness of clickable demos versus traditional FAQs in supporting users' experience in digital banking platforms, focusing on emotional and cognitive responses, task performance, and user satisfaction. Guided by the Cognitive Load Theory (CLT) (Sweller, 1988) and Multimedia Learning Theory (MLT) (Mayer & Moreno, 2003), this research examined how varying levels of interaction with the support tool affect users' experience when learning different tasks in a digital banking platform. This chapter summarizes key findings, discusses theoretical and practical implications, and provides suggestions for future research, pointing out the need for tailored instructional design in digital support strategies for customer success.

Research Questions and Key Findings

This study aimed to contribute to a deeper understanding of user support tools in digital banking and provide key findings to improve the user experience, platform design, and customer success for the banking industry. These findings can also be translated to other industries that have switched to or are switching to digital platforms. The key research question that drove this study was: *To what extent are clickable demos more or less effective compared to traditional FAQ tools when users learn to use a feature in digital banking platforms?* To address this question, the study goal was to clarify better which instructional tools best facilitate digital banking interactions, contributing with key findings into user support and customer success in digital banking environments and potentially in other digital platforms.

The results of the study suggested that while clickable demos can improve task efficiency under certain conditions, their overall impact on user experience such as emotional states, cognitive load, and satisfaction is context-dependent and not always superior to FAQs.

Positive emotional valence was a key factor in improving performance and satisfaction while reducing perceived effort, whereas increased arousal affected perceived effort but not task performance. Ultimately, the effectiveness of clickable demos over FAQs largely depends on task complexity, highlighting the importance of taking into consideration the nature and difficulty of the task when selecting the digital support tool.

Contributions & Implications

This study contributed to both theoretical understanding and practical applications in user experience by building on current research around Cognitive Load and Multimedia Theories and providing practical implications to the customer success teams of banking platforms.

This study extended the application of Cognitive Load Theory (Sweller, 1988) and Multimedia Learning Theory (Mayer & Moreno, 2003) in digital banking, offering insights into how the level of interaction of different instructional tools affects cognitive and emotional states in complex, high-stakes-oriented platforms. The results confirmed that CLT is context-dependent, and suggested that the task complexity, may have higher impact in cognitive and emotional responses. These results challenge existing assumptions that higher interactivity will always improve cognitive processing and emotional engagement and proposes that a tailored approach to instructional design based on task complexity may promote more favorable results for the user experience.

Additionally, the study questioned the expected advantages of interactive multimedia tools in improving user engagement and satisfaction. While clickable demos, as expected by MLT principles, do improve engagement for more complex tasks, this improvement is not uniformly observed across all tasks. These findings suggested a potential need to refine MLT frameworks to consider how task-specific factors may moderate the effects of interactive media on cognitive and emotional states. Which suggests that both theories might be very complementary to each other when studying the relative effectiveness between both support tools, and potentially when comparing with others.

From a practical point of view, this study provided actionable insights not only for digital banking platforms but also for other industries undergoing digital transformation. The findings indicated that clickable demos can effectively increase task performance, but their benefits over FAQs are not as straightforward and consistent as initially anticipated. When adding the variable of the cost-benefit of producing tailored clickable demos versus using a more economic approach like FAQ, UX practitioners, product managers and customer success teams should consider a hybrid approach, employing both clickable demos and FAQs based on the complexity of user tasks. When tasks are perceived as highly difficult, clickable demos may be a support tool that offers added value by guiding users in through the task and providing a smoother onboarding to it. In the case of task that may be perceived as simpler and possibly more familiar, FAQs might be sufficient to provide the guidance required by the users.

The study results also confirmed the impact of perceived effort on users' satisfaction while completing the tasks. Digital platforms should prioritize efficiency-focused designs that help minimizing the perceived task difficulty.

Recommendations for Future Research

The research conducted during this study opens a few avenues for further investigation. Given the limitations of a controlled lab setting and a sample mainly composed by tech-savvy participants from Quebec, future studies should aim to diversify participants demographics, including users with lower levels of digital literacy, and conduct experiments in more naturalistic settings. In that same strain, future experiments would be benefited from testing the production version of the digital banking platform rather than in a controlled and limited prototype. This approach would help validate the generalizability of the findings.

Future research should examine additional moderating factors, such as user motivation, familiarity with digital banking tools, and personal learning preferences, as these may affect the effectiveness of instructional tools. Another important factor to investigate is the discoverability of these tools, and understanding when and where users expect to receive support and how these expectations evolve over time. Further research could

include a longitudinal study focused on users' satisfaction and engagement with digital support tools for longer periods, potentially revealing interesting results on the learning process of a digital banking platform feature along the time. Lastly, this study can be expanded to compare other types of support tools, like chat-bots, and AI driven assistance. Customer success leads and UX designers may get benefited with a better understanding of other support tools comparison.

Conclusion

As conclusion, this study revealed the importance of defining the right support tools based on user needs and task complexity, and it challenges the assumption that more interactive tools always provide better experiences. As digital banking and other industries continue their digital transformation journeys, no matter how advanced they're in it, the results provided in this research can guide the development of user-centered support strategies that improves task performance, reduce cognitive load, and promotes greater customer satisfaction. I hope this research serves as an initial foundation for further exploration in digital support optimization and contributes to a highly strategic approach to designing user-centric and inclusive support tools for an inevitably complex digital world.

