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# Exploring the Impact of Gestural Interaction Technologies on the Experience: A Marketing and HCI Perspective

**Quentin SELLIER**

**Doctoral dissertation** 09 | 2023

**Université catholique de Louvain**
LOUVAIN RESEARCH INSTITUTE IN MANAGEMENT AND ORGANIZATIONS

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**Quentin SELLIER**

Doctoral dissertation submitted for the degree
of Doctor in Economics and Management Sciences

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Doctoral Thesis

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# Abstract

It is now essential for businesses to provide the best experience to their customers to ensure their competitiveness. As a result, technologies are continuously evolving to offer more immersive, rich, and comprehensive experiences. Notably, some of these technologies, originally rooted in the realm of video games known for their captivating immersion, have found new applications in e-commerce and are poised to play a significant role in the future metaverse. Among these technologies is gestural interaction, which leverages meaningful human body movements to control computer-based information systems.

However, from a marketing perspective, the impact of gestural interaction on the consumer experience remains largely unexplored. A deeper understanding of this relationship could empower practitioners to effectively integrate gestural interaction technology and identify crucial considerations during its development and implementation. Moreover, from a human-computer interaction perspective, there is a pressing need to establish comprehensive methods for evaluating the user experience associated with gestural interaction technologies.

Therefore, this doctoral thesis addresses three principal objectives. Firstly, it delves into the notion of experience and its various facets as presented in different literatures. Secondly, it investigates the application of gestural interaction technologies in the context of consumption to evaluate its effects on the overall consumer experience. Lastly, the thesis proposes and defines a model and method for assessing the holistic quality of experience when employing gestural interaction technologies.

② Acknowledgments

I am deeply grateful to everyone who has played a crucial role in supporting me throughout my doctoral journey. Without their encouragement, guidance, and kindness, this research project would not have been possible. I extend my heartfelt appreciation to my supervisors, Prof. Ingrid Poncin and Prof. Jean Vanderdonckt, for their trust in me and my research. Their support and valuable advice have been essential in this thesis. Their expertise has been a driving force behind this research, and I feel privileged to have had the opportunity to collaborate with them.

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I would like to acknowledge and thank my colleagues from the CCMS research center, the HCI team, and the Louvain Research Institute in Management and Organizations. The academic exchange has been enlightening, and I am appreciative of all the feedbacks I received during our interactions. I am especially grateful to the administrative staff for their efforts in facilitating these events and ensuring a conducive environment for research. I would also like to thank the Social Media Lab for allowing me to carry out several experiments and for all their help. Finally, I am grateful for having benefited from the FSR research grants (ref ARH/LJB/01137236), as well as for participating in the European project Symbiotik.

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In closing, I want to acknowledge everyone who has contributed to my growth as a researcher and as an individual. I would especially like to thank my family and friends. Your support and encouragement have been indispensable, and I am deeply grateful for the privilege of having such wonderful mentors, colleagues, and friends by my side. Thank you all for being a part of this incredible journey.

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# General Introduction

## 1. Research context

It is now essential for businesses to provide the best experience to their customers to ensure their competitiveness (Pine & Gilmore, 1998; Verhoef et al., 2009; Lemon & Verhoef, 2016). According to Salesforce, 80% of customers consider the overall experience as a crucial factor in selecting a brand over its competitors. Additionally, an overwhelming 67% of customers express that their expectations for a positive experience have reached new heights. Expectations in terms of experience are therefore enormous and are growing day by day.

In this goal to always offer the best experience, technologies are constantly evolving to provide more and more immersive, rich and complete experiences. Some of these technologies originally come from the world of video games and are known for their immersive capacity. Many of them have gone beyond their initial framework to be now used in the context of consumption, or even in the future metaverse.

One of these trending technologies is the gestural interaction (Daugherty et al., 2015). This consists of the interaction between an individual, producing movements with any part of the body, and a computer system, capable of interpreting those movements. This topic is particularly interesting as gestural interaction is considered intuitive and natural because it is based on the gestural communication that humans acquire naturally (Baudel & Beaudouin-Lafon, 1993). Yet, while this technology is promising (Vanderdonckt & Vatavu, 2018), we still don't know the impact on the experience. Moreover, it has already been studied in some fields, for example of video games, but not yet in the context of consumption. It is particularly important as we should consider emotional and cognitive aspect of the consumption experience. Understanding this would enable marketers to integrate this type of technology efficiently, with the objective of providing a more complete and richer consumer experience.

*The consumer and customer experience*

The notion of experience has gained in popularity in human-computer interaction and even became a buzzword employed by practitioners and researchers alike (Hassenzahl & Tractinsky, 2006). A product should no longer be seen as an object offering various functionalities and benefits but rather an experience (Hassenzahl et al., 2003). This also applies to marketing where this notion has gained popularity since its apparition 40 years ago (Holbrook & Hirschman, 1982).

The consumer experience appeared in the 80$^{th}$ with the emergence of the consumer research as a new discipline. In the latter, consumers began to be seen as non-rational beings and researchers started to consider the emotional aspect in the relationship between an individual and a company. This later resulted in the apparition of experiential marketing and, today, different research streams exist, some preferring to use the term of "customer experience" and others the "consumer experience". The major authors for the consumer experience are Holbrook and Hirschman who, in 1982, developed the consumption experience. They then carried out several works specifying this postulate (Holbrook, 2006).

We can describe the consumer experience as directed toward the pursuit of fantasies, affect, and fun (Holbrook & Hirschman, 1982). It depends on the object with which we are interacting, the preferences of the consumer, and the situation in which this interaction occurs. It has the particularity of focusing more on the personal meanings of the consumption experience and tends to be studied in naturalistic settings. It is also very common to study its antecedents and outcomes (Antéblian et al., 2013). We are here in an approach of understanding the consumer as an individual who is not necessarily a rational, information-driven, utility-maximizing decision makers.

This concept is often assimilated to the customer experience, with which it shares the same origin of the consumption experience of Holbrook and Hirschman (1982). However, the specific term "customer experience" was first introduced in 1998 by Pine and Gilmore. A popular definition of the customer experience is the one from Lemon and Verhoef (2016), developing that it is the totality of a person's responses from every interaction with a company during the customer journey. It is considered an essential marketing tool to handle to ensure the competitiveness of a company (McGall, 2015). It is now accepted that the customer experience and consumer experience are subjective and context-specific (Becker & Jaakkola, 2020). Although the customer experience is traditionally related to service marketing, it is now starting to be used in human-computer interaction (Rusu et al., 2018).

*The usability and user experience*

In order to evaluate user interfaces, the usability has been and still is one of the most popular indicators used by researchers and practitioners. This construct includes the dimensions of effectiveness, efficiency, and satisfaction (Sauro, 2015), therefore cognitive and rational dimensions. Some researchers consider that these dimensions have become too restrictive to assess users' preferences, and especially in the context of gestural interaction (van Beurden et al., 2012). To overcome this problem, some specialists started to use the user experience, which extends the dimensions of the usability (Poushneh & Vasquez-Parraga, 2017). It is officially defined by ISO 9241-210 (2018) as "A person's perceptions and responses that result from the use or anticipated use of a product, system or service". The preferred mode of evaluation is the use of a simple multi-item questionnaire. However, the user experience is still restrictive on its human aspects as its final purpose remains to evaluate the quality of a system.

This is especially the case for gestural interaction, where only a few methods exist today to evaluate the experience (Wickeroth et al., 2009). These methods tend to be simplistic, and do not cover the complexity and richness of human gesture properties. Existing studies focused on only one property, for example memorability (Nacenta et al., 2013) and social acceptance, do not integrate their results in a holistic framework and do not take into account the context of use.

*Gestural interaction technologies*

We usually consider that the discipline of human-computer interaction appeared in the 1980s. During this time, the researchers mainly focused on creating systems, and more particularly interfaces, that were easy to use and easy to learn. With the continuous improvement of motion-sensing technologies (LaViola, 2013), we observed a shift towards more natural user interfaces (Baudel & Beaudouin-Lafon, 1993) taking benefit of these technologies, and in particular gestural interaction. It consists of relying on any meaningful movement by any human body to control a computer-based information system (Kendon, 2004). It could be a 2D surface gesture issued by a finger on a smartphone, a 2D1/2 gesture of someone's hand moving space and projected onto a screen, or a full-body 3D gesture issued in space (cf. Figure 1).

Gesture-based interfaces offer numerous advantages over traditional interaction devices, particularly in virtual reality (VR) and augmented reality (AR) environments. Firstly, these interfaces significantly enhance user efficiency by enabling a wider range of actions to manipulate systems compared to traditional interfaces. Hands and hand gestures, in particular, provide natural and intuitive communication and manipulation of 3D content due to their abundant degrees of freedom (Villarreal-Narvaez et al., 2020). Secondly, gesture-based interfaces enable users to perform three-dimensional movements, aligning the data and interface within the same 3D space. Lastly, these interfaces can adapt and change configurations based on functional requirements, offering flexibility in their usage (Wickeroth et al., 2009).

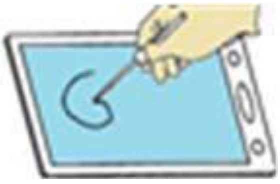
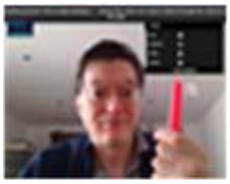
| | |
|---|---|
|  | 2D gesture: movement of a human body part or of a device on an interactive surface, such as a smartphone, a smartboard or a screen. |
|  | 2D1/2 gesture: movement of a human body part performed in space (3D) but projected on a surface (2D). |
|   | 3D gesture: movement of a human body part performed in space (3D) and treated as such. |

Figure 1: Examples of possible gestures with a computer system.

Gestural interaction remains one of the last human senses subject to fundamental challenges in terms of its appropriate exploitation in mainstream product and services development. More physical/digital products and services already or will support gestural interaction (Saffer, 2008). One of the main reasons for this popularity is that gestures may provide a richer user experience than with classical user interfaces (Vanderdonckt & Vatavu, 2018). However, this effect on experience has yet to be tested. Moreover, current methods aimed at evaluating experience tend to take into account only a few rational aspects and leave aside all other human properties. This is particularly problematic as gestural interaction is considered natural because it is based on the gestural communication that humans acquire naturally (Baudel & Beaudouin-Lafon, 1993).

## 2. Research motivations

Two main gaps emerge from the literature. The first is the little current knowledge we have of gestural interaction technologies and their impact on our experiences. The second is the need for new methods to assess the quality of gestural interaction interfaces, taking into account all aspects of human nature, including emotional aspects. Each of these two elements correspond respectively to more marketing and human-computer interaction perspectives.

*The marketing perspective*

In today's fast-paced and dynamic business landscape, marketers are constantly on the lookout for new technologies, methods, and interfaces that can enhance the experience (Lemon & Verhoef, 2016). Over the years, the field of marketing has undergone a significant transformation, primarily driven by the rapid advancements in technology and the ever-evolving preferences and needs of consumers. Marketers understand the importance of embracing innovation and leveraging emerging tools and platforms to stay competitive and effectively engage target audiences (Lemon & Verhoef, 2016; Yohn, 2019). They have come to the realization that relying solely on traditional marketing tools may no longer be sufficient to capture modern consumers (Pine & Gilmore, 1998). To navigate this intricate landscape successfully, we must continuously explore novel approaches that enable to connect with customers in meaningful and impactful ways.

This has led us to focus our attention on gestural interaction, which has emerged as one of the last frontiers for exploiting human senses in mainstream product and services development. While we know that gestural interaction has the potential to offer individuals a richer experience than a traditional user interface (Vanderdonckt & Vatavu, 2018), we still ignore its concrete impact on the user experience but also on the consumer experience. It is particularly important as the consumer experience is broader than the user experience and considers even more subjective and emotional aspects of individuals. By studying this, we can gain a more comprehensive perspective on the various implications and challenges involved. Such research would not only enable marketers to efficiently use gestural interaction technologies but also shed light on the key aspects to consider during interface development and implementation in a business context. By delving deeper into this realm, we aim to provide a more comprehensive and enriched consumer experience, addressing both rational and subjective aspects.

*The HCI perspective*

Many methods exist for evaluating the quality of a user interface (UI) in general, but not that many are specifically tailored to gesture UIs, a UI that brings into play the rich palette of all human movements for interacting with a system. Rohrer, 2014's classification distinguishes between methods producing qualitative measures capturing attitudinal UI quality attributes, such as preference, and methods producing quantitative measures expressing behavioral UI quality attributes, such as performance. This distinction is important since attitudinal measures represent end users' self-reported measure when interacting with the UI while behavioral measures report what end users really do when interacting. End users may report a preference that is radically different from what they actually do: this expresses the eternal divergence between the end users' preference (what they say) and their performance (what they actually do).

It also emerges that there is currently a lack of subjective and affective measures, which are essential to human nature. According to ISO 9241-210 (2018) definition, the user experience could include all the users' emotions, beliefs, preferences, perceptions, physical and psychological responses, behaviors and accomplishments that occur before, during, and after use. The decisive benefits of gesture UI are not just revealed through usability, but much more through the experience, which encompasses a broader class of quality factors, such as enjoyment, stimulation, and identification (van Beurden, 2012).

Frequently, gestures are modelled in laboratory settings where usability testing should be carried out to evaluate the extent to which the gesture interface can be used by specified users in a specified context of use (Calvary, 2003) to achieve specified goals with effectiveness, efficiency, and satisfaction. However, the wide diversity of gesture UIs makes it difficult to decide which quality factors should be taken into account in a usability test (Xia et al., 2022). This observation also holds for methods evaluating the experience of gesture UIs. A thorough evaluation of a gesture UI should go beyond than merely assessing its usability, namely by evaluating its experience. In principle, these evaluation methods apply to any interface, whatever their modality, since they have been designed and presented as such.

*The complementarity between these two fields*

Current research in that domain is not yet successful because it requires knowledge from different disciplines (marketing and human-computer interaction). These shortcomings limit the potential benefits of gestural interaction for products and services, as they are managed by different stakeholders:

- For the customers first because gestures may not correspond to their expectations (Morris et al., 2010) and may not consider the context of use in which they will be used (Vanattenhoven, 2019), thus making their products and services hard to use or not being usable enough to their full potential.

- For the products and services integrators because designing a usable gesture set along with an efficient gesture recognizer requires many resources to be properly incorporated.

This situation is particularly problematic as it is essential for the fields of marketing and human-computer interaction to communicate, one of the reasons being the complementarity of the points of view. This communication challenge is crucial for researchers but also for practitioners (De Keyser et al., 2020). Combining the knowledge of these two disciplines can offer significant added value and a wealth of opportunities. As an example, the discipline of human-computer interaction brings a deep understanding of user behaviour, preferences, and interaction patterns. By incorporating this knowledge into marketing strategies, companies could develop interfaces that are intuitive, appealing, and user-friendly. For all these reasons, we are already seeing more and more large user-centered companies incorporating user experience design into their marketing and branding strategies (Lee et al., 2018).

In order to address the aforementioned challenges, this thesis has different objectives. The first is to understand deeply the notion of experience and its associated concepts coming from different literatures. The second main objective is to explore the use of gesture interaction technologies in a consumption context in order to assess its effect on the experience. Lastly, we aim at exploring and defining a model and a method to assess the overall quality of the experience when using gestural interaction technologies.

## 3. Epistemological positionning

First of all, it is important to explain our epistemological positioning in this research. The latter aims to reflect the assumptions and beliefs of the researcher about reality, human beings and their behavior (Creswell & Plano Clark, 2017; Hudson & Ozanne, 1988). More specifically, epistemology studies the nature and generation of knowledge (Creswell & Plano Clark, 2017). Traditionally, the research in social sciences has been dominated by a positivist approach (Anderson, 1986), although several interpretivist movements have also emerged (Hirschman, 1985, 1986). More recently, we have seen the emergence of post-positivism, having the advantage of responding to the limits of the two previous approaches (Hudson & Ozanne, 1988). These 3 approaches are detailed in the following paragraphs.

*Positivism*

The positivist approach is characterized by its assumption that only one reality exists and that it is the only truth. It is therefore objective, observable and it is possible to divide it and measure it precisely (Bagozzi, 1984; Hudson & Ozanne, 1988). An important characteristic of the positivist approach is the place of researchers, who puts themselves outside the observed world for the sake of objectivity, in order to limit their influence (Clausen et al., 2010; Hudson & Ozanne, 1988).

In this approach, consumer behavior is explained by external factors (Hudson & Ozanne, 1988). The objective is to predict relationships between variables and to create a global model that can apply to any consumer, regardless of the context (Anderson, 1986; Hudson & Ozanne, 1988). Laboratory experimentation is privileged, since it makes it possible to control the context in order to be able to focus individually on each variable inferring behavior. Therefore, a strong belief is that these experiments in a controlled environment reflect the behaviors in a natural environment.

However, several research streams present the limits of the positivist approach. According to them, it is impossible to define universal laws using only finite observations. In addition, the absolute objectivity of certain objects is contested. For some, behaviors and context are interconnected, so it is incorrect to try to study these phenomena independently (Henriques et al., 1998; Hudson & Ozanne, 1988).

