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A new methodological approach to study user emotion continuity in multi-device environments

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Résumé

L'utilisation concurrente de plusieurs appareils est devenue un comportement courant pour les consommateurs, et les interactions avec les services digitaux sont davantage réparties entre plusieurs dispositifs numériques. Ainsi, les stratégies omnicanales visant à accroître le degré d'intégration des canaux pour offrir une expérience client continue sont toujours plus fréquentes dans les entreprises. Cependant, en raison de difficultés techniques, les chercheurs en UX ne disposent toujours pas d'une mesure implicite, fiable et continue de l'expérience utilisateur adaptée à l'usage de plusieurs dispositifs dans une interaction omnicanale. Ce mémoire introduit donc une méthodologie de collecte de données psychophysiologiques inter-dispositifs visant à: (1) détecter automatiquement quel appareil est utilisé; et (2) produire une mesure continue de la valence émotionnelle et de la charge cognitive à travers tous les appareils, en fonction des transitions entre appareils détectées. Cette méthodologie est testée pour sa précision et utilisée pour évaluer la présence d'une réponse émotionnelle en lien avec les transitions d'appareils. Les résultats suggèrent que la méthodologie de collecte de données psychophysiologiques inter-dispositifs proposée identifie correctement l'appareil utilisé et fournit une mesure valide, fiable, et continue de la valence émotionnelle et de la charge cognitive entre les appareils. Les résultats mettent en lumière la présence d'une réponse émotionnelle à certaines transitions entre appareils. La méthodologie présentée dans ce mémoire est détaillée de manière à pouvoir être reproduite par d'autres chercheurs. Des pistes pour des recherches ultérieures et des améliorations méthodologiques sont discutées, ainsi que les implications des principaux résultats de cette thèse.

Mots clés: Omnicanal · Inter-Dispositifs · Interaction Continue · Mesures Psychophysiologiques

Méthodes de recherche: Évaluation Utilisateur · Analyse d'Expression Faciale · Pupillométrie

Abstract

Using multiple devices simultaneously has become commonplace behavior for customers, and interactions with brands are increasingly distributed across several digital devices. As such, omnichannel strategies aimed at raising the degree of integration among channels to provide a seamless customer experience are ever more frequent in firms of all sizes. Due to technical challenges however, UX researchers still lack an implicit, reliable, and continuous measure of user experience adapted to multi-device frameworks in omnichannel interactions. This thesis thus introduces a multi-device psychophysiological data collection methodology that: (1) detects which device is being used automatically; and (2) produces a continuous measure of emotional valence and cognitive load across devices, according to the detected device transitions. This methodology is tested for accuracy, and further used to evaluate the presence of an emotional response linked to device transitions. Results suggest that the proposed multi-device psychophysiological data collection methodology correctly identifies used device and provides a valid, reliable, and continuous measure of emotional valence and cognitive load across devices. Results also shine a light on the presence of an emotional response to certain device transitions. The methodology presented in this thesis is thoroughly detailed to make it replicable by other researchers. Ideas for further research and methodological improvements of multiple device use in omnichannel journeys are discussed, as well as the implications of the main findings of this thesis.

Keywords: Omnichannel · Cross-Device · Seamlessness · Psychophysiological Measures

Research Methods: User Evaluation · Facial Expression Analysis · Pupillometry

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List of Abbreviations and Acronyms

AIS – Association for Information Systems

CLT – Cognitive Load Theory

CPUM – Cross-Platform Usability Measurement

CX – Customer Experience

DDA – Device Detection Algorithm

EDA – Electrodermal Activity

HCI – Human-Computer Interaction

UX – User Experience

UXPA – User Experience Professionals' Association

Foreword

Approval of Thesis. This thesis in User Experience (UX) in a Business Context is composed of two scientific articles and has been submitted with the approval from the Academic Affairs office of the Masters of Science (M.Sc.) program.

Methodological Article. The first chapter of this thesis – an article proposing a novel methodology for the continuous measurement of interactions in multi-device environments with psychophysiological inferences – has been submitted in its present form to the journal *Multimedia Tools and Applications* in July 2023 and is currently under review.

Research Article. The second chapter of this thesis – an article exploring the emotional response to device switching transitions in omnichannel task contexts – is being prepared for submission to the journal *AIS Transactions on Human-Computer Interaction*.

Managerial Article. The third chapter of this thesis – a professional article recommending approaches for the study of multi-device experiences – is being prepared for submission to the *User Experience Professionals Association (UXPA) Magazine*.

Ethics Certificate. The data collection involved in the making of this thesis was initially approved by the Research Ethics Board (REB) of HEC Montréal in January 2022, under project number #2022-4850.

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Co-Authors Consent. All co-authors of the first, second, and third chapters of this thesis have provided their written consent to be included in this thesis.

Competing Interests. The author certifies to have no affiliations or involvement with any organization with any financial or non-financial interest in the subject matter or materials of this manuscript.

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My first thanks goes to Anastasia Tarasova, my other half and constant companion, whose support, care, and confidence helped me navigate the troubled waters of academia to a fair shore. This thesis is in a large part the product of her work, and surely could not have been done without her tender and soft assistance. I am eternally grateful to have you in my life, my love.

I would also like to thank all the staff of the Tech3Lab (Montréal, Canada), whose help in realizing this research was invaluable. The core of this research is the creation of a new psychophysiological data collection methodology, and such an endeavor required usual input from all the teams. Many thanks to David Brieugne for managing the logistics of this project; Salima Tazi and Xavier Côté for ensuring the fine work of all psychophysiological tools; François Courtemanche for the creation of the smartphone support; Shang-Lin Chen for the development of the DDA; and Carl St-Pierre for his help in coding statistical analyses. Thanks as well to the research assistants who prepared and conducted experiments, and those who helped me smile on a bad day. Mostly, special thanks to Frédérique Bouvier and her UX team – Marine Farge and Luis Carlos Castiblanco – for acting as my mentors throughout my entire stay in the Tech3Lab, always encouraging me forward and providing thoughtful counsel. I have cherished every moment working with you, and thank you dearly for letting me grow in your shape.

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Lastly, I would like to extend my thanks to the NSERC, PROMPT, and industrial partners that were involved in the funding of this research project. Their contributions allowed for significant scientific discoveries, and the realization of this thesis in the best possible conditions.

INTRODUCTION

The last fifteen years have been marked by the mobile internet revolution. Since the introduction of the iPhone in 2007, smartphone ownership has risen to 85% of the population in the United States (Pew Research Center, 2021). Along with PCs and tablets, whose ownership rates lie at 77% and 53% respectively, they are the most commonly used devices by customers. It is estimated that every user in the United States owns 5.3 connected devices on average (Pymnts, 2022) and customers have steadily adapted to multi-screening behavior and distributed interactions with brands across devices (Google, 2012; Microsoft Advertising, 2013).

The multiplication of channels and brand touchpoints has led to an extensive fragmentation of the customer journey, which is more dynamic and less linear than ever before (Carroll & Guzmán, 2013). The number of omnichannel shoppers – who simultaneously use multiple touchpoints along the customer journey – is expected to increase to 74.7 million households in 2025 (Nielsen, 2020) and companies are increasingly focused on making omnichannel journeys more accessible. The marketing literature has thus defined the concept of omnichannel retailing as “the complete alignment of different channels resulting in an optimal brand-customer experience” (Huré et al., 2017, p. 315). Omnichannel journeys centered on multiple digital devices have been classified as “device switching experiences” and identified as one of the main developments of recent years, especially due to the Covid-19 pandemic intensifying their prevalence (Cocco & De-Juan-Vigaray, 2022; Verhoef, 2021).

In the field of Human-Computer Interaction (HCI), multiple device use is studied as “cross-device behavior” (Brudy et al., 2019). Research has found that users switch across devices multiple times a day in short and long intervals, almost unconsciously, with a low level of awareness (Dong et al., 2022; Oulasvirta & Sumari, 2007). Users switch across devices according to perceived task-fit, aiming to take advantage of device form factors and functionalities to achieve their objective (Chen & Koufaris, 2020; Santosa & Wigdor, 2013). Several patterns of cross-device behavior applicable to both purchasing and non-purchasing contexts have been identified and classified in accordance to the degree of integration among devices (Jokela et al., 2015).

Integration among channels is an important factor of Customer Experience (CX) in omnichannel and device switching contexts (Neslin, 2022), and experiences should be crafted across a combination of channels for optimal results (Verhoef et al., 2015). To study this phenomenon the extant literature has defined seamlessness (or fluency), as “the perception of a continuous and consistent journey across all channels with a single retailer” (Cocco & Demoulin, 2022, p. 462). Perceived seamlessness across channels has been identified as a key determinant of omnichannel service usage (Shen et al., 2018) and shown to be positively related to customer satisfaction, retention, and ultimately sales growth (Cao & Li, 2015; Wang & Jiang, 2022). The study of seamlessness across channels is thus relevant and valuable for firms aiming to provide a great omnichannel experience.

The measurement of CX and seamlessness in device switching contexts is a principal concern of researchers, because current instruments are insufficient or non-adapted to multiple device use (Lemon & Verhoef, 2016). Empirical research on this phenomenon has so far mostly relied on self-reported and behavioral measures (de Haan et al., 2018; Wu et al., 2019), which can be prone to retrospective biases (Ariely, 1998). Only a handful of studies have made use of implicit psychophysiological measurements in cross-device environments (Roy et al., 2020; Singh et al., 2020; Wu et al., 2020), and we reckon that the use of implicit measures could provide a richer and more continuous picture of CX (de Guinea et al., 2014; Ganglbauer et al., 2009). However, technical challenges stemming from several psychophysiological tools which rely on fixed user positions (e.g., eye-trackers and facial expression recognition) has so far prevented widespread use of such measures in multi-device interactions.

Current research into cross-device interactions has so far focused on its cognitive aspects, revealing that transitions between devices and displays have an impact on cognitive load (Van Cauwenberge et al., 2014), and identifying the manners in which users minimize this impact (Grudin, 2001; Rädle et al., 2015). Human cognition and emotion deeply intertwine (Plaas, & Kalyuga, 2019), and both antecedents and features of multi-device use have been shown to impact user satisfaction and wellbeing (Rigby et al., 218; Lascau et al., 2019). Some researchers have even proposed digital self-control tools for the mitigation of stress and negative experiences in cross-device environments (Kim et al., 2017; Monge Raffarello & De Russis, 2021). However, the unavailability of continuous measures for emotion in multiple device use has so far prevented the study of emotional responses to device transitions in omnichannel task contexts.

Research Questions

Studying emotional continuity in cross-device interactions requires answering the methodological question beforehand, so this research has two stated objectives. First, design a psychophysiological data collection protocol adapted to multi-device interactions, validate its capacity to produce a continuous measure, and render it replicable for other researchers. Second, check for the existence of an emotional response to device transitions through psychophysiological inferences.

This research introduces a novel psychophysiological data collection methodology for multiple device use, which allows the continuous implicit measurement of emotional valence and cognitive load across devices using facial expression recognition and pupillometry, respectively. This methodology relies on duplicate data collection instruments per device, and purpose-built software – Device Detection Algorithm (DDA) – which uses facial positioning data to predict which device the user interacts with. The DDA also compiles separate data sources in a unified timeline, switching data collection tools when users transition across devices. Thus, to reach the first research objective, this research aims at answering these three research questions:

RQ1 – To what extent can we automatically predict through head orientation data which device the users are interacting with in device switching omnichannel contexts?

RQ2 – To what extent can we continuously measure users' emotional valence with psychophysiological instruments in device switching omnichannel contexts?

RQ3 – To what extent can we continuously measure users' cognitive load with psychophysiological instruments in device switching omnichannel contexts?

To achieve the second research objective, an exploratory study involving multiple device use was conducted with the (previously validated) psychophysiological data collection methodology. The study goal was to check the existence of a significant emotional valence and/or arousal variation occurring in response to device transitions. The study was therefore aimed at answering the following question:

RQ4 – To what extent do transitions between devices in the context of device switching omnichannel tasks have an effect on users' emotions?

Contributions

From a methodological standpoint, this thesis contributes to the extant cross-device literature by introducing a validated measurement methodology for continuous recording of emotional valence and cognitive load. The methodology allows for richer empirical research of multi-device use by providing a more granular and complete picture of the experience (Ganglbauer et al., 2009), which includes the moments of transition between devices. Measuring the experience implicitly in those moments is crucial, because the behavior is itself almost unconscious, requiring a low level of awareness (Dong et al., 2022). Further, the proposed methodology facilitates the design and operationalization of more experiments on cross-device behavior by other researchers that replicate the procedure.

From a theoretical standpoint, this research contributes to the literature by offering early evidence of an emotional response to device transitions. During certain cross-device transitions, user emotional valence and arousal levels experience a significant increase or decrease. Coupled with the increase in cognitive load brought about by device transitions (Van Cauwenberge et al., 2014) and the many links between human cognition and emotion (Plaas & Kalyuga, 2019), the presence of an emotional dimension to seamless experiences enhances our current understanding of multi-device behavior. Further research into the factors affecting emotional responses during device transitions could lead to a more complete study of seamlessness and channel integration.

Thesis Structure

This thesis is structured in two separate scientific articles addressed to the HCI community, and a managerial article addressed to the wider User Experience (UX) Research community. The first article – presented in **Chapter 1** – covers the methodological aspect of this research and aims to answer the first three research questions. The second article – presented in **Chapter 2** – explores emotional continuity in multi-device interactions. The managerial article – presented in **Chapter 3** – emphasizes the importance of cross-device evaluations and provides recommendations for designing multi-device experiments. The following paragraphs provide a summary of each article.

The first chapter of this thesis provides background on current omnichannel and device switching data collection methods and measurements before proposing a novel psychophysiological methodology and presenting it in detail for other researchers to replicate. The proposed methodology is then tested for accuracy in a validation study involving 22 participants, and results suggest that DDA is a valid and reliable indicator of used device. Furthermore, the collection of pupil size data provides a continuous measure of cognitive load across all device transitions. However, emotional valence is measured continuously in only a majority of the tested device transitions, and improvements to the methodology are discussed. This chapter has been submitted in its present form to the journal *Multimedia Tools and Applications* and is currently under review.

The second chapter of this thesis provides literature background on the components and outcomes of seamlessness in multi-device environments and a review of the cognitive and emotional outcomes of cross-device behavior, before suggesting that device transitions might generate significant emotional responses. A laboratory experiment involving 21 participants is conducted, and results offer early evidence of a significant emotional response affecting certain device transitions. Insights on the possible factors affecting emotional responses in device transitions are discussed for future research to uncover. This chapter is being prepared for submission to the journal *AIS Transactions on Human-Computer Interaction*.

Lastly, the third chapter of this thesis consists in a managerial article addressed to UX Researchers. It explains the importance of conducting cross-device evaluations to test complete brand ecosystems, and introduces the benefits of the novel multi-device psychophysiological data collection methodology. Moreover, the managerial article provides guidance rooted in practical experience on how to conduct multi-device user evaluations, covering both technical and experimental design issues. This chapter is being prepared for submission to the *User Experience Professionals Association (UXPA) Magazine*.

Student Contributions and Responsibilities

All articles of this thesis were written in the context of user tests realized in the Tech3Lab of HEC Montréal (Canada). The following table provides an overview of the student's contributions across all phases of this thesis, as well as other parties' contributions. The percentage of student involvement and input is detailed for each step of the process.

Stage in the process	Contribution
Research Question	Identified gaps in literature to define the research problem and its implications. [**90%**] – Problematic initially conceived by the industrial partner. – Contextualization of the problematic in academic research by the student.
Literature Review	Conducted the relevant search and thorough scan of scientific articles to understand the current body of academic knowledge on cross-device omnichannel experiences. [**100%**]
Experimental Design	Application to the Research Ethics Board (REB) of HEC Montréal. [**90%**] – Preparation of documentation related to the submission by the student. – Application reviewed by thesis co-supervisors and Tech3Lab operations staff. Development of the experimental protocol and stimuli for both articles. [**100%**] – Conception of experiment procedure, questionnaires and instruments by the student. – Design of video stimuli for methodological article data collection by the student. – Election of stimuli for research article data collection by the student.
Data Collection	Recruitment of participants for both data collections. [**50%**] – Participants for methodological article data collection recruited by industrial partner. – Participants for research article data collection recruited by the student and Tech3Lab. Inception and installation of multi-device laboratory setup. [**80%**] – Design of multi-device setup and data collection instruments by the student. – Creation of smartphone eye-tracker support by Tech3Lab R&D staff (François Courtemanche). – Assembly of multi-device data collection instruments with help from Tech3Lab staff (Salima Tazi and Xavier Côté). – Development of DDA by Tech3Lab Statistics staff (Shang-Lin Chen). – Extensive testing and polishing of laboratory setup by the student. Pre-testing and data collection operations management. [**100%**] – Coordination and preparation of pre-test operations by the student. – Moderation and observation of all user tests by the student, for both data collections. – Technical support and organization of data collection staff by Tech3Lab management.
Statistical Analysis	Conducted the analysis of psychophysiological data in relation to both articles. [**80%**] – Extraction and treatment of the data to synchronize all instruments by the student. – Programming of statistical analyses on Stata 17 with help from Tech3Lab statistician. – Interpretation and presentation of results by the student.
Redaction	Wrote the articles and thesis in their current form. [**100%**] – Article co-authors and thesis co-supervisors provided comments and corrections.

Table 1. Student contributions and responsibilities in this thesis.

CHAPTER 1: Methodological Article

Continuous recording of psychophysiological measures in omnichannel human-computer interactions: A validation study[1]

Juan Fernández-Shaw, Pierre-Majorique Léger, François Courtemanche, Salima Tazi, Xavier Côté, Shang-Lin Chen, Constantinos Coursaris, Romain Pourchon, and Sylvain Sénécal

Abstract: Switching between multiple digital devices along the omnichannel purchasing journey has become a prevalent behavior. The measurement of customer experiences in device switching contexts currently relies on surveys and online retailer data, but the use of psychophysiological measures in this context could provide a deeper understanding of customer journeys. Hence, this paper proposes a multi-device psychophysiological data collection methodology that automatically detects which device the participant is using and relies on several eye-trackers and webcams to capture participants' psychophysiological measures in device switching omnichannel contexts. The methodology is tested for accuracy in a validation study involving 22 participants. Results show that it correctly predicts the device being used in 77.24% of the cases, and that the methodology allows for continuous collection of pupillometry – an indicator of cognitive workload – and emotional valence. The aim of the present paper is to render this methodology replicable, so a detailed account of the used laboratory setup, technological apparatus, and validation procedure is provided.

Keywords: Customer Experience · Omnichannel · Device Switching · Psychophysiology

1.1 Introduction

In the US, it is estimated that every user owns 5.3 connected devices on average (Pymnts, 2022) and that the number of omnichannel shoppers will increase to 74.7 million households by 2025 (Nielsen, 2020). The proliferation of mobile devices and omnichannel behavior has led to a fragmentation of the customer journey, and customers simultaneously use several channels and

[1] This article has been submitted to the following journal: *Multimedia Tools and Applications*.

touchpoints at their disposal to discover, evaluate, and ultimately purchase goods and services (Carroll & Guzmán, 2013). The use of multiple devices along the customer journey (i.e., device switching) has been identified as a crucial behavioral development in recent years (Verhoef, 2021). Measuring customer experience (CX) in device switching omnichannel contexts has thus become a principal concern among researchers and practitioners (Lemon & Verhoef, 2016).

Acquiring a better understanding of CX in device switching omnichannel contexts is an essential endeavor for firms, as this phenomenon has been proven to have a direct impact on customer behavior and performance (de Haan et al., 2018; Han et al., 2022) resulting in higher sales outcomes (Xu et al., 2017). Customer demand for more seamless experiences across devices is high (Optimizely, 2021) and the need for further integration between all touchpoints is a top priority for firms in several industries (Wong et al., 2021). The relevance of multi-device use was further intensified at the onset of the Covid-19 pandemic, as many retailers were forced to open new digital channels and build omnichannel strategies due to the closure of physical stores (Cocco & De-Juan-Vigaray, 2022).

The methods used so far in the measurement of CX in device switching omnichannel contexts mostly consist of customer surveys (i.e., self-reported and retrospective measures) and web analytics data from retailers (i.e., behavioral measures). Furthermore, automatic and unconscious actions taken by users – such as switching between devices – tend not to be accurately measured by traditional methods due to retrospective bias (Ariely, 1998). However, recent developments in the field of Human-Computer Interaction (HCI) have brought about psychophysiological measurement methods that allow for a continuous and more granular evaluation of CX (Ganglbauer et al., 2009). These implicit measurement instruments – which measure the automatic and unconscious physiological responses to stimuli – allow for the accurate inference of psychological constructs (e.g., emotion and cognitive load) that are important determinants and consequences of device use (de Guinea et al., 2014; Riedl & Léger, 2016; Tams et al., 2014).

Due to technical limitations these instruments have not been widely used in the study of CX in omnichannel contexts and, to our knowledge, they have only been applied once in multi-device environments (Wu et al., 2020). We posit that the widespread use of implicit psychophysiological instruments can provide a richer understanding of users' lived experiences in device switching omnichannel contexts.

This study thus proposes a multi-device psychophysiological data collection methodology that allows for the automatic detection of the device the user interacts with during device switching omnichannel experiences, and continuous measurement of emotional valence and cognitive load across several devices. This solution introduces the Device Detection Algorithm (DDA), which uses head orientation data to detect which device the user is facing and compiles separate datasets – from different sources – into a single continuous dataset. Ultimately, the methodology allows users to complete experimental tasks across three devices – PC, smartphone, and telephone – and uses duplicate webcams and eye-trackers to capture the users' facial expressions and pupil diameter continuously throughout the entire experiment. These measures are used to infer users' emotional valence, cognitive load, and evaluate the device switching omnichannel CX. The proposed methodology is minutely described in *Section 3* for other researchers to be able to replicate the laboratory procedure, and empirically tested for accuracy and reliability answering the following research questions:

RQ1 – To what extent can we automatically predict through head orientation data which device the users are interacting with in device switching omnichannel contexts?

RQ2 – To what extent can we continuously measure users' emotional valence with psychophysiological instruments in device switching omnichannel contexts?

RQ3 – To what extent can we continuously measure users' cognitive load with psychophysiological instruments in device switching omnichannel contexts?

A validation study involving 22 participants was conducted to assess the capacity of the proposed multi-device methodology to continuously measure emotion and cognitive load across devices with psychophysiological inferences. Based on the obtained results, this study contributes to the extant omnichannel device switching literature in three main ways: (1) adapting and validating the use of psychophysiological instruments for the measurement of CX in omnichannel device switching contexts, thus permitting richer empirical studies of this phenomenon; (2) allowing for a more granular scrutiny of channel integration and seamlessness with the analysis of automatic and non-conscious emotional valence and cognitive load during device switching transitions; and (3) facilitate the design and operationalization of the methodology for other researchers to conduct experiments where participants switch freely between devices.