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Declaration of responsible use of Gen AI

I acknowledge that I used ChatGPT's model GPT-4 (<https://chatgpt.com/>) in February 2024, to support the early stages of my literature review. This tool was employed specifically to help clarify key concepts, generate relevant keywords, and identify potential research directions. The outputs served as a starting point for deeper investigation using peer-reviewed academic sources. Example prompts included: "What are the main Human-Computer Interaction Theories related to help tools in digital banking platforms?" and "Help me better understand [keyword] within the context of HCI." The literature review itself was developed independently through critical reading and synthesis of scholarly materials.

I declare that I used ChatGPT model GPT-4o (<https://chatgpt.com/>) from May 2024 to March 2025, as a writing support. The results helped me structure parts of the text, while ensuring internal consistency: I used the following prompt: "Help me structure in a more formal and grammatically accurate way the following text. Your only job is to suggest grammar improvements, reduce redundancy and fix spelling issues. You will only use my words, keep my tone of voice, and preserve the citations provided. Respect internal consistency and do not provide any additional content. [Text to be revised]"

I declare that I used ChatGPT model GPT-4o and GPT-o1 (<https://chatgpt.com/>) from August 2024 to December 2024, as code debugger when encountering issues with the SAS code utilized for statistical analysis. I used the following prompt: "In the following code, help me identified the typo that is preventing me from obtaining the expected result, I'm trying to run a [statistical test] in SAS code. [Code with bug]"

I declare that I used Grammarly AI review suggestions (<https://app.grammarly.com/>) from February 2024 to March 2025 as a writing and style support.

I declare that I used DeepL Translate (<https://www.deepl.com/en/translatorfrom>) from November 2024 to March 2025 as the main translation tool from English to French for my thesis abstract.

Appendix 1: Co-Authors Consent Form

Authorization by co-authors of an article included in a master's thesis or doctoral dissertation

Office
of the Registrar

3000 chemin de la Côte-Sainte-Catherine
Montreal, Quebec, Canada H3T 2A7

HEC MONTRÉAL

When a student is not the sole author of an article to be included in his/her thesis or dissertation, he/she must obtain the authorization of all the other co-authors for this purpose and attach the signed authorization to the article in question. **There must be a separate authorization form for each article included in the thesis or dissertation.**

1. Student

Monroy Guevara, Juan Francisco

11336733

Last name, First name

HEC ID number

Master of science in administration (MSc)

User Experience

Program of study

Specialisation

2. Article

Authors: Juan Francisco Monroy Guevara, Sylvain Sénécal, and Ruxandra M. Luca

Title: Comparing Clickable Demos and FAQ Tools in Digital Banking: A Study on

Publication: International Journal of Bank Marketing

Current status of article : ☐ published ☐ submitted for publication ☒ in preparation

3. Student declaration

For each article published or submitted for publication, the student must briefly describe his/her role in the research work and, if applicable, the extent of his/her contribution to the article in comparison with those of the other co-author(s). If an article is in preparation, the student must describe his/her current or planned contribution to the research work and the article.

The student's role in the article involved conducting the literature review, performing research and analysis, and serving as the primary author of the article. This work was co-supervised by Sylvain Sénécal and Ruxandra M. Luca, who provided feedback, made

Juan Francisco Monroy Guevara

Digitally signed by Juan Francisco Monroy Guevara
Date: 2024.12.06 15:11:10 -0500

2024-12-05

Student's signature

Date

4. Declaration by all other co-authors

As co-author of the above-mentioned article, I authorize Juan Francisco Monroy Guevara

to include the article in his/her ☒ master's thesis / ☐ doctoral dissertation, entitled:

Comparing Clickable Demos and FAQ Tools in Digital Banking: A Study on Effectiveness, Efficiency and Cognitive Load

(Title of thesis or dissertation)

Sylvain Sénécal



Dec 6, 2024

Co-author

Signature

Date

Ruxandra M. Luca



Dec 6, 2024

Co-author

Signature

Date

Co-author

Signature

Date

Co-author

Signature

Date

Appendix 2: Questionnaires

Perceived Satisfaction (Self-reported): Satisfaction was measured using a 3-item 7-point Likert scale (1 =Strongly Disagree, 7 = Strongly Agree) (Kim & Son, 2009) where participants evaluated the following statements:

- i. *“I am content with the service provided by the banking platform”*
- ii. *“I am satisfied with the service provided by the banking platform”*
- iii. *“What I receive from the banking platform meets my expectations for this type of service”*

Perceived Effort (Self-reported): The perceived effort was also assessed through a 3 - item 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree) (Wang & Benbasat, 2009). Participants responded to the items:

- i. *“The task on the banking platform took too long.”*
- ii. *“The task on the banking platform required too much effort.”*
- iii. *“The task on the banking platform was too complex.”*

Appendix 3: Lab setup



Appendix 4.1: Experiment Lab Setup.



Appendix 4.2: Observation Room

[Inner endpaper]