*Interpretivism*

In the interpretivist approach, several realities exist and are the reflection of individual perceptions (Hudson & Ozanne, 1988). Consumer behavior is interrelated with their environment, making the context important to consider (Anderson, 1986; Burrell & Morgan, 2017; Lincoln & Guba, 1985). In this approach, the researchers seek to understand behaviors from the inside and to promote consumer perceptions (Hudson & Ozanne, 1988). It is also considered that it is impossible to distinguish a cause from an effect, and that the process of understanding is endless, so that we can only speak of current interpretations when studying a phenomenon (Hudson & Ozanne, 1988).

Given the importance of the context, the researchers are considered as interacting with the subject and thus part of the subject's reality during the study (Reason & Rowan, 1981). We therefore favor studies in natural environments (Hudson & Ozanne, 1988), following an inductive and dynamic approach. Given the importance of context, the researchers favor “thick description” of historical and contextual aspects (Lincoln & Guba, 1985), and they remain open to new information in addition to their a priori knowledge.

However, just like positivism, interpretivism has limitations. First of all, the close relationship between researchers and subjects can create several biases, in particular because, as close as they can be, the researchers cannot experience what the subjects feel. In addition, the validity of the findings is sometimes questioned, especially given the complexity of understanding an experience rather than observing it (Hudson & Ozanne, 1988).

*Post-positivism*

In post-positivism, we combine the assumptions of positivism and interpretivism. Researchers believe that there is only one reality, such as in positivism, but that context plays an important role. Therefore, interactions between individuals and their environment must also be taken into account (Creswell, 2009). In addition, post-positivist researchers strive to reach the truth by getting as close as possible to reality, but the goal is to understand it rather than uncover it. Therefore, the context is widely studied because it helps to give a better understanding of the observed phenomena (Byrne & Ragin, 2009; Creswell, 2009).

Post-positivists use different methods of triangulation to study causal relationships and understand a phenomenon while taking into account the context. We can notably mention the simultaneous use of quantitative and qualitative methods to obtain different observations of reality. The quantitative method makes it possible to have an overall, more objective view of the phenomenon studied, while the qualitative allows it to be understood in depth in one or more defined contexts (Caracelli & Greene, 1993; Creswell, 2009; Patton, 1990).

In this doctoral thesis, our objective is to explain reality, and to understand it through the experience of individuals. We also believe that there is one reality but that the environment and context of use should be taken into account as it impacts the experience. We favor an extensive vision of the experience and of the impact of technologies on individuals, including emotional and affective aspects. For all these reasons, we adopt a post-positivist approach. As advised, we are therefore implementing different triangulation methods, whether at the level of the used literature (marketing and human-computer interaction), methods (systematic literature reviews, in-depth interviews, observations, laboratory experiment, etc.), techniques (thematic coding, structural equation modeling, machine learning, etc.) and measurements (objective and subjective). This triangulation of methods enables to have complementary observations of the reality and to understand it more in-depth.

## 4. Research questions and thesis overview

The goal of this thesis is to (1) understand deeply the notion of experience, (2) explore the use of gesture interaction technologies in a consumption context, and (3) define a model and a method in order to evaluate the overall quality of the experience when using gestural-interaction technologies. This can be further decomposed into the following main research questions:

- *RQ1. What is the experience and how it differs in different fields of research?* The notion of experience has become popular in human-computer interaction and marketing. However, the abundance of research papers from different fields on the subject can lead to fragmentation and confusion. This hampers effective research and makes it difficult to connect different fields. The need for communication between the fields of marketing and human-computer interaction is crucial due to the complementary perspectives they offer, both for researchers and practitioners (De Keyser et al., 2020). There is therefore a need to facilitate multidisciplinary communication between marketing and human-computer interaction and emphasize the complementary viewpoints they bring to the table.

- *RQ2. What are the dimensions to consider to assess the experience when in a gestural interaction with an information system?* In the case of gestural interaction, usability is not enough: the entire experience (Hassenzahl et al., 2010) should be taken into account, thus including emotional and psychological dimensions or factors. Some studies do exist that address some of these properties, such as memorability of gestures or social acceptance of gestures, but these are still restrictive in their approach. In addition, they are not incorporated into a holistic framework that enable to characterize the experience.

- *RQ3. What is the impact of gestural interaction on the experience?* Creating a positive experience is a key source of competitive advantage for companies (Lemon & Verhoef, 2016). A good experience makes a person five times more likely to recommend a company and more likely to purchase in the future (Yohn, 2019). Besides, gestural interaction technologies appear as a promising way to provide individuals a more immersive and richer experience than with classical user interfaces (Vanderdonckt & Vatavu, 2018). However, we currently ignore the concrete impact of this type of interaction on the experience, whereas it is necessary for an efficient adoption of such interfaces.

- *RQ4. What are the key aspects to consider when designing and implementing gestural interaction interfaces?* This question goes hand in hand with the previous one. The objective is to know what the key elements are when developing an interface seeking to provide a rich experience. While RQ3 is more focused on the consumers using the technology, this fourth question is aimed at practitioners. The goal is to highlight the important aspect to consider when designing and building such interfaces, but also to address the challenge of implementation in a consumption context.

- *RQ5. How to produce a method in order to assess this experience?* Based on the dimensions to consider for gestural interaction, it should be possible to assess both preference and performance, according to the context of use (Calvary et al., 2003), and obtain results indicating the overall experience of the interaction. Moreover, following a post-positivist approach, it should be possible to develop a method giving an extensive understanding of the experience, combining objective and subjective measures, and taking into account affective and emotional aspects of the individuals.

Figure 2 provides an overview of this dissertation. Each rectangle represents a major task, the first conducted being the "Literature Reviews" (top left). By following the arrows, we arrive at the next tasks, based on the results of the previous ones. The four essays of this thesis are indicated in red and the five research questions in blue.

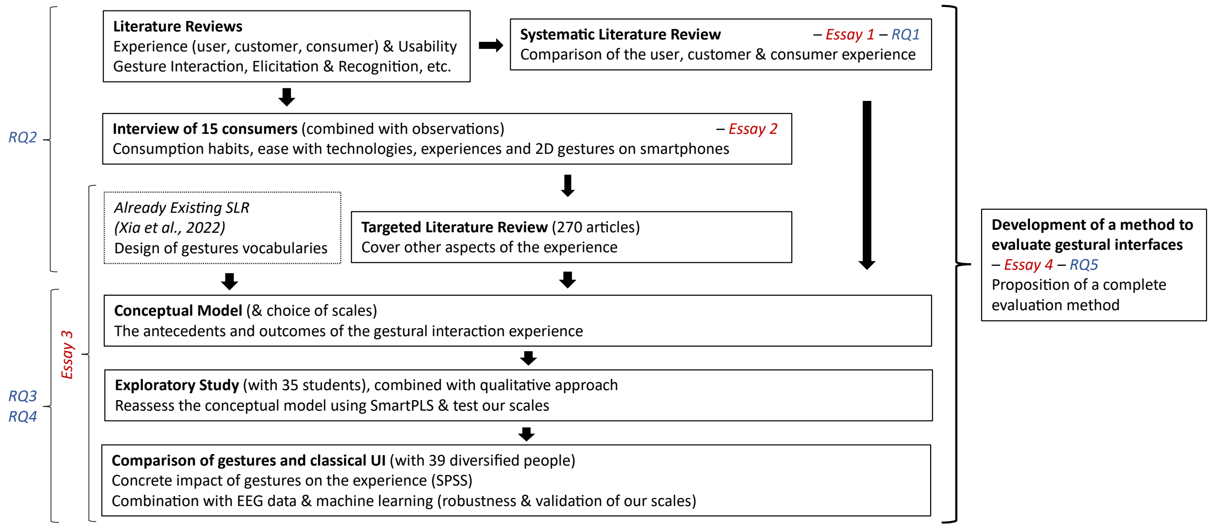



Figure 2: Overview of this thesis.

Each essay therefore comprises one or more tasks and contributes to different research questions. These essays are explained in more detail below:

*Essay 1: Systematic literature review of the user, customer and consumer experience*

This task aims to complement our first literature reviews focusing on specific aspects of the experience and addresses the research question RQ1. This question refers to the experience, a concept now declined through different constructs in the disciplines of marketing and human-computer interaction. However, the similarities and differences of these concepts are not yet clearly established. To this end, we clearly define and differentiate the constructs that are relevant to the experience. We then realize a systematic literature review of the articles developing several constructs of experience and expose the existing confusion in the literature. Finally, we formulate guidelines to practitioners and researchers in human-computer interaction in order to give the human and emotional aspects a more important place in this discipline.

*Essay 2: Affective consumer responses and gestural interaction experience*

The objectives of this qualitative work are multiple, the main one being the highlighting of the important aspects of affective consumer responses and their role in the gestural interaction experience. To this end, we recruit consumers and conduct in-depth interviews covering general aspects of the experience, technologies, and more specifically 2D gestural interaction with a smartphone. At the end, we also organize an observation session with a scenario and a debriefing.

*Essay 3: Impact of the gestural interaction technologies on the experience*

This task is expected to address the research questions RQ3 and RQ4. In this essay, we first complete a targeted literature review which enables to highlight the important factors already mentioned in the literature. Thanks to our two complementary approaches, literature reviews and qualitative work, the first objective of this step is to select the relevant factors to take into account in order to build a conceptual model. Once the factors have been selected and a questionnaire constructed, a structural model will be presented. Doing this will allow us, through several studies, to better understand the gestural interaction experience and also to directly compare gestures with a classical user interface. This will enable to assess the concrete impact on the experience, and especially in a consumption context. Additionally, in order to cross-analyze the data, we will explore the use of alternative research methods such as the use of electroancephalographic data.

*Essay 4: Method for evaluating the gestural interaction experience*

This task is expected to address RQ5. For this purpose, a method will be defined in terms of steps, along with their guidelines. This task will exploit the results of the previous tasks to be integrated into a general-purpose model. This strict method will serve as a tool for using our model. Its objective is to guarantee an important representative design to our project by producing a solution that can be used by researchers but also practitioners. The defined method will then be tested in a real evaluation context. It is important to specify that the objective of this thesis is to outline a method and not to validate it empirically, which can take several years. For example, the SUS questionnaire (Brooke, 1996), which is the reference for a quick usability assessment, took about twenty years before being used more intensively, and has been applied several dozen times on multiple systems.

## 5. Contributions

As theoretical contributions, this research first highlights the different constructs of the experience across multiple literatures, addressing the heterogeneity and providing a comprehensive understanding of the experience. This should benefit the collaboration between the fields of marketing and human-computer interaction. By integrating the knowledge and perspectives from these disciplines, new opportunities of research and benefits can be realized (De Keyser et al., 2020). Secondly, we identify important aspects to consider when studying gestural interaction technologies, including the significance of affective consumers' responses during evaluation. By doing this, we hope to help future research in this domain. One of our latest goals is to propose a novel approach to evaluate gestural interfaces. This model should enable researchers to have a comprehensive understanding of gestural interaction technologies and how to evaluate the experience with these (van Beurden, 2012; Calvary, 2003).

With regard to our methodological contributions, we show the interest of triangulating a wide range of research methods (Caracelli & Greene, 1993; Creswell, 2009; Patton, 1990). For instance, we utilize systematic and targeted literature reviews across multiple disciplines, allowing for a comprehensive analysis of the gestural interaction experience, and demonstrating the disparities. Then, we employ qualitative and quantitative approaches to triangulate results and increase the robustness of findings. Regarding the data type, we also triangulate objective and subjective measures, including tools that are traditionally uncommon in these fields of research. This allows us on the one hand to show the convergence of certain results, and on the other hand the complementarity of others. By doing so, we also explore the use of these methods and tools in order to refine their use in future work and other research. Finally, we introduce a method enabling to use alternative measures in social science studies through a machine learning approach. This enables to highlight the important aspect of the data to consider for the analysis.

Regarding managerial and even societal contributions, we emphasize the collaboration between the fields of human-computer interaction and marketing, encouraging a multi-disciplinary approach that benefits from the complementarity of different points of view. One of our main goals is to provide insights into the factors influencing the gestural interaction experience and offer valuable guidance for designing and implementing effective gestural interfaces. By doing so, we want to guide practitioners into the use of these technologies in real consumption context. This could improve the experience provided for all or certain categories of consumers (Lemon & Verhoef, 2016; Yohn, 2019). For instance, we know that these technologies can be particularly useful for some consumers with disabilities (Giroux et al., 2022), or even in health situations such as the covid-19 pandemic. In addition, this is a hot topic given the recent announcement of a future “metaverse”, also taking advantage of this type of technology. Finally, we stress the need for a comprehensive evaluation method specific to gestural interfaces. This method should allow for more accurate evaluation of interfaces.

# Essay 1: User, Customer and Consumer experience: A Multidisciplinary Systematic Literature Review

Communication:

*Sellier, Quentin ; Poncin, Ingrid ; Vanderdonckt, Jean. User, Customer and Consumer Experience: Highlighting the Heterogeneity in the Literature. 16th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications - Volume 2: HUCAPP (Vienna, Austria, 08/02/2021 to 10/02/2021). doi:10.5220/0010316202290236.*

The full paper has been published in the proceedings of the conference.

## 1. Introduction

The notion of experience has gained in popularity in human-computer interaction and even became a buzzword employed by practitioners and researchers alike (Hassenzahl & Tractinsky, 2006). A product should no longer be seen as an object offering various functionalities and benefits but rather an experience (Hassenzahl et al., 2003). This also applies to marketing where this notion has gained popularity since its apparition 40 years ago (Holbrook & Hirschman, 1982).

However, the multiplication of papers dealing with the experience, especially through different research fields, created fragmentations and theoretical confusions (Becker and Jaakkola, 2020). These confusions and this lack of a unified view undermine the effectiveness of researching and managing the experience (Law et al., 2008) but also make it especially complicated to connect different literatures.

This situation is particularly problematic as it is essential for the fields of marketing and human-computer interaction to communicate, one of the reasons being the complementarity of the points of view. This communication challenge is crucial for researchers but also for practitioners (De Keyser et al., 2020). As an example of multidisciplinary work, more and more large user-centered companies are now incorporating user experience design into their marketing and branding strategies (Lee et al., 2018).

The purpose of this work is therefore to facilitate multidisciplinary communication between the disciplines of marketing and human-computer interaction, and more precisely to help connect the different constructs of the experience. In order to have an in-depth understanding of the problem studied, we first clarify the constructs of user, customer and consumer experience, in particular by exposing their particularities and how they are linked. Given the multiplication of papers combining several constructs of the experience, we then carry out a systematic literature review and highlight the ontological heterogeneity in the literature. We finally consider a possible explanation by exposing the theoretical foundations and the topics covered.

## 2. Theoretical background

This part aims to provide a clear vision of the consumer, customer, and user experience. Each construct will be defined individually with a brief history of its evolution and an explanation of its particularities. We will also see the articulations between these constructs and how they influence each other.

### *2.1.Consumer experience*

The construct appeared in the 80th with the emergence of the consumer research as a new discipline. In the latter, consumers began to be seen as non-rational beings and researchers started to consider the emotional aspect in the relationship between an individual and a company. This later resulted in the apparition of experiential marketing and, today, different research streams exist, some preferring to use the construct of customer experience and others the consumer experience. The major authors for the consumer experience are Holbrook and Hirschman who, in 1982, developed the consumption experience. They then carried out several works specifying this postulate (Holbrook, 2006).

Although there is no widely accepted definition, we can describe the consumer experience as directed toward the pursuit of fantasies, affect, and fun (Holbrook & Hirschman, 1982). It depends on the object with which we are interacting, the preferences of the consumer, and the situation in which this interaction occurs.

This construct has the particularity of focusing more on the personal meanings of the consumption experience and tends to be studied in naturalistic settings. It is also very common to study its antecedents and outcomes (Antéblian et al., 2013). We are here in an approach of understanding the consumer as an individual who is not necessarily a rational, information-driven, utility-maximizing decision makers.

### *2.2.Customer experience*

As previously explained, this construct originally comes from the consumer experience of Holbrook and Hirschman (1982). However, the specific term "customer experience" was first introduced by Pine and Gilmore (1998). Although it is traditionally related to service marketing, it is now starting to be used in human-computer interaction (Rusu et al., 2018).

A popular definition of the customer experience is the one from Lemon & Verhoef (2016), developing that it is the totality of individuals' responses from every interaction with a company during the entire journey that takes them from discovering a brand or product to any post-purchase interactions. It is now considered an essential marketing tool to handle to ensure the competitiveness of a company (McGall, 2015).

The particularity of the customer experience is that it integrates several points of contact during the customer journey, and thus specific interactions. The dimensions that compose this construct are the sensorial, emotional, cognitive, pragmatic, lifestyle, and relational (Gentile et al, 2007). A possible measurement method is to use the customer's feedback and perceptions during the customer journey. There is also a strong emphasis on the role of the brand.

### *2.3.User experience*

The user experience initially comes from the construct of usability. The latter includes the effectiveness, efficiency, and satisfaction (Sauro, 2015), therefore cognitive and rational dimensions. However, these dimensions have become too restrictive to assess users' preferences, especially in the context of gestural interaction (van Beurden et al., 2012). To overcome this problem, specialists started to employ the user experience, which extends the dimensions of the usability (Poushneh & Vasquez-Parraga, 2017), and especially with emotional aspects (Cruz et al., 2015).