1.2 Literature Review

1.2.1 Omnichannel Customer Experience

The mobile internet revolution has led to an extensive fragmentation of the customer journey which is now more dynamic, accessible, and less linear than ever before (Carroll & Guzmán, 2013; Grewal & Roggeveen, 2020). The simultaneous use of different customer channels within the same purchasing journey has been denominated "omnichannel retailing" by academics and practitioners, in contrast to "multichannel retailing" which operates under the assumption that customer channels will be used in sequential order along the journey, but not simultaneously (Lazaris & Vrechopoulos, 2014). In academic literature, the omnichannel approach in business-to-consumer contexts has been defined as "the complete alignment of the different channels and touchpoints, resulting in an optimal-brand customer experience" (Huré et al., 2017). This definition places a clear focus on integrated and aligned channels, but also evokes the seamless customer experience that derives from it.

Customer experience (CX) is a concept first created by marketing practitioners that has increasingly been adopted by the academic community to describe the "sum total of feelings, perceptions and attitudes created during successive stages of consumption process as a result of the interactive process" between a business and its customers (Jain et al., 2017). This concept has a holistic nature and aims to encompass every aspect of a company's offering: customer care, advertising, packaging, product and service features, ease of use, reliability, price, etc. (Meyer & Schwager, 2007). The importance of CX to business leaders and marketing practitioners cannot be understated, as it is believed to be central to a company's competitive strategy (N. Bolton et al., 2014) and customer satisfaction (Verhoef et al., 2009).

Measuring CX in omnichannel contexts has been a principal concern of researchers in recent years (Lemon & Verhoef, 2016), because existing measurement instruments of CX are insufficient. Their channel-specific nature makes for fragmented measures (Gahler et al., 2022), and "stretching" those instruments to be applied in new interaction contexts can yield imprecise items and invalid measures (MacKenzie, 2003). Therefore, several new measurement scales adapted to omnichannel journeys have been developed, both to evaluate omnichannel customer experience as a whole and related constructs. For the former, the perceived omnichannel customer experience (OCX) measurement scale acts as a reliable predictor of customer behavior (Rahman et al., 2022), and the omnichannel-capable CX scale can serve to identify pain points across channels and improve customer profiling (Gahler et al., 2022). For the latter, Frasquet-Deltoro et al. introduce a measurement scale centered on brand experience as a determinant of customer satisfaction and loyalty (Frasquet-Deltoro et al., 2021), and other authors have focused on the measurement of seamlessness and channel integration to evaluate customer experiences across channels (Cao & Li, 2015; Y. P. Chang & Li, 2022; Cocco & Demoulin, 2022).

Researchers in the field of omnichannel CX also developed a novel data collection methodology for capturing the complete omnichannel experience. Real-time experience tracking (RET) consists in asking participants to complete SMS microsurveys over a set period of time – generally a week to a month – every time they encounter one of the brands included in the study (Macdonald et al., 2012). This data collection method allows for the comparison of different touchpoints across the customer journey, and can be used to perform a competitive analysis of omnichannel strategies (Baxendale et al., 2015). Though advances in the measurement of omnichannel CX are being made, in the end a consensus among researchers on a unified, rigorous, and empirically-validated measurement instrument and methodology for omnichannel customer experiences is still lacking to this day (Rahman et al., 2022).

Empirical studies on omnichannel experiences have demonstrated the use of one channel can affect customer behavior across other channels along the journey, and that channel relevance is determined by purchasing phases (Chin et al., 2012; Verhoef et al., 2007; R. J.-H. Wang et al., 2015). However, integrating channels in all phases of the experience stimulates sales growth for firms (Cao & Li, 2015), and the seamless experience provided to customers has a positive effect on their satisfaction (Rodríguez-Torrico et al., 2020). Furthermore, perceived fluency across channels (i.e., the extent to which customers feel the experience as natural, unhindered, and continuous) is a key determinant of omnichannel service usage (Shen et al., 2018). CX is a significant attribute of consumer behavior in an omnichannel context, and the emotional and cognitive components of said experience directly influence purchase intention (Rahmawati, 2022).

Overall, the findings of these studies suggest that it is important for firms to craft experiences holistically across a combination of channels and carefully choose their omnichannel strategy, so that channel integration and perceived seamlessness maximize value for customers (Neslin, 2022; Verhoef et al., 2015).

1.2.2 Device Switching

Another phenomenon that derives from omnichannel customer experiences is that of device switching. In this context, device switching refers to the process of transitioning between different online digital devices – such as computers, smartphones and tablets – while performing a task (e.g., two-factor authentication, cross-device search) (de Haan et al., 2018). This move towards omnichannel experiences centered on multiple digital devices – rather than multiple channels of different nature – has been noticeably strong in several industries, such as travel and banking, and could propagate to others (Verhoef, 2021). Several of the foremost technology companies have also, in recent years, filed patents to facilitate device switching among their services (A. Chang et al., 2017; Horvitz et al., 2012; Vyrros et al., 2016). The study of customer experiences in device switching omnichannel contexts is therefore a primordial concern for academics aiming to understand customer behavior, and for firms aiming to reap the profits.

The findings of research into the antecedents of device switching reveal that perceived task-fit forms users' expected satisfaction and attitude towards multiple device use, and that this attitude triggers intention to use multiple devices in users (Chen & Koufaris, 2020). The study of cross-device search – which centers around performance in information search tasks when using multiple devices – has concluded that the most frequent motivation for switching devices is unsatisfied information needs (Wu et al., 2019). This conclusion is also reached by Han et al., who argue that device switching in a purchasing context occurs parallel to a two-stage decision-making process: in the early stages of the journey, customers prefer mobile devices for breadth in search; whereas in the later stages of the journey they prefer PC for depth in search (Han et al., 2022). The task is not the only determinant of device switching, however. Other personal and environmental factors, such as social influence and perceived self-efficacy also influence the reasons for this behavior (Van Nguyen et al., 2022, 2023).

Device switching behavior heavily influences the customers' purchasing performance. Cross-device browsing behavior between smartphones, tablets, and PCs has been found to enhance sales outcomes (Xu et al., 2017). Conversion rates are higher when customers switch to a fixed device from a mobile device, especially if the product perceived risk and price are higher (de Haan et al., 2018). Research has shown that similarity between online channels on different devices has a negative impact on the customers' perceived value and it is recommended to clarify the usefulness of each channel (Mencarelli et al., 2021). The general conclusion is clear: firms need to focus on multi-device customer journeys, and adapt their conversion efforts and measurements to a combination of devices rather than each in isolation (de Haan et al., 2018).

Empirical studies on device switching experiences use a wide range of quantitative methods to study customer behavior. The most common is the use of web analytics data logs from online retailers across various devices collected over the course of a month to a year (de Haan et al., 2018; Han et al., 2022; Kaatz et al., 2019; Xu et al., 2017). Using this technique, researchers were able to identify the specific moments along the purchasing journey in which the customers switched devices, and the effects it had on the subsequent purchase. Other researchers made use of crowdsourced surveys (Chen & Koufaris, 2020; Wu et al., 2019) and surveys sent among the customers of a firm (Van Nguyen et al., 2023) to study customer behavior, using CX scales that were adapted to take into account multiple devices. On the other hand, the Cross-Platform Usability Measurement (CPUM) model developed by Majrashi et al. proposes a new usability test procedure that allows for participants to complete tasks horizontally with multiple user interfaces using them sequentially (i.e., one after another) (Majrashi et al., 2020). This test procedure allows for the accurate collection of efficiency, effectiveness, and continuity measures to identify potential cross-device usability issues (Majrashi et al., 2021).

1.2.3 Psychophysiological Instruments and Measures

The use of psychophysiological instruments to measure CX has been a crucial development in the evaluation of HCI in recent years (Riedl & Léger, 2016). Originally developed for the field of neuroscience and neuropsychology, these instruments measure the implicit (i.e., automatic and unconscious) responses of subjects towards stimuli, in contrast to traditional explicit (i.e., intentional and conscious) measures (de Guinea et al., 2014). Because they offer data throughout the process of experience – without interrupting the flow of the interaction – they permit more granular analyses and generally allow for deeper and expanded insights (Ganglbauer et al., 2009). Psychophysiological instruments allow to mitigate the effect of retrospective bias – which affects self-reported measures of pain and length of an interaction by placing a heavy focus on peak moments of the experience (Ariely, 1998; Langer et al., 2005; Redelmeier & Kahneman, 1996) – and provide accurate insights about peak emotional and cognitive responses (Giroux-Huppé et al., 2019). Furthermore, different psychophysiological methods can be used simultaneously to measure an experience (multimodal approach) for more robust analyses of particular constructs (Vanneste et al., 2021; Z. Wang et al., 2020).

Few researchers have proposed measurement methods involving psychophysiological tools to empirically assess customer experiences in device switching omnichannel contexts. To our knowledge only Roy et al., Singh et al., and Wu et al. have made use of such implicit measurements when evaluating participants' experiences across channels, and only the latter focuses on device switching behavior (Roy et al., 2020; Singh et al., 2020; Wu et al., 2020). A combination of explicit and implicit data collection methods has the potential to render a deeper comprehension of the customer experience and reduce common method biases (de Guinea et al., 2014; Tams et al., 2014). We suggest that there is a need for more accurate data on customer experience in a device switching omnichannel context. Notably, the implicit collection of emotional valence and cognitive load data across devices using psychophysiological tools will provide more insights into the users' lived experiences, rather than their perceived experience (Cuvillier et al., 2021; Giroux-Huppé et al., 2019).

However, collecting these measures with psychophysiological instruments in device switching omnichannel contexts is technically complex, because data collection tools are usually centered on individual devices. Psychophysiological data collection of both emotional valence and cognitive load – with facial expression recognition and pupillometry – requires subjects to take on a specific position (i.e., facing a device). This prevents the continuous measurement of physiological signals if the subject turns to another device and imposes a psychophysiological analysis of CX per device, rather than of the entire experience across all devices.

1.2.4 Proposed Approach

In this study, we introduce a psychophysiological data collection methodology adapted to device switching omnichannel experiences. This methodology relies on duplicate psychophysiological data collection instruments that capture the same physiological signals separately on various devices, and a dedicated Device Detection Algorithm (DDA). The DDA serves two main purposes in the proposed methodology: (1) automatically detect which device the subject is facing throughout the experiment using head orientation data; and (2) compile all separate psychophysiological data sources according to subject transitions between devices. This allows for a continuous measurement of physiological signals across devices, given that data sources are swapped whenever subjects switch between devices.

To compile the separate psychophysiological data sources according to subject transitions, the DDA is incorporated into the data synchronization solution and acts in the post-processing phase. For each datapoint, the DDA checks which device is being used and retains psychophysiological measures associated with that device. For instance, when the subject transitions from the computer to the smartphone the DDA will swap cognitive load measures from the computer eye-tracker to that of the smartphone. Using this process, the DDA outputs a continuous measurement of the experience across all devices in the laboratory setup.

The objective of the proposed methodology is to permit the continuous measurement of psychophysiological data over multiple devices, and could be potentially used alongside the CPUM test procedure to design experiments spanning several devices (Majrashi et al., 2020). Specifically, the focus of this study is the continuous measurement of emotional valence and cognitive load in device switching omnichannel contexts. As such, the hypotheses that were tested in this study and allow us to validate the proposed methodology are the following:

H1: DDA allows to capture an accurate and continuous measure of which device is being used in device switching omnichannel experiences.

H2: DDA allows to capture a continuous measurement of emotional valence in device switching omnichannel experiences.

H3: DDA allows to capture a continuous measurement of cognitive load in device switching omnichannel experiences.

To answer the research questions and test these hypotheses, a validation study of the proposed methodology was undertaken. To test the DDA's capacity to measure emotional valence and cognitive load continuously in transitions across devices, the collected measures were checked against a stable emotional valence and cognitive load provided artificially by the participants of the study. A detailed account of the methodology and validation study procedure followed to test the hypotheses is presented in *Section 3*.

1.3 Methodology

1.3.1 Sample

A total of 22 participants recruited by a third-party specialized firm engaged in the validation study for this laboratory setup. The participants were aged between 26 and 64 years old (Mean = 43.18 and St. Dev. = 12.23). The gender distribution was equal. During recruitment potential participants were screened for visual acuity and to ensure they did not wear either glasses or contact lenses when interacting with computer or smartphone screens, as they could impact the quality of eye-tracking data. A technical malfunction in the synchronization hardware impacted the data collection from three participants. Thus, the analysis was conducted on a total of 19 participants. This study was approved by the Research Ethics Board of our institution (certificate #2022-4850).

1.3.2 Laboratory Setup

The multi-device psychophysiological data collection methodology was built with the stated purpose of allowing subjects to freely switch between three devices during the experiment, whilst only being able to use one device at a time. Each device included in the laboratory setup was placed side by side on the desk at a comfortable distance for the subject to use, and separated by approximately 30 cm of empty space from other devices (see **Figure 1**). Subjects had to rotate the position of their chair to face one device or another, in a radius of approximately 90º. Special care was given when arranging the setup so that all screens were placed at eye-level (approximately 20 cm above the desk) to avoid subjects having to bend upwards or downwards when switching devices.

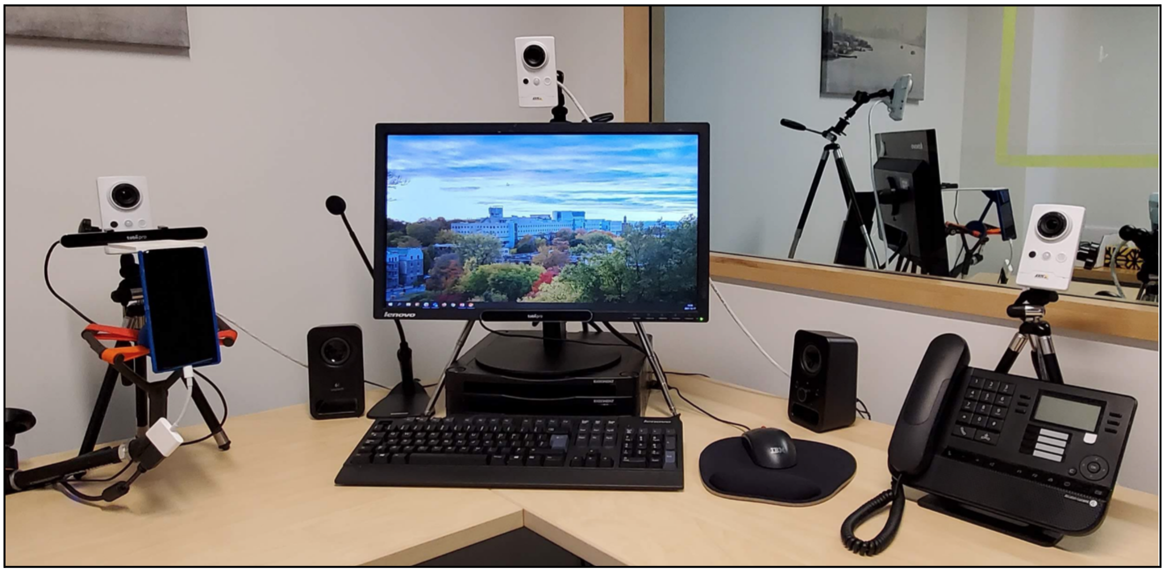

Figure 1. Picture of the proposed multi-device laboratory setup.

The setup was evaluated using the three following devices: computer, smartphone, and landline telephone. These three devices were chosen because they grant access to the most commonly used communication channels between customers and firms (The Northridge Group, 2022). Together these devices form a traditional home office setup, and allow to replicate common use cases (e.g., calling customer service while online shopping). Other devices, such as tablets and voice assistants, could however be integrated in the setup to replace any of these three.

The desktop computer was at the center of the desk. Participants did not have access to the central unit but could see the computer screen and interact with the keyboard and mouse. The desktop computer screen used for this laboratory setup was a T2224pD 21.5 inches LCD screen from Lenovo Group Ltd. (Hong-Kong, China). The smartphone was to the left of the desktop computer on the desk and mounted on a custom-built support. This support maintained both the smartphone and the eye-tracker vertically, so that both moved concomitantly to prevent data losses. The smartphone used in this laboratory setup was an iPhone 7 from Apple Inc. (Cupertino, USA). The landline telephone was to the right of the desktop computer on the desk. Participants were asked to keep their head straight and face forward during their interactions with this device. The landline telephone used for this laboratory setup was an 8029 Premium DeskPhone from Alcatel-Lucent S.A. (Boulogne-Billancourt, France).

1.3.3 Instruments and Measures

The proposed multi-device psychophysiological data collection methodology allows the study of emotional valence and cognitive load in device switching omnichannel contexts. To measure these constructs, we used inferences of implicit physiological signals. A summary of the psychophysiological data collection tools used in this setup can be found in **Table 2**, and a complete visual diagram is available in **Figure 2**.

Emotional valence was measured by FaceReader 8.1, a facial expression recognition tool developed by Noldus Information Technology BV (Wageningen, Netherlands). Automatic facial coding tools detect the micro-movements of facial muscles to measure emotional valence every 1/10th of a second on a scale from –1 to +1, for unpleasant and pleasant emotions respectively (Loijens & Krips, 2021). This software has proven to be as effective as humans in recognizing facial expressions and is considered a reliable indicator of basic emotions (Lewinski et al., 2014). This setup used three webcams to continuously capture the subjects' faces across interactions with all devices. All the webcams used in this laboratory setup were the same – C922 Pro HD from Logitech International S.A. (Lausanne, Switzerland) – and their video feeds were recorded in a synchronous manner by MediaRecorder 2.5 (Noldus Information Technology BV, Wageningen, Netherlands). These three videos were analyzed separately by FaceReader 8.1 in the post-processing phase to retrieve emotional valence.

Pupillometry (i.e., pupil size) was measured by Tobii Pro Lab, an eye-tracking software developed by Tobii AB (Stockholm, Sweden). Eye-tracking solutions use a pattern of near-infrared lights to register high-resolution images and optimize a 3D model of the subjects' eyes. They measure pupil diameter in millimeters for each eye approximately every 1/100th of a second (Tobii, 2022). Cognitive load has been shown to have a positive relationship with pupil size as long as distance and lighting conditions are controlled (Jerčić et al., 2020; Laeng et al., 2012). This setup used two screen-based Tobii Pro Nano (Tobii AB, Stockholm, Sweden) eye-trackers to continuously capture the subjects' gaze and pupil size across devices. The smartphone eye-tracker was placed above the screen on the custom-built support, whereas the computer eye-tracker was placed under the screen on the frame. Each eye-tracker was configured and calibrated independently and connected to a separate instance of Tobii Pro Lab.

Constructs	Measures	Collection Tools	Analysis Tools
Emotion	Emotional Valence	Webcam [x3] MediaRecorder 2.5	FaceReader 8.1
Cognitive Load	Pupillometry	Tobii Pro Nano [x2] Tobii Pro Lab [x2]	Tobii Pro Lab [x2]

Table 2. Psychophysiological data collection and analysis tools of the laboratory setup.

The quantity of psychophysiological tools used in this multi-device methodology made it impossible to launch data collection simultaneously across all tools. This resulted in recordings being asynchronous and using each their own timeframe. The recordings therefore had to be exported and harmonized in post-processing following the indirect synchronization method (Courtemanche et al., 2018).

Recorded psychophysiological data was synchronized using the SyncBox hardware solution (Noldus Information Technology BV, Wageningen, Netherlands). This device was connected via cable to all computers that recorded data and sent an TTL (Transistor-Transistor Logic) signal at a periodic rate during the entire experiment. TTL signals were received at the exact same time and interpreted by the collection tools as event markers. For each participant, these synchronization markers were stored in a The Observer XT 11 (Noldus Information Technology BV, Wageningen, Netherlands) file and used as guides to synchronize all psychophysiological data recorded in a unified timeframe (Zimmerman et al., 2008). The synchronization of the dataset was handled automatically in post-processing by the Cobalt Photobooth software (Léger et al., 2019) and processed by the DDA for the compilation of separate data sources.

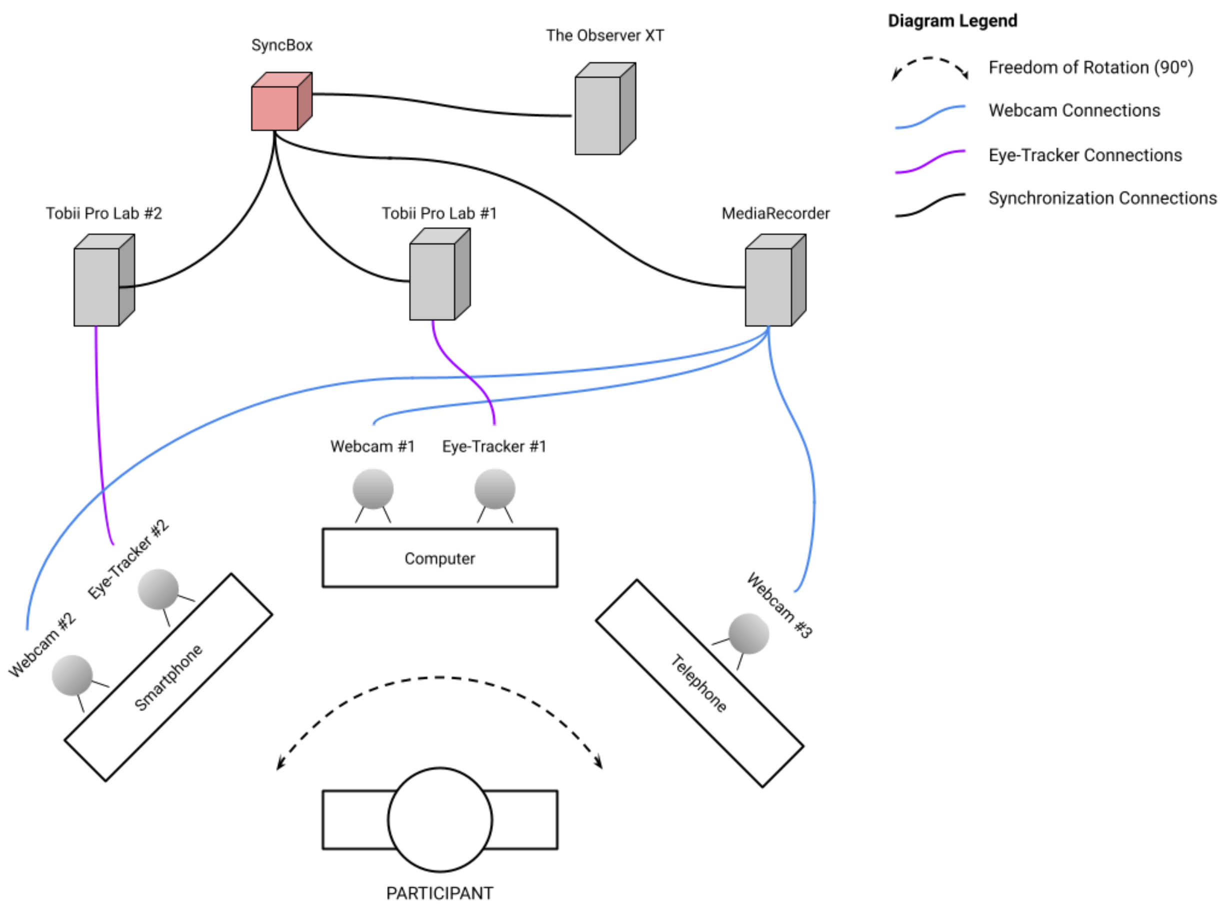

Figure 2. Visual representation of the complete laboratory setup and data collection tools.