This construct is officially defined by ISO 9241-210 (2018) as "A person's perceptions and responses that result from the use or anticipated use of a product, system or service". It is influenced by the context, the user and the system (Roto et al., 2011). Important elements for a good user experience are the pragmatic quality, hedonic quality and global attractiveness (Hassenzahl et al., 2003).

The main particularity of this construct is that it tends to focus on one person-product interaction in a specific context (Ceccacci et al., 2017). This enables to be evaluated directly after the interaction, for example via a multi-item questionnaire such as AttrakDiff (Hassenzahl et al., 2003). Unlike the two other constructs, the main focus here is on the product and the assessment of its quality.

### *2.4.The links between the constructs*

Our postulate is that these three constructs capture different aspects of a same overall experience. They are also linked and influence each other in several ways. For example, we can consider that the user experience is one particular point of contact in the customer journey and therefore has an impact on the customer experience, which in turn influences the more holistic consumer experience. We can also have the opposite logic since our past experiences influence our future experiences (Lemon & Verhoef, 2016). In this scenario, the customer experience that individuals have with a company will influence the next user experiences they will have with the company's products.

Given these links, it sometimes becomes too restrictive to take only one construct into account. It is therefore essential to guarantee an efficient communication between these fields of research and to combine the points of view. For some practitioners, the customer experience is already considered to be closely related to the user experience (Sirapracha & Tocquer, 2012). On the researchers' side, some studies are also starting to move in this direction, such as that of Lee et al., (2018) which empirically validates a model combining elements of the user experience, customer experience and brand equity. For the marketing literature, we can cite Becker and Jaakkola (2020) who carry out a systematic review of the literature focusing on the customer experience and involving the consumer experience. However, as we will see in our analyses, these links have also given rise to a certain heterogeneity in the literature.

## 3. Research method

In order to analyze the multidisciplinary works on the experience, we focus on the articles developing more than one construct in the same paper. To guarantee a complete view, we adopt the PRISMA methodology (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). This approach, inspired by Moher et al. (2009) and summed up in Figure 3, enables to reproduce our study.

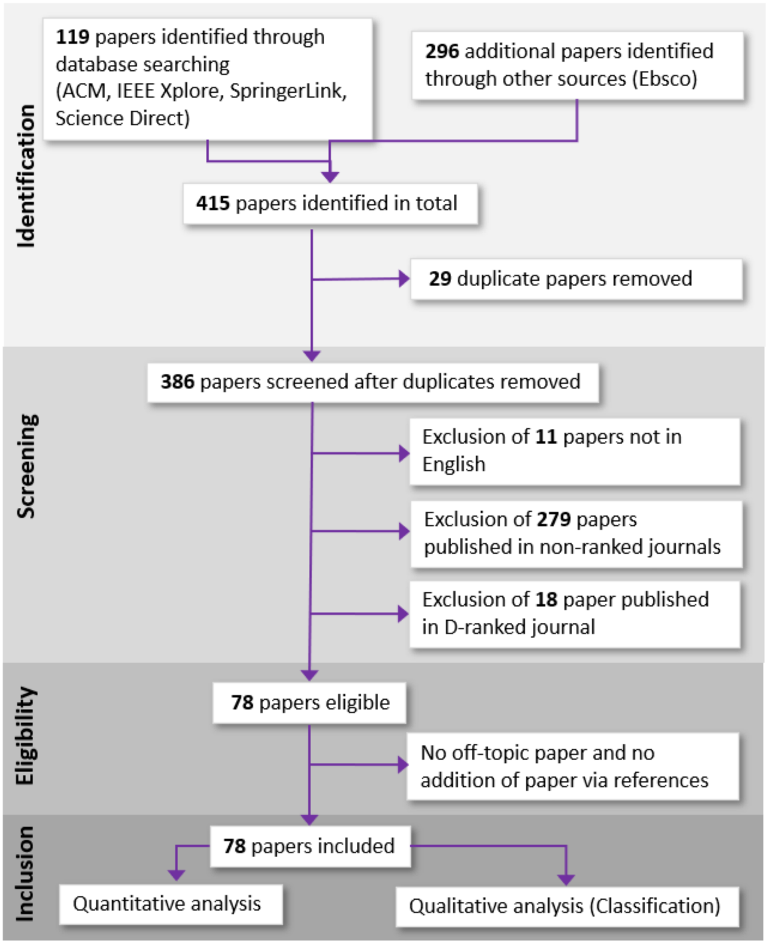



Figure 3: PRISMA diagram.

### *3.1.Identification*

We searched for relevant papers by establishing four different research scenarios, each leading to its own query:

- Q = "User* Experience*" AND "Consumer* Experience*" AND "Customer* Experience*"
- Q = "User* Experience*" AND "Consumer* Experience*"
- Q = "User* Experience*" AND "Customer* Experience*"
- Q = "Consumer* Experience*" AND "Customer* Experience*"

The first one focus on the paper mentioning the three constructs of experience. The other scenarios cover the three possible pairs of terms. In order to analyze a maximum of documents, no publication date restriction has been established.

We ran those queries on the following major digital libraries: (1) ACM Digital Library; (2) IEEE Xplore; (3) Elsevier ScienceDirect; and (4) SpringerLink. We also used (5) Ebsco as a multi-publisher source to ensure the completeness and coherence of the references, validate independent query results, and cover other publishers as well. At the end of this process, a total of 29 duplicates were deleted.

### *3.2.Screening*

This second phase consists in defining and applying inclusion or exclusion criteria. Each paper was evaluated with respect to its relevance and its form. We only kept papers written in English that underwent a peer-review process, and for which the full text was available.

Another criterion being the quality, we also evaluated the ranking of the journals or conferences in which the articles are published. Given the use of multiple publishers from different fields of research, the UNIFI ranking was used in order to have a wide scope for the classification of the papers. At the end of this process, 18 D-ranked documents were deleted.

### *3.3 Eligibility*

To analyze the disciplines while keeping maximum objectivity, the choice of the field of research assigned to the articles was made via the journal's discipline, using the most recent Scopus ranking. However, in our case, we would like to know how several constructs are treated together, regardless of the discipline. We thus decided to keep all the articles.

This phase is also dedicated to the verification of the completeness of our corpus. We thus checked the references cited in the papers of our corpus in order to eventually add them. However, no article was added during this phase.

As another verification, we used Scopus to extract the 100 most cited articles for each of the 3 constructs of the experience. Two articles were duplicated due to the use of the three different queries and we thus ended up with a total of 298 articles. These only two duplicates were already present in our corpus, which is another element ensuring its completeness.

### *3.4.Inclusion*

This last phase consists in verifying quantitative and qualitative aspects of our corpus of papers. These analyses are detailed in the following section developing the results.

Quantitative analysis: we employed Zotero - a multi-platform bibliography management software tool for collecting, organizing, and sharing research sources - to create a collection of papers. We also used PaperMachines, a Zotero extension for visualizations.

Qualitative analysis: qualitative classifications of each paper were manually performed with regards to various dimensions of analysis, for example the definitions used, dimensions evaluated, evaluation methods, etc.

## 4. Results

As schematized in Figure 4, our final corpus includes 78 papers. The full list is available in Appendix 1. During this section, we carry out analyses on the full corpus, by construct of experience, and by research scenario.

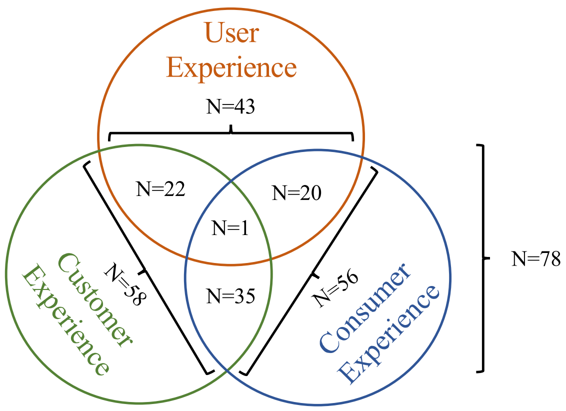



Figure 4: Part of the literature analyzed.

Half of the documents in our corpus are published in management journals or conferences and the third in computer science. The remaining references are mainly in social sciences and engineering. Figure 5 details this repartition and shows that the majority of the articles have been published recently.

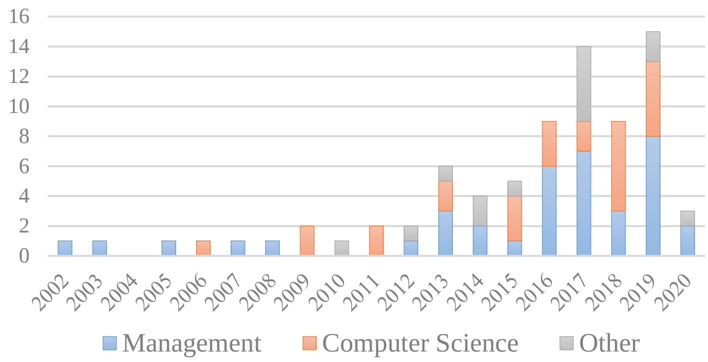



Figure 5: Years of publication and disciplines of the articles from our final corpus.

### *4.1.Differentiation of the constructs*

Although all the articles of our corpus mention several constructs, not all of them make a concrete distinction between them. For instance, some are in fact papers that focus on the customer experience but once use the term "user experience" as a synonym. In this analysis, we observe what proportion of articles properly develop several constructs at the same time. The results are aggregated in Table 1.

Table 1: Classification of the references based on the main construct(s) they develop, per research scenario.

| User & Customer (n = 22) | |
|---|---|
| Only User | 11 (50%) |
| Only Customer | 5 (23%) |
| Neither User nor Customer | 4 (18%) |
| User & Customer | 2 (9%) |

| User & Customer & Consumer (n = 1) |
|---|
| The only reference of this scenario is considered as “Only Consumer”. |

| User & Consumer (n = 20) | |
|---|---|
| Only User | 12 (60%) |
| Only Consumer | 3 (15%) |
| Neither User nor Consumer | 5 (25%) |
| User & Consumer | 0 (0%) |

| Customer & Consumer (n = 35) | |
|---|---|
| Only Customer | 17 (48%) |
| Only Consumer | 9 (26%) |
| Neither Customer nor Consumer | 9 (26%) |
| Customer & Consumer | 0 (0%) |

It appears that the majority of the articles are focusing on just one construct. Whatever the scenario, about a quarter of the papers are not focusing on the experience. By analyzing their content, we see that these are articles sometimes using the experience to illustrate their main point but without giving a definition and leaving it a marginal place in the article. Only the "User Experience & Customer Experience" scenario includes articles developing both of the terms. In these, we can cite the article of Lee et al. (2018) whose goal is to create a model unifying the constructs of the experience. This illustrates the fact that the customer experience is starting to be used in human-computer interaction, as stated by Rusu et al. (2018). We thus observe variabilities in the use of the constructs of experience. A possible explanation for this is developed in the next analyses.

### *4.2.Theoretical foundations*

We use CiteSpace - a tool to visualize and analyze trends and patterns in scientific literature (Chen, 2006) - to analyze the networks of the references cited by the articles of our full corpus. We notice that the networks are little concentrated, with the largest one regrouping only 7% of the references. By analyzing in details the references of these networks, we observe that these are grouped by sub-subjects disconnected from each other. For example, some major networks focus on the consumer experience in retailing context, the brand equity, or the experience in tourism and hospitality industry.

These analyzes enable us to observe that there are important disparities in the theoretical foundations of the different constructs of experience. Moreover, this variability is sometimes observed within the same constructs.

### *4.3.Precision of the constructs*

In this part, we focus on the treatment accorded to the different constructs in the papers. We look at whether a definition is given, what dimensions are eventually mentioned and how they are measured. The details of these analyses are available in Table 2.

It appears that whatever the construct, the articles refer to different definitions. For the customer experience, the definitions of Pine and Gilmore (1998) and Lemon and Verhoef (2016) are slightly more popular, even if their use is far from generalized. The situation is similar for the dimensions composing the constructs. In terms of evaluation, the use of questionnaire is the most popular method, although the measurement items are also different. These analyses, showing a heterogeneity in the definitions and dimensions used, illustrate that the theory is not stabilized yet.

Table 2: Precision given to the constructs.

| | Consumer Experience | Customer Experience | User Experience |
|---|---|---|---|
| Total number of articles | 56 (100%) | 58 (100%) | 43 (100%) |
| Number defining the construct | 7 (12,5%) | 13 (22,4%) | 8 (18,6%) |
| Number mentioning dimensions of the construct | 7 (12,5%) | 8 (13,8%) | 13 (30,2%) |
| Number evaluating dimensions | 4 (7,1%) | 4 (6,9%) | 11 (25,6%) |

### *4.4.Topics covered in the corpus*

We use PaperMachines to analyze the topics of the papers using the word frequencies. The articles involving the user and consumer experience tend to deal with the topics of mobile apps and, more generally, technologies, models and data. For the user and customer experience scenario, the topics are similar but focus slightly more on the logistics and delivery aspect. In the last scenario – "Customer Experience & Consumer Experience" – the situation is also similar, but the keywords "brand" and "product" have a slightly higher importance than in the two other scenarios. We thus observe slight differences even though the topics remain similar.

We can also ask ourselves if there are more significant differences in the topics if we don't make the analysis per research scenarios but rather on the full corpus and per construct. For this, we use again CiteSpace to perform an analysis of the networks of the keywords used in the papers of our full corpus. The main network alone includes 69% of the keywords. When analyzing it, we can observe that the network is organized according to the initial research area of the constructs. However, just like in the previous analysis, the topics remain connected.

In order to ensure that our corpus of 78 documents isn't a biased sample, we used the 100 most cited articles for each of the 3 constructs of the experience to process the same CiteSpace analysis. It enables us to observe that this sample of 298 articles behaves in the same way as our 78-documents corpus, whether at the level of the topics or of the theoretical foundation.

## 5. Discussion

### *5.1.Clarification of the constructs*

We exposed the peculiarities of the different constructs of experience. The user experience tends to focus on one human-product interaction studied in a given context while the customer experience includes several interactions during the customer journey. The consumer experience aims to understand consumers as non-rational beings.

Despite these peculiarities, these constructs capture different aspects of the same overall holistic experience and thus influence each other. It therefore becomes crucial to enable effective communication between human-computer interaction and marketing. Some studies are starting to move in this direction, but some work is still necessary.

### *5.2.Current heterogeneity*

We looked at the articles developing several constructs in the same paper and highlighted the heterogeneity in the literature. To identify these references, we went through the PRISMA methodology via 4 different research scenarios. At the end of the 4 stages of the process - identification, screening, eligibility and inclusion - we ended up with 78 articles.

It appears that the majority of the articles of our corpus do not differentiate the constructs. Rather, these are articles focusing on a particular construct, or even none, and sometimes using other terms as synonyms. Only the scenario where we were looking for articles mentioning both user experience and customer experience revealed references that properly develop these constructs together.

These variabilities were explained via several analyses. First, we saw that the theoretical foundations are disparate, sometimes within the same constructs. Moreover, there is neither reference definitions nor dimensions widely used for each of the constructs, which shows that the theory is not stabilized yet. However, even if there are some minor particularities, the topics are strongly linked.

### *5.3.Design considerations*

Following the work we performed, we can formulate some suggestions to researchers and practitioners working with the constructs of the experience:

- We suggest opting for a multi-constructs approach whenever possible, to benefit from the complementarity of points of view. From a managerial perspective, the implementation of management strategies consistent with the user experience creates an increased level of customer experience and brand equity (Lee et al., 2018). For example, Apple is known to have a strong competitive advantage in terms of user experience (Wan et al., 2013).

- We advise to first link the user experience to the customer experience, without taking into account the consumer experience. These first two constructs are naturally closer, which was felt throughout our analyses. This is probably why some works linking these constructs already exist (Lee et al., 2018). In addition, by its nature, it is harder to measure the consumer experience, unlike the other two constructs that emerge through points of interaction.
- Given the important variability in the definitions and dimensions used, we suggest limiting to a few popular works that are already well established, such as Pine and Gilmore (1998), Lemon and Verhoef (2016), Hassenzahl et al. (2003) and ISO 9241-210 (2018). This would also enable to start creating a certain homogeneity in the literature.
- We advise specialists to familiarize themselves with these other constructs even if it is outside the scope of their discipline. The present work and the few references cited above are, we believe, a good starting point.

## 6. Conclusion and limitations

This essay aimed to improve communication between the fields of human-computer interaction and marketing, and more particularly to unify the constructs of experience. Doing so makes it easier to benefit from the richness of complementary viewpoints. To this end, the constructs were first delimited and defined. We then conducted a systematic literature review in order to identify the articles combining the use of the constructs of the experience. We have found that most articles in the corpus do not differentiate the constructs of the experience, and often use the terms interchangeably. We have also seen that the theoretical foundations are disparate and not yet stabilized, with no widely used definitions or dimensions. However, despite some minor differences, the topics are strongly linked.

Despite our systematic and rigorous approach to this analysis, some limitations persist. We had to make choices in the keywords used during the identification of articles in order not to disperse. For example, we carried out research with the "consumer experience" but not the "consumption experience". We also had to put aside other concepts that could potentially be considered as constructs of experience but without specifically mentioning the term "experience" in their name.