1.3.4 Procedure

Upon arriving at the facilities, participants were asked to give their formal and written consent to the collection of their physiological data. The research team then moved forward with the calibration of both eye-trackers, starting first with the smartphone. Following the eye-tracking manufacturer guidelines, the calibration consisted in asking participants to look intently at various points of the screen as indicated by the research assistant. If unsatisfactory, the calibration was repeated before proceeding with the experiment. Participants then completed a total of three tasks.

The first task required participants to rotate their position in order to face a particular device at a specific time. Instructions were given by an automated voice which told participants what device to transition to and emitted a beeping sound when the transition had to be performed. Between each transition, participants were asked to remain still and face the device they had just turned to. All the participants transitioned between all three devices in the same order, to ensure that all six possible transitions were tested. This task also served as a warmup for participants, given that subsequent tasks would build up on this model and add further instructions.

The second task required participants to reproduce a facial expression and maintain it during the transitions that followed. The facial expression participants had to reproduce and artificially hold during transitions was presented to them on the computer screen as an emoji. Participants had to first reproduce the “happy” emotion, and halfway through the task they were asked to reproduce the “angry” emotion. These two opposite emotions (in terms of emotional valence) were chosen because they are easily emulated and identifiable. Like in the previous task instructions were communicated by an automated voice, transition moments were indicated via a beeping sound, and transitions were performed in the same order by all participants.

The third task required participants to look intently at a specific point of the screen when transitioning between devices. During the task, both the computer and smartphone screens were divided into four equally sized boxes marked with a letter. Asking participants to focus on a specific box before and after the transition ensured that their eyes were kept open and that cognitive load during the task was constant. Because the telephone did not have an active screen (and was not equipped with an eye-tracker), participants were only asked to transition between the computer and the smartphone in this task. As in previous tasks, instructions were communicated by an automated voice, transition moments were indicated via a beeping sound, and transitions were performed in the same order by all participants. **Figure 3** provides an overview of the transitions required of each task.

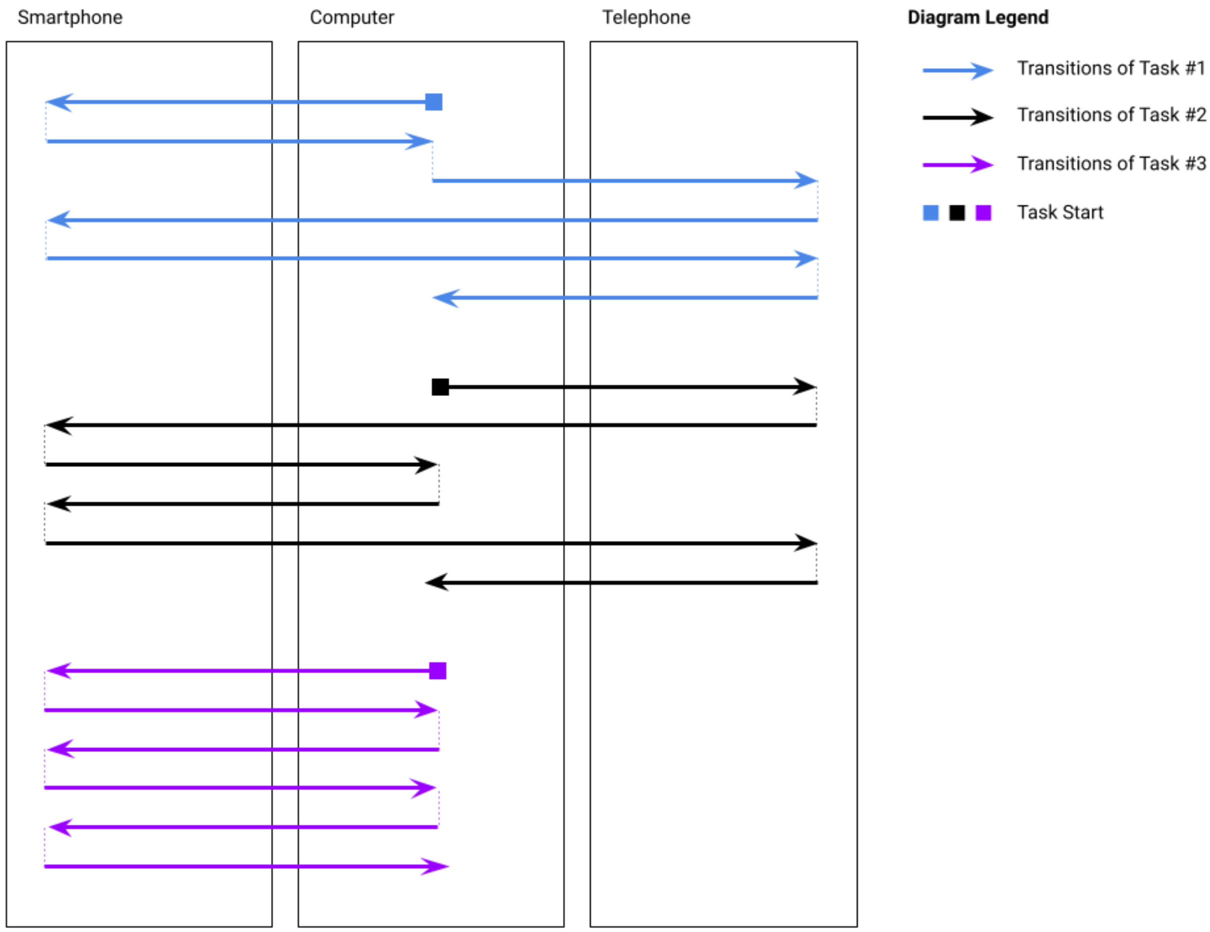

Figure 3. Transitions performed when completing the three experimental tasks.

1.3.5 Data Extraction and Analysis

To detect which device the subjects are facing, the DDA uses head orientation data provided by FaceReader 8.1 (Noldus Information Technology BV, Wageningen, Netherlands). This software produces for each datapoint (1/10th of a second) the difference in degrees from looking straight forward at the webcam in three axes: yaw (X), pitch (Y) and roll (Z). The further these metrics are from 0, the more deviated the subjects' faces are with respect to the center of the webcam lens (Noldus, 2018). The DDA uses these metrics to calculate, for each datapoint and each webcam, the overall deviation of subjects' faces. This measure is called DFC (Deviation From Center) and is computed using the following formula:

$$DFC = \sqrt{X^2 + Y^2 + Z^2}$$

The higher the DFC value, the more deviated the subjects' faces were with respect to the center of the webcam lens, all axes considered. For each datapoint the DDA retains the webcam with the lowest DFC value as the one the subject was facing, and thus predicts the device being used at that moment. Transitions are therefore defined as the moments in which DDA detects a change in the device faced by the subject.

To compile the separate psychophysiological data sources according to subject transitions, the DDA is incorporated into the data synchronization solution and acts in the post-processing phase. For each datapoint, the DDA checks which device is being used and retains psychophysiological measures associated with that device. For instance, when the subject transitions from the computer to the smartphone the DDA will swap cognitive load measures from the computer eye-tracker to that of the smartphone. Using this process, the DDA outputs a continuous measurement of the experience across all devices in the laboratory setup.

To measure the accuracy of the DDA, all predictions about the device participants were interacting with were contrasted against researchers' observations. All recordings were examined in post-processing by the researchers and transitions between devices were timestamped, thus yielding a precise timeline of when participants had used each device. The analysis was performed on repeated measures collected on 19 participants, with each datapoint representing 1/10th of a second (n = 93074). Accuracy was calculated using the following formula, for each device and overall:

$$Accuracy = \frac{correct\ predictions}{total\ predictions}$$

To test the capacity of the proposed multi-device methodology to continuously detect emotional valence and cognitive load with psychophysiological tools when participants transition between devices, the difference in collected psychophysiological signals before and after each transition was tested for equality to zero. Given that participants were required to keep their emotion and cognitive load artificially constant during the transitions (in the second and third task respectively), psychophysiological data collection tools should detect the same emotional valence and pupil size values before and after the transitions. To execute this analysis, emotional valence and pupil size data were extracted three seconds before and three seconds after each transition and were then averaged. The difference between those averages was subject to a non-parametric bilateral test (Wilcoxon Signed-Rank Test) to inspect whether they were significantly different from zero.

Participants whose physiological data was missing in one or more transitions due to technical issues were discarded from the analysis. The analysis of continuity in the measurement of emotional valence was performed on repeated measures collected on 11 participants, who each completed 6 transitions while keeping their emotion artificially constant ($n = 66$). The analysis of continuity in the measurement of cognitive load was performed on repeated measures collected on 10 participants, who each completed 6 transitions while keeping their cognitive load artificially constant ($n = 60$).

1.4 Results

1.4.1 Accuracy of the Device Detection Algorithm

The results of the analysis conducted to check the accuracy of the DDA indicated that 77.24% of the total number of predictions it made were correct, even though accuracy differed between devices (see **Table 3**). The maximum accuracy rate was on the computer (95.75%) and the minimum was on the telephone (75.07%), revealing a 20.68 percentage point difference between the two. On the smartphone 85.56% of the predictions were correct.

Device	Correct Predictions	Total Predictions	Accuracy Rate
Computer	55100	57545	95.75%
Smartphone	12951	15113	85.69%
Telephone	3839	5114	75.07%
Overall	**71890**	**93074**	**77.24%**

Table 3. Accuracy rate of the DDA, per device and overall.

Because this laboratory setup counts with three distinct devices, the behavior of a DDA yielding random predictions would be expected to have an overall 33.33% accuracy rate. The present algorithm yielded an overall accuracy rate of 77.24% by analyzing head orientation data, which is superior to the expected random result. Results thus lend support to H1, and we can conclude that this algorithm is a good predictor of the device the participant is interacting with. However, there are still 22.76% incorrect predictions which can surely be reduced with further improvements to the algorithm and laboratory setup.

1.4.2 Continuous Measurement of Emotional Valence

The results of the analysis conducted to test continuous measurement of emotional valence in transitions between devices indicated that, at a 5% significance level, the difference in detected emotional valence when device switching is equal to zero in four out of six of the tested transitions (see **Table 4**).

Transition	**Average** valence before	**Average** valence after	**Difference** between averages	**p-value**[1]
Transition 1 Computer to Telephone	0.3069	0.3961	-0.0892	0.4769
Transition 2 Telephone to Smartphone	0.2668	0.6996	-0.4329	**0.0128 ****
Transition 3 Smartphone to Computer	0.6687	0.6795	-0.0108	0.7897
Transition 4 Computer to Smartphone	0.1192	-0.0896	0.2088	**0.0208 ****
Transition 5 Smartphone to Telephone	-0.0913	-0.0594	-0.0319	0.9292
Transition 6 Telephone to Computer	-0.0488	-0.0820	0.0331	0.7221

Table 4. Results of the analysis of emotional valence detected in transitions.
[1] Level of Bilateral Test: $^{**}p \leq 0.05$; $^{***}p \leq 0.01$.

These results allow us to conclude that the multi-device psychophysiological data collection setup allows for the continuous measurement of emotional valence in most – but not all – device switching transitions. The previously defined H2 is thus partially supported.

H2 is not supported for Transition 2 and Transition 4, meaning that the difference in detected valence before and after these transitions is significantly different from zero. The results seem to suggest that the smartphone emotional valence data collection setup (common destination device of these two transitions) could be at fault for this disparity. For the latter however, it could be that the change from “happy” to “angry” emotion in-between Transitions 3 and 4 caused detected valence to vary unusually before the transition, thus impacting the average difference.

1.4.3 Continuous Measurement of Cognitive Load

The results of the analysis conducted to check the continuous measurement of cognitive load in transitions between devices indicated that, at a 5% significance level, the difference in detected pupil size when device switching is equal to zero in all tested transitions (see **Table 5**).

Transition	**Average** pupil size before	**Average** pupil size after	**Difference** between averages	**p-value**[1]
Transition 1 Computer to Smartphone	3.8513	3.6286	0.2226	0.2026
Transition 2 Smartphone to Computer	3.8560	4.0761	-0.2200	0.3863
Transition 3 Computer to Smartphone	3.5274	3.6518	-0.1245	0.7989
Transition 4 Smartphone to Computer	3.5719	3.3317	0.2402	0.0745
Transition 5 Computer to Smartphone	3.6947	3.6720	0.0228	0.9594
Transition 6 Smartphone to Computer	3.5128	3.3635	0.1493	0.0593

Table 5. Results of the analysis of pupil size detected in transitions.
[1] Level of Bilateral Test: $**p \leq 0.05$; $***p \leq 0.01$.

These results allow us to conclude that the multi-device psychophysiological data collection setup allows for the continuous measurement of cognitive load in all transitions. The previously defined H3 is thus supported.

1.5 Discussion

In the proposed multi-device psychophysiological data collection methodology, DDA is a reliable indicator of the device the participant is using by analyzing head orientation data, though there are differences in accuracy among devices (H1). DDA partially supports the continuous measurement of emotional valence with facial expression analysis software, as transitions towards the smartphone lead to significant variation in collected valence (H2). However, the continuous measurement of cognitive load in device switching transitions with duplicate eye-trackers on several devices is supported (H3).

The difference between the DDA accuracy results for each device can be explained by two factors: the experimental procedure and the positioning of the webcams in the laboratory setup. Because all the instructions to the participants were given on the computer, they spent a larger amount of time facing this device, which explains the disparity in total number of predictions between devices. On the other hand, we argue that the positioning of the telephone webcam – which was lower than the other two – impacted the ability of FaceReader 8.1 to perform its analysis and provide head orientation data, which explains why the accuracy results for this device are the lowest. We surmise that placing the telephone webcam at eye-level would improve the accuracy rate, but further research is needed to prove this alternative.

From a methodological standpoint, the proposed multi-device method sets the foundation for a more complete study of device switching omnichannel CX thanks to the use of psychophysiological instruments. Researchers investigating CX in device switching contexts have developed methods and tools that make use of retrospective psychometric scales (Gahler et al., 2022; Rahman et al., 2022) and behavioral observations (de Haan et al., 2018; Han et al., 2022; Xu et al., 2017). The addition of non-intrusive psychophysiological inferences of emotional valence and cognitive load to new and currently established cross-device usability test procedures, such as CPUM (Majrashi et al., 2020), will permit richer empirical research on this phenomenon.

In particular, the continuous measurement of emotional valence and cognitive load across devices offered by the proposed methodology allows for more granular analysis of channel integration and seamlessness. These two attributes are of primordial importance in omnichannel literature, and proven to directly impact sales growth, customer satisfaction, and service usage (Cao & Li, 2015; Rodríguez-Torrico et al., 2020; Shen et al., 2018). The relationships between these attributes, emotional valence, cognitive load, and their effect on CX can thus now be studied and empirically tested with psychophysiological inferences. For instance, we reckon that the degree of seamlessness in transitions across devices could have an impact on users' emotional and cognitive state, and experiments into this phenomenon can presently be pursued.

On the other hand, the use of the DDA to automatically detect transitions across devices facilitates more fluid experiments. Rather than directing participants to a specific device in a set order (Majrashi et al., 2020; Wu et al., 2020), giving participants the freedom to choose and switch devices in an experiment could deepen the understanding of device choice and its antecedents. The DDA has the added impact of reducing data post-processing and synchronization efforts by automatically yielding accurate device use start and end timestamps, and automatically compiling psychophysiological signals originated from different sources.

This study has implications for practitioners as well, particularly user experience and marketing teams looking to better understand device switching omnichannel customer behavior to enhance loyalty and boost rates of conversion. The proposed multi-device methodology is relatively inexpensive to build and easy to use, allowing firms to evaluate with minutiae their omnichannel offering (or that of a competitor) and gather accurate data about the users' lived experience. Testing interfaces, channels, and other features as part of an ecosystem composed of several devices rather than in isolation could provide more insights about customer behavior and experience in real device switching omnichannel contexts.

Nonetheless there are several limitations to the proposed methodology, and improvements to the multi-device psychophysiological data collection setup are needed. First, data was collected in a laboratory setting with participants in a seated position, thus impacting the generalizability of the findings to authentic contexts. Second, the continuous measurement of emotional valence could not be supported with this study, and we reckon that a further method validation study changing the placement of the smartphone webcam (or using the integrated front camera) might ratify all the initial objectives of this methodology. The DDA could also be further enhanced by the integration of gaze behavior data which, in conjunction with head orientation data, would surely provide more accurate precisions. The accuracy of a combined analysis of what the subject is facing (head orientation) and what the subject is looking at (gaze behavior) to automatically determine device use in device switching omnichannel contexts is an important question for future research to answer.

1.7 Conclusion

In this study, we propose a multi-device psychophysiological data collection methodology and test its capacity to continuously measure emotion and cognitive load in device switching omnichannel contexts through psychophysiological inferences. This setup relies on duplicate psychophysiological data collection instruments installed on each device – PC, smartphone, and telephone – to capture the complete device switching omnichannel experience. Through a validation study, we find that head orientation data is an automatic and reliable predictor of which device is being used, and it is shown that the methodology allows for the continuous measurement of cognitive load when transitioning between devices. The measurement of emotional valence, on the other hand, is shown to be only partially continuous, as transitions towards the smartphone from both other devices lead to significant variations in collected data. Future research should aim to replicate the results with authentic device switching transitions (i.e., the participant choosing when and what device to switch to) to expand the scope of the proposed methodology. Moving forward, we reckon that the proposed methodology could broaden to simulate non-office environments (i.e., living rooms, public transit, schools, etc) and thus account for more devices commonly used in those environments (i.e., gaming consoles, wearables, voice assistants, etc). This would allow for a more far-reaching study of device switching omnichannel experiences – which is now almost exclusively focused on retail and work interactions – to focus on entertainment, educational, and other activities.

References

Ariely, D. (1998). Combining experiences over time: The effects of duration, intensity changes and on-line measurements on retrospective pain evaluations. *J. Behav. Decis. Mak.*, 11, 19–45. https://doi.org/10.1002/(SICI)1099-0771(199803)11:1<19::AID-BDM277>3.0.CO;2-B

Baxendale, S., Macdonald, E. K., & Wilson, H. N. (2015). The Impact of Different Touchpoints on Brand Consideration. *Journal of Retailing*, 91(2), 235–253. https://doi.org/10.1016/j.jretai.2014.12.008

Cao, L., & Li, L. (2015). The Impact of Cross-Channel Integration on Retailers' Sales Growth. *Journal of Retailing*, 91(2), 198–216. https://doi.org/10.1016/j.jretai.2014.12.005

Carroll, D., & Guzmán, I. (2013). The New Omni-Channel Approach to Serving Customers. Accenture. https://www.scribd.com/document/354676791/Accenture-New-Omni-Channel-Approach-Serving-Customers

Chang, A., Ming Li, J., & Singh, T. (2017). System and method for seamlessly transitioning device-based interaction (Patent No. AU2014357376B2). https://patents.google.com/patent/AU2014357376B2/en

Chang, Y. P., & Li, J. (2022). Seamless experience in the context of omnichannel shopping: Scale development and empirical validation. *Journal of Retailing and Consumer Services*, 64, 102800. https://doi.org/10.1016/j.jretconser.2021.102800

Chen, C.-W., & Koufaris, M. (2020). Multi-Device Use: Understanding the Motivations behind Switching between Multiple Devices during a Task. *International Journal of Human–Computer Interaction*, 36(12), 1178–1193. https://doi.org/10.1080/10447318.2020.1726106

Chin, E., Felt, A. P., Sekar, V., & Wagner, D. (2012). Measuring user confidence in smartphone security and privacy. *Proceedings of the Eighth Symposium on Usable Privacy and Security*, 1–16. https://doi.org/10.1145/2335356.2335358

Cocco, H., & De-Juan-Vigaray, M. D. (2022). A typology of omnichannel retailer activities during the COVID-19 pandemic. *International Journal of Retail & Distribution Management*, 50(8/9), 1062–1094. https://doi.org/10.1108/IJRDM-10-2021-0506

Cocco, H., & Demoulin, N. T. M. (2022). Designing a seamless shopping journey through omnichannel retailer integration. *Journal of Business Research*, 150, 461–475. https://doi.org/10.1016/j.jbusres.2022.06.031

Courtemanche, F., Léger, P.-M., Dufresne, A., Fredette, M., Labonté-LeMoyne, É., & Sénécal, S. (2018). Physiological heatmaps: A tool for visualizing users' emotional reactions. *Multimedia Tools and Applications*, 77(9), 11547–11574. https://doi.org/10.1007/s11042-017-5091-1

Cuvillier, M., Léger, P.-M., & Sénécal, S. (2021). Quantity over quality: Do single-item scales reflect what users truly experienced? *Computers in Human Behavior Reports*, 4, 100097. https://doi.org/10.1016/j.chbr.2021.100097

de Guinea, A. O., Titah, R., & Léger, P.-M. (2014). Explicit and Implicit Antecedents of Users' Behavioral Beliefs in Information Systems: A Neuropsychological Investigation. *J. Manag. Inf. Syst.*, 30(4), 179–210. https://doi.org/10.2753/MIS0742-1222300407

de Guinea, A. O., Titah, R., Leger, P.-M., & Micheneau, T. (2012). Neurophysiological Correlates of Information Systems Commonly Used Self-Reported Measures: A Multitrait Multimethod Study. *2012 45th Hawaii International Conference on System Sciences*, 562–571. https://doi.org/10.1109/HICSS.2012.448

de Haan, E., Kannan, P. K., Verhoef, P. C., & Wiesel, T. (2018). Device Switching in Online Purchasing: Examining the Strategic Contingencies. *Journal of Marketing*, 82(5), 1–19. https://doi.org/10.1509/jm.17.0113

Frasquet-Deltoro, M., Molla-Descals, A., & Miquel-Romero, M.-J. (2021). Omnichannel retailer brand experience: Conceptualisation and proposal of a comprehensive scale. *Journal of Brand Management*, 28(4), 388–401. https://doi.org/10.1057/s41262-021-00233-x

Gahler, M., Klein, J. F., & Paul, M. (2022). Customer Experience: Conceptualization, Measurement, and Application in Omnichannel Environments. *Journal of Service Research*, 26(2), 155–299. https://doi.org/10.1177/10946705221126590

Ganglbauer, E., Schrammel, J., Deutsch, S., & Tscheligi, M. (2009). Applying Psychophysiological Methods for Measuring User Experience: Possibilities, Challenges and Feasibility. *Workshop on User Experience Evaluation Methods in Product Development*, 4.