In addition, this work mainly focuses on papers at the crossroads between several constructs of the experience. It would be interesting to focus on all the papers specific to each single construct, as for example Becker and Jaakkola (2020) did for the customer experience. Another interesting aspect to explore, highlighted by the paper by Lee et al. (2018), is the role of the brand experience in the 3 constructs that we analyzed. Moreover, in order to continue this work of multidisciplinary link between constructs, it becomes necessary to create and validate quantitative models as the one of Lee et al. (2018). This step is essential to enable the unification of the experience.

# Essay 2: The Role of Affective Consumer Responses in the Understanding of the Gestural Interaction Experience

Communication:

*Sellier, Quentin ; Poncin, Ingrid ; Vanderdonckt, Jean. Using Gestural Interaction Technology to Improve the Consumer Experience: An Abstract. 2022 Academy of Marketing Science Annual Conference (AMS) (Monterey, USA, 25/05/2022 to 27/05/2022).*

## 1. Introduction

Gestural interaction became one of the trending topics in human-computer interaction. This new modality is now starting to be used everywhere (Daugherty et al., 2015) and might provide individuals a global richer experience than with classical user interfaces (Vanderdonckt & Vatavu, 2018). This is a significant asset when we know that a good experience (Lemon & Verhoef, 2016) makes a person five times more likely to recommend a company and more likely to purchase in the future (Yohn, 2019).

However, there is currently a great lack of user-centric approaches. Current research in human-computer interaction maximizes the effectiveness and efficiency of systems but sometimes to the detriment of user preferences. In addition, the performance of a system is often measured with usability (Nielsen & Levy, 1994), which includes purely rational dimensions, while it is now accepted that consumers are not necessarily rational decision-makers (Holbrook & Hirschman, 1982). This situation is particularly problematic given the nature of the gestural interaction, involving emotional and affective aspects of the experience (Hassenzahl et al., 2010). In this specific case, usability is not enough: the entire holistic experience should be taken into account (Hassenzahl et al., 2010), thus including affective and emotional dimensions. It is in particular for this reason that, although the human-computer interaction literature refers to the individual as a "user", we will also use the term "consumer", specific to the marketing literature, given our desire to take into account the context. Therefore, several questions remain unanswered:

- What elements specific to the affective response of individuals are relevant to address in the case of gestural interaction? To answer this question, we first have to investigate the potential contribution of affective responses of individuals to gestural interaction experience. Then, we will have to elicit what particular elements are relevant to more specifically address gestural interaction experience. While doing our analyses, it will be important to adopt a holistic view of the consumer experience and take into account the context of use.
- What is the impact of the gestural interaction experience on purchasing and consumption practices? We are now in a context where it is more than common to make purchases using the smartphones, therefore gesturally interacting via the touch surface. We can also consider that every interaction with an interface represents a key touchpoint in the customer journey (Lemon & Verhoef, 2016), and therefore plays a role in the consumer

experience. However, we still know very little about the consequences of this type of interaction on consumption practices. Once again, it will be important to take the context into account while answering this question.

To gain a better understanding of the process underlying gestural interaction experience, and specifically the importance of the affective and emotional dimensions, we adopted a qualitative research methodology and conducted 15 in-depth interviews and observations in a consumption context with a smartphone. In-depth interviews aim to uncover rich knowledge of customer perceptions, opinions, and motivations (Rubin & Rubin, 2011; Stokes & Bergin, 2006) and enable us to move away from classic human-computer interaction frameworks. Observations provide additional knowledge on unconscious role of gestural interaction in a context of consumption during the customer journey.

The contributions of this qualitative work are threefold. First, we extend prior research on the gestural interaction experience by observing the key role of affective dimensions in consumers' responses. Then, we shed light to more specific elements such as intuitiveness, perceived control and immersion. Lastly, we show the crucial role of gestural interaction experience in particular touchpoints of the customer journey and consequently on the consumer experience, specifically in the case of impulse buying.

## 2. Theoretical background

In this section, we will develop our theoretical background for two important literatures intervening in this paper. The first is the consumer experience, present in marketing and more particularly in consumer research. The other important literature is the gestural interaction, and more particularly the resulting experience, coming from the discipline of human-computer interaction.

### *2.1.Consumer experience*

The consumer experience appeared in the $80^{th}$ with the emergence of the consumer research as a new discipline. In the latter, consumers began to be seen as non-rational beings and researchers started to consider the emotional aspect in the relationship between an individual and a company. This later resulted in the apparition of experiential marketing and, today, different research streams exist, some preferring to use the term of "customer experience" and others the "consumer experience". The major authors for the consumer experience are Holbrook and Hirschman who, in 1982, developed the consumption experience. They then carried out several works specifying this postulate (Holbrook, 2006).

Although there is no widely accepted definition, we can describe the consumer experience as directed toward the pursuit of fantasies, affect, and fun (Holbrook & Hirschman, 1982). It depends on the object with which we are interacting, the preferences of the consumer, and the situation in which this interaction occurs. It has the particularity of focusing more on the personal meanings of the consumption experience and tends to be studied in naturalistic settings. It is also very common to study its antecedents and outcomes (Antéblian et al., 2013). We are here in an approach of understanding the consumer as an individual who is not necessarily a rational, information-driven, utility-maximizing decision makers.

This concept is often assimilated to the customer experience, with which it shares the same origin of the consumption experience of Holbrook and Hirschman (1982). However, the specific term "customer experience" was first introduced in 1998 by Pine and Gilmore. Although it is traditionally related to service marketing, it is now starting to be used in human-computer interaction (Rusu et al., 2018).

A popular definition of the customer experience is the one from Lemon & Verhoef (2016), developing that it is the totality of a person's responses from every interaction with a company during the customer journey. It is now considered an essential marketing tool to handle to ensure the competitiveness of a company (McGall, 2015). The particularity of the customer experience is that it integrates several points of contact during the customer journey, and thus specific interactions. A popular measurement method is to use the customer's feedback and perceptions during the customer journey. It is now accepted that the customer and consumer experience are subjective and context-specific (Becker & Jaakkola, 2020).

### *2.2.Gestural interaction experience*

We usually consider that the discipline of human-computer interaction appeared in the 1980s. During this time, the researchers mainly focused on creating systems, and more particularly interfaces, that were easy to use and easy to learn. With the continuous improvement of motion-sensing technologies (LaViola, 2013), we observed a shift towards more natural user interfaces (Baudel & Beaudouin-Lafon, 1993) taking benefit of these technologies, and in particular gestural interaction. This subcategory evolved over time but, while researchers in human-computer interaction are now more interested in the implementation and recognition of 3D gestures, 2D touch surface interaction is still the most influential type of interaction covered in this literature (Villarreal-Narvaez et al., 2020).

There are two main aspects to differentiate in the discipline of human-computer interaction: the development part, conveying the creation of interfaces and in this case the recognition of gestures, and the evaluation part of these interfaces. For this second aspect, which we focus on in this thesis, the usability has been and still is one of the most popular indicators used by researchers and practitioners. This construct includes the dimensions of effectiveness, efficiency, and satisfaction (Sauro, 2015), therefore cognitive and rational dimensions.

Some researchers consider that these dimensions have become too restrictive to assess users' preferences, and especially in the context of gestural interaction (van Beurden et al., 2012). To overcome this problem, some specialists started to use the user experience, which extends the dimensions of the usability (Poushneh & Vasquez-Parraga, 2017). It is officially defined by ISO 9241-210 (2018) as "A person's perceptions and responses that result from the use or anticipated use of a product, system or service". The preferred mode of evaluation is the use of a simple multi-item questionnaire (Sellier et al., 2021). However, the user experience is still restrictive on its human aspects as its final purpose remains to evaluate the quality of a system.

Therefore, the specific term "gestural interaction experience" that we sometimes use in this thesis reflects our desire to study the interaction with a gesture-based user interface in a more holistic context, including affective and emotional dimensions. We therefore borrow the theory and the methods of the consumer experience literature to apply to the case of gestural interaction. Regarding this transdisciplinary approach, we adopt a qualitative approach centered on the consumer and carried out in a naturalistic environment, taking into account the context of use.

## 3. Methodology

In this part, we will develop our methodology, going through the collection, analysis and control of our data. We will explain why we decided to conduct thematic online interviews, combined with observation, and how we constructed our sample of 15 people.

### *3.1.Data collection*

In-depth interviews were conducted online with informants to collect data in natural settings (Miles & Huberman, 1994) and also in order to adapt to the health crisis of covid-19. All the session were conducted by the same interviewer to ensure consistency (Riedel et al., 2018). We developed a thematic interview guide based on the literature review (Miles & Huberman, 1994). Although the guide provided some structure, we conduct interviews in a thematic manner to allow informants to communicate their perceptions about some predefined topics while letting them discuss other topics that were not included in the interview guide (Rubin & Rubin, 2011). Informants were first invited to describe their recent online experience with websites and to describe their favorite website. The aim was to let them speak freely about a recent online experience and explore what they liked and disliked during this experience.

The choice to opt for interviews as a support for our qualitative analysis comes from our analytical interest. We are interested here in individuals as social subjects and in activities as social objects. Since we are interested in the experience of these individuals, which is subjective and not always conscious, the interviews offer the possibility of digging deeply into the feelings of each individual.

Then, in terms of interviews, we choose thematic interviews. These have the advantages of being particularly relevant to open and exploratory work like this one. With a semi-structured interview, there would be the risk of being too closed in our questions and missing important aspects. In addition, given that the objective is to reveal unacknowledged motivations, it is more relevant to let the interviewees speak more freely and therefore to opt for these thematic interviews, knowing that there is always the possibility of deepening points that we think are important. We could also have opted for a focus group, but there would have been the risk of remaining only on the surface of each individual, especially since we are interested in people with drastically different profiles.

Since we conduct online interviews and we are interested in personal experience in a natural environment, we choose to carry out our sessions under the theme of purchases in physical stores and online. This has the advantage of speaking to many people, even in the health situation we were, and to enable us to study the impact of gestural interaction experience in this specific context that particularly interests us. After a phase of presentations, we approach the topic of purchases in general. We then move more specifically with "technologies" in general to finally end on the gestural interaction topic.

In order to triangulate the methods, we also wanted to combine these interviews with an observation phase. In this way, it makes it possible to compare what individuals say and feel with their actual behavior. Moreover, since the experience is something that is lived, it is relevant to observe individuals in these situations. This triangulation also has multiple advantages regarding the trustworthiness of our data, which will be develop in the following part.

To carry out these observations, our sessions with the consumers begin with an interview and end with a scenario in which each person is in gestural interaction with the touchscreen of a smartphone. This observation phase is also followed by a quick debrief. More specifically, this scenario involves asking the person to go to the IKEA website and search for a particular piece of furniture. Given the desire to get as close as possible to a real experience, the choice of furniture is established according to the preferences of the interviewee. Then, various tasks are asked such as looking for specific information (for example the dimensions of the product) and observing the photos (change photos, zoom in, go back, etc.). This observation phase is also another argument against the realization of a focus group given that we ask the individuals to perform tasks.

The choice of online modality means that the interview location is the candidates' own home. Regarding the profile of the interviewees, we wanted to vary. We have not set any exclusion criteria except that we only focus on adults. In particular, we did not ask these people to be in charge of their household groceries because we do not focus on food purchases and we want to explore different behaviors, including those of people who do less shopping.

As suggested by Corbin and Strauss (1990), the interview guide (available in Appendix 2) has evolved throughout the data collection phase to ensure that it integrated any new topic that emerged. We conducted interviews until we reached theoretical saturation, and no additional information would emerge from continuing the interviews (Lincoln & Guba, 1985). By the 12$^{th}$ interview, no new information had been identified, and we concluded that we had reached saturation. However, following Riedel et al. (2018), an additional 3 interviews were conducted to ensure that theoretical saturation had been achieved, which was confirmed to be the case. Interviews lasted from 35 to 75 minutes and were audio-recorded and transcribed, producing 246 pages with 104,664 words.

Regarding the selection criterion, we wanted to have a male / female parity without being too rigid on this criterion either. We wanted diversity in the age, the occupation (student, civil servant, office employee, manual worker, independent, pensioner), family situation (single, married, etc.) and the number of children. Finally, we also wanted to explore different purchasing behaviors, including various product categories, and interview people with different ease or difficulties with technologies.

Recruitment of candidates took place online, via messages on social networks, for example on Facebook groups composed of several tens of thousands of members. The people agreeing to carry out the sessions then contacted the researchers by private message and a time slot was defined according to the preferences of the interviewee. Since these sessions took place online, and therefore at home, the investment of the interviewees was relatively limited and there was therefore no real entry to negotiate. The advantage of this approach was that it was relatively easy to find candidates, especially since most people were confined to their homes, and it made it easier to find people with complementary profiles for our study. This place of interviews also made it easy for candidates to open up and we tended to adopt a familiar tone between each other. We also decided not to go through a recruitment agency to avoid the "professionals" of the interview.

The first interview session took place on June 10, 2020 and the last on July 27, therefore a month and a half later. The transcripts and first analyzes took place in parallel with the interviews. In this way, we were able to operate in "waves" of 2 to 4 interviews in order to be able to continuously adapt to the missing profiles. This approach was particularly interesting given the exploratory aspect of this study; the first interviews having allowed us to see more clearly on the interesting profiles to interview later. As we can see in Table 3, we interviewed 15 adults in total: 9 women and 6 men, with a mean age of 41.

Table 3: Summary of the profiles of our candidates.

| Id | Sex | Age | Occupation | Family situation | Nb. of children |
|---|---|---|---|---|---|
| P1 | M | 25 | Commercial real estate prospector | In a relationship | 0 |
| P2 | F | 37 | Employee in IT banking | In a relationship | 0 |
| P3 | F | 55 | Civil servant | Married | 1 |
| P4 | F | 57 | Pensioner | Married | 2 |
| P5 | M | 21 | Student (in physiotherapy) | Single | 0 |
| P6 | M | 24 | AI developer (in a large consulting company) | Single | 0 |
| P7 | F | 39 | Civil servant | Single | 1 |
| P8 | M | 43 | Manual worker | In a relationship | 0 |
| P9 | F | 31 | Civil servant | In a relationship | 2 |
| P10 | F | 51 | Cleaner | Married | 2 |
| P11 | M | 34 | Accountant | Married | 3 |
| P12 | F | 43 | Primary teacher | Married | 3 |
| P13 | M | 63 | Independent physiotherapist | Married | 1 |
| P14 | F | 37 | Civil servant | Single | 0 |
| P15 | F | 55 | Pensioner | Single | 2 |

### 3.2.Data analysis

We used thematic analysis to analyze and interpret the corpus of data. Thematic analysis is a method that identifies, analyzes, and reports patterns (themes) within data to obtain a rich and detailed description of it (Boyatzis, 1998; Braun & Clarke, 2006). The analysis was both deductive and inductive (Valos et al., 2017) by adopting a "theory-driven" approach, with themes and codes identified in prior literature and a "data-driven approach" with other codes emerging from the data (Braun & Clarke, 2006).

Based on Braun and Clarke (2006), we analyzed data following six phases. First, we became familiar with the data by transcribing the interviews and reading the different transcripts closely. This enabled us to obtain a holistic understanding of the informants' experience (Bowen, 2009). Second, we coded the interview transcripts using NVivo 11 software to generate initial codes. Open coding was used to identify core categories and codes in individual transcripts to group data. Third, we searched for themes by sorting the different codes and collating them with potential themes. Axial coding was used to explore relationships between concepts and themes (Bowen, 2009; Strauss & Corbin, 1990). Fourth, we reviewed the themes at the level of the coded data extracts and the entire data set. Fifth, we named and defined the themes. Finally, we produced a report that presented and interpreted the findings. We related findings to relevant theories and literature to enhance the interpretation of the findings (Braun & Clarke, 2006).

### 3.3.Data control

As suggested by Lincoln and Guba (1985), we have considered four trustworthiness criteria as part of the research design during data collection and analysis: credibility, transferability, dependability, and confirmability.

Credibility is enhanced in two ways to guarantee the internal validity of the results (Lincoln & Guba, 1985). First, the data analysis was supported by literature searches and discussions with other researchers to challenge ideas. Second, we engaged in peer debriefings about the findings during data analysis (Riedel et al., 2018).

In terms of transferability, the detailed presentation of the sample and thick descriptions of the data enabled us to contextualize the findings, enabling readers to interpret the interview data by themselves and enhancing the transferability of the findings (Decrop & Derbaix, 2010).

Then, three researchers from different fields examined both the process and product of the study as external auditors and affirmed the confirmability and the dependability of the results (Decrop

& Derbaix, 2010; Riedel et al., 2018). We also employed a reflexive approach and critically considered the decisions made during the analysis process (Riedel et al., 2018).

One of the biggest strengths of our research design lies in the multiplication of the triangulation techniques implemented (Denzin, 2017). One of their advantages is the positive impact on our criteria of trustworthiness (Lincoln & Guba, 1986; Pellemans, 1999), and more particularly on credibility, transferability and confirmability.