Giroux-Huppé, C., Sénécal, S., Fredette, M., Chen, S. L., Demolin, B., & Léger, P.-M. (2019). Identifying Psychophysiological Pain Points in the Online User Journey: The Case of Online Grocery. In A. Marcus & W. Wang (Eds.), *Design, User Experience, and Usability. Practice and Case Studies* (pp. 459–473). Springer International Publishing. https://doi.org/10.1007/978-3-030-23535-2_34

Grewal, D., & Roggeveen, A. L. (2020). Understanding Retail Experiences and Customer Journey Management. *Journal of Retailing*, 96(1), 3–8. https://doi.org/10.1016/j.jretai.2020.02.002

Han, S., Han, J. K., Im, I., Jung, S. I., & Lee, J. W. (2022). Mapping consumer's cross-device usage for online search: Mobile- vs. PC-based search in the purchase decision process. *Journal of Business Research*, 142, 387–399. https://doi.org/10.1016/j.jbusres.2021.12.051

Horvitz, E., Iqbal, S. T., & Karlson, A. K. (2012). Methods for supporting users with task continuity and completion across devices and time (United States Patent No. US20120011511A1). https://patents.google.com/patent/US20120011511A1/en

Huré, E., Picot-Coupey, K., & Ackermann, C.-L. (2017). Understanding omni-channel shopping value: A mixed-method study. *Journal of Retailing and Consumer Services*, 39, 314–330. https://doi.org/10.1016/j.jretconser.2017.08.011

Jain, R., Aagja, J., & Bagdare, S. (2017). Customer experience – a review and research agenda. *Journal of Service Theory and Practice*, 27(3), 642–662. https://doi.org/10.1108/JSTP-03-2015-0064

Jerčić, P., Sennersten, C., & Lindley, C. (2020). Modeling cognitive load and physiological arousal through pupil diameter and heart rate. *Multimedia Tools and Applications*, 79(5), 3145–3159. https://doi.org/10.1007/s11042-018-6518-z

Kaatz, C., Brock, C., & Figura, L. (2019). Are you still online or are you already mobile? – Predicting the path to successful conversions across different devices. *Journal of Retailing and Consumer Services*, 50, 10–21. https://doi.org/10.1016/j.jretconser.2019.04.005

Laeng, B., Sirois, S., & Gredebäck, G. (2012). Pupillometry: A Window to the Preconscious? *Perspectives on Psychological Science*, 7(1), 18–27. https://doi.org/10.1177/1745691611427305

Langer, T., Sarin, R., & Weber, M. (2005). The retrospective evaluation of payment sequences: Duration neglect and peak-and-end effects. *J. Econ. Behav. Organ.*, 58(1), 157–175. https://doi.org/10.1016/j.jebo.2004.01.001

Lazaris, C., & Vrechopoulos, A. (2014). From Multichannel to "Omnichannel" Retailing: Review of the Literature and Calls for Research. *2nd International Conference on Contemporary Marketing Issues*,(ICCMI), 6, 1–6. https://doi.org/10.13140/2.1.1802.4967

Léger, P.-M., Courtemanche, F., Fredette, M., & Sénécal, S. (2019). A Cloud-Based Lab Management and Analytics Software for Triangulated Human-Centered Research. In F. D.

Davis, R. Riedl, J. vom Brocke, P.-M. Léger, & A. B. Randolph (Eds.), *Information Systems and Neuroscience* (pp. 93–99). Springer International Publishing. https://doi.org/10.1007/978-3-030-01087-4_11

Lemon, K. N., & Verhoef, P. C. (2016). Understanding Customer Experience Throughout the Customer Journey. *Journal of Marketing*, 80(6), 69–96. https://doi.org/10.1509/jm.15.0420

Lewinski, P., den Uyl, T. M., & Butler, C. (2014). Automated facial coding: Validation of basic emotions and FACS AUs in FaceReader. *Journal of Neuroscience, Psychology, and Economics*, 7, 227–236. https://doi.org/10.1037/npe0000028

Loijens, L., & Krips, O. (2021). FaceReader Methodology Note. Noldus Information Technology BV. https://info.noldus.com/hubfs/resources/noldus-white-paper-facereader-methodology.pdf

Macdonald, E. K., Wilson, H. N., & Konuş, U. (2012, September 1). Better Customer Insight—In Real Time. *Harvard Business Review.* https://hbr.org/2012/09/better-customer-insight-in-real-time

MacKenzie, S. B. (2003). The dangers of poor construct conceptualization. *Journal of the Academy of Marketing Science*, 31(3), 323–326. https://doi.org/10.1177/0092070303031003011

Majrashi, K., Hamilton, M., Uitdenbogerd, A., & Al-Megren, S. (2021, May 9). Cross-Device User Interactive Behavioural Patterns. *CHI 2021 Workshop on User Experience for Multi-Device Ecosystems: Challenges and Opportunities.* https://doi.org/10.1145/1122445.1122456

Majrashi, K., Hamilton, M., Uitdenbogerd, A. L., & Al-Megren, S. (2020). Cross-Platform Usability Model Evaluation. *Multimodal Technologies and Interaction*, 4(4), Article 4. https://doi.org/10.3390/mti4040080

Mencarelli, R., Rivière, A., & Lombart, C. (2021). Do myriad e-channels always create value for customers? A dynamic analysis of the perceived value of a digital information product during the usage phase. *Journal of Retailing and Consumer Services*, 63, 102674. https://doi.org/10.1016/j.jretconser.2021.102674

Meyer, C., & Schwager, A. (2007, February). Understanding customer experience. *Harvard Business Review*, 85(2), 116–126, 157.

N. Bolton, R., Gustafsson, A., McColl-Kennedy, J., J. Sirianni, N., & K. Tse, D. (2014). Small details that make big differences: A radical approach to consumption experience as a firm's differentiating strategy. *Journal of Service Management*, 25(2), 253–274. https://doi.org/10.1108/JOSM-01-2014-0034

Neslin, S. A. (2022). The omnichannel continuum: Integrating online and offline channels along the customer journey. *Journal of Retailing*, 98(1), 111–132. https://doi.org/10.1016/j.jretai.2022.02.003

Nielsen. (2020, February 24). It's Time to Think Omnichannel Shopper, Not Just Omnichannel. NIQ. https://nielseniq.com/global/en/insights/analysis/2020/its-time-to-think-omnichannel-shopper-not-just-omnichannel/

Noldus. (2018). FaceReader Reference Manual. Noldus Information Technology.

Optimizely. (2021, November 18). Digital Experience Elements that Are Most Important to Internet Users Worldwide, Aug 2021 [Graph]. *Insider Intelligence.* https://www.emarketer.com/chart/252645/digital-experience-elements-that-most-important-internet-users-worldwide-aug-2021-of-respondents

Pymnts. (2022, July). Average Number of Connected Devices Owned in Selected Markets as of January 2022 [Graph]. *Statista.* https://www.statista.com/statistics/1345616/connected-devices-owned/

Rahman, S. M., Carlson, J., Gudergan, S. P., Wetzels, M., & Grewal, D. (2022). Perceived Omnichannel Customer Experience (OCX): Concept, measurement, and impact. *Journal of Retailing*, 98(4), 611–632. https://doi.org/10.1016/j.jretai.2022.03.003

Rahmawati, R. A. (2022). New Journey Through Young Customer Experience in Omnichannel Context: The Role of Personalization. *Journal of Theoretical and Applied Management,* 15(2), 301–311. https://doi.org/10.20473/jmtt.v15i2.36236

Redelmeier, D. A., & Kahneman, D. (1996). Patients' memories of painful medical treatments: Real-time and retrospective evaluations of two minimally invasive procedures. *Pain*, 66(1), 3–8. https://doi.org/10.1016/0304-3959(96)02994-6

Riedl, R., & Léger, P.-M. (2016). Fundamentals of NeuroIS: Information Systems and the Brain. *Springer*. https://doi.org/10.1007/978-3-662-45091-8

Rodríguez-Torrico, P., Trabold Apadula, L., San-Martín, S., & San José Cabezudo, R. (2020). Have an omnichannel seamless interaction experience! Dimensions and effect on consumer satisfaction. *Journal of Marketing Management*, 36(17–18), 1731–1761. https://doi.org/10.1080/0267257X.2020.1801798

Roy, A., Sénécal, S., Léger, P.-M., Demolin, B., Bigras, É., & Gagne, J. (2020). Measuring Users' Psychophysiological Experience in Non-linear Omnichannel Environment. In C. Stephanidis, A. Marcus, E. Rosenzweig, P.-L. P. Rau, A. Moallem, & M. Rauterberg (Eds.), *HCI International 2020—Late Breaking Papers: User Experience Design and Case Studies* (pp. 762–779). Springer International Publishing. https://doi.org/10.1007/978-3-030-60114-0_50

Shen, X.-L., Li, Y.-J., Sun, Y., & Wang, N. (2018). Channel integration quality, perceived fluency and omnichannel service usage: The moderating roles of internal and external usage experience. *Decision Support Systems*, 109, 61–73. https://doi.org/10.1016/j.dss.2018.01.006

Singh, J., Goyal, G., & Gill, R. (2020). Use of neurometrics to choose optimal advertisement method for omnichannel business. *Enterprise Information Systems*, 14(2), 243–265. https://doi.org/10.1080/17517575.2019.1640392

Tams, S., Hill, K., Guinea, A. O. de, Thatcher, J., & Grover, V. (2014). NeuroIS—Alternative or Complement to Existing Methods? Illustrating the Holistic Effects of Neuroscience and Self-Reported Data in the Context of Technostress Research. *Journal of the Association for Information Systems*, 15(10). https://doi.org/10.17705/1jais.00374

The Northridge Group. (2022, January 21). Communication Channels Easy to Use in Customer Service in the U.S. from 2019 to 2020 [Graph]. *Statista*. https://www.statista.com/statistics/816704/communication-channels-easy-to-use-with-customer-service-united-states/

Tobii. (2022, May 9). Measuring Pupil Size. Tobii AB. https://connect.tobii.com/s/article/measuring-pupil-size

Van Nguyen, A. T., Halibas, A. S., McClelland, R., & Thuan, N. H. (2023). Configurational analysis of conditions influencing customers' channel switching intention in omnichannel retailing: A fuzzy-set analysis. *Quality & Quantity.* https://doi.org/10.1007/s11135-023-01633-8

Van Nguyen, A. T., McClelland, R., & Thuan, N. H. (2022). Exploring customer experience during channel switching in omnichannel retailing context: A qualitative assessment. *Journal of Retailing and Consumer Services*, 64, 102803. https://doi.org/10.1016/j.jretconser.2021.102803

Vanneste, P., Raes, A., Morton, J., Bombeke, K., Van Acker, B. B., Larmuseau, C., Depaepe, F., & Van den Noortgate, W. (2021). Towards measuring cognitive load through multimodal physiological data. *Cogn. Technol. Work*, 23(3), 567–585. https://doi.org/10.1007/s10111-020-00641-0

Verhoef, P. C. (2021). Omni-channel retailing: Some reflections. *Journal of Strategic Marketing*, 29(7), 608–616. https://doi.org/10.1080/0965254X.2021.1892163

Verhoef, P. C., Kannan, P. K., & Inman, J. J. (2015). From Multi-Channel Retailing to Omni-Channel Retailing. *Journal of Retailing*, 91(2), 174–181. https://doi.org/10.1016/j.jretai.2015.02.005

Verhoef, P. C., Lemon, K. N., Parasuraman, A., Roggeveen, A., Tsiros, M., & Schlesinger, L. A. (2009). Customer Experience Creation: Determinants, Dynamics and Management Strategies. *Journal of Retailing*, 85(1), 31–41. https://doi.org/10.1016/j.jretai.2008.11.001

Verhoef, P. C., Neslin, S. A., & Vroomen, B. (2007). Multichannel customer management: Understanding the research-shopper phenomenon. *International Journal of Research in Marketing*, 24(2), 129–148. https://doi.org/10.1016/j.ijresmar.2006.11.002

Vyrros, A. H., Shepherd, M. E., Edwards, D. R., Wood, J., Pollack, D. B., de Filippis, P., Drummond, J., Santamaria, J., & Novick, G. (2016). Managing notifications across multiple devices (United States Patent No. US9288164B2). https://patents.google.com/patent/US9288164B2/en

Wang, R. J.-H., Malthouse, E. C., & Krishnamurthi, L. (2015). On the Go: How Mobile Shopping Affects Customer Purchase Behavior. *Journal of Retailing*, 91(2), 217–234. https://doi.org/10.1016/j.jretai.2015.01.002

Wang, Z., Zhou, X., Wang, W., & Liang, C. (2020). Emotion recognition using multimodal deep learning in multiple psychophysiological signals and video. *Int. J. Mach. Learn. Cybern.*, 11(4), 923–934. https://doi.org/10.1007/s13042-019-01056-8

Wong, J., Scheibenreif, D., & Phifer, G. (2021, June 28). Transcend Omnichannel Thinking and Embrace Multiexperience for Improved Customer Experience. *Gartner*. https://www.gartner.com/en

Wu, D., Dong, J., & Liu, C. (2019). Exploratory study of cross-device search tasks. *Information Processing & Management*, 56(6), 102073. https://doi.org/10.1016/j.ipm.2019.102073

Wu, D., Dong, J., Tang, Y., & Capra, R. (2020). Understanding task preparation and resumption behaviors in cross-device search. *Journal of the Association for Information Science and Technology*, 71(8), 887–901. https://doi.org/10.1002/asi.24307

Xu, K., Chan, J., Ghose, A., & Han, S. P. (2017). Battle of the Channels: The Impact of Tablets on Digital Commerce. *Management Science*, 63(5), 1469–1492. https://doi.org/10.1287/mnsc.2015.2406

Zimmerman, P., Bolhuis, L., Willemsen, A., Meyer, E., & Noldus, L. (2008). The Observer XT: A tool for the integration and synchronization of multimodal signals. *Behavior Research Methods*, 41, 731–735. https://doi.org/10.3758/BRM.41.3.731

<u>CHAPTER 2:</u> Research Article

The impact of device switching on users' emotions in the context of an omnichannel task: An explorative study based on psychophysiological data[2]

Juan Fernández-Shaw, Pierre-Majorique Léger, and Sylvain Sénécal

Abstract: Customer journeys and digital services have become distributed over multiple devices, leading to users commonly engaging in device switching and cross-device behavior. The apparent complexity of using multiple devices has led to much research on cognitive aspects and outcomes of this behavior, but almost none about its emotional implications for users. Hence, this paper suggests that transitions across devices provoke significant emotional responses in users. A study involving 21 participants and psychophysiological inferences of emotion is undertaken to test these hypotheses. Results show that, while there exists an emotional reaction to transitions across devices in omnichannel task contexts, it only affects certain device transitions and can be both positive and negative. Implications and ideas for further research are also discussed.

Keywords: Omnichannel · Device Switching · Cross-device · Seamlessness · Emotion

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2.1 Introduction

Interactions with digital services are increasingly split over several devices and users have been quick to adopt the use of multiple devices to perform tasks (Google, 2012; Microsoft Advertising, 2013). In retail contexts this phenomenon has been denominated "device switching" and is an essential part of the broader omnichannel literature (de Haan et al., 2018; Verhoef, 2021), which considers that customers nowadays follow a fragmented customer journey because they simultaneously use different channels and touchpoints to purchase goods and services (Carroll & Guzmán, 2013). In the field of Human-Computer Interaction (HCI), user interaction

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with multiple displays and devices is studied under the umbrella of "cross-device behavior" and has been a continued focus of research in recent years (Brudy et al., 2019).

Firms have been striving to adapt their services to multiple device use and integrate their channels to provide seamless (i.e., continuous and consistent) experiences to users. Research has shown that the perceived degree of integration among channels is positively associated with customer satisfaction and retention (Cocco & Demoulin, 2022; Wang & Jiang, 2022), and ultimately sales growth for firms (Cao & Li, 2015). Therefore understanding the motivations, characteristics, and outcomes of transitions across devices in the context of omnichannel tasks is therefore a major concern for researchers in both marketing and HCI areas of study (Han et al., 2022; Santosa & Wigdor, 2013).

The use of multiple devices has been shown to have an impact on cognitive load, as the complexity of keeping track of several displays requires considerable effort on the part of the user (Hamilton & Wigdor, 2014; Van Cauwenberge et al., 2014). When switching between devices and platforms, users experience higher cognitive load and limited attention, which has been found to be a significant factor in their experience (Majrashi et al., 2018a). Therefore to achieve a higher standard of seamlessness across devices, researchers and firms have mainly focused on finding ways to ease the cognitive burden that comes when transitioning across devices (Grudin, 2001; Rädle et al., 2015).

Recent research in affective neuroscience posits that human cognition and emotion have an inseparable nature, and that they affect one another in a variety of manners (Plass & Kalyuga, 2019). Because multi-device interactions require a higher cognitive effort, research has studied its emotional impact and found that both antecedents to multiple device use and cross-device product features can have a significant effect on user satisfaction (Bailey & Konstan, 2006; Karlson et al., 2010; Rigby et al., 2018; Liu et al., 2023). Furthermore, the impact of multiple device use on emotional and psychological wellbeing is a rising consideration of researchers and designers (Lascau et al., 2019), and digital tools aimed at easing the emotional burden of such interactions are being developed (Kim et al., 2017; Monge Roffarello & De Russis, 2021).

We thus suggest that transitions across devices in the context of omnichannel tasks might have a significant effect on customers' emotional journeys. To our knowledge, current research has so far mainly focused on perceived satisfaction and broader wellbeing in multi-device interactions, but no study has determined whether transitioning across devices generates emotional responses. This research thus explores the existence of an emotional response to transitions between devices along the following line:

RQ4 – To what extent do transitions between devices in the context of device switching omnichannel tasks have an effect on users' emotional journey?

A laboratory study involving 21 participants was conducted to appraise users' emotional response when transitioning between multiple devices – computer, smartphone, and voice assistant – in an omnichannel task context. This study used a novel psychophysiological data collection methodology adapted to multi-device environments to measure, in an implicit and continuous manner, the variation in users emotional states during transitions across several devices.

The results of this research contribute to the existing device switching and cross-device literature in two principal ways: (1) conceptualizing and showing the existence of an emotional response brought about by certain device switching transitions; and (2) providing insights and ideas for further research on the factors that might influence emotional responses to device transitions.

2.2 Literature Review

2.2.1 Omnichannel Device Switching Experiences

Omnichannel retailing consists in the simultaneous use of several digital and physical customer channels within the same purchasing journey made possible thanks to the proliferation of devices in customers' homes and pockets (Lazaris & Vrechopoulos, 2014). In contrast to multichannel retailing – which assumes that channels will be used in sequential order along the journey –, the omnichannel approach has paved the way for more dynamic and less linear interactions with brands, thus making customer journeys more fragmented and complex than ever before (Carroll & Guzmán, 2013; Grewal & Roggeveen, 2020). The omnichannel approach to retailing in business-to-consumer contexts has been defined in the extant literature as "the complete alignment of different channels and touchpoints resulting in an optimal brand-customer experience" (Huré et al., 2017, p. 315).

A subset of omnichannel customer journeys focused exclusively on the use of digital channels has been denominated by academics as "device switching" experiences. In particular, this phenomenon refers to the process of transitioning between different online digital devices – such as computers, smartphones and tablets – while performing a task (e.g., two-factor authentication, cross-device search) (de Haan et al., 2018). The change towards experiences centered on multiple digital devices has been noticeably strong since the onset of the Covid-19 pandemic, as many retailers were forced to open new digital channels and build omnichannel strategies due to the closure of physical stores (Cocco & De-Juan-Vigaray, 2022). The banking, travel and technology industries have been especially quick to offer device switching experiences, and analysts estimate that it will propagate to other industries in the coming years (Verhoef, 2021).

Users have been quick to adapt to using multiple devices in a variety of manners. Past research has shown that in work environments transitions between devices occur multiple times a day, and sometimes in intervals of less than five minutes (Oulasvirta & Sumari, 2007). Other researchers have identified common patterns of use when interacting with multiple devices and categorized them according to level of synergy between devices (Jokela et al., 2015). Though still a nascent phenomenon, the body of current research is being cemented and dedicated taxonomies have recently been published (Brudy et al., 2019).

Research into the antecedents of device switching behavior has centered around perceived task-fit, as users take advantage of the different device form factors and functionalities at their disposal to complete a task (Santosa & Wigdor, 2013). Perceived task-fit forms users' expected satisfaction and attitude towards using multiple devices, which triggers intention to use multiple devices (Chen & Koufaris, 2020). Thus, researchers have strived to identify contexts and tasks which drive cross-device behavior. In information search, unsatisfied information needs are the main motivation for switching devices and tasks prompting this behavior often relate to specific questions (Karlson et al., 2010; Wu et al., 2019). In online purchasing contexts, users generally switch from mobile to fixed devices as they progress along the customer journey, searching information first in breadth and then in depth (Han et al., 2022). However, recent research has shown that other personal and environmental factors also influence the attitude towards and intention to use multiple devices (Van Nguyen et al., 2022, 2023).

2.2.2 Seamlessness Across Channels

In device switching omnichannel contexts, integration among different channels and touchpoints is primordial to providing a good customer experience. A seamless experience is the "perception of a continuous and consistent shopping journey across channels with a single retailer" and can be further studied alongside these dimensions (Cocco & Demoulin, 2022, p. 469). Continuity refers to the customer progression across channels, and the ability to move interchangeably between channels at any moment of the journey (Wäljas et al., 2010). Other authors have defined the extent to which customers feel the experience as natural, unhindered and continuous across channels and devices as perceived fluency, and shown that it is a key determinant of omnichannel service usage (Shen et al., 2018). Consistency refers to the perception of equal information and benefits across channels (e.g., price, product assortment, offers), which makes for an easier customer journey and avoids competition among channels (Piotrowicz & Cuthbertson, 2014).

The literature is still unclear about whether improving device integration through more consistency or continuity provides a better outcome. In favor of the former, research has shown that performance is higher when user interfaces are consistent in position, size and order across devices (Majrashi, 2019; Majrashi et al., 2018b). A higher degree of consistency across channels also has a significant positive effect on satisfaction for customers (Rodríguez-Torrico et al., 2020; Wang & Jiang, 2022). In favor of the latter, other research shows that task continuity is a more important concern than consistency, in order to minimize task disconnects (Pyla et al., 2006). In the same vein, Mencarelli et al. (2021) argue that rather than making each online channel similar and risk a negative impact on customers' perceived value, firms should design channels in a complementary manner and clarify the usefulness of each one.

Independently of how it is achieved, a higher degree of integration across channels has a significant positive effect on satisfaction for customers, which directly impacts customer retention, and ultimately sales growth for firms (Cao & Li, 2015; Cocco & Demoulin, 2022;

Wang & Jiang, 2022). Overall, the findings of the extant literature suggest that firms should focus on multi-device customer journeys and craft experiences across a combination of channels in a holistic manner, so that channel integration and perceived seamlessness in transitions maximize value for customers (Neslin, 2022; Verhoef et al., 2015).

2.2.3 Cognitive Cost of Transitions

Multitasking theory states that human cognition (i.e., the ability to coordinate thought and action towards obtaining a goal) is a limited resource that is spent in effortful switches back and forth between tasks (Miller & Wallis, 2009; Wickens, 2008). The same phenomenon is appreciated when users evolve in cross-device and cross-platform environments. Limited attention when moving or switching devices has been found to be a factor in cross-platform user experience (Majrashi et al., 2018a), and keeping track of multiple similar devices leads to increased cognitive load and a significant challenge (Hamilton & Wigdor, 2014). Similarly research has found that, compared to single-screen viewing, second-screen viewing leads to a lower recall and comprehension of factual information due to the mediating effect of increased cognitive load (Van Cauwenberge et al., 2014). In the end, researchers agree that studying users' cognition in cross-device behavior is primordial, because of the low level of awareness in the behavior (Dong et al., 2022).

To ease the cognitive cost of performing tasks while switching between multiple devices, users have developed specific behaviors. In professional contexts, multi-device work is usually planned beforehand to anticipate technological constraints (Oulasvirta & Sumari, 2007). Other research has shown that users have a tendency to apply spatially aware techniques in cross-device environments (i.e., organize devices through specific spatial configurations) to reduce their mental demand (Hamilton & Wigdor, 2014; Rädle et al., 2015), in both individual and collaborative contexts (Desolda et al., 2019). Users are prone to dedicate displays to particular activities, such as using a second screen for support information of the primary task, thus allowing rapid glances that reduce the cognitive load of switching between devices (Grudin, 2001). On the other hand, technological platforms have also made improvements to the seamlessness of interactions across devices that reduce cognitive load. In particular cross-device synchronization of files and data, which requires cognitive effort and time-consuming interaction with multiple devices resulting in hindrances on productivity (Oulasvirta & Sumari, 2007;

Santosa & Wigdor, 2013), has been mostly replaced by the hands-free and automatic synchronization via online cloud servers (Duso & Schiersch, 2022).

Recent research in affective neuroscience has shown that human emotions are interconnected with cognition, and studying their relationship constitutes a key research line for furthering the literature (Ginns & Leppink, 2019). Though the mechanics of their relationship is still unclear, the current literature has identified several manners in which cognition and emotion could affect one another both positively and negatively (Plass & Kalyuga, 2019). Some emotional states are conducive to motivation and broader cognitive resources, whereas others narrow those resources and increase extraneous processing requirements. While the cognitive aspect of transitions across devices has been a focus of study in the literature, the emotional component of such interactions has so far not been widely studied.

2.2.4 Emotional Cost of Transitions

Because multi-device interactions require a higher cognitive effort of users, current research suggests that there might also be a significant emotional impact to cross-device use. Contrary to single-device products, there is still a lack of UX guidelines for the design of interactions across devices, and most multi-device experiences can still be unsatisfactory and frustrating (Zhang et al., 2021). Furthermore, the antecedents of cross-device behavior can also lead to reduced user satisfaction. When searching for information on mobile, unsatisfied needs and frustration are the main reasons for switching to computers (Karlson et al., 2010); and when streaming on-demand content, users will use unfavorable devices for viewing (e.g., smartphones) if none other are available (Rigby et al., 2018). Research has also identified that certain cross-device features have a significant negative effect on user satisfaction, such as operation latency and reiterated notifications (Bailey & Konstan, 2006; Liu et al., 2023).

Taking a broader perspective, some researchers have called for cross-device interactions that improve user work quality as well as their psychological and emotional wellbeing (Lascau et al., 2019). The prevalent use of multiple devices for unrelated multi-tasking (e.g., off-tasks and cyberloafing) has prompted researchers to study its negative impact on user wellbeing and productivity. They show that multiple device use is a difficult roadblock for users to manage and that digital self-control tools, though rarely adapted to cross-device behavior, can significantly reduce user mental effort and stress levels (Kim et al., 2017; Monge Roffarello & De Russis, 2021). Ultimately, all findings of the extant literature suggest a significant emotional component to the use of certain devices in multi-device contexts.

We thus suggest that transitions between devices in the context of omnichannel experiences might also generate a significant emotional response in users, either positive or negative. To our knowledge, the emotional cost during device switching transitions has so far not been studied in the literature and could prove to be an important factor influencing perceived seamlessness and intention to use multiple devices. Therefore, this research aims at exploring the existence of an emotional variation in transitions across devices.

In the extant HCI literature, the study of users' emotional responses to digital artifacts has been, for the most part, underpinned by the circumplex model of affect. This model comes from the field of psychology and posits that all affective states (i.e., emotions) are the product of two independent neurophysiological systems: emotional valence and arousal (Posner et al., 2005; Russell, 1980). Emotional valence is defined as the degree of pleasantness (or unpleasantness) felt by a person in response to a stimuli, and emotional arousal stands for the degree of activation felt by a person in response to stimuli (Fontaine et al., 2013). When measuring these two constructs independently, researchers are able to accurately identify users' emotional states, their variation, and represent them on a two-axis circular graphic.

In this study, we explore whether switching between different devices sequentially while completing an omnichannel task has an effect on users emotional response. As such, the two hypotheses that were tested in this study are the following:

H4: Transitions between devices in the context of a device switching omnichannel task can have a significant effect on emotional valence.

H5: Transitions between devices in the context of a device switching omnichannel task can have a significant effect on emotional arousal.

To answer the research questions and test these hypotheses, a laboratory study was undertaken. This study employed psychophysiological inferences of emotional valence and arousal to evaluate participants' emotional responses to transitions in omnichannel multi-device sequential task contexts (Majrashi et al., 2020; Fernández-Shaw et al., 2023). A detailed account of the methodology is presented in *Section 3*, and results are provided in *Section 4* of this paper.

2.3 Methodology

2.3.1 Experimental Design

This study adopted a within-subjects experimental design, and participants completed all four tasks in a randomized order. To examine cross-device transitions, each task was divided into three subtasks requiring the use of a different device (Majrashi et al., 2020), with participants completing all subtasks sequentially and in order. Instructions were given on paper so they could be consulted at all times. Participants were asked to switch between devices of their own volition once they felt that the previous subtask was completed, but could not move back to a previous device within a task. They used a total of three devices: computer, smartphone, and voice assistant (see **Table 6**). The devices and data collection tools were arranged according to the methodology presented by Fernández-Shaw et al. (2023) to allow for the precise and continuous measurement of variations in emotion occurring in response to transitions across devices.

Task	**1st Subtask**	**2nd Subtask**	**3rd Subtask**
Task 1 Mortgage Loans	Computer Banking Website	Voice Assistant Google Search	Smartphone Google Maps
Task 2 Credit Cards	Computer Banking Website	Smartphone Mobile Website	Voice Assistant Google Calendar
Task 3 Savings Account	Voice Assistant Google Search	Computer Banking Website	Smartphone Banking App
Task 4 Vehicle Loan	Smartphone Banking App	Computer Banking Website	Voice Assistant Google Calendar

Table 6. Devices and interface used in each subtask.

2.3.2 Participants

A total of 21 participants recruited among the students of our institution engaged in this study. The participants were aged between 18 and 39 years old (Mean = 26.19 and St. Dev. = 5.78). Gender distribution was unequal (i.e. 18 women and 3 men) by random chance, as no demographic data was taken into consideration for recruitment purposes. The screening questionnaire excluded participants who wore glasses or contact lenses when using digital devices or had special dermatological conditions, as these issues could impact the quality of collected psychophysiological signals. A technical malfunction with the synchronization hardware impacted the data collection for two participants. Thus, the analysis was conducted on a total of 19 participants. This study was approved by the Research Ethics Board (REB) of our institution (certificate #2022-4850).

2.3.3 Procedure

Upon arriving at the facilities of the usability laboratory, participants were explained the basics of the experiment and asked to provide their formal and written consent to the collection of physiological data. Afterwards the research team installed physiological sensors on the participants and data quality was assessed (if unsatisfactory, new sensors were installed). Participants then watched a 40 second video which served to establish a baseline in psychophysiological inferences, before moving on with the four experimental tasks of the experience.

The tasks were completed on the public user interfaces of a bank and Google LLC (Mountain View, United States). Banking was chosen as the focus for this study because the industry has been quick to adopt multi-device omnichannel experiences (Verhoef, 2021), and synergies across interfaces abound (e.g., two-factor authentication). Each experimental task was centered around a product line of the banking firm (e.g., mortgage loans) and reflected real pre-purchase customer behavior. In the second task for instance, participants were asked to: Find specific details on credit cards, plan a meeting with a financial advisor, and add that event to their personal calendar. The experiment was designed so that participants used three different interfaces for each task, thus requiring them to switch devices two times per task. All possible device switching transitions were covered (see **Figure 4**).

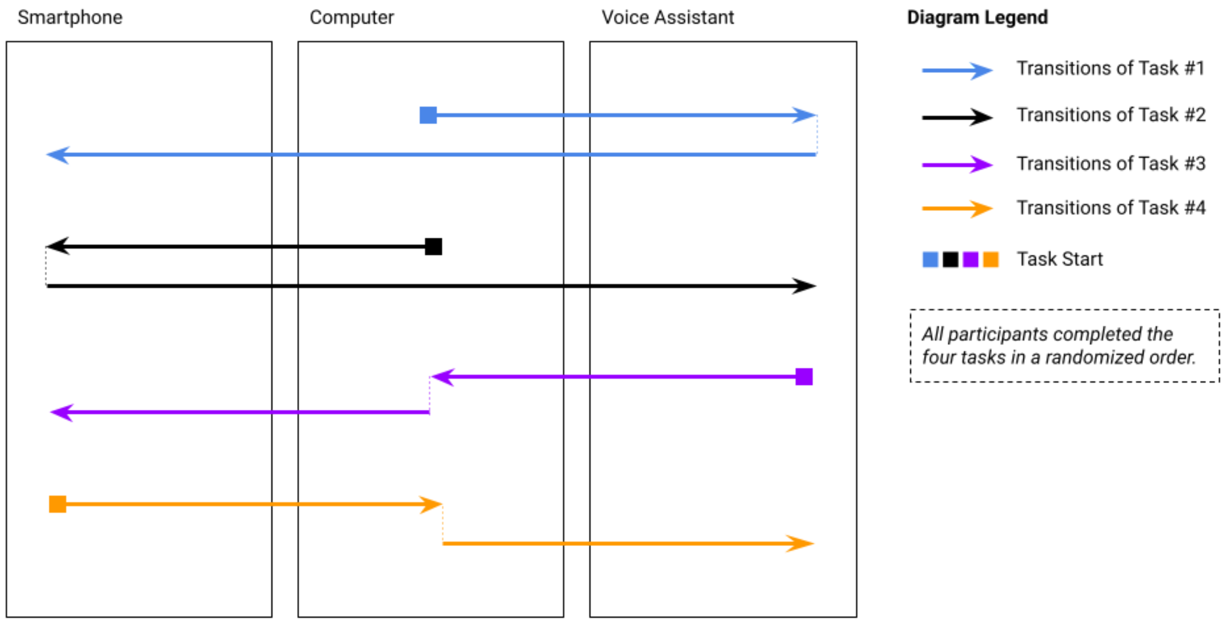

Figure 4. Transitions performed when completing the four experimental tasks.

2.3.4 Instruments and Measures

Emotional valence was measured by FaceReader 8.1, a facial expression recognition tool developed by Noldus Information Technology BV (Wageningen, Netherlands). This software models emotional valence as a continuous variable ranging from –1 to +1 every 1/10th of a second, equalling unpleasant and pleasant emotions respectively (Loijens & Krips, 2021). This software is considered a reliable indicator of basic emotions and has been used in a variety of studies pertaining to digital interfaces (Lewinski et al., 2014). As participants could rotate towards three devices, the methodological procedure presented by Fernández-Shaw et al. (2023) consisting in using duplicate psychophysiological data collection tools per device (i.e. webcams) was followed to measure emotional valence in a continuous manner.

Arousal was measured by Biopac MP-150, an electrodermal activity (EDA) data collection system developed by Biopac Systems (Goleta, United States). This system uses sensors placed on the off-hand of the participant to evaluate eccrine activity in response to events and stimuli (Benedek & Kaernbach, 2010). This measure – called phasic EDA – is used as a reliable inference of arousal with physiological signals, ranging from a calm to an excited state (Maia & Furtado, 2016). As the participants wore the sensors on themselves, continuous measurement of arousal across devices was guaranteed without the need for a special configuration.

Recorded psychophysiological signals were synchronized using the indirect method (Courtemanche et al., 2018) by way of the SyncBox and The Observer XT 11 solution (Noldus Information Technology BV, Wageningen, Netherlands), which consists in periodic signals sent to data collection tools and used as guides to harmonize all data sources in a single timeline (Zimmerman et al., 2008). This operation was handled automatically in post-processing by the Cobalt Photobooth solution (Léger et al., 2019).

2.3.5 Data Extraction and Analysis

To study the effect of transitions across devices on the participants' emotions, psychophysiological valence and arousal measurements three seconds before and after each transition were extracted, averaged and their difference computed. The differences between these averages illustrate the changes in emotional valence and arousal brought about by each transition. Transitions across devices were automatically identified by the Device Detection Algorithm (DDA), a program which uses head orientation data to accurately predict the device participants are interacting with (Fernández-Shaw et al., 2023).

Task	Transition	Device of Origin	Device of Destination
1	**Transition 1**	Computer	Voice Assistant
	Transition 2	Voice Assistant	Smartphone
2	**Transition 3**	Computer	Smartphone
	Transition 4	Smartphone	Voice Assistant
3	**Transition 5**	Voice Assistant	Computer
	Transition 6	Computer	Smartphone
4	**Transition 7**	Smartphone	Computer
	Transition 8	Computer	Voice Assistant

Table 7. Transitions between devices sorted by task.

To test whether transitions across devices in the context of an omnichannel task have a significant effect on emotional valence and arousal, a regression model using transitions as an indicator variable was built. The analysis was performed on repeated measures collected on 19 participants, and each completed 8 transitions in the scope of the four tasks (see **Table 7**).

Transitions with missing physiological data due to technical issues with the collection tools were discarded from the analysis. Thus, the regression analysis of transitions on emotional valence was conducted on a total of n=148 observations. On the other hand, the regression analysis of transitions on arousal was conducted on a total of n=131 observations.

2.4 Results

2.4.1 Effect of Transition on Valence

H4 concerns the effect of device transitions on emotional valence in omnichannel contexts. The linear regression model built to test this hypothesis is significant at a 5% confidence level (p-value = 0.0160). The full accounting of this model's goodness-of-fit statistics can be found in Appendix 1, and the complete results of the bilateral pairwise comparison between device transitions, with coefficient and standard error metrics, can be found in **Table 8**.

The results of the pairwise comparison between device transitions on emotional valence show that, when compared to each other, the effect of seven out of eight device transitions on emotional valence is not significant. However, at a 5% confidence level there is a significant difference in the variance of participants' valence between Transition 5 with respect to Transition 1 (p-value = 0.0359), Transition 4 (p-value = 0.0281), and Transition 6 (p-value = 0.0047). It is estimated that the change in participants' emotional valence during Transition 5 is higher than during Transition 1 by a factor of 0.1184, Transition 4 by a factor of 0.1055, and Transition 6 by a factor of 0.1260. Positive factors in the change of emotional valence in Transition 5 mean that, on average, participants experienced a significantly higher increase in emotional valence (i.e., a more pleasant emotion) during this transition than with the other three.

These results suggest that, overall, device transitions seem not to have an effect on participants' emotional valence levels in this experiment. However, some specific device transitions – such as Transition 5 in this study – can explain a positive variation in participant's emotional valence levels when compared to each other. As we are able to identify certain specific transitions that elicit significant emotional valence responses in users, we thus consider the previously defined H4 to be supported.

	Transition 1		Transition 2		Transition 3		Transition 4		Transition 5		Transition 6		Transition 7		Transition 8	
	b / (s.e.)	p[1]	b / (s.e.)	p[1]	b / (s.e.)	p[1]	b / (s.e.)	p[1]	b / (s.e.)	p[1]	b / (s.e.)	p[1]	b / (s.e.)	p[1]	b / (s.e.)	p[1]
Transition 1	—		-0.0488 (0.0528)		-0.0191 (0.0399)		-0.0129 (0.0291)		**-0.1184** **(0.0524)**	**	0.0076 (0.0354)		-0.0414 (0.0468)		-0.0674 (0.0514)	
Transition 2	0.0488 (0.0528)		—		0.0297 (0.0553)		0.0359 (0.0450)		-0.0696 (0.0621)		0.0564 (0.0507)		0.0074 (0.0571)		-0.0186 (0.0492)	
Transition 3	0.0191 (0.0399)		-0.0297 (0.0553)		—		0.0062 (0.0362)		-0.0993 (0.0637)		0.0268 (0.0474)		-0.0222 (0.0501)		-0.0483 (0.0665)	
Transition 4	0.0129 (0.0291)		-0.0359 (0.0450)		-0.0062 (0.0362)		—		**-0.1055** **(0.0444)**	**	0.0206 (0.0366)		-0.0284 (0.0450)		-0.0545 (0.0534)	
Transition 5	**0.1184** **(0.0524)**	**	0.0696 (0.0621)		0.0993 (0.0637)		**0.1055** **(0.0444)**	**	—		**0.1260** **(0.0394)**	***	0.0770 (0.0653)		0.0510 (0.0758)	
Transition 6	-0.0076 (0.0354)		-0.0564 (0.0507)		-0.0268 (0.0474)		-0.0206 (0.0366)		**-0.1260** **(0.0394)**	***	—		-0.0490 (0.0575)		-0.0751 (0.0584)	
Transition 7	0.0414 (0.0468)		-0.0074 (0.0571)		0.0222 (0.0501)		0.0284 (0.0450)		-0.0770 (0.0653)		0.0490 (0.0575)		—		-0.0261 (0.0571)	
Transition 8	0.0674 (0.0514)		0.0186 (0.0492)		0.0483 (0.0665)		0.0545 (0.0534)		-0.0510 (0.0758)		0.0751 (0.0584)		0.0261 (0.0571)		—	
Constant	-0.0169 (0.0260)		0.0319 (0.0414)		0.0022 (0.0315)		-0.0040 (0.0169)		**0.1014** **(0.0464)**	**	-0.0246 (0.0324)		0.0244 (0.0390)		0.0505 (0.0488)	

Table 8. Bilateral pairwise comparison between transitions on valence.

[1] Level of Bilateral Test: **$p \leq 0.05$; ***$p \leq 0.01$.

2.4.2 *Effect of Transition on Arousal*

H5 concerns the effect of device transitions on emotional arousal in omnichannel contexts. The linear regression model built to test this hypothesis is significant at a 5% confidence level (p-value = 0.0363). The full accounting of this model's goodness-of-fit statistics can be found in Appendix 2, and the complete results of the bilateral pairwise comparison between device transitions, with coefficient and standard error metrics, can be found in **Table 9**.

The results of the pairwise comparison between device transitions on emotional arousal show that, when compared to each other, the effect of six out of eight device transitions on emotional arousal is not significant. However, at a 5% confidence level there is a significant difference in the variance of participants' arousal levels between Transition 2 with respect to Transition 3 (p-value = 0.0299) and Transition 7 (p-value = 0.0487). It is estimated that the change in participants' emotional arousal during Transition 2 is lower than during Transition 3 by a factor of 0.5078 and Transition 7 by a factor of 0.2429. At the same time, there is a significant difference in the variance of participants' arousal levels between Transition 3 with respect to Transition 6 (p-value = 0.0200), estimated to be higher in the former by a factor of 0.3992. This means that Transition 2 generated, on average, a lesser degree of arousal than transitions 3 and 7; whereas Transition 3 generated more excitation and arousal than Transition 6.

These results suggest that, overall, device transitions seem not to have an effect on participants' emotional arousal levels. However, some specific device transitions – such as Transitions 2 and 3 in this study – can explain positive and negative variations in participants' emotional arousal levels when compared to each other. As we are able to identify certain specific transitions that elicit significant emotional arousal responses in users, we thus consider the previously defined H5 to be supported.