- Data source triangulation: In addition to the primary data which are the individual sessions carried out, we can take advantage of different sources in the literature, therefore secondary data (Denzin, 2017). As explained in the development of our research problem, there is currently little human-computer interaction literature focusing on the individuals, but that doesn't mean we are starting from scratch either. We can also benefit from an important literature related to the experience in marketing and more specifically in consumer research.
- Triangulation of techniques: We have designed our individual sessions to combine an interview with an observation session, followed by a debriefing. This enables in particular to explore what is more unconscious in the individual in the experience lived (Denzin, 2017). In addition, this enables us to create robustness in our study, which is of particular interest to us in this essay.
- Triangulation of researchers: This study has the advantage of benefiting from the work of three different researchers. The first one is a PhD student, the researcher who conducted all the sessions, guaranteeing stability in the interviews carried out. The other two researchers have complementary profiles for this research question and evolve in different fields of research: Pr. Ingrid Poncin in marketing and Pr. Jean Vanderdonckt in human-computer interaction. This triangulation of researchers has the main advantage of reducing personal bias in the analysis and interpretation of the results (Denzin, 2017).
- Theoretical triangulation: As explained previously, we use theories from different research fields. This is in particular why the researchers participating in this study have these different profiles. As an example of the theories used, we can mention the user experience, coming from the human-computer interaction literature, the customer experience in marketing, and the consumer experience in consumer research.

We also specify that we took all the necessary precautions to guarantee the anonymity of the candidates. The surnames and any other data allowing the individuals to be identified have been removed, and only the 3 researchers carrying out this study have access to the recordings, transcripts and analyzes. In addition, all candidates gave their informed consent to the recording and processing of sessions before they begin, and we took the time to answer their questions.

## 4. Results

In this section, we will develop the results of the interviews and observations. We will first see the importance of the intuitiveness in the gestural interaction and the immersion as a solid indicator of the quality of the experience. Thereafter, we will move to other aspects of the affective response of the individuals such as the trust, anxiety and satisfaction. A summary of the main characteristics and opinions of each candidate is available in Table 4.

Table 4: Main characteristics and opinions of each candidate.

| Id | Age | Comfort with technology | Difficulties during the scenario | Smartphone / computer preference | Reasons for this preference |
|---|---|---|---|---|---|
| P1 | 25 | High | None | Smartphone | - Practicality<br>- Easy interaction |
| P2 | 37 | Moderate | Some | Smartphone | - Practicality<br>- Comfort |
| P3 | 55 | Low | Some | Smartphone | - Practicality |
| P4 | 57 | Very low | Many | Computer | - Habit |
| P5 | 21 | High | None | Smartphone | - Practicality<br>- Ease of use |
| P6 | 24 | Very high | Some | Computer | - Habit<br>- Advanced features |
| P7 | 39 | High | None | Smartphone | - Practicality<br>- Comfort |
| P8 | 43 | Moderate | None | Smartphone | - Practicality<br>- Speed |
| P9 | 31 | Moderate | Almost none | Computer (but it tends to change) | - Habit |
| P10 | 51 | Very low | Many | Smartphone | - Practicality |
| P11 | 34 | High | None | Computer | - Size of the screen<br>- Habit |
| P12 | 43 | Very low | Many | Computer | - Size of the screen<br>- More information |
| P13 | 63 | Low | Smartphone too old to perform the tasks | Computer (but would like to switch to smartphone) | - Practicality<br>- Speed |
| P14 | 37 | Moderate | None | Smartphone | - Practicality<br>- As complete as a computer |
| P15 | 55 | Low | Some | Computer | - Size of the screen |

### *4.1.Intuitiveness, a critical component of gestural interaction*

A first observation regarding gestural interaction is that there is a mechanical and intuitive side to it, especially for people comfortable with technologies. As an illustration, we have the following testimony during the simulation phase on a smartphone, on the IKEA website. During this exercise, the person completed the requested task quickly and without ever really thinking. We observed a certain habit of the action but also of navigation on a smartphone.

> “I open Safari, I type in the search bar "ikea" ... I click on the first link since it is their site. Above that I have the bar "what are you looking for?", I click on it and I type “lamp”. […] I close the bottom page which offers me to configure cookies etc. I click on the cross directly; it does not interest me. And there I scroll; I look at the lamps that I like.” P1 | M | 25

The intuitiveness is a factor already widely used in the literature on gestural interaction and is defined as the degree to which a gesture refers to existing knowledge (Raskin, 1994). Some authors argue that gestural interaction is intuitive and natural because it is based on the gestural communication that humans acquire naturally (Baudel & Beaudouin-Lafon, 1993). It is important to note that we are talking about a learning process and not a pre-established language that we are trying to mimic. For example, the "pinch to zoom" movement is not based on an existing movement but was created from scratch and yet is considered natural and intuitive (Wigdor & Wixon, 2011), as we have also noted during our sessions. The intuitiveness is therefore subjective and dependent on the knowledge and experiences of each person.

This observation was also confirmed in the post-scenario debriefing. Several participants confirmed the possibility of being able to "juggle" easily on a smartphone, so to navigate naturally to carry out several actions easily. Having intuitive and natural gestures is so important that it is now one of the requirements of consumers. They expect to find the same standards regardless of the websites and platforms.

> “When we are on the phone it is sure that there is still the ease of being able to juggle, hop I go back, I look at the same photo for the third time, I enlarge it.” P9 | F | 31

> “To zoom it's very practical, I mean it works like all websites.” P1 | M | 25

We can explain those reactions by the desire of consumers to exercise control at all stages of the service process (Bateson, 1985; Van Raaij & Pruyn, 1998). Tyler (1989) argues that people's desire to have control over a decision-making process is not simply as means to achieve fair outcomes. We can also link this to the Pleasure-Arousal-Dominance model (Mehrabian, 1996) in which the 3rd dimension opposes having control and feeling controlled (Coutrix & Mandran, 2012). The consumers must therefore feel in control with their gestures or otherwise they will have the impression that it is rather the system that controls them, which will impact the experience from an emotional point of view.

A particularly interesting testimony is that of P6, a participant very comfortable with technologies. He explains that the ideal controller would be to be able to use his movements in a very natural way, which would even enable easy interaction for people who are not used to this. In the Technology Acceptance Model (Davis, 1989), the perceived ease of use is one of the main factors influencing the experience. People therefore seek the most easy and natural interaction possible, namely gestures, and it provides them a richer experience than with classical user interfaces.

> "In terms of controls I think things are getting better and better, where obviously the best would be to be able to just use your fingers in a very natural way. […] But otherwise, [gestural interaction] is easier if you're not used to it. If you put a grandmother in front of virtual reality and she can just catch an object, she will understand how to catch an object; if you put her in front of a pc, she will not understand what is going on." P6 | M | 24

However, as we can see from the following testimony, the smartphone is not always considered the most convenient and easy option. The following participant explains that he prefers to use his fingers via his smartphone but, for more "advanced" tasks, he prefers the computer. We can explain this with the PAD model and its dimension of being in control vs being controlled (Mehrabian, 1996). When it comes to performing a more "advanced" task, participants feel less in control with their smartphone's touchscreen and therefore prefer to use their computer, even if that means losing a little practicality and the intuitive interaction.

> "Ah me, I prefer all gestures with the fingers. On the other hand, everything that is word processing and everything that is a little more, I will say advanced, Excel on smartphone for example, I would never use. But for all that is websites I prefer, I think that with my fingers it goes faster than with the mouse. I suppose that with a pc you have to click right or left to go from one photo to another while here it is fluid" P1 | M | 25

As detailed in Table 4, some participants also have an overall preference for the computer rather than the smartphone, whatever the task. The people with this preference tend to be those less comfortable with technologies, the others generally preferring the smartphone. This can be explained by the intuitiveness of the gestural interaction and the fact that it depends on the participant's existing knowledge (Raskin, 1994). Those who are more comfortable with technologies have a better knowledge regarding it and tend to experience a more intuitive interaction. They therefore feel more easily in control when using their smartphone and have a better overall experience, which explains their overall preference for the smartphone.

However, we have two notable exceptions of participants who are very comfortable with technologies and prefer their computer rather than their smartphone: P6 and P11. This could be explained by their jobs, respectively AI developer and accountant, making them our participants working the most with their computer. Their perceived control is therefore higher with their computer than with their smartphone, which impacts their overall preference. We would also explain this with the Technology Acceptance Model (Davis, 1989). Their intensive use of "advanced" features on computers means that their perceived ease of use of the computer is higher and that they therefore have a better overall experience with it than with their smartphone.

> “I am used to working on my computer. Since I was 18, I've been doing stuff on the PC where I code, I do graphics, that kind of stuff” P6 | M | 24

### *4.2.The link between intuitive gestural interaction and impulse buying*

Another interesting aspect related to this intuitive interaction is its connection to impulse buying. First of all, we can define impulse buying as a sudden and immediate purchase with no pre-shopping intentions (Piron, 1991). It has been described as an unplanned, compelling, and hedonically complex purchasing behavior (Chan et al., 2017). Due to its impulsive nature, the affective plays a major role in this type of purchase, which can even stimulate an emotional conflict (Rook, 1987).

During our sessions, a participant described making this type of purchase because she does not realize that she made a few intuitive movements to select some products and pay. She also gives a concrete example of the Wish website, on which a simple movement is necessary to pay, giving the impression that she has just swiped, not paid.

> “It's so easy because you sit down and you get bored and then finally you ticked two little boxes and there is that feeling of… intangible. We do not realize that we have slipped a finger. So I love the Wish website, it's great because […] when you arrive at the end of your basket, there is a little line that says "swipe to pay". And so it's great because you swipe, you pay, since your card remain memorized in the program, and we have this feeling that well we just swiped, we did not really pay.” P7 | F | 39

One of the ways we could explain the link between gestural interaction and impulse buying is through the local presence, which refers to the sense of a product being present with a consumer in his or her own environment. It has been shown that the vividness and interactivity of some websites features increases this local presence (Ning Shen & Khalifa, 2012), which in turn influences the desire to buy impulsively (Vonkeman et al., 2017). In our case, we can consider that the gestural interaction is one of these features, which would explain our observations and the statement of P7 buying impulsively on the Wish application.

We were also able to observe during the scenario several cases of people navigating intuitively on the IKEA site and, after having virtually manipulated a product (for example by zooming in to see details), declared to be very happy with the product, some even considering buying it. It has been shown that merely touching a product increases the perceived ownership of this product (Peck & Shu, 2009), which in turn influences its valuation. The consumers will then tend to buy the product more easily if they feel that its perceived value is greater than its price. What is particularly relevant in our case is that it has been shown that virtually touching a product also has this effect of influencing the perceived ownership (Peck et al., 2013; Brasel & Gips, 2014), and therefore increases the valuation of the product.

### *4.3.Anxiety, trust and perceived reliability*

As with all technologies, some people experience angst or even anxiety while interacting with a computer system. This phenomenon was perceived more in the observation phase than in the actual interview of the candidates. This feeling manifested itself mainly through apprehension when explaining to candidates the task at hand. This state of mind was particularly marked for P4, one of our older candidates who was less comfortable with technologies.

Once the scenario was finished, although some people encountered several difficulties, all said it was actually easy. According to Werner et al. (2020), people with strong gerontechnology anxiety (i.e. the anxiety linked to technologies and perceived by users that are generally older) benefit significantly from a quick training of gestural commands. In our case, participants feel more comfortable after completing the task than before because they have been able to "practice" by doing it once and would feel more comfortable if they had to do it again.

This also shows us that ease of use is a subjective feeling as some people, often less comfortable with technologies, are used to having to put in a lot of effort and experience difficulties in getting to their ends. It is for this reason in particular that in the Technology Acceptance Model (Davis, 1989), we speak of “perceived” ease of use and not “absolute”. However, the amount of effort required still played a role as the candidates who had more difficulties still generally had bad experiences, even though they said it was easy. Again, this could be explained by the fact that people who are less comfortable with technologies generally have less knowledge and experience of it, which makes the interaction less intuitive, gives a weaker sense of perceived control, and makes the overall experience less good (Davis, 1989).

During our sessions, we were also able to note that more anxious people seem to be more easily satisfied with living a "normal" situation with a technology, where other people would be neutral. For example, we have the following two testimonies in which the first person, more anxious, declares having had a good experience because her order went as planned, while the second is neutral.

> “The good experiences are all the things that I received by delivery, for example Amazon, which corresponded well to what I expected.” P4 | F | 57

> “I mean, what I ordered, it arrived on time, it was the quality that was described and then voila, I had no good or bad surprises.” P5 | M | 21

However, despite this declared higher satisfaction, anxiety and lack of control seem to take over the overall experience, as we had in our case with P4 who did not have a good experience. Therefore, the satisfaction taken alone is not a foolproof indicator of the quality of the experience, at least if it is not combined with a "fun" or "enjoyment" aspect.

Regarding the origin of this anxiety, Mehrabian (1996) explains with the PAD model that anxiety-related traits are caused by non-pleasure, high arousal, and a feeling of not being in control. The link with the third dimension has already been established several times in this paper and was particularly striking for P4, who even told that she generally does not like new technologies since she always needs to control everything.

> “It's because I always need to be in control.” P4 | F | 57

For the first dimension of the PAD, the pleasure, we were not able to observe any perceived enjoyment during the observation phase. Regarding the arousal, P4 was very attentive, and her first reaction was always to be suspicious, which therefore corresponds to the profile linked to anxiety established by Mehrabian (1996). This was observed in her sayings during the interview and confirmed during the observation session. This observed suspicion also enables us to link this loss of control to the trust she is ready to grant, which here tends to be quite low.

> “I am still a little wary despite everything on this kind of platform. It still scares me a little, I'm too suspicious in fact, too anxious.” P4 | F | 57

> “I find that sometimes the evaluations are so positive that it may be too good [to be true].” P4 | F | 57

We also had opposite examples of participants who had full trust in a brand and therefore had no problem accepting cookies on the website, when in normal times they were more reluctant. It should also be noted that these two participants both had good overall experiences during the scenario. This is particularly marked for P8 who describes himself as a "won customer" for IKEA and who, following a bad experience with a competing chain of stores, says he no longer wants to set foot in those other stores.

> “He asks to accept cookies. As it is IKEA, I do it, because I trust them, I have already been a customer on several occasions.” P8 | M | 43

> “When it comes to sites like this, I don't question myself, I just accept it directly. When I go to sites that I know a little less about, I may be more inclined to refuse.” P7 | F | 39

We can link these observations to the perceived reliability, defined as a user's subjective impression of how much confidence can be placed in the system (Rose et al., 2012; Sauro, 2015). We see that some people trust the interface (in this case the IKEA website), which they perceived to be reliable, and tend to have a better overall experience. Therefore, the perceived reliability and trust also emerge as important elements for a good experience with a computer system.

### 4.4. Immersion, a solid indicator of the quality of the experience

Although all the participants chose the product they wanted to search for on the IKEA website, only a part really needed the product, the others choosing at random. A first observation is that people who really needed the product have had a better overall experience than others, regardless of the level of comfort with the technology. This may therefore suggest that the perceived usefulness of the interaction plays a role in the experience, as suggested by the Technology Acceptance Model (Davis, 1989). For example, P6 didn't need the product at all and if he did, he wouldn't have looked for it on this site anyway. Although he is the most comfortable person with technology, he has not had a good experience. He is the only participant who found the website to be rather poorly made and tended to use a lot of irony or even cynicism.

> “I open a piece of furniture at random, I come across a 404 page. There it is really a very enriching experience” P6 | M | 24

When we focus on people who had a good experience, we notice that a common trait is present in their behavior while performing tasks: the immersion. This factor can be defined as “the extent to which the computer displays are capable of delivering an illusion of reality to the senses of the human participant” (Slater & Wilbur, 1997). It appears in any case in which an individual is plunged, involved or absorbed in a totally different world (Fornerino et al., 2006). It can range from partial to total, and even until a state of “flow” is reached (Fornerino, et al., 2008; Hoffman & Novak, 1996; Novak et al., 2000). This last factor describes the state of mind of individuals psychologically absorbed in the activity they perform (Nakamura & Csikszentmihalyi, 2014). It is often characterized by inattention to time and circumstances surrounding the individual. In our sessions, the majority of the participants who had a good experience tended to seem more absent, leave blanks longer than in the rest of the session and even sometimes start sentences without finishing them. It was particularly striking for P3 and P8 who, during the interview part of the session, tended to talk a lot and not leave blank, whereas here it was the opposite. This link between immersion and good experience has already been noted in the literature and there are several claims that the immersion is the “heart of the experience” (Charfi & Volle, 2011; Poncin et al., 2015).

We could imagine that these traits were due to the concentration required to perform the given tasks. However, they have been observed in people less comfortable with the technologies, such as P3, P10 and P12, but also in participants more comfortable. We also had cases of people who are uncomfortable with technologies and who did not have such phases, such as P4. Therefore, the required concentration alone doesn’t explain these moments of absence.

There are also several reasons to believe that these phases of immersion are at least partly due to the intuitiveness of the gestural interaction. One of the first appropriation steps in the immersion process is to relate the codes of the interaction to what the user already knows (Poncin & Garnier, 2012). As gestural interaction is considered natural because it is based on the gestural communication that humans acquire naturally (Baudel & Beaudouin-Lafon, 1993), the gestural interaction has the advantage of allowing more connection with what the user already knows, and therefore to facilitate the immersion. We have also seen that gestural interaction is appreciated for its intuitive nature, and it has also been shown the intuitiveness and fluidity can create a favorable basis for the immersion and virtual experience (Poncin & Garnier, 2010)

Moreover, the notion of immersion was not only observed in the scenario but also present in some of the participant's speeches. As an illustration, we have the following testimony of a participant declaring scrolling for hours on her smartphone and making purchases without too much thought, because a simple gesture was enough to pay.  We therefore still find this notion of inattention to passing time, linked here to impulse buying. According to Poncin et al. (2015), the feeling of immersion may be having a positive effect on various responses such as attitudes, satisfaction, and buying intentions.

> “When it comes to clothes I tend to sit comfortably in my chair with my smartphone, and then I scroll for hours and choose things that I don't really need, but I choose anyway” P7 | F | 39

We found that another indicator enabling to assess the quality of the experience was the perceived enjoyment, shown through the apparent emotions of the participants. This factor, already used in different literatures, is a subjective measure of the pleasure the individual takes when using the system. The integration of this dimension has been shown to be particularly interesting in the context of gestural interaction (van Beurden et al., 2012). It is often called "fun" in the consumer experience, of which it is one of the founding pillars (Holbrook & Hirschman, 1982). It is also present in the PAD model, and it represents what the consumer is ultimately looking for.

The absence of perceived enjoyment was particularly marked among the participants who chose a piece of furniture at random, who tended to remain purely descriptive in the actions they carried out and not to show any particular emotion. However, some of the participants tended to stay in the descriptive without involving emotion during the whole session, which made it not necessarily easy to assess their perceived enjoyment during the scenario. For this reason, the traits specific to the immersion were globally easier to identify and represented a better indicator of the quality of the experience. It may be explained by the fact that the gestural interaction is subjective and dependent on each individual (Archer, 1997). For example, when performing gesture elicitation studies, older people tend to prefer semantic gestures (imitating somethings of the user's reality) while younger people use abstract gestures (representing abstract drawings) more often (Lambillotte et al., 2017). There are also cultural differences when performing gestures. As an illustration, it has been shown that Germans tend to use more gestures than Koreans, and that they show more emotions when performing them (Kim & Lausberg, 2018).

## 5. Discussion

In this section, we will make connections between our findings and the literature in marketing and human-computer interaction. It is divided into 2 parts, each corresponding to the main research questions. We will first develop the importance of affective consumer responses in the gestural interaction experience. Next, we will focus on the role of the gestural interaction experience on consumption and purchasing practices.

### *5.1.The importance of the affective response in the gestural interaction experience*

We first observed that people who chose to search for an item that they really needed tended to have a better overall experience. These people saw an opportunity to complete a task that was really useful to them, confirming the link between perceived usefulness and quality of experience (Davis, 1989). Regarding the other factor pairing with the usefulness, the ease of use (Davis, 1989), we saw that the gestural interaction has the advantage of being more intuitive and therefore makes easier to interact with an interface.

However, this feeling was not shared by everyone, and mainly for participants less comfortable with technologies. Some people see new technologies as a loss of control on their part, thus increasing the feeling of being rather controlled by the system (Coutrix & Mandran, 2012), which tends to provide a poorer experience. These participants are those with a tendency to experience anxiety, characterized by an absence of pleasure, a feeling of not being in control and a high arousal. They also do not easily give their trust, unlike some others who have a high brand confidence and therefore perceive their website as reliable (Rose et al., 2012; Sauro, 2015), positively impacting their overall experience.

One statement that was common to all participants was that the tasks were actually easy, although some had a lot of difficulties. For those people, the fact of carrying out these tasks serves as training and improves their knowledge in terms of interaction, which has a positive impact on the feeling of intuitiveness of the interaction. This then has a positive impact on the feeling of perceived control, which is a dimension to which we have often come back in this paper. This affective dimension enables us to explain a lot of observations we made and has a clear and direct impact on the gestural interaction experience.

We found that a factor that made it possible to quickly assess the quality of the experience was the traits specific to the perceived immersion of the participants, observed through the inattention to time and circumstances surrounding the individual. Indeed, participants having a good experience were more likely to leave blanks, keep their eyes on their smartphones or start sentences without finishing them. Some authors even consider immersion to be the "heart of the experience" (Charfi & Volle, 2011; Poncin et al., 2015).

We have seen that this state is particularly relevant to address in the context of gestural interaction. Indeed, in the first appropriation step of the immersion process, the users relate what they experience to what is familiar to them (Poncin & Garnier, 2012). Since the gestural interaction is natural (Baudel & Beaudouin-Lafon, 1993), it makes it possible to reach this stage of immersion more quickly. Another explanation is via the high intuitiveness of the gestural interaction, also having a positive impact on the immersion (Poncin & Garnier, 2010).

### *5.2.The impact of the gestural interaction experience on impulse buying*

In this work, we have placed our sessions under the theme of purchasing, allowing us to directly study the context of use. An important phenomenon that we have observed during our sessions is the link between the gestural interaction experience and impulse buying. The topic of online impulse buying is increasingly studied (Chan et al., 2017), given its importance. It is estimated that about 40% of all online consumer expenditure is attributable to these types of buying (Liu et al., 2013). However, the specific aspect of the gestural interaction has been starting to be studied only recently (Liu et al., 2019).

During our sessions, we were first able to observe a link between immersion and impulse buying, in particular via the example of the participant scrolling for hours to buy things that she does not need. We have also seen a connection between these purchases and the intuitive nature of gestural interaction. The latter was explained through the local presence (Ning Shen & Khalifa, 2012; Vonkeman et al., 2017) which would be increased within the framework of this gestural interaction, but also via the perceived ownership which increases the perceived valuation of an object by touching it virtually (Peck & Shu, 2009; Peck et al., 2013; Brasel & Gips, 2014).

Figure 6 summarizes the process highlighted in this work. First, the user's knowledge, linked to the ease with technologies, positively influences the feeling of intuitiveness of the interaction. Intuitive gestures then give a feeling of being in control and play a positive role on the immersion and local presence. These three elements impact the perceived ownership, which itself can lead to impulse buying in some cases. For the bottom path, intuitive gestural interaction increases the perceived ease of use and positively impact the appropriation, which themselves play a role in impulse buying. Given these links between gestural interaction and impulse buying, it makes even more sense to consider affective aspects in the dimensions of this experience.

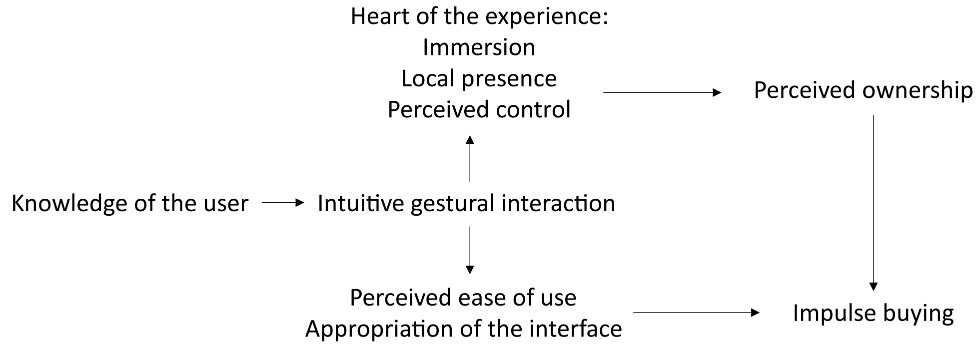



Figure 6: Diagram of the process highlighted in this work.

## 6. Conclusion and limitations

Gestural interaction with a computer system is a powerful modality of interaction. However, there are several challenges to overcome in order to fully embrace this technology, the main one being the current ignorance of the affective response of individuals. We therefore asked ourselves the questions “What elements specific to the affective response of individuals are relevant to address in the case of gestural interaction?” and “What is the impact of the gestural interaction experience on purchasing and consumption practices?”.

In order to answer these, we first develop our theoretical background, drawing on the literature from marketing and human-machine interaction. We then move on to the methodology we have adopted. First, we develop our data collection, explaining in particular why we have chosen to carry out online thematic interviews combined with observations. In this part, we also explain how we composed our sample of participants and what are the characteristics of these recruited people. Subsequently, we develop our data analysis methods, via the NVivo software, and we finally carry out a part on data control. In this one, we develop in particular the various techniques of triangulation put in place.

After that, we develop the results that emerged. We mainly develop the importance of the intuitiveness, its link with impulse buying, and also the case of trust, anxiety and perceived reliability. These findings were confronted to the literature in human-computer interaction and marketing, allowing us to answer to our two research questions. For the first one, focusing on the affective response of individuals following a gestural interaction experience, we have highlighted the role of the perceived control, impacted by the intuitiveness of the gestural interaction and having a major effect on the feeling of immersion. We then showed the effect of intuitive gestural interaction on impulse buying, whether through the enhanced immersion or through the theories of local presence and perceived ownership.

It should be borne in mind that this study has several limitations. First of all, we had to focus on a "specific" gestural interaction, namely 2D gestures on smartphone touch surfaces. In order to fully generalize our results to gestural interaction, it would be particularly relevant to carry out 3D gestural interaction sessions using different devices. We also decided not to make different observations over time and to opt for a diachronic point of view. This would however be an interesting work to carry in a future study, whether it is to study a potential learning effect in gestural interaction or to study consumption aspects via multiple touchpoints of the customer journey.

From a theoretical point of view, this work highlights the importance of affective consumer responses in the understanding of the gestural interaction experience. We also shed light to specific dimensions such as the intuitiveness, perceived control and immersion, and we propose a model explaining their influences. From a practical point of view, we show the crucial role of gestural interaction experience in particular touchpoints of the customer journey and consequently on the consumer experience, specifically in the case of impulse buying.

# Essay 3: Understanding the Impact of Gestural Interaction Technologies on the Experience

Communications:

*Sellier, Quentin ; Poncin, Ingrid ; Vanderdonckt, Jean. Exploration of the Impact of 3D Gestural Interaction on the Customer Experience. 28th International Conference on Recent Advances in Retailing and Consumer Science (Baveno, Italy, 23/07/2022 to 26/07/2022).*

*Sellier, Quentin ; Poncin, Ingrid ; Vanderdonckt, Jean. Using gestural interaction technologies to provide a richer and more immersive consumer experience: triangulation of self-reported scales and electroencephalographic data. European Marketing Academy Annual Conference (EMAC) (Odense, Denmark, 23/05/2023 to 26/05/2023).*

*Sellier, Quentin ; Racat, Margot ; Poncin, Ingrid. Understanding the Role of Sensory-Enabling Technologies in the Reinforcement of Consumers' Natural Experience: An Abstract. Academy of Marketing Science World Marketing Congress (AMSWMC) (Canterbury, United Kingdom, 11/07/2023 to 14/07/2023).*

## 1. Introduction

It is now essential for businesses to provide the best consumer experience to ensure their competitiveness (Pine & Gilmore, 1998; Verhoef et al., 2009; Lemon & Verhoef, 2016). In this goal, technologies are constantly evolving to provide more and more immersive, rich and complete experiences. Some of these technologies originally come from the world of video games and are known for their immersive capacity. Many of them have gone beyond their initial framework to be now used in the context of e-commerce, or even in the future metaverse. One of these trending technologies is the 3D gestural interaction (Daugherty et al., 2015). This consists of the interaction between an individual, producing movements with any part of the body, and a computer system, capable of interpreting those movements.

This topic is particularly interesting as gestural interaction is considered intuitive and natural because it is based on the gestural communication that humans acquire naturally (Baudel & Beaudouin-Lafon, 1993). Yet, while we know some of the advantages of this type of technology in the context of video games, it has not yet been studied in the context of e-commerce. It is particularly important as we should consider emotional and cognitive aspect of the consumption experience. Understanding this would enable marketers to integrate this type of technology efficiently, with the objective of providing a more complete and richer consumer experience.

While we know that gestural interaction has the potential to offer individuals a richer experience than a traditional user interface (Vanderdonckt & Vatavu, 2018), we still ignore its concrete impact, and especially on the consumer experience. It is particularly important as the consumer experience is broader than the user experience and considers subjective and emotional aspects of individuals (Sellier et al., 2021). Understanding these would enable practitioners to pay particular attention to the important aspects to consider when designing such interfaces, with the objective of providing a more complete and rich consumer experience. Therefore, we formulate the following research questions: “what are the key aspects to consider when designing gestural interaction interfaces?” and “how does the gestural interaction impact the consumer experience?”.

In order to answer there, we gathered different variables from marketing and human-computer interaction literatures. We then built a digital catalog controllable by gestures and carried out two data collections in which the participants realize an experience of interaction with the catalogue. In the first exploratory study, we analyze the data using SmartPLS. In the second study, using the data from questionnaires and EEG data, we mix a classical statistical approach with a machine learning approach.

## 2. Construction of a conceptual model

In this section, we will develop our data collection method as well as the key factors integrated into our model. In order to select the most representative variables to use in our model, we were able to take advantage of a systematic literature review of 237 articles already existing, which we completed with a targeted literature review of 270 articles.

### *2.1.Methodology*

To collect a corpus of representative literature, we were able to benefit from a systematic literature review on the design of gesture vocabularies (Xia et al., 2022). This article analyzes a final corpus of 237 articles and identifies 13 key factors to take into account when designing gestures, from a physical, cognitive, situational and system point of view. These factors, mentioned in Figure 7, served as a founding base for our model.

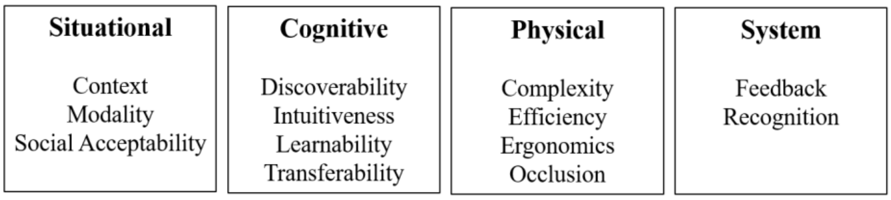



Figure 7: Factors identified as essential in the design of gestures (Xia et al., 2022).

However, this work focuses on gestures but does not include any emotional or affective aspect of the interaction. We therefore carried out a targeted literature review to cover other aspects of the experience that results from a gestural interaction. We ran different queries in ACM Digital Library, IEEE Xplore Digital Library and Google Scholar. Those queries were specific to gestures, such as “gesture evaluation”, “gesture properties” or “gesture experience”, but also terms specific to the experiences such as “user experience”, “customer experience” or “consumer experience”. We then went to a screening phase of these articles in order to keep only those relevant in the context of this essay. This phase also allowed us to add articles to our corpus by browsing the cited references of the papers, leaving us with a total of 270 articles. The full list of retained papers is available in Appendix 3.

After the identification and screening, we analyzed the content of the articles in our corpus. For each, we noted all the elements mentioned which could be related to important factors of the gestures and the experience resulting from a gestural interaction. We also noted the definitions given as well as the modes of evaluation of these dimensions. Doing this allowed us to take into account that some factors with different names, especially from different literature, actually define similar concepts. After merging our data, taking synonyms into account, we ended up with a table summarizing the most used factors to consider in our model. The completion of this complementary literature review enabled us in particular to identify the most used factors relating to more emotional and affective aspects of the experience.

### *2.2.Selected factors and conceptual model*

The factors retained in our model are developed below. We are here in a more holistic approach aiming to cover the experience process in a comprehensive way. We are therefore not on a reductionist approach aiming to measure the experience through a limited number of aspects, and without any overlapping (Schankin et al., 2022). In order to facilitate understanding, the factors have been organized in four categories: gestures, overall interaction with the interface, quality of the experience and consequences. This choice of categories comes from an adaptation of the categories identified by Xia et al., (2021) in their systematic literature review.

The first category takes into account aspects related to the gestures. These comprise physical and cognitive factors. The factors developed are important indicators to take into account when developing gesture vocabulary, for example by going through user-centered approaches such as gesture elicitation studies (Wobbrock et al., 2009). Such approaches are important since it has been shown that the user experience is improved when the vocabulary of gestures is based on real-life social and physical scenarios (Grandhi et al., 2011).

- *Discoverability*. It refers to the ability of users who are new to the system to find out how it works and what gestures to perform to control it (Wobbrock et al., 2005). It is an important aspect as it enables to quickly navigate in an interface without going through a complete training. It is sometimes called guessability or approachability.
- *Intuitiveness*. This factor is the degree to which a gesture refers to existing knowledge (Raskin, 1994), often because it is based on an existing movement or a metaphor. It directly influences the learnability and other cognitive and physical load factors related to the gestures (Manresa-Yee et al., 2013).

- *Learnability*. This factor, also called memorability (Nacenta et al., 2013), refers to the ease with which a new user can learn to use the interface and achieve maximal performance gestures (Dix, 2003). This factor is influenced by the intuitiveness as it is easier to learn how to use an interface based on intuitive gesture.
- *Transferability*. This factor measures to what extend learning a gesture modifies its performance when changing context (Perkins et al., 1992). For instance, a gesture may become easier to perform because it is used in other applications to perform similar tasks.
- *Ergonomics*. According to the norm ISO 9241, the ergonomics are the human anatomical, anthropometric, physiological and biomechanical characteristics related to physical activity. In our case, the produced gestures must be comfortable and allow a long-term use without causing too much muscular fatigue.
- *Complexity*. It represents the degree to which a gesture is complicated to perform from a physical or mental load perspective. This complexity is supposed to be adapted to the task, for example by providing simpler gestures for tasks performed frequently.