	Transition 1 b / (s.e.)	p[1]	Transition 2 b / (s.e.)	p[1]	Transition 3 b / (s.e.)	p[1]	Transition 4 b / (s.e.)	p[1]	Transition 5 b / (s.e.)	p[1]	Transition 6 b / (s.e.)	p[1]	Transition 7 b / (s.e.)	p[1]	Transition 8 b / (s.e.)	p[1]
Transition 1	—		0.1508 (0.1562)		-0.3570 (0.2249)		-0.0317 (0.1082)		-0.0243 (0.0942)		0.0422 (0.1091)		-0.0921 (0.1437)		-0.0959 (0.1565)	
Transition 2	-0.1508 (0.1562)		—		**-0.5078 (0.2154)**	**	-0.1824 (0.0876)		-0.1750 (0.1435)		-0.1086 (0.1101)		**-0.2429 (0.1148)**	**	-0.2466 (0.1599)	
Transition 3	0.3570 (0.2249)		**0.5078 (0.2154)**	**	—		0.3253 (0.1822)		0.3327 (0.1837)		**0.3992 (0.1563)**	**	0.2649 (0.1880)		0.2611 (0.1927)	
Transition 4	0.0317 (0.1082)		0.1824 (0.0876)		-0.3253 (0.1822)		—		0.0074 (0.0874)		0.0739 (0.0565)		-0.0605 (0.0749)		-0.0642 (0.1243)	
Transition 5	0.0243 (0.0942)		0.1750 (0.1435)		-0.3327 (0.1837)		-0.0074 (0.0874)		—		0.0665 (0.0897)		-0.0678 (0.1030)		-0.0716 (0.1258)	
Transition 6	-0.0422 (0.1091)		0.1086 (0.1101)		**-0.3992 (0.1563)**	**	-0.0739 (0.0565)		-0.0665 (0.0897)		—		-0.1343 (0.0888)		-0.1381 (0.1196)	
Transition 7	0.0921 (0.1437)		**0.2429 (0.1148)**	**	-0.2649 (0.1880)		0.0605 (0.0749)		0.0678 (0.1030)		0.1343 (0.0888)		—		-0.0038 (0.1316)	
Transition 8	0.0959 (0.1565)		0.2466 (0.1599)		-0.2611 (0.1927)		0.0642 (0.1243)		0.0716 (0.1258)		0.1381 (0.1196)		0.0038 (0.1316)		—	
Constant	-0.0051 (0.1043)		-0.1559 (0.1091)		**0.3519 (0.1619)**	**	0.0266 (0.0453)		0.0192 (0.0703)		-0.0473 (0.0313)		0.0870 (0.0671)		0.0908 (0.1084)	

Table 9. Bilateral pairwise comparison between transitions on arousal.

[1] Level of Bilateral Test: $^{**}p \leq 0.05$; $^{***}p \leq 0.01$.

2.5 Discussion

The results of this study offer early evidence of the existence of emotional responses to transitions between devices in omnichannel tasks contexts, as our technique was able to identify which device transitions generate significant emotional responses in users. Though affecting only certain specific transitions, we have detected significant variations in emotional valence (H4) and arousal (H5) happening during device switching. These variations can take the form of both significant increases and decreases in user emotional valence and arousal levels occurring in only certain device transitions.

The existence of an emotional response to transitions across devices furthers the extant literature's body of knowledge on device switching behavior. Many authors have only studied the outcomes of this behavior in terms of cognition, demonstrating that transitions across devices increase cognitive load and reduce attention (Majrashi et al., 2018a; Van Cauwenberge et al., 2014); and identifying several manners in which to reduce the complexity of multiple device interaction (Grudin, 2001; Rädle et al., 2015). We thus reckon that the addition of an emotional component to multi-device transitions – either positively or negatively related – opens a new avenue for broader research in the outcomes of this behavior.

This study is unable to provide reasons for why certain transitions do provoke positive or negative emotional responses in users. However, we suggest that some already identified antecedents to multi-device behavior surely play a role in this relationship. Perceived task-fit informs user attitude towards using multiple devices (Chen & Koufaris, 2020; Santosa & Wigdor, 2013) and could be a factor in explaining their attitude towards switching to certain devices (e.g., users contrived to switch to devices non-adapted to the task at hand might have a more negative response). In cross-device search, users switching devices due to unsatisfied information needs might have a different emotional response to the transition than others (Karlson et al., 2010; Wu et al., 2019). Further research, and the identification of transition criteria that are prone to generate an emotional response could be of great benefit to both academia and industry.

For practitioners, the existence of an emotional response when switching across devices demonstrates the need to ensure that channel integration efforts have a positive effect on user affective states, rather than focusing solely on performance. In omnichannel environments, cognitive and emotional components of customer experience can influence purchase intention (Rahmawati, 2022). Further empirical research and design recommendations on multi-device interactions that consider the combined effect of cognitive and emotional user responses to device switches will thus be beneficial for firms aiming to achieve a higher degree of seamlessness.

Despite these contributions, this study is only the first exploratory step in the study of emotional responses to cross-device behavior and comes with its own set of limitations. First, data was collected in a laboratory setting with participants in a seated position, thus impacting the generalizability of the findings to authentic contexts. Second, this study failed to provide any valuable insights on the causes of the detected emotional response, and further research on this phenomenon could identify the characteristics of transitions prone to create emotional responses (e.g., perceived task-fit, environment). Further, this study did not have the means to experiment with different levels of channel integration, and we reckon that studying its relationship would yield further insights to seamlessness in cross-device contexts. Finally, the results of this laboratory study are based on a small sample of participants and its findings should be further tested by other researchers and methodologies to provide a solid foundation for this phenomenon.

2.6 Conclusion

In this study, we posit the existence of an emotional response occurring during user transitions across devices in omnichannel task contexts. Through a laboratory study involving psychophysiological inferences of emotional valence and arousal, we find that certain transitions do indeed explain part of the variation in participant emotions. Those transitions can have both positive and negative effects on user emotional valence and arousal. The evaluation of user emotional states should therefore be of prime concern for the measurement of seamlessness. We discuss the implications of this result for cross-device and omnichannel literature, as well as practitioners. Moving forward, research should center on identifying the characteristics of transitions generating emotional responses and its overall link with cognitive responses to device transitions.

References

Bailey, B. P., & Konstan, J. A. (2006). On the need for attention-aware systems: Measuring effects of interruption on task performance, error rate, and affective state. Computers in Human Behavior, 22(4), 685–708. https://doi.org/10.1016/j.chb.2005.12.009

Benedek, M., & Kaernbach, C. (2010). A continuous measure of phasic electrodermal activity. *Journal of Neuroscience Methods*, 190(1–5), 80–91. https://doi.org/10.1016/j.jneumeth.2010.04.028

Brudy, F., Holz, C., Rädle, R., Wu, C.-J., Houben, S., Klokmose, C. N., & Marquardt, N. (2019). Cross-Device Taxonomy: Survey, Opportunities and Challenges of Interactions Spanning Across Multiple Devices. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–28. https://doi.org/10.1145/3290605.3300792

Cao, L., & Li, L. (2015). The Impact of Cross-Channel Integration on Retailers' Sales Growth. *Journal of Retailing*, 91(2), 198–216. https://doi.org/10.1016/j.jretai.2014.12.005

Carroll, D., & Guzmán, I. (2013). The New Omni-Channel Approach to Serving Customers. Accenture. https://www.scribd.com/document/354676791/Accenture-New-Omni-Channel-Approach-Serving-Customers

Chen, C.-W., & Koufaris, M. (2020). Multi-Device Use: Understanding the Motivations behind Switching between Multiple Devices during a Task. *International Journal of Human–Computer Interaction*, 36(12), 1178–1193. https://doi.org/10.1080/10447318.2020.1726106

Cocco, H., & De-Juan-Vigaray, M. D. (2022). A typology of omnichannel retailer activities during the COVID-19 pandemic. *International Journal of Retail & Distribution Management*, 50(8/9), 1062–1094. https://doi.org/10.1108/IJRDM-10-2021-0506

Cocco, H., & Demoulin, N. T. M. (2022). Designing a seamless shopping journey through omnichannel retailer integration. *Journal of Business Research*, 150, 461–475. https://doi.org/10.1016/j.jbusres.2022.06.031

Courtemanche, F., Léger, P.-M., Dufresne, A., Fredette, M., Labonté-LeMoyne, É., & Sénécal, S. (2018). Physiological heatmaps: A tool for visualizing users' emotional reactions. *Multimedia Tools and Applications*, 77(9), 11547–11574. https://doi.org/10.1007/s11042-017-5091-1

de Haan, E., Kannan, P. K., Verhoef, P. C., & Wiesel, T. (2018). Device Switching in Online Purchasing: Examining the Strategic Contingencies. *Journal of Marketing*, 82(5), 1–19. https://doi.org/10.1509/jm.17.0113

Desolda, G., Ardito, C., Jetter, H.-C., & Lanzilotti, R. (2019). Exploring spatially-aware cross-device interaction techniques for mobile collaborative sensemaking. International *Journal of Human-Computer Studies*, 122, 1–20. https://doi.org/10.1016/j.ijhcs.2018.08.006

Dong, J., Duan, R., & Liang, S. (2022). Users' mental models of cross-device search under controlled and autonomous motivations. *Aslib Journal of Information Management*, 75(1), 68–89. https://doi.org/10.1108/AJIM-02-2022-0057

Duso, T., & Schiersch, A. (2022). Let's Switch to the Cloud: Cloud Adaption and Its Effect on IT Investment and Productivity (SSRN Scholarly Paper No. 4221050). https://doi.org/10.2139/ssrn.4221050

Fernández-Shaw, J., Léger, P.M., Courtemanche, F., Tazi, S., Côté, X., Chen, S.L., Coursaris, C., Pourchon, R. & Sénécal, S.(2023) Continuous recording of psychophysiological measures in omnichannel human-computer interactions: A validation study. [Manuscript submitted for publication]. HEC Montréal. – See *Chapter 1* of the present thesis.

Fontaine, J. J. R., Scherer, K. R., & Soriano, C. (2013). Components of emotional meaning: A sourcebook. OUP Oxford.

Ginns, P., & Leppink, J. (2019). Special Issue on Cognitive Load Theory: Editorial. Educational Psychology Review, 31(2), 255–259. https://doi.org/10.1007/s10648-019-09474-4

Google. (2012). The New Multi-screen World: Understanding Cross-platform Consumer Behavior. Google. https://www.thinkwithgoogle.com/_qs/documents/681/the-new-multi-screen-world-study_research-studies.pdf

Grewal, D., & Roggeveen, A. L. (2020). Understanding Retail Experiences and Customer Journey Management. *Journal of Retailing*, 96(1), 3–8. https://doi.org/10.1016/j.jretai.2020.02.002

Grudin, J. (2001). Partitioning digital worlds: Focal and peripheral awareness in multiple monitor use. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 458–465. https://doi.org/10.1145/365024.365312

Hamilton, P., & Wigdor, D. J. (2014). Conductor: Enabling and understanding cross-device interaction. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2773–2782. https://doi.org/10.1145/2556288.2557170

Han, S., Han, J. K., Im, I., Jung, S. I., & Lee, J. W. (2022). Mapping consumer's cross-device usage for online search: Mobile- vs. PC-based search in the purchase decision process. *Journal of Business Research*, 142, 387–399. https://doi.org/10.1016/j.jbusres.2021.12.051

Huré, E., Picot-Coupey, K., & Ackermann, C.-L. (2017). Understanding omni-channel shopping value: A mixed-method study. *Journal of Retailing and Consumer Services*, 39, 314–330. https://doi.org/10.1016/j.jretconser.2017.08.011

Jo, D. H., & Lee, S. M. (2019). Understanding the Omni-Channel Acceptance: Focused on TTF and UTAUT Models. *Journal of Internet Computing and Services*, 20(1), 113–124. https://doi.org/10.7472/JKSII.2019.20.1.113

Jokela, T., Ojala, J., & Olsson, T. (2015). A Diary Study on Combining Multiple Information Devices in Everyday Activities and Tasks. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 3903–3912. https://doi.org/10.1145/2702123.2702211

Karlson, A. K., Iqbal, S. T., Meyers, B., Ramos, G., Lee, K., & Tang, J. C. (2010). Mobile taskflow in context: A screenshot study of smartphone usage. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2009–2018. https://doi.org/10.1145/1753326.1753631

Kim, J., Cho, C., & Lee, U. (2017). Technology Supported Behavior Restriction for Mitigating Self-Interruptions in Multi-device Environments. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 1(3), 1–21. https://doi.org/10.1145/3130932

Labonte-LeMoyne, E., Cameron, A.-F., Sénécal, S., Fredette, M., Faubert, J., Lepore, F., & Léger, P.-M. (2022). What's that on Your Phone? Effects of Mobile Device Task Type on Pedestrian Performance. *Human Factors*, 00187208221141175. https://doi.org/10.1177/00187208221141175

Lascau, L., Wong, P. N. Y., Brumby, D. P., & Cox, A. L. (2019). Why Are Cross-Device Interactions Important When It Comes To Digital Wellbeing?

Lazaris, C., & Vrechopoulos, A. (2014). From Multichannel to "Omnichannel" Retailing: Review of the Literature and Calls for Research. *2nd International Conference on Contemporary Marketing Issues,(ICCMI)*, 6, 1–6. https://doi.org/10.13140/2.1.1802.4967

Léger, P.-M., Courtemanche, F., Fredette, M., & Sénécal, S. (2019). A Cloud-Based Lab Management and Analytics Software for Triangulated Human-Centered Research. In F. D. Davis, R. Riedl, J. vom Brocke, P.-M. Léger, & A. B. Randolph (Eds.), *Information Systems and Neuroscience* (pp. 93–99). Springer International Publishing. https://doi.org/10.1007/978-3-030-01087-4_11

Lewinski, P., den Uyl, T. M., & Butler, C. (2014). Automated facial coding: Validation of basic emotions and FACS AUs in FaceReader. *Journal of Neuroscience, Psychology, and Economics*, 7, 227–236. https://doi.org/10.1037/npe0000028

Liu, X., Zhang, Y., Yan, Z., & Ge, Y. (2023). Defining 'seamlessly connected': User perceptions of operation latency in cross-device interaction. International Journal of Human-Computer Studies, 177, 103068. https://doi.org/10.1016/j.ijhcs.2023.103068

Loijens, L., & Krips, O. (2021). FaceReader Methodology Note. Noldus Information Technology BV. https://info.noldus.com/hubfs/resources/noldus-white-paper-facereader-methodology.pdf

Maia, C. L. B., & Furtado, E. S. (2016). A study about psychophysiological measures in user experience monitoring and evaluation. *Proceedings of the 15th Brazilian Symposium on Human Factors in Computing Systems*, 1–9. https://doi.org/10.1145/3033701.3033708

Majrashi, K. (2019). Post-transitioning user performance on cross-device menu interfaces. *International Journal of Human-Computer Studies*, 130, 130–151. https://doi.org/10.1016/j.ijhcs.2019.06.001

Majrashi, K., Hamilton, M., & Uitdenbogerd, A. (2018a). Evaluating Cross-Device Transitioning Experience in Seated and Moving Contexts.

Majrashi, K., Hamilton, M., & Uitdenbogerd, A. L. (2018b). Task Continuity and Mobile User Interfaces. *Proceedings of the 17th International Conference on Mobile and Ubiquitous Multimedia*, 475–481. https://doi.org/10.1145/3282894.3289742

Majrashi, K., Hamilton, M., Uitdenbogerd, A. L., & Al-Megren, S. (2020). Cross-Platform Usability Model Evaluation. *Multimodal Technologies and Interaction*, 4(4), Article 4. https://doi.org/10.3390/mti4040080

Mencarelli, R., Rivière, A., & Lombart, C. (2021). Do myriad e-channels always create value for customers? A dynamic analysis of the perceived value of a digital information product during the usage phase. *Journal of Retailing and Consumer Services*, 63, 102674. https://doi.org/10.1016/j.jretconser.2021.102674

Microsoft Advertising. (2013). Cross Screen Engagement: Multi-screen Pathways Reveal New Opportunities for Marketers to Reach and Engage Customers (Connected Experiences). Microsoft. https://www.coursehero.com/file/42587494/Microsoft-Advertising-Insights-Cross-Screen-Engagement-White-Paperpdf/

Miller, E. K., & Wallis, J. D. (2009). Executive Function and Higher-Order Cognition: Definition and Neural Substrates. *In Encyclopedia of Neuroscience* (pp. 99–104). Elsevier. https://doi.org/10.1016/B978-008045046-9.00418-6

Monge Roffarello, A., & De Russis, L. (2021). Coping with Digital Wellbeing in a Multi-Device World. Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems, 1–14. https://doi.org/10.1145/3411764.3445076

Neslin, S. A. (2022). The omnichannel continuum: Integrating online and offline channels along the customer journey. *Journal of Retailing*, 98(1), 111–132. https://doi.org/10.1016/j.jretai.2022.02.003

Oulasvirta, A., & Sumari, L. (2007). Mobile kits and laptop trays: Managing multiple devices in mobile information work. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1127–1136. https://doi.org/10.1145/1240624.1240795

Piotrowicz, W., & Cuthbertson, R. (2014). Introduction to the Special Issue Information Technology in Retail: Toward Omnichannel Retailing. *International Journal of Electronic Commerce*, 18(4), 5–16. https://doi.org/10.2753/JEC1086-4415180400

Plass, J. L., & Kalyuga, S. (2019). Four Ways of Considering Emotion in Cognitive Load Theory. Educational Psychology Review, 31(2), 339–359. https://doi.org/10.1007/s10648-019-09473-5

Posner, J., Russell, J. A., & Peterson, B. S. (2005). The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. *Development and Psychopathology*, 17(3), 715–734. https://doi.org/10.1017/S0954579405050340

Pyla, P. S., Tungare, M., & Pérez-Quiñones, M. A. (2006). Multiple User Interfaces: Why Consistency is Not Everything, and Seamless Task Migration is Key. *Proceedings of the CHI 2006 Workshop on the Many Faces of Consistency in Cross-Platform Design*.

Rädle, R., Jetter, H.-C., Schreiner, M., Lu, Z., Reiterer, H., & Rogers, Y. (2015). Spatially-aware or Spatially-agnostic? Elicitation and Evaluation of User-Defined Cross-Device Interactions. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 3913–3922. https://doi.org/10.1145/2702123.2702287

Rahmawati, R. A. (2022). New Journey Through Young Customer Experience in Omnichannel Context: The Role of Personalization. *Journal of Theoretical and Applied Management*, 15(2), 301–311. https://doi.org/10.20473/jmtt.v15i2.36236

Rigby, J. M., Brumby, D. P., Gould, S. J. J., & Cox, A. L. (2018). “I Can Watch What I Want”: A Diary Study of On-Demand and Cross-Device Viewing. Proceedings of the 2018 ACM

International Conference on Interactive Experiences for TV and Online Video, 69–80. https://doi.org/10.1145/3210825.3210832

Rodríguez-Torrico, P., Trabold Apadula, L., San-Martín, S., & San José Cabezudo, R. (2020). Have an omnichannel seamless interaction experience! Dimensions and effect on consumer satisfaction. *Journal of Marketing Management*, 36(17–18), 1731–1761. https://doi.org/10.1080/0267257X.2020.1801798

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39, 1161–1178. https://doi.org/10.1037/h0077714

Santosa, S., & Wigdor, D. (2013). A field study of multi-device workflows in distributed workspaces. *Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 63–72. https://doi.org/10.1145/2493432.2493476

Shen, X.-L., Li, Y.-J., Sun, Y., & Wang, N. (2018). Channel integration quality, perceived fluency and omnichannel service usage: The moderating roles of internal and external usage experience. *Decision Support Systems*, 109, 61–73. https://doi.org/10.1016/j.dss.2018.01.006

Van Cauwenberge, A., Schaap, G., & Van Roy, R. (2014). “TV no longer commands our full attention”: Effects of second-screen viewing and task relevance on cognitive load and learning from news. *Computers in Human Behavior*, 38, 100–109. https://doi.org/10.1016/j.chb.2014.05.021

Van Nguyen, A. T., Halibas, A. S., McClelland, R., & Thuan, N. H. (2023). Configurational analysis of conditions influencing customers’ channel switching intention in omnichannel retailing: A fuzzy-set analysis. *Quality & Quantity*. https://doi.org/10.1007/s11135-023-01633-8

Van Nguyen, A. T., McClelland, R., & Thuan, N. H. (2022). Exploring customer experience during channel switching in omnichannel retailing context: A qualitative assessment. *Journal of Retailing and Consumer Services*, 64, 102803. https://doi.org/10.1016/j.jretconser.2021.102803

Verhoef, P. C. (2021). Omni-channel retailing: Some reflections. *Journal of Strategic Marketing*, 29(7), 608–616. https://doi.org/10.1080/0965254X.2021.1892163

Verhoef, P. C., Kannan, P. K., & Inman, J. J. (2015). From Multi-Channel Retailing to Omni-Channel Retailing. *Journal of Retailing*, 91(2), 174–181. https://doi.org/10.1016/j.jretai.2015.02.005

Wäljas, M., Segerståhl, K., Väänänen-Vainio-Mattila, K., & Oinas-Kukkonen, H. (2010). Cross-platform service user experience: A field study and an initial framework. *Proceedings of the 12th International Conference on Human Computer Interaction with Mobile Devices and Services*, 219–228. https://doi.org/10.1145/1851600.1851637

Wang, J., & Jiang, X. (2022). The Impact of Omnichannel Shopping Experience and Channel Integration on Customer Retention: Empirical Evidence from China. *The Journal of Asian Finance, Economics and Business*, 9(2), 229–242. https://doi.org/10.13106/JAFEB.2022.VOL9.NO2.0229

Wickens, C. D. (2008). Multiple Resources and Mental Workload. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 50(3), 449–455. https://doi.org/10.1518/001872008X288394

Wu, D., Dong, J., & Liu, C. (2019). Exploratory study of cross-device search tasks. *Information Processing & Management*, 56(6), 102073. https://doi.org/10.1016/j.ipm.2019.102073

Zhang, R., Shi, Y., Schuller, B., André, E., Oviatt, S., Quigley, A., Marquardt, N., Aslan, I., & Ju, R. (2021). User Experience for Multi-Device Ecosystems: Challenges and Opportunities. Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems, 1–5. https://doi.org/10.1145/3411763.3441325

Zimmerman, P., Bolhuis, L., Willemsen, A., Meyer, E., & Noldus, L. (2008). The Observer XT: A tool for the integration and synchronization of multimodal signals. *Behavior Research Methods*, 41, 731–735. https://doi.org/10.3758/BRM.41.3.731

CHAPTER 3: Managerial Article

Evaluating multi-device UX: Purpose, methodology and guidelines[3]

Juan Fernández-Shaw, Pierre-Majorique Léger, and Sylvain Sénécal

Summary: Measuring seamlessness across devices is an essential endeavor for UX researchers working with omnichannel companies, given its positive impact for both users and firms. New methodological innovations now allow for the continuous measurement of user emotional and cognitive states when interacting with multiple devices through the use of psychophysiological instruments, thus permitting richer insights on this phenomenon. Five recommendations for the evaluation of multi-device UX with psychophysiological instruments sourced in practical experience are presented and discussed.

3.1 Introduction

Users nowadays have multiple fixed and mobile devices at their disposal to engage with brands, and customer journeys have become more distributed and convoluted as a result. In the US, the number of omnichannel shoppers is expected to increase to more than 70 million households by 2025 (Nielsen, 2020), and recent events such as the Covid-19 pandemic have intensified these trends. Improving the User Experience (UX) of omnichannel customer journeys has thus been a constant objective of many consumer-facing companies, and a main focus of research. Until recently however, UX researchers still lack a unified measurement procedure for this phenomenon.