For this second category, we move away from the gestures themselves to focus more on the interface and the subjective performance of the system. We are also starting to integrate more holistic factors that play an important role in the resulting experience. The peculiarity of this work is that we won’t evaluate these factors in an absolute way but rather in a subjective way by asking the end users their opinions. This choice is justified by the fact that we are interested in the experience of individuals, which is therefore a subjective representation.

- *Feedback*. The signals that the interface returns in order to communicate with the users, on the basis of their actions. For example, the interface can send a visual signal in order to make it understood that a gesture has been recognized.
- *Naturalness*. This affective dimension refers to the subjective feeling of whether the interaction “act and feel like a natural” to the individual, resulting in a feeling of effortlessness and enjoyment (Wigdor & Wixon, 2011). Given its nature, all the factors relating to the gestures facilitating this interaction influence the quality of the naturalness felt, itself directly impacting the experience. Some authors argue that gestural interaction is natural because it is based on the gestural communication that humans acquire naturally (Baudel & Beaudouin-Lafon, 1993). It is important to note that we are talking about a learning process and not a pre-established language that we are trying to mimic. For example, the "pinch to zoom" movement is not based on an existing movement but was created from scratch and yet is considered natural (Wigdor & Wixon, 2011).

- *Reliability*. This is a user's impression of how much confidence can be placed in the system. This aspect enables to address issues of security and anxiety, i.e. emotional factors more present in the customer and consumer experience, sometimes called under the form of "trust" (Rose et al., 2012; Sauro, 2015). By giving confidence in the system, this factor will influence the subjective control of users.
- *Ease of use*. As for the previous ones, this factor is a recurrent indicator in the evaluation of systems or the experience. This indicates the subjective amount of effort that must be put in to use the system properly. It is used in conjunction with usefulness in the Technology Acceptance Model (Davis, 1989). The easier the interaction is, the more it presents an interest for the user (Manresa-Yee et al., 2013).
- *Usefulness*. Subjective feeling of how the use of the interface can be of added value in order to execute one or multiple given tasks. An interface perceived as useful by a user is considered to have a positive user-performance relationship (Davis, 1989), and gives a reason for interacting.
- *Novelty*. This affective variable captures the novelty effect of the interaction. More particularly, it covers the creative aspect of the interface and its mode of interaction (Hinderks et al., 2019). The objective here is to catch the interest of the users and make the experience more playful.

This third category includes the factors corresponding to the heart of the experience. Unlike the previous ones, which were conditions for creating a good experience, the factors in this category are rather indicators of the quality of the experience.

- *Immersion*. This factor, often called “flow” in the customer experience literature (Novak et al., 2000 ; Agarwal & Karahanna, 2000), describes the state of mind of individuals psychologically absorbed in the activity they perform (Nakamura & Csikszentmihalyi, 2014). This state is often characterized by inattention to time and circumstances surrounding the individual.
- *Emotional state*. This factor enables to assess the global emotional state of individuals after interacting with the system. A quick measure of this state can be done through the Pleasure-Arousal-Dominance (PAD) model (Mehrabian, 1995). This model dichotomizes each of its three dimensions: pleasure versus displeasure, arousal versus non-arousal, and dominance versus submissiveness. Using it in our model makes it possible in particular to address the dimension of perceived control.

- *Playfulness*. We can view this factor as a state triggered by elements that “engage people’s attention or involve them into activity for play, amusement or creative enjoyment” (Kuts, 2009, p.9). The integration of this dimension is particularly interesting in the context of gestural interaction (van Beurden et al., 2012), for which it can be a good indicator of the experience. This factor can also be called "fun" in the consumer experience literature, of which it is one of the founding pillars (Holbrook & Hirschman, 1982).

While the three factors of the previous category were indicators of the quality of the experience, this last category includes the factors corresponding to the consequences of the experience, taking place after the interaction is completed.

- *Satisfaction*. This is a global subjective judgment on the quality of the interaction that has taken place (Khalifa & Liu, 2007), whether after a purchase with a company or, in our case, a gestural interaction with a user interface. This term is also one of the three metrics of the usability (ISO 9241; ISO 25010; Law et al., 2014).
- *Intention to use*. As specified in the Technology Acceptance Model, the intention to use is a solid indicator to assess the potential of a technology (Davis, 1989), in our case a gesture-based user interface. This intention comes directly from the experience resulting from the interaction (Rose et al., 2012).

Highlighting these variables and their relationships allowed us to build the following model, available in Figure 8. In order to facilitate understanding, the variables have been colored according to their category inspired by Xia et al., 2022. Some of these relationships will be explained in more detail in the results of our study 1 and in the discussion. As in Cedillo et al (2021), we divide the model by the moment each factor plays its role regarding the interaction. This more human-computer interaction approach enables to have a vision of the process when interacting with gesture-based interfaces.

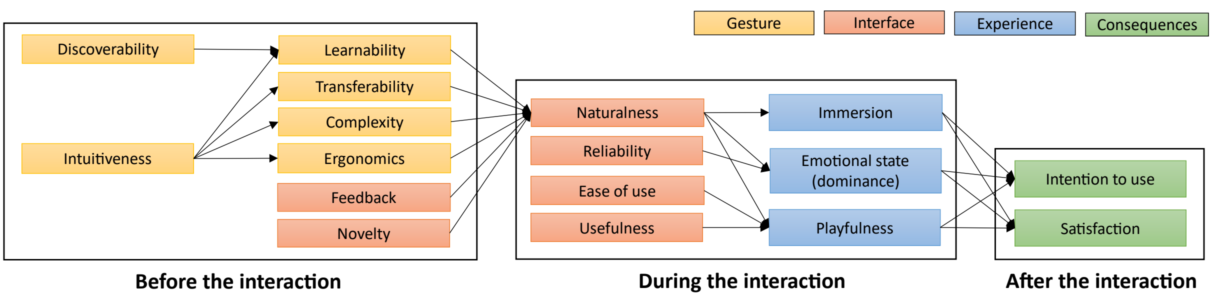



Figure 8: Conceptual model of the experience resulting from the interaction with a gesture-based user interface.

### *2.3.Measures of the model*

In the table 5 we develop each of our variables with its different measurement items used in our reference questionnaire. The variables here are taken from the conceptual model we have developed, to which we have added other aspects to enrich the explanation of the gestural interaction experience. Our questionnaire presents these statements to the respondent and asks them to answer on a 7-point scale. The majority of the proposed items correspond to existing questionnaires already validated, the reference of which is indicated in the last column. In order to respect the initial format of the scales, some ask respondents to read a statement and answer from "Totally disagree" to "Totally agree", while others oppose two terms and ask to be more or less close to these terms.

We started from “UEQ+” (Schrepp & Thomaschewski, 2019), a flexible and modular method for evaluating the user experience of any interface. More particularly, it is a tool that contains a larger list of user experience modules that can be combined to build a concrete questionnaire adapted to the research question and interface. One of the greatest advantages of this approach is that we can optimize our questionnaire to suit our needs. Each available scale in UEQ+ has been adapted to match the same format and has been applied and validated in at least one study published by its authors. A more precise reference for each scale development is given in Table 5.

After selecting relevant scales of UEQ+, we added other scales so that our questionnaire was adapted to the gestural interaction experience. Some variables that were present in our conceptual model are now covered by other variables. We then added the other missing variables by looking for other scales or, if none were available, by creating an ad hoc measure. It should be noted that many scales had to be modified or created in order to adapt specifically to the case of gestural interaction.

Table 5: Variables and items considered in our questionnaire.

| Variable | Item | | Reference |
|---|---|---|---|
| Digital skill | Skill1 | I consider myself knowledgeable about the Internet and digital practices. | Adaptation of Rose et al., 2012 |
| | Skill2 | I am extremely skilled at using digital technologies. | |
| | Skill3 | I am an expert of the Internet and digital technologies. | |
| | Skill4 | I know somewhat more that most users about the Internet and digital practices. | |
| Attractiveness | In my opinion, the product is generally | | UEQ+ (Laugwitz et al., 2008) |
| | Attr1 | Annoying - Enjoyable | |
| | Attr2 | Bad - Good | |
| | Attr3 | Unpleasant - Pleasant | |
| | Attr4 | Unfriendly - Friendly | |
| Efficiency | To achieve my goals, I consider the product as | | UEQ+ (Laugwitz et al., 2008) |
| | Effi1 | Slow - Fast | |
| | Effi2 | Inefficient - Efficient | |
| | Effi3 | Impractical - Practical | |
| | Effi4 | Cluttered - Organized | |
| Perspicuity (getting familiar) | In my opinion, handling and using the product are | | UEQ+ (Laugwitz et al., 2008) |
| | Persp1 | Not understandable - Understandable | |
| | Persp2 | Difficult to learn - Easy to learn | |
| | Persp3 | Complicated - Easy | |
| | Persp4 | Confusing - Clear | |
| Dependability | In my opinion, the reactions of the product to my input and command are | | UEQ+ (Laugwitz et al., 2008) |
| | Depen1 | Unpredictable - Predictable | |
| | Depen2 | Obstructive - Supportive | |
| | Depen3 | Not secure - Secure | |
| | Depen4 | Does not meet expectations - Meets expectations | |
| Stimulation | In my opinion, handling and working with the product are | | UEQ+ (Laugwitz et al., 2008) |
| | Stim1 | Not interesting - Interesting | |
| | Stim2 | Boring - Exiting | |
| | Stim3 | Inferior - Valueable | |
| | Stim4 | Demotivating - Motivating | |
| Novelty | In my opinion, the idea behind the product and its design are | | UEQ+ (Laugwitz et al., 2008) |
| | Nove1 | Dull - Creative | |
| | Nove2 | Conventional - Inventive | |
| | Nove3 | Usual - Leading edge | |
| | Nove4 | Conservative - Innovative | |
| Trust | Regarding the use of my personal information and data, the product is | | UEQ+ (Hinderks et al., 2016) |
| | Trust1 | Insecure - Secure | |
| | Trust2 | Untrustworthy - Trustworthy | |
| | Trust3 | Unreliable - Reliable | |
| | Trust4 | Non-transparent - Transparent | |
| Personalization | Regarding my personal requirements and preferences, the product is | | UEQ+ (Schrepp & Thoma-schewski, 2019) |
| | Pers1 | Not adjustable - Adjustable | |
| | Pers2 | Not changeable - Changeable | |
| | Pers3 | Inflexible - Flexible | |
| | Pers4 | Not extendable - Extendable | |

Table 5: Variables and items considered in our questionnaire (continued).

| | | | |
|---|---|---|---|
| Usefulness | | I consider the possibility of using the product as | UEQ+ (Schrepp & Thoma-schewski, 2019) |
| | Usef1 | Useless - Useful | |
| | Usef2 | Not helpful - Helpful | |
| | Usef3 | Not beneficial - Beneficial | |
| | Usef4 | Not rewarding - Rewarding | |
| Aesthetics | | In my opinion, the visual design of the product is | UEQ+ (Schrepp & Thoma-schewski, 2019) |
| | Aest1 | Ugly - Beautiful | |
| | Aest2 | Lacking style - Stylish | |
| | Aest3 | Unappealing - Appealing | |
| | Aest4 | Unpleasant - Pleasant | |
| Intuitive use | | In my opinion, using the product is | UEQ+ (Schrepp & Thoma-schewski, 2019) |
| | Intui1 | Difficult - Easy | |
| | Intui2 | Illogical - Logical | |
| | Intui3 | Not plausible - Plausible | |
| | Intui4 | Inconclusive - Conclusive | |
| Engagement | Enga1 | I spend a lot of my time on this type of website. | Adaptation of Vivek et al., 2014 |
| | Enga2 | I am very involved in this type of website. | |
| | Enga3 | I try to fit this type of website into my schedule. | |
| | Enga4 | I am passionate about this type of website. | |
| | Enga5 | My days would not be the same without this type of website. | |
| | Enga6 | I like to spend time on this type of website. | |
| Discoverability | Disc1 | I could easily guess how to use the interface. | Ad hoc |
| | Disc2 | Finding out how to control the interface was not complicated. | |
| | Disc3 | The gestures to perform to control the interface were easy to discover. | |
| PAD state (Pleasure Arousal Dominance) | | Imagine that you are using the interface, how do you feel? | Adaptation of Mehrabian & Russell, 1974 |
| | PAD1 | Unhappy - Happy | |
| | PAD2 | Unsatisfied - Satisfied | |
| | PAD3 | Despairing - Hopeful | |
| | PAD4 | Annoyed - Pleased | |
| | PAD5 | Relaxed - Stimulated | |
| | PAD6 | Calm - Excited | |
| | PAD7 | Sluggish - Frenzied | |
| | PAD8 | Unaroused - Aroused | |
| | PAD9 | Restricted - Free | |
| | PAD10 | Guided - Autonomous | |
| | PAD11 | Controlled - Controlling | |
| | PAD12 | Influenced - Influential | |
| Playfulness | | Imagine you are using the interface; how much do you experience the following feelings? | Adaptation of Agarwal & Karahanna, 2000 |
| | Play1 | Spontaneous | |
| | Play2 | Imaginative | |
| | Play3 | Flexible | |
| | Play4 | Creative | |
| | Play5 | Playful | |
| | Play6 | Original | |
| | Play7 | Inventive | |

Table 5: Variables and items considered in our questionnaire (continued).

| | | | |
|---|---|---|---|
| Efficiency & Effectiveness | Effec1 | I can do the desired task successfully with no effort. | Adaptation of Lee et al., 2018 |
| | Effec2 | I can complete the desired task successfully without wasting time. | |
| | Effec3 | I can complete the desired task accurately. | |
| Ergonomics | Ergo1 | The use of the interface is physically comfortable. | Ad hoc |
| | Ergo2 | The movements I made to control the interface did not bother me. | |
| | Ergo3 | The use of the interface is cognitively comfortable. | |
| Complexity | Comp1 | Controlling the interface is easy. | Ad hoc |
| | Comp2 | I had no difficulty controlling the interface. | |
| | Comp3 | I find the interface no more complex to control than any other system. | |
| Learnability | Lear1 | It was easy to learn how the interface works. | Ad hoc |
| | Lear2 | The mastery of the interface was not complex to acquire. | |
| | Lear3 | I felt a progression in my ease in controlling the system. | |
| Transferability | Tran1 | The interface control is similar to that of other applications. | Ad hoc |
| | Tran2 | The actions I made to control the interfaces were similar to those I use in other contexts. | |
| | Tran3 | I controlled the interface the same way I control my smartphone. | |
| Telepresence | Telep1 | Using this interface creates a new world for me, and this world suddenly disappears when I stop browsing. | Adaptation of Rose et al., 2012 |
| | Telep2 | I forget my immediate surroundings when I use this interface. | |
| | Telep3 | This interface makes me forget where I am. | |
| | Telep4 | After using tis interface, I feel like I come back to the “real world” after a journey. | |
| Immersion level | Imme1 | For some moments, I lost consciousness of what was around me. | Adaptation of Fornerino et al., 2008 |
| | Imme2 | When using the interface, my body was in front of the computer, but my mind was in the world created by the interface. | |
| | Imme3 | The virtual catalog made me forget the realities of the outside world. | |
| | Imme4 | While using the interface, it didn't matter what happened before or what would happen after. | |
| | Imme5 | The virtual catalog made me forget my immediate environment. | |
| Satisfaction | Sati1 | It was good to experience this interface. | Adaptation of Chung et al., 2014 |
| | Sati2 | Being a user of this interface was a satisfying experience. | |
| | Sati3 | Overall I am happy with this interface. | |
| Future use | Futu1 | If I have the chance, I intend to reuse this interface. | Ad hoc |
| | Futu2 | I intend to speak positively about this interface to my relatives. | |
| | Futu3 | If I have the opportunity, I intend to come back to this website later. | |

Table 5: Variables and items considered in our questionnaire (continued).

| | | | |
|---|---|---|---|
| Social acceptability | SoAcc1 | I'm comfortable to interact with the interface in this environment. | Ad hoc |
| | SoAcc2 | I'm comfortable to interact with the interface with this audience. | |
| | SoAcc3 | I don't feel any shame while interacting with the interface. | |
| Feedback | Feed1 | The system gives me visual or auditory feedback when it recognizes my gestures. | Ad hoc |
| | Feed2 | It is easy to see if the system recognizes my gestures. | |
| | Feed3 | When performing the gestures, I have no doubts if they are correctly recognized. | |
| Naturalness | Natu1 | The use of the interface is natural. | Ad hoc |
| | Natu2 | Controlling the interface feels natural to me. | |
| | Natu3 | I find interacting with gestures to be more natural than using a mouse. | |

In the following studies, the environment and the tasks are controlled as we will be in a laboratory with a strict protocol. The modality of interaction is invariable in study 1 given that we use the same device only allowing to interact with the hand. Regarding the user, we ask demographic questions such as the age, occupation and gender, and we added a digital skill scale in order to evaluate the ease with digital technologies.

## 3. Study 1: Exploratory data collection

### *3.1.Development of an interface*

We constructed an IKEA-like digital catalog fully controllable by our mid-air hand gestures, based on the Large User Interface project (Parthiban et al., 2022). The interface is controlled using the Leap Motion Controller, a small (80×30×13mm), inexpensive and easy-to-deploy device that connects to a computer via its USB port. It allows us to easily study 3D gestures, presenting advantages in terms of novelty and naturalness, and therefore being more interesting to study. Moreover, this digital catalog allows to study the technology but also the experience in a concrete retailing context.

The interface that enables to use this sensor is the Large User Interface (LUI), managed by The MIT Media Lab (Sluÿters et al., 2022). It is aimed at allowing people to naturally interact by gesture to manipulate multimedia contents on a large display, such as a wall display or a tabletop. Initially, this interface works with a set of pre-recorded gestures. However, the system we used in this work replaced the commands by a gesture recognition algorithm selected following a benchmarking. Thereafter, a gesture elicitation study was then carried out (Wobbrock et al., 2009). The aim of this type of study is to provide a gesture recognition algorithm with enough data to function properly and to implement gestures chosen by end users rather than arbitrarily selected by the researchers. The set of gestures that resulted from this process is available in Figure 9 and an in-depth explanation of this interface will be carried out in essay 4.

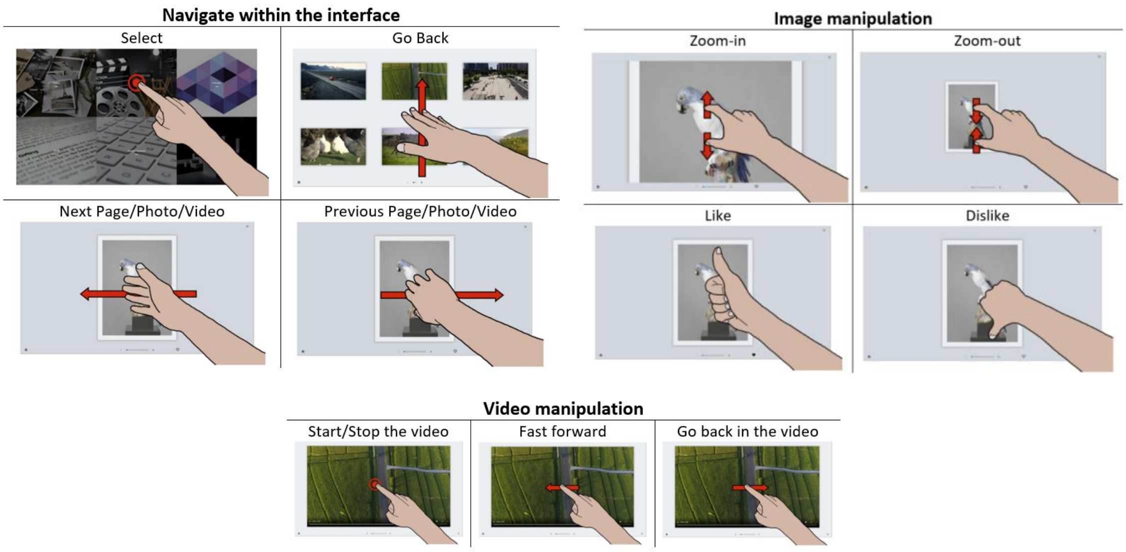



Figure 9: Illustration of each action and its assigned gesture in the interface.

The catalog is controllable by only one hand at a time, and it is possible to change the hand controlling the system in order to adapt to the dominant hand of the user. Note that the initial version of LUI integrates a series of voice commands, which is an aspect abandoned in this version. In addition to changes in how it works, the interface has also been redesigned to look like an IKEA digital catalog. Screenshots of the interface are available in Appendix 4, and a demonstration is available in the following video link: https://youtu.be/7xQSAu0dpoE.

### *3.2.Methodology*

This proposed protocol is based on the one initially defined in the first evaluation of the LUI interface (Parthiban & Lee, 2019). First, a setup phase is carried out by the experimenters. They install a large 80inch 8k television as well as the LeapMotion device. The latter is placed 1.80 meters from the television, at the user's chest height. Therefore, this height is adapted during the passage of each participant. During this time, the participant completes the consent form and answers a few questions (age, gender, occupation, dominant hand, frequency of use of: computers, smartphones/tablets, motion-sensing devices).

As suggested in the first evaluation of LUI (Parthiban & Lee, 2019), participants first have the opportunity to freely discover the interface for 3 minutes. This step makes it possible in particular to test the discoverability of gestures. For this phase, the participants are correctly placed at 1.80 meters from the screen, in front of the LeapMotion device, and the only instruction given to them is that this system is controlled by the gestures they perform using their hands above the device. Apart from that, no indication is given to them, including the available features of the interface and the corresponding gestures.

Once this first phase is completed, the participants are given a video tutorial showing all the existing commands and the corresponding gestures. They are then offered to play again this video as many times as they want since they will then have two tasks to perform. The following tasks were designed to exploit all the gestures initially present in LUI but also all those added via the gesture recognition algorithm.

The first task is the video viewing scenario: the user must use the “videos” application, choose a video to watch and are told they can fast forward if they want. In the second task, participants are instructed to freely browse the interface and add the products they like to their basket. In order to motivate the participants to really get involved in this shopping situation, they are notified that they have a chance to be drawn and win one of the items they like. The duration of this second task is free, i.e., it is up to the participant to indicate when they estimate they have finished shopping ($M_{time}$= 250 seconds ; *SD* = 110 seconds).

During this task and the previous one, if participants ask for help regarding the gestures, we give them an A4 sheet summarizing all the possible actions of the interface and the corresponding gestures. We also allow ourselves to repeat the instructions of the task if necessary. Other than these cases, no other help is provided. If the participants says orally that they give up, the task ends, and we move to the next step.

At the end of the session, the participants are asked to evaluate all the items of our questionnaire detailed in Table 5 on a 7-point Likert scale. It is then followed by a small debriefing interview during which they have the possibility to comment their experience, the system or anything else. These interviews will also be used to illustrate our main results. As it is a first exploratory data collection, the sample of participants is composed of 35 students, aged between 19 and 23 ($M_{age}$ = 20, 66% female), and in which 4 were left-handed.

### *3.3.Results*

As the sample is composed of only 35 participants, we opted to use partial least squares structural equation modeling (PLS-SEM) in order to analyze our results, based on our conceptual model. While using covariance-based structural equation modeling is still more popular than PLS path modeling, the latter is gaining in popularity even faster, and particularly in marketing literature (Hair et al., 2017). One relevant advantage of this method is that PLS-SEM retains its basic functionality even with small samples as the method does not estimate all model parameters simultaneously, but rather one equation at a time (Rigdon et al., 2017). In PLS tools, we decided to focus on SmartPLS, which is particularly appropriate in certain cases, especially with samples that do not follow a normal distribution or other statistical conditions (Hair et al., 2019).

Since we have multiple objectives, we present different models each having their own limitations. We first created a main model comprising the majority of our variables, available in Figure 10. This model started from the conceptual model we developed previously, with some modifications. These are due to several reasons. First of all, in order to concretely implement what we had found conceptually in a real study, we had to make several minor changes as well as use different tools such as UEQ+. This tool has several advantages already presented but requires some adaptation of the variables we measure. Finally, when building the PLS model, we had to remove some variables after checking the discriminant validity (HTMT ratio of less than 0.9) of the variable and their relations between each other. The relations between the variable are indicated, as well as their effect sizes and significance. The $R^2$ is also indicated in the rectangle of each variable.

Contrary to Figure 8, we are here in a more marketing approach having a vision of the experience as being holistic. It is therefore no longer a process following different moments of the interaction. However, like Figure 8, we have kept the same color categories to more easily identify the variables. This model enables us to have a global vision of our work. Yet, the main limitation is that this model includes too many constructs compared to our sample size (Wong, 2013). To overcome this problem, we also present two smaller models, comprising 5 and 6 constructs. These two models detail important sub-models of our global model and will be explained in more details.

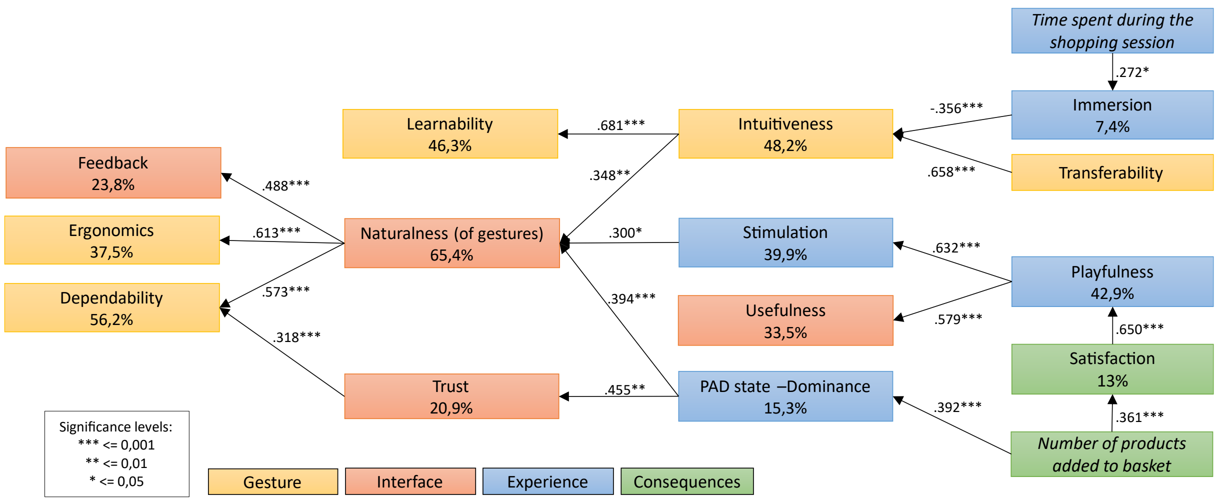



Figure 10: Global PLS model obtained after analysis via SmartPLS.

A first use of this global model is that it highlights the important variables to consider when designing a gestural interaction interface. It also enables us to observe the impact of the gestural interaction on various factors specific to retailing. Indeed, the time devoted to the shopping session is impacted by the immersion of the consumer, the shopping time not having been defined in advance and left to the choice of the participant. Therefore, the stronger the customer's immersion, the more time will be devoted to the shopping session. This is already explained in the literature by the nature of immersion, which is characterized in particular by an intention to time (Nakamura & Csikszentmihalyi, 2014) when the individual is psychologically absorbed. This aspect of immersion also emerges in the debriefing interviews.

"We have the impression of being ourselves in the website and not just facing a screen with a mouse." P17 | F | 20

Another interesting factor is the number of liked products, which tends to increase with the overall satisfaction and the feeling of control. Satisfaction is itself dependent on the playfulness, directly impacted by the gestural modality of the interaction. There is therefore a real financial interest in making efforts to provide an interaction that is both fun and in which the customer feels in control.

In addition to highlighting important variables, this global model enables us to detail some important relationships. One of the main paths put forward in this model includes naturalness as a central factor and is available in Figure 11.

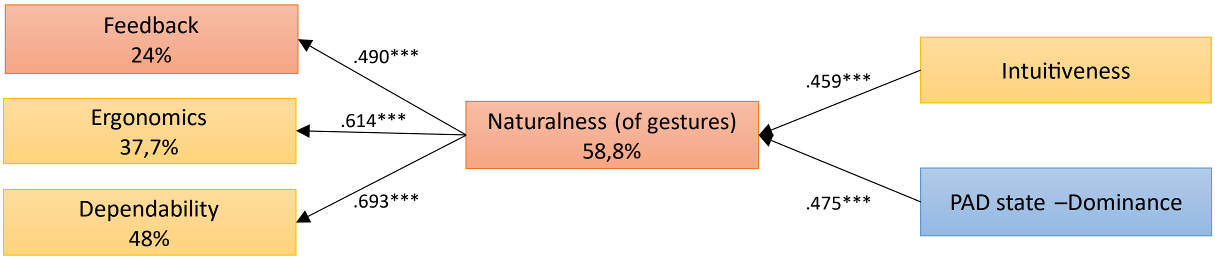



Figure 11: PLS model centered on the naturalness.

Despite its more subjective nature, the naturalness can be explained by several variables specific to gesture design, namely the presence of feedback, the overall ergonomic of the interaction and the dependability of the interface. This thus corresponds to the human-computer interaction literature where the presence of feedback is perceived as fundamental for most user interfaces (Schneiderman, 1998) as it enables individuals to match their mental model to the functionalities of the interface (Norman, 2013). As for the other two variables, the difficulty is to succeed in defining gestures that are both easy to remember and execute, and which make it possible to provide an interaction that is secure and predictable. A particularly relevant method to address this challenge is to carry out gesture elicitation studies (Wobbrock et al., 2009), in which users are directly questioned on which gestures would be the most appropriate according to them to carry out a given action. However, the limitations of this type of user-led methodologies are that everyone is unique and therefore it is almost impossible to obtain a result that is universally recognized (Xia et al., 2022). It is therefore not a solution that is perfect, but which nevertheless improves the situation.

On the other side of this model, the naturalness of the interaction has a positive effect on the perceived intuitiveness and the impression of feeling in control of the situation. First, the impact on intuitiveness appears to be central in this mode of interaction, in particular because it ensures that the gestures implemented correspond to the expectations of the users (Lao et al., 2009). The importance of the intuitiveness will be detailed in Figure 12. Regarding the PAD state, the third dimension opposes feeling in control of the situation to feeling controlled (Coutrix & Mandran, 2012), in this case by the system. The naturalness therefore appears as essential in its role of allowing users to feel in control of the situation. It is particularly relevant as customers desire to exercise control at all stages of the service process (Bateson, 1985; Raaij & Pruyn, 1998). This notion of the centrality of naturalness also appeared during the debriefing interviews with the participants.

> "It's super innate. It's much more innate than using a computer with a mouse, keyboard." P28 | F | 19

> "You feel freer. You have nothing in hand, necessarily, you have the impression of controlling the machine yourself " P11 | M | 19

When we are interested in what makes an interaction intuitive, we observe that it is strongly linked with the ease of learning and not by the discoverability of gestures, which has even been removed from the model.

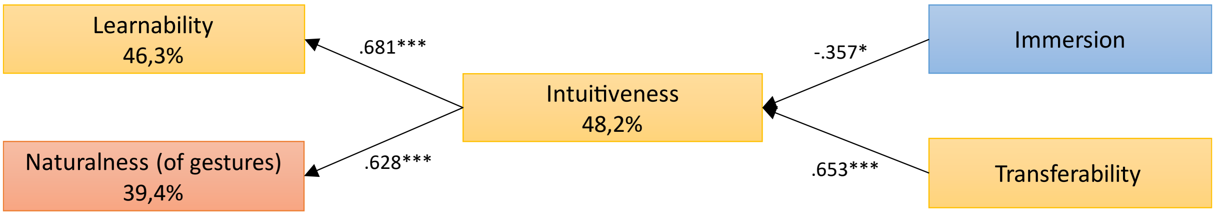



Figure 12: PLS model centered on the intuitiveness.

This result corresponds to an important observation that was made during the sessions and confirmed using the feedback made during the debriefing. When performing the free discovery phase, 49% of the participants did not discover any gestures and therefore remained stuck for 3 minutes in the main menu. Yet these people were ultimately happy with the overall interaction they had with the interface. Most described that after seeing the tutorial, the gestures were easy and intuitive, even if they did not discover those on their own.

> "I didn't really know how to go about it so suddenly I was doing a bit of a mess. But in the end, when you understand the gestures to be made, the movements to be made, it's tit for tat. [...] You can scroll, zoom, with more natural movements than on a mouse." P19 | M | 21

In the literature in human-computer interaction, discoverability is highlighted as being an important factor in the context of an interaction with an interface (Xia et al., 2022). However, it emerges here that a weak discoverability can be compensated by a high learnability, at least for the case of 3D gestural interaction. We could explain this by the new and therefore destabilizing nature of this mode of interaction. Users have few references in their lives to discover by themselves how to use the interface (Wigdor & Wixon, 2011). However, given this novelty character, the experience can still be rich if it is easy to learn how to use the interface. We therefore recommend being extra careful when explaining how to operate this type of interface, whether through video tutorials or even personalized support.

## 4. Study 2: Comparison of gestures and classical user interfaces

### *4.1.Metrics and hypotheses*

In this second study, we cross-analyze self-reported scales with brain activity data to take advantage of the convergence and complementarity of these methods (Poncin & Derbaix, 2004). Brain activity consists of a set of bursts of electrical signals that travel through cells. This signal can be detected using a neural (EEG) helmet that records these slight electrical signals. The electrodes of the neural helmets are capable of capturing signals distinguished into four classes according to the dominant frequency: Beta waves (frequency greater than 13 Hz), waves Alpha (frequency between 8Hz and 13Hz), Theta Waves (frequency between 4 Hz and 7 Hz) and Delta waves (frequency below 4 Hz). Each frequency corresponds to the state of the subject that emits them (Radüntz, 2018).

The headset used in this study is a "Diadem", a dry-EEG (no gel needed) manufactured by the company Bitbrain, used to monitor emotional and cognitive states while remaining comfortable