3.2 The Path to Seamlessness

For omnichannel firms and customers, having a presence in all channels and devices is not nearly as important as the degree of integration of those channels. Research in the field of Human-Computer Interaction (HCI) has determined that channel integration can best be

[3] This article is intended for publication in: *User Experience Professionals Association (UXPA) Magazine*.

understood upon analysis of seamlessness (i.e., the perception of a continuous and consistent shopping journey across channels). In this definition, continuity refers to users' affordance to move interchangeably between channels, and consistency refers to the perception of equal information across channels (Cocco & Demoulin, 2022). Users experience a seamless purchasing journey when they move across all channels uninterrupted and can smoothly transition between all devices, never skipping a beat.

Firms are pursuing a higher degree of integration across channels because of the financial rewards within reach. Marketing research has shown that perceived seamlessness is positively associated with customer retention and sales growth (Cao & Li, 2015). User demand for a seamless experience across brand touchpoints is high, and the lack of channel integration heavily impacts their experience. The relationship between seamlessness and customer satisfaction has been confirmed by recent research as a crucial mediator of customer retention (Wang & Jiang, 2022). The focus of firms has thus shifted to crafting seamless experiences across a combination of channels in a holistic manner, so that value for customers is maximized.

Though the need for more integrated and seamless experiences is evident, and its benefits to both users and brands well-documented, an important question arises: How do you measure and assess such an intangible concept? Is there a clear-cut manner to know whether the new feature you are developing will impact your seamlessness? Unfortunately, no. There still isn't any standard on the measurement of seamlessness, and it seems that for the moment every UX researcher uses their own method. Recent theoretical and technological advances in the field of HCI might prove this wrong – and sooner than expected.

3.3 Methodological Innovations

As digital artifacts have evolved around us, so have the methodologies used in UX evaluations. The growing use of psychophysiological instruments (i.e., measures of automatic and unconscious physical responses towards stimuli) by HCI researchers has permitted deeper and expanded insights into users' lived experiences. For instance eye-trackers allow to analyze gaze behavior and cognitive load through meticulous observation of pupils, and facial expression recognition software discerns emotions thanks to large scale artificial neural networks. However, these instruments have so far been rarely applied to the study of multiple device interactions, because users' high degree of mobility across devices entails numerous technical challenges.

A new methodology developed at the Tech3Lab (Montréal, Canada) and which is currently under peer-review allows researchers to conduct UX experiments with psychophysiological instruments in cross-device interactions. This laboratory setup relies on duplicate data collection tools – one eye-tracker and webcam on every tested device – to measure emotion and cognitive load independently, and a dedicated synchronization software that stitches the experience together according to user transitions. Facial positioning data is used to detect, automatically and with a high degree of accuracy, user transitions across devices (Fernández-Shaw et al., 2023). Ultimately, this methodology produces a continuous measurement of UX in interactions with multiple devices, as can be appreciated in **Figure 5**.

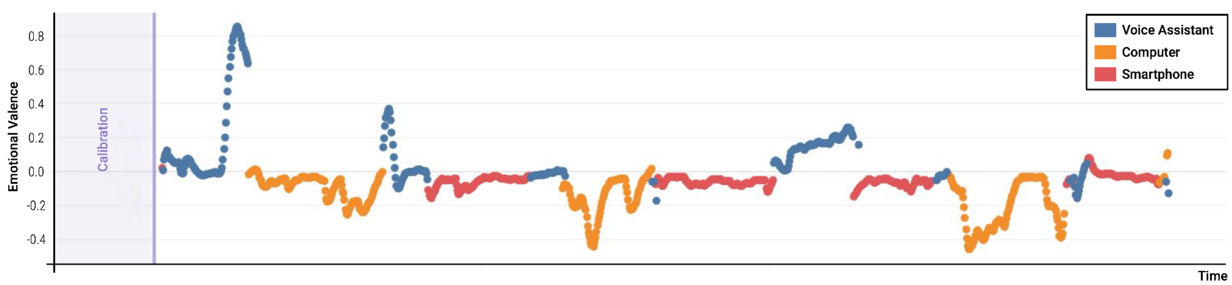

Figure 5. Evolution of emotional valence during an experiment across three devices.

Thanks to this novelty, UX researchers have in their toolbox a psychophysiological data collection methodology adapted to cross-device use, ready to be applied in a variety of empirical studies. Research into seamlessness may now employ continuous measurements of multi-device experiences to analyze with more granularity the antecedents, characteristics and outcomes of channel integration. The scope of analysis enlarges to comprise an entire ecosystem rather than independent devices, and researchers can gain a deeper understanding of users' emotional and cognitive responses in multi-device interactions.

3.4 Cross-device Evaluations

In UX Research, multiplying the number of devices being tested compounds the possibility of technical issues. Here are five hard-learned lessons about preparing and designing experiments involving the use of multiple devices, so that you can avoid common pitfalls.

- **Synchronization is the key.** When using duplicate and multi-modal data collection tools, whether psychophysiological or observational, the challenge radicates in synchronizing their output on a single timeline for a continued evaluation of the experience across devices. Researchers cannot rely on their ability to start all instruments at the exact same time, so it is recommended to have a computer act as "conductor" during the study by sending periodic signals to every other data collection tool. In the post-processing phase, these signals are used as anchors to consolidate all separate data.

- **Positioning the user.** In multi-device environments, users require a certain degree of mobility to complete tasks across devices. However certain data collection instruments – particularly eye-trackers – necessitate that users stay in specific positions to function properly. Restricting the user's range of movement, either through instructions or physical constraints, is therefore recommended to prevent possible data losses. To achieve this effect users could for instance be seated on a desk chair without wheels, thus allowing them to rotate around the vertical axis, without changing their location in the testing room.

- **Allow users to freely switch across devices.** Research suggests that transitioning to another device in the completion of a task is a behavior requiring a low level of awareness, thus making research into its cognitive process crucial (Dong et al., 2022). In experimental settings however, this means that users will frequently – and almost unconsciously – switch across devices. Rather than curbing users to follow a narrow path, multi-device experimental designs should measure and encourage this spontaneity. Task instructions should be broad in scope to let users evolve naturally across devices, and analysis metrics planned to comprise all device-task permutations.

- **Types of multi-device use.** Several patterns of cross-device use have been identified in recent research, and divided in two categories: sequential and simultaneous use (Jokela et al., 2015). In the former, devices are used independently of each other. In the latter however, several devices are used in concert with varying degrees of integration, from resource lending to multitasking. Certain tasks are more fitted to distinct behaviors, and users will choose according to perceived task-fit how to use multiple devices.

Experimental designs across devices can thus emulate one behavioral pattern at a time to constrain the user and limit technical hurdles.

- **Third-party channels.** Though UX researchers might be tempted to study brand ecosystems in isolation, on purpose-built prototypes they control, users generally employ multiple devices to interact with several digital services at once. While performing a task on a device, users might quickly switch to other devices for support functions (e.g., calendar management, information search). To maximize external validity and emulate real cross-device behavior in experimental settings, researchers should therefore design tasks involving commonly used third-party services and test their degree of integration with the tested artifact.

3.5 Conclusion

When studying seamlessness across several devices in experimental settings UX researchers face a constant trade-off between constraining users to strict paths or granting them the freedom to move naturally. Though methodological advances are made and we offer a series of advice on how to design multi-device UX evaluations, researchers still lack clear experimental cross-device procedures and rely on case-by-case measurements. As the need for studying interactions across devices and omnichannel experiences rises, so does the need for a unified and validated measurement instrument of seamlessness. Future academic and professional research should take on this task and set the foundation for deeper empirical research on this phenomenon.

References

Cao, L., & Li, L. (2015). The Impact of Cross-Channel Integration on Retailers' Sales Growth. *Journal of Retailing*, 91(2), 198–216. https://doi.org/10.1016/j.jretai.2014.12.005

Cocco, H., & Demoulin, N. T. M. (2022). Designing a seamless shopping journey through omnichannel retailer integration. *Journal of Business Research*, 150, 461–475. https://doi.org/10.1016/j.jbusres.2022.06.031

Dong, J., Duan, R., & Liang, S. (2022). Users' mental models of cross-device search under controlled and autonomous motivations. *Aslib Journal of Information Management*, 75(1), 68–89. https://doi.org/10.1108/AJIM-02-2022-0057

Fernández-Shaw, J., Léger, P.M., Courtemanche, F., Tazi, S., Côté, X., Chen, S.L., Coursaris, C., Pourchon, R. & Sénécal, S.(2023) Continuous recording of psychophysiological measures in omnichannel human-computer interactions: A validation study. [Manuscript submitted for publication]. HEC Montréal. – See *Chapter 1* of the present thesis.

Jokela, T., Ojala, J., & Olsson, T. (2015). A Diary Study on Combining Multiple Information Devices in Everyday Activities and Tasks. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 3903–3912. https://doi.org/10.1145/2702123.2702211

Nielsen. (2020, February 24). It's Time to Think Omnichannel Shopper, Not Just Omnichannel. NIQ. https://nielseniq.com/global/en/insights/analysis/2020/its-time-to-think-omnichannel-shopper-not-just-omnichannel/

Wang, J., & Jiang, X. (2022). The Impact of Omnichannel Shopping Experience and Channel Integration on Customer Retention: Empirical Evidence from China. *The Journal of Asian Finance, Economics and Business*, 9(2), 229–242. https://doi.org/10.13106/JAFEB.2022.VOL9.NO2.0229

CONCLUSION

This thesis had the following research objectives: (1) design a psychophysiological data collection methodology adapted to multi-device environments; and (2) explore emotional responses to multiple device use. Two laboratory user evaluations were realized, with 22 and 21 participants, respectively. First to validate the aims of the proposed methodology, automatic detection of used device and continuous measurement of emotional valence and cognitive load. Second to study emotional responses occurring during device transitions in omnichannel purchasing settings. The last section of this thesis will thus be dedicated to presenting the methodological challenges encountered as well as its main findings, before further opening up to the contributions and limitations of this research.

Methodological Challenges

Due to its methodological nature, this research faced and overcame several important technological challenges. On the hardware front, collecting psychophysiological data across devices through duplicate instruments on each device required careful technical planning of the setup and rigorous execution of the protocol. In total, the moderation room had four computers and five control displays, interconnected to guarantee data synchronization. All duplicated physiological data collection sensors were the same model to ensure data compatibility. Furthermore, participants had to be positioned in a special chair allowing them to rotate but not move to limit their movement and prevent data losses during the evaluation. Every data collection tool was calibrated individually for each participant to safeguard data continuity.

The proposed multi-device psychophysiological data collection methodology relied on the Device Detection Algorithm (DDA), a purpose-built software that had to be conceived and developed within the scope of this study. The DDA uses facial positioning data extracted from FaceReader 8.1 (Noldus Information Technology BV, Wageningen, Netherlands) to predict the device being used, and feeds the information into a data synchronization solution – Cobalt Photobooth (Léger et al., 2019) – to output a continuous measure across devices. Another important methodological challenge stemmed from the rarity of cross-device interfaces and stimuli upon which to experiment and study user behavior. In this research, the authors had to either create their own stimuli or use publicly available interfaces. The former is an extremely time-consuming endeavor, and the latter is outside the researcher's purview, and thus subject to change during the data collection process.

Main Findings

The results of the two articles that are presented in this thesis allow to answer the stated research questions. The results further permit to support or reject the stated hypothesis, and **Table 12** provides a complete summary of the main findings.

Hypothesis		Finding
Chapter 1: Methodological Article		
H1	DDA allows to capture an accurate and continuous measure of which device is being used in device switching omnichannel experiences.	Supported
H2	DDA allows to capture a continuous measurement of emotional valence in device switching omnichannel experiences.	Partially Supported
H3	DDA allows to capture a continuous measurement of cognitive load in device switching omnichannel experiences.	Supported
Chapter 2: Research Article		
H4	Transitions between devices in the context of device switching omnichannel tasks can have a significant effect on emotional valence.	Supported
H5	Transitions between devices in the context of device switching omnichannel tasks can have a significant effect on emotional arousal.	Supported

Table 10. Summary of main findings.

In the first article, the proposed multi-device psychophysiological data collection methodology was validated in almost all respects. First, DDA predictions of used device through head orientation data were demonstrated to be reliable and accurate for a majority of the time (H1), and its ability to unify data instruments was confirmed. The DDA was further shown to provide continuous measures of emotional valence for most cases, with transitions to the smartphone prompting further improvements (H2). Finally, the ability of the DDA to capture a continuous measure of cognitive load through pupillometry in multi-device environments was validated across all tested devices (H3).

In the second article, the results offer early evidence of a significant variation in emotional valence and arousal occurring during certain device transitions (H4 & H5). This variation in user emotional states can be both positive and negative, and factors that might influence such an emotional response are discussed.

Theoretical and Managerial Contributions

The main contribution of this research to the extant literature on device switching and cross-device experience is methodological, as researchers can now reliably make use of psychophysiological measures when experimenting with multi-device environments. Along with other recent methods for multiple device use evaluations, such as psychometric instruments and user testing procedures (Majrashi et al., 2020; Rahman et al., 2022), this study sets the foundation for further empirical studies of cross-device interactions. The granularity and continuity of measurements offered by this methodology will permit richer analysis of seamlessness and channel integration, given that implicit measures are better suited to measure behaviors requiring a low-level of awareness (de Guinea et al., 2014; Dong et al., 2022). The DDA will also facilitate the design, data extraction, and analysis of more fluid multi-device experiments by significantly reducing post-processing time through automation.

From a theoretical standpoint, this research contributes to the current body of knowledge through the discovery and introduction of an emotional response to certain device transitions. This provides a new avenue for research into the outcomes of cross-device behavior, and complements the previously identified increase in cognitive load during device transitions (Van Cauwenberge et al., 2014). Studying the emotional response is critical for researchers aiming to uncover the antecedents of device switching, and we reckon that perceived task-fit and task performance could be factors that explain emotional responses to transitions (Chen & Koufaris, 2020; Karlson et al., 2010).

For firms and the wider UX research community, this thesis contributes by making the evaluation of full brand ecosystems distributed across devices more available and easily replicable. The richer study of seamlessness and channel integration will be of great importance to customer satisfaction, retention, and ultimately sales growth (Cao & Li, 2015; Cocco & Demoulin, 2022; Wang & Jiang, 2022). The presence of an emotional response to certain transitions across devices further means that omnichannel integration efforts engaged by firms should now consider user affective states, as well as cognitive states. These two components are of particular importance in predicting purchase intention in omnichannel contexts, and should therefore be valuable endeavors for companies.

Limitations and Future Research

This research has several limitations, the most glaring of which is surely the relatively low number of participants involved in both laboratory experiments that were performed (22 and 21 respectively). All findings rely on this small sample of the population, and further studies of this phenomenon with more participants would reveal more insights. Moreover, some participant data had to be discarded due to technical issues with synchronization software. We reckon that future research using the proposed methodology would benefit from validating its accuracy with a small pre-experimental task and higher number of participants. This would thus ensure the replicability of the results presented in this research. Further, because the data was collected in a laboratory setting with participants in a seated position, the results and findings of the present thesis can not be generalized to authentic contexts.

As discussed in the methodological article, the proposed methodology did not fully validate all its hypotheses, and further technological improvements to the setup and measurement instruments could provide more continuous and precise measures. In order to measure emotional valence continuously across devices and capture the users' facial expression as seamlessly as possible, we reckon that the use of integrated cameras (e.g., the front camera of a smartphone) could provide better measures. The DDA could also be further improved through the use of user gaze behavior data from the eye-trackers which, combined with facial positioning data, could be a more reliable indicator of the device being used.

Another limitation affecting the research article is its inability to account for, and thus identify, any relevant factors impacting emotional responses as a result of device transitions. The design of seamless experiences could greatly benefit from this, and we reckon that further research should strive to obtain a better understanding of this phenomenon. Anything from task characteristics, degree of channel and device integration, or performance factors (e.g., success, time on task) could play a significant role in explaining emotional responses to transitions.

Moving forward, we believe that both the proposed methodology and literature on multiple device use could – and should – expand to border contexts and environments. The current body of literature on this phenomenon is centered on work and purchasing experiences, and the methodology described in this study simulates an office environment (i.e., all devices placed on a desk). Expanding the current limits of cross-device research to include more empirical studies on diverse environments – for instance entertainment, education, and industry – could deepen our current understanding; and we thus reckon that the proposed methodology should be further developed with additional devices, configurations and user setups to be validated and used in experiments.

Bibliography

Ariely, D. (1998). Combining experiences over time: The effects of duration, intensity changes and on-line measurements on retrospective pain evaluations. J. Behav. Decis. Mak., 11, 19–45. https://doi.org/10.1002/(SICI)1099-0771(199803)11:1<19::AID-BDM277>3.0.CO;2-B

Bailey, B. P., & Konstan, J. A. (2006). On the need for attention-aware systems: Measuring effects of interruption on task performance, error rate, and affective state. Computers in Human Behavior, 22(4), 685–708. https://doi.org/10.1016/j.chb.2005.12.009

Baxendale, S., Macdonald, E. K., & Wilson, H. N. (2015). The Impact of Different Touchpoints on Brand Consideration. Journal of Retailing, 91(2), 235–253. https://doi.org/10.1016/j.jretai.2014.12.008

Benedek, M., & Kaernbach, C. (2010). A continuous measure of phasic electrodermal activity. Journal of Neuroscience Methods, 190(1–5), 80–91. https://doi.org/10.1016/j.jneumeth.2010.04.028

Brudy, F., Holz, C., Rädle, R., Wu, C.-J., Houben, S., Klokmose, C. N., & Marquardt, N. (2019). Cross-Device Taxonomy: Survey, Opportunities and Challenges of Interactions Spanning Across Multiple Devices. Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, 1–28. https://doi.org/10.1145/3290605.3300792

Cao, L., & Li, L. (2015). The Impact of Cross-Channel Integration on Retailers' Sales Growth. Journal of Retailing, 91(2), 198–216. https://doi.org/10.1016/j.jretai.2014.12.005

Carroll, D., & Guzmán, I. (2013). The New Omni-Channel Approach to Serving Customers. Accenture. https://www.scribd.com/document/354676791/Accenture-New-Omni-Channel-Approach-Serving-Customers

Chang, A., Ming Li, J., & Singh, T. (2017). System and method for seamlessly transitioning device-based interaction (Patent No. AU2014357376B2). https://patents.google.com/patent/AU2014357376B2/en

Chang, Y. P., & Li, J. (2022). Seamless experience in the context of omnichannel shopping: Scale development and empirical validation. Journal of Retailing and Consumer Services, 64, 102800. https://doi.org/10.1016/j.jretconser.2021.102800

Chen, C.-W., & Koufaris, M. (2020). Multi-Device Use: Understanding the Motivations behind Switching between Multiple Devices during a Task. International Journal of Human–Computer Interaction, 36(12), 1178–1193. https://doi.org/10.1080/10447318.2020.1726106

Chin, E., Felt, A. P., Sekar, V., & Wagner, D. (2012). Measuring user confidence in smartphone security and privacy. Proceedings of the Eighth Symposium on Usable Privacy and Security, 1–16. https://doi.org/10.1145/2335356.2335358

Cocco, H., & De-Juan-Vigaray, M. D. (2022). A typology of omnichannel retailer activities during the COVID-19 pandemic. International Journal of Retail & Distribution Management, 50(8/9), 1062–1094. https://doi.org/10.1108/IJRDM-10-2021-0506

Cocco, H., & Demoulin, N. T. M. (2022). Designing a seamless shopping journey through omnichannel retailer integration. Journal of Business Research, 150, 461–475. https://doi.org/10.1016/j.jbusres.2022.06.031

Courtemanche, F., Léger, P.-M., Dufresne, A., Fredette, M., Labonté-LeMoyne, É., & Sénécal, S. (2018). Physiological heatmaps: A tool for visualizing users' emotional reactions. Multimedia Tools and Applications, 77(9), 11547–11574. https://doi.org/10.1007/s11042-017-5091-1

Cuvillier, M., Léger, P.-M., & Sénécal, S. (2021). Quantity over quality: Do single-item scales reflect what users truly experienced? Computers in Human Behavior Reports, 4, 100097. https://doi.org/10.1016/j.chbr.2021.100097

de Guinea, A. O., Titah, R., & Léger, P.-M. (2014). Explicit and Implicit Antecedents of Users' Behavioral Beliefs in Information Systems: A Neuropsychological Investigation. J. Manag. Inf. Syst., 30(4), 179–210. https://doi.org/10.2753/MIS0742-1222300407

de Guinea, A. O., Titah, R., Leger, P.-M., & Micheneau, T. (2012). Neurophysiological Correlates of Information Systems Commonly Used Self-Reported Measures: A Multitrait Multimethod Study. 2012 45th Hawaii International Conference on System Sciences, 562–571. https://doi.org/10.1109/HICSS.2012.448

de Haan, E., Kannan, P. K., Verhoef, P. C., & Wiesel, T. (2018). Device Switching in Online Purchasing: Examining the Strategic Contingencies. Journal of Marketing, 82(5), 1–19. https://doi.org/10.1509/jm.17.0113

Desolda, G., Ardito, C., Jetter, H.-C., & Lanzilotti, R. (2019). Exploring spatially-aware cross-device interaction techniques for mobile collaborative sensemaking. International Journal of Human-Computer Studies, 122, 1–20. https://doi.org/10.1016/j.ijhcs.2018.08.006

Dong, J., Duan, R., & Liang, S. (2022). Users' mental models of cross-device search under controlled and autonomous motivations. Aslib Journal of Information Management, 75(1), 68–89. https://doi.org/10.1108/AJIM-02-2022-0057

Duso, T., & Schiersch, A. (2022). Let's Switch to the Cloud: Cloud Adaption and Its Effect on IT Investment and Productivity (SSRN Scholarly Paper No. 4221050). https://doi.org/10.2139/ssrn.4221050

Fernández-Shaw, J., Léger, P.M., Courtemanche, F., Tazi, S., Côté, X., Chen, S.L., Coursaris, C., Pourchon, R. & Sénécal, S.(2023) Continuous recording of psychophysiological measures in omnichannel human-computer interactions: A validation study. [Manuscript submitted for publication]. HEC Montréal. – See *Chapter 1* of the present thesis.

Fontaine, J. J. R., Scherer, K. R., & Soriano, C. (2013). Components of emotional meaning: A sourcebook. OUP Oxford.

Frasquet-Deltoro, M., Molla-Descals, A., & Miquel-Romero, M.-J. (2021). Omnichannel retailer brand experience: Conceptualisation and proposal of a comprehensive scale. Journal of Brand Management, 28(4), 388–401. https://doi.org/10.1057/s41262-021-00233-x

Gahler, M., Klein, J. F., & Paul, M. (2022). Customer Experience: Conceptualization, Measurement, and Application in Omnichannel Environments. Journal of Service Research, 26(2), 155–299. https://doi.org/10.1177/10946705221126590

Ganglbauer, E., Schrammel, J., Deutsch, S., & Tscheligi, M. (2009). Applying Psychophysiological Methods for Measuring User Experience: Possibilities, Challenges and Feasibility. Workshop on User Experience Evaluation Methods in Product Development, 4.

Ginns, P., & Leppink, J. (2019). Special Issue on Cognitive Load Theory: Editorial. Educational Psychology Review, 31(2), 255–259. https://doi.org/10.1007/s10648-019-09474-4

Giroux-Huppé, C., Sénécal, S., Fredette, M., Chen, S. L., Demolin, B., & Léger, P.-M. (2019). Identifying Psychophysiological Pain Points in the Online User Journey: The Case of Online Grocery. In A. Marcus & W. Wang (Eds.), Design, User Experience, and Usability. Practice and Case Studies (pp. 459–473). Springer International Publishing. https://doi.org/10.1007/978-3-030-23535-2_34

Google. (2012). The New Multi-screen World: Understanding Cross-platform Consumer Behavior. Google. https://www.thinkwithgoogle.com/_qs/documents/681/the-new-multi-screen-world-study_research-studies.pdf

Grewal, D., & Roggeveen, A. L. (2020). Understanding Retail Experiences and Customer Journey Management. Journal of Retailing, 96(1), 3–8. https://doi.org/10.1016/j.jretai.2020.02.002

Grudin, J. (2001). Partitioning digital worlds: Focal and peripheral awareness in multiple monitor use. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 458–465. https://doi.org/10.1145/365024.365312

Hamilton, P., & Wigdor, D. J. (2014). Conductor: Enabling and understanding cross-device interaction. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 2773–2782. https://doi.org/10.1145/2556288.2557170

Han, S., Han, J. K., Im, I., Jung, S. I., & Lee, J. W. (2022). Mapping consumer's cross-device usage for online search: Mobile- vs. PC-based search in the purchase decision process. Journal of Business Research, 142, 387–399. https://doi.org/10.1016/j.jbusres.2021.12.051

Horvitz, E., Iqbal, S. T., & Karlson, A. K. (2012). Methods for supporting users with task continuity and completion across devices and time (United States Patent No. US20120011511A1). https://patents.google.com/patent/US20120011511A1/en

Huré, E., Picot-Coupey, K., & Ackermann, C.-L. (2017). Understanding omni-channel shopping value: A mixed-method study. Journal of Retailing and Consumer Services, 39, 314–330. https://doi.org/10.1016/j.jretconser.2017.08.011

Jain, R., Aagja, J., & Bagdare, S. (2017). Customer experience – a review and research agenda. Journal of Service Theory and Practice, 27(3), 642–662. https://doi.org/10.1108/JSTP-03-2015-0064

Jerčić, P., Sennersten, C., & Lindley, C. (2020). Modeling cognitive load and physiological arousal through pupil diameter and heart rate. Multimedia Tools and Applications, 79(5), 3145–3159. https://doi.org/10.1007/s11042-018-6518-z

Jo, D. H., & Lee, S. M. (2019). Understanding the Omni-Channel Acceptance: Focused on TTF and UTAUT Models. Journal of Internet Computing and Services, 20(1), 113–124. https://doi.org/10.7472/JKSII.2019.20.1.113

Jokela, T., Ojala, J., & Olsson, T. (2015). A Diary Study on Combining Multiple Information Devices in Everyday Activities and Tasks. Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, 3903–3912. https://doi.org/10.1145/2702123.2702211

Kaatz, C., Brock, C., & Figura, L. (2019). Are you still online or are you already mobile? – Predicting the path to successful conversions across different devices. Journal of Retailing and Consumer Services, 50, 10–21. https://doi.org/10.1016/j.jretconser.2019.04.005

Karlson, A. K., Iqbal, S. T., Meyers, B., Ramos, G., Lee, K., & Tang, J. C. (2010). Mobile taskflow in context: A screenshot study of smartphone usage. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 2009–2018. https://doi.org/10.1145/1753326.1753631

Kim, J., Cho, C., & Lee, U. (2017). Technology Supported Behavior Restriction for Mitigating Self-Interruptions in Multi-device Environments. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 1(3), 1–21. https://doi.org/10.1145/3130932

Labonte-LeMoyne, E., Cameron, A.-F., Sénécal, S., Fredette, M., Faubert, J., Lepore, F., & Léger, P.-M. (2022). What's that on Your Phone? Effects of Mobile Device Task Type on Pedestrian Performance. Human Factors, 00187208221141175. https://doi.org/10.1177/00187208221141175

Laeng, B., Sirois, S., & Gredebäck, G. (2012). Pupillometry: A Window to the Preconscious? Perspectives on Psychological Science, 7(1), 18–27. https://doi.org/10.1177/1745691611427305

Langer, T., Sarin, R., & Weber, M. (2005). The retrospective evaluation of payment sequences: Duration neglect and peak-and-end effects. J. Econ. Behav. Organ., 58(1), 157–175. https://doi.org/10.1016/j.jebo.2004.01.001

Lascau, L., Wong, P. N. Y., Brumby, D. P., & Cox, A. L. (2019). Why Are Cross-Device Interactions Important When It Comes To Digital Wellbeing?

Lazaris, C., & Vrechopoulos, A. (2014). From Multichannel to "Omnichannel" Retailing: Review of the Literature and Calls for Research. 2nd International Conference on Contemporary Marketing Issues,(ICCMI), 6, 1–6. https://doi.org/10.13140/2.1.1802.4967

Léger, P.-M., Courtemanche, F., Fredette, M., & Sénécal, S. (2019). A Cloud-Based Lab Management and Analytics Software for Triangulated Human-Centered Research. In F. D. Davis, R. Riedl, J. vom Brocke, P.-M. Léger, & A. B. Randolph (Eds.), Information Systems and Neuroscience (pp. 93–99). Springer International Publishing. https://doi.org/10.1007/978-3-030-01087-4_11

Lemon, K. N., & Verhoef, P. C. (2016). Understanding Customer Experience Throughout the Customer Journey. Journal of Marketing, 80(6), 69–96. https://doi.org/10.1509/jm.15.0420

Lewinski, P., den Uyl, T. M., & Butler, C. (2014). Automated facial coding: Validation of basic emotions and FACS AUs in FaceReader. Journal of Neuroscience, Psychology, and Economics, 7, 227–236. https://doi.org/10.1037/npe0000028

Liu, X., Zhang, Y., Yan, Z., & Ge, Y. (2023). Defining 'seamlessly connected': User perceptions of operation latency in cross-device interaction. International Journal of Human-Computer Studies, 177, 103068. https://doi.org/10.1016/j.ijhcs.2023.103068

Loijens, L., & Krips, O. (2021). FaceReader Methodology Note. Noldus Information Technology BV. https://info.noldus.com/hubfs/resources/noldus-white-paper-facereader-methodology.pdf

Macdonald, E. K., Wilson, H. N., & Konuş, U. (2012, September 1). Better Customer Insight—In Real Time. Harvard Business Review. https://hbr.org/2012/09/better-customer-insight-in-real-time

MacKenzie, S. B. (2003). The dangers of poor construct conceptualization. Journal of the Academy of Marketing Science, 31(3), 323–326. https://doi.org/10.1177/0092070303031003011

Maia, C. L. B., & Furtado, E. S. (2016). A study about psychophysiological measures in user experience monitoring and evaluation. Proceedings of the 15th Brazilian Symposium on Human Factors in Computing Systems, 1–9. https://doi.org/10.1145/3033701.3033708

Majrashi, K. (2019). Post-transitioning user performance on cross-device menu interfaces. International Journal of Human-Computer Studies, 130, 130–151. https://doi.org/10.1016/j.ijhcs.2019.06.001

Majrashi, K., Hamilton, M., & Uitdenbogerd, A. (2018a). Evaluating Cross-Device Transitioning Experience in Seated and Moving Contexts.

Majrashi, K., Hamilton, M., & Uitdenbogerd, A. L. (2018b). Task Continuity and Mobile User Interfaces. Proceedings of the 17th International Conference on Mobile and Ubiquitous Multimedia, 475–481. https://doi.org/10.1145/3282894.3289742

Majrashi, K., Hamilton, M., Uitdenbogerd, A. L., & Al-Megren, S. (2020). Cross-Platform Usability Model Evaluation. Multimodal Technologies and Interaction, 4(4), Article 4. https://doi.org/10.3390/mti4040080

Majrashi, K., Hamilton, M., Uitdenbogerd, A., & Al-Megren, S. (2021, May 9). Cross-Device User Interactive Behavioural Patterns. CHI 2021 Workshop on User Experience for Multi-Device Ecosystems: Challenges and Opportunities. https://doi.org/10.1145/1122445.1122456

Mencarelli, R., Rivière, A., & Lombart, C. (2021). Do myriad e-channels always create value for customers? A dynamic analysis of the perceived value of a digital information product during the usage phase. Journal of Retailing and Consumer Services, 63, 102674. https://doi.org/10.1016/j.jretconser.2021.102674

Meyer, C., & Schwager, A. (2007, February). Understanding customer experience. Harvard Business Review, 85(2), 116–126, 157.

Microsoft Advertising. (2013). Cross Screen Engagement: Multi-screen Pathways Reveal New Opportunities for Marketers to Reach and Engage Customers (Connected Experiences). Microsoft.

https://www.coursehero.com/file/42587494/Microsoft-Advertising-Insights-Cross-Screen-Engagement-White-Paperpdf/

Miller, E. K., & Wallis, J. D. (2009). Executive Function and Higher-Order Cognition: Definition and Neural Substrates. In Encyclopedia of Neuroscience (pp. 99–104). Elsevier. https://doi.org/10.1016/B978-008045046-9.00418-6

Monge Roffarello, A., & De Russis, L. (2021). Coping with Digital Wellbeing in a Multi-Device World. Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems, 1–14. https://doi.org/10.1145/3411764.3445076

N. Bolton, R., Gustafsson, A., McColl-Kennedy, J., J. Sirianni, N., & K. Tse, D. (2014). Small details that make big differences: A radical approach to consumption experience as a firm's differentiating strategy. Journal of Service Management, 25(2), 253–274. https://doi.org/10.1108/JOSM-01-2014-0034

Neslin, S. A. (2022). The omnichannel continuum: Integrating online and offline channels along the customer journey. Journal of Retailing, 98(1), 111–132. https://doi.org/10.1016/j.jretai.2022.02.003

Nielsen. (2020, February 24). It's Time to Think Omnichannel Shopper, Not Just Omnichannel. NIQ. https://nielseniq.com/global/en/insights/analysis/2020/its-time-to-think-omnichannel-shopper-not-just-omnichannel/

Noldus. (2018). FaceReader Reference Manual. Noldus Information Technology.

Optimizely. (2021, November 18). Digital Experience Elements that Are Most Important to Internet Users Worldwide, Aug 2021 [Graph]. Insider Intelligence. https://www.emarketer.com/chart/252645/digital-experience-elements-that-most-important-internet-users-worldwide-aug-2021-of-respondents

Oulasvirta, A., & Sumari, L. (2007). Mobile kits and laptop trays: Managing multiple devices in mobile information work. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 1127–1136. https://doi.org/10.1145/1240624.1240795

Pew Research Center. (2021). Mobile Fact Sheet. Pew Research Center: Internet, Science & Tech. https://www.pewresearch.org/internet/fact-sheet/mobile/

Piotrowicz, W., & Cuthbertson, R. (2014). Introduction to the Special Issue Information Technology in Retail: Toward Omnichannel Retailing. International Journal of Electronic Commerce, 18(4), 5–16. https://doi.org/10.2753/JEC1086-4415180400

Plass, J. L., & Kalyuga, S. (2019). Four Ways of Considering Emotion in Cognitive Load Theory. Educational Psychology Review, 31(2), 339–359. https://doi.org/10.1007/s10648-019-09473-5

Posner, J., Russell, J. A., & Peterson, B. S. (2005). The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. Development and Psychopathology, 17(3), 715–734. https://doi.org/10.1017/S0954579405050340

Pyla, P. S., Tungare, M., & Pérez-Quiñones, M. A. (2006). Multiple User Interfaces: Why Consistency is Not Everything, and Seamless Task Migration is Key. Proceedings of the CHI 2006 Workshop on the Many Faces of Consistency in Cross-Platform Design.

Pymnts. (2022, July). Average Number of Connected Devices Owned in Selected Markets as of January 2022 [Graph]. Statista. https://www.statista.com/statistics/1345616/connected-devices-owned/

Rädle, R., Jetter, H.-C., Schreiner, M., Lu, Z., Reiterer, H., & Rogers, Y. (2015). Spatially-aware or Spatially-agnostic? Elicitation and Evaluation of User-Defined Cross-Device Interactions. Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, 3913–3922. https://doi.org/10.1145/2702123.2702287

Rahman, S. M., Carlson, J., Gudergan, S. P., Wetzels, M., & Grewal, D. (2022). Perceived Omnichannel Customer Experience (OCX): Concept, measurement, and impact. Journal of Retailing, 98(4), 611–632. https://doi.org/10.1016/j.jretai.2022.03.003

Rahmawati, R. A. (2022). New Journey Through Young Customer Experience in Omnichannel Context: The Role of Personalization. Journal of Theoretical and Applied Management, 15(2), 301–311. https://doi.org/10.20473/jmtt.v15i2.36236

Redelmeier, D. A., & Kahneman, D. (1996). Patients' memories of painful medical treatments: Real-time and retrospective evaluations of two minimally invasive procedures. Pain, 66(1), 3–8. https://doi.org/10.1016/0304-3959(96)02994-6

Riedl, R., & Léger, P.-M. (2016). Fundamentals of NeuroIS: Information Systems and the Brain. Springer. https://doi.org/10.1007/978-3-662-45091-8

Rigby, J. M., Brumby, D. P., Gould, S. J. J., & Cox, A. L. (2018). "I Can Watch What I Want": A Diary Study of On-Demand and Cross-Device Viewing. Proceedings of the 2018 ACM International Conference on Interactive Experiences for TV and Online Video, 69–80. https://doi.org/10.1145/3210825.3210832

Rodríguez-Torrico, P., Trabold Apadula, L., San-Martín, S., & San José Cabezudo, R. (2020). Have an omnichannel seamless interaction experience! Dimensions and effect on consumer satisfaction. Journal of Marketing Management, 36(17–18), 1731–1761. https://doi.org/10.1080/0267257X.2020.1801798

Roy, A., Sénécal, S., Léger, P.-M., Demolin, B., Bigras, É., & Gagne, J. (2020). Measuring Users' Psychophysiological Experience in Non-linear Omnichannel Environment. In C. Stephanidis, A. Marcus, E. Rosenzweig, P.-L. P. Rau, A. Moallem, & M. Rauterberg (Eds.), HCI International 2020—Late Breaking Papers: User Experience Design and Case Studies (pp. 762–779). Springer International Publishing. https://doi.org/10.1007/978-3-030-60114-0_50

Russell, J. A. (1980). A circumplex model of affect. Journal of Personality and Social Psychology, 39, 1161–1178. https://doi.org/10.1037/h0077714

Santosa, S., & Wigdor, D. (2013). A field study of multi-device workflows in distributed workspaces. Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing, 63–72. https://doi.org/10.1145/2493432.2493476

Shen, X.-L., Li, Y.-J., Sun, Y., & Wang, N. (2018). Channel integration quality, perceived fluency and omnichannel service usage: The moderating roles of internal and external usage experience. Decision Support Systems, 109, 61–73. https://doi.org/10.1016/j.dss.2018.01.006

Singh, J., Goyal, G., & Gill, R. (2020). Use of neurometrics to choose optimal advertisement method for omnichannel business. Enterprise Information Systems, 14(2), 243–265. https://doi.org/10.1080/17517575.2019.1640392

Tams, S., Hill, K., Guinea, A. O. de, Thatcher, J., & Grover, V. (2014). NeuroIS—Alternative or Complement to Existing Methods? Illustrating the Holistic Effects of Neuroscience and Self-Reported Data in the Context of Technostress Research. Journal of the Association for Information Systems, 15(10). https://doi.org/10.17705/1jais.00374

The Northridge Group. (2022, January 21). Communication Channels Easy to Use in Customer Service in the U.S. from 2019 to 2020 [Graph]. Statista. https://www.statista.com/statistics/816704/communication-channels-easy-to-use-with-customer-service-united-states/

Tobii. (2022, May 9). Measuring Pupil Size. Tobii AB. https://connect.tobii.com/s/article/measuring-pupil-size

Van Cauwenberge, A., Schaap, G., & Van Roy, R. (2014). "TV no longer commands our full attention": Effects of second-screen viewing and task relevance on cognitive load and learning from news. Computers in Human Behavior, 38, 100–109. https://doi.org/10.1016/j.chb.2014.05.021

Van Nguyen, A. T., Halibas, A. S., McClelland, R., & Thuan, N. H. (2023). Configurational analysis of conditions influencing customers' channel switching intention in omnichannel retailing: A fuzzy-set analysis. Quality & Quantity. https://doi.org/10.1007/s11135-023-01633-8

Van Nguyen, A. T., McClelland, R., & Thuan, N. H. (2022). Exploring customer experience during channel switching in omnichannel retailing context: A qualitative assessment. Journal of Retailing and Consumer Services, 64, 102803. https://doi.org/10.1016/j.jretconser.2021.102803

Vanneste, P., Raes, A., Morton, J., Bombeke, K., Van Acker, B. B., Larmuseau, C., Depaepe, F., & Van den Noortgate, W. (2021). Towards measuring cognitive load through multimodal physiological data. Cogn. Technol. Work, 23(3), 567–585. https://doi.org/10.1007/s10111-020-00641-0

Verhoef, P. C. (2021). Omni-channel retailing: Some reflections. Journal of Strategic Marketing, 29(7), 608–616. https://doi.org/10.1080/0965254X.2021.1892163

Verhoef, P. C., Kannan, P. K., & Inman, J. J. (2015). From Multi-Channel Retailing to Omni-Channel Retailing. Journal of Retailing, 91(2), 174–181. https://doi.org/10.1016/j.jretai.2015.02.005

Verhoef, P. C., Lemon, K. N., Parasuraman, A., Roggeveen, A., Tsiros, M., & Schlesinger, L. A. (2009). Customer Experience Creation: Determinants, Dynamics and Management Strategies. Journal of Retailing, 85(1), 31–41. https://doi.org/10.1016/j.jretai.2008.11.001

Verhoef, P. C., Neslin, S. A., & Vroomen, B. (2007). Multichannel customer management: Understanding the research-shopper phenomenon. International Journal of Research in Marketing, 24(2), 129–148. https://doi.org/10.1016/j.ijresmar.2006.11.002

Vyrros, A. H., Shepherd, M. E., Edwards, D. R., Wood, J., Pollack, D. B., de Filippis, P., Drummond, J., Santamaria, J., & Novick, G. (2016). Managing notifications across multiple devices (United States Patent No. US9288164B2). https://patents.google.com/patent/US9288164B2/en

Wäljas, M., Segerståhl, K., Väänänen-Vainio-Mattila, K., & Oinas-Kukkonen, H. (2010). Cross-platform service user experience: A field study and an initial framework. Proceedings of the 12th International Conference on Human Computer Interaction with Mobile Devices and Services, 219–228. https://doi.org/10.1145/1851600.1851637

Wang, J., & Jiang, X. (2022). The Impact of Omnichannel Shopping Experience and Channel Integration on Customer Retention: Empirical Evidence from China. The Journal of Asian Finance, Economics and Business, 9(2), 229–242. https://doi.org/10.13106/JAFEB.2022.VOL9.NO2.0229

Wang, R. J.-H., Malthouse, E. C., & Krishnamurthi, L. (2015). On the Go: How Mobile Shopping Affects Customer Purchase Behavior. Journal of Retailing, 91(2), 217–234. https://doi.org/10.1016/j.jretai.2015.01.002

Wang, Z., Zhou, X., Wang, W., & Liang, C. (2020). Emotion recognition using multimodal deep learning in multiple psychophysiological signals and video. Int. J. Mach. Learn. Cybern., 11(4), 923–934. https://doi.org/10.1007/s13042-019-01056-8

Wickens, C. D. (2008). Multiple Resources and Mental Workload. Human Factors: The Journal of the Human Factors and Ergonomics Society, 50(3), 449–455. https://doi.org/10.1518/001872008X288394

Wong, J., Scheibenreif, D., & Phifer, G. (2021, June 28). Transcend Omnichannel Thinking and Embrace Multiexperience for Improved Customer Experience. Gartner. https://www.gartner.com/en

Wu, D., Dong, J., & Liu, C. (2019). Exploratory study of cross-device search tasks. Information Processing & Management, 56(6), 102073. https://doi.org/10.1016/j.ipm.2019.102073

Wu, D., Dong, J., Tang, Y., & Capra, R. (2020). Understanding task preparation and resumption behaviors in cross‐device search. Journal of the Association for Information Science and Technology, 71(8), 887–901. https://doi.org/10.1002/asi.24307

Xu, K., Chan, J., Ghose, A., & Han, S. P. (2017). Battle of the Channels: The Impact of Tablets on Digital Commerce. Management Science, 63(5), 1469–1492. https://doi.org/10.1287/mnsc.2015.2406

Zhang, R., Shi, Y., Schuller, B., André, E., Oviatt, S., Quigley, A., Marquardt, N., Aslan, I., & Ju, R. (2021). User Experience for Multi-Device Ecosystems: Challenges and Opportunities. Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems, 1–5. https://doi.org/10.1145/3411763.3441325

Zimmerman, P., Bolhuis, L., Willemsen, A., Meyer, E., & Noldus, L. (2008). The Observer XT: A tool for the integration and synchronization of multimodal signals. Behavior Research Methods, 41, 731–735. https://doi.org/10.3758/BRM.41.3.731

Appendices

Appendix 1. Regression model goodness-of-fit statistics of transition on valence.

Statistic	Value[1]
N	148
F (7, 19)	3.39
p-value	**0.0160 ****
R2	0.0646
R2 (Adjusted)	0.0179
Root MSE	0.1527

[1] Level of Significance: *p ≤ 0.10; **p ≤ 0.05.

Appendix 2. Regression model goodness-of-fit statistics of transition on arousal.

Statistic	Value[1]
N	131
F (7, 19)	2.82
p-value	**0.0363 ****
R2	0.1222
R2 (Adjusted)	0.0722
Root MSE	0.3969

[1] Level of Significance: *p ≤ 0.10; **p ≤ 0.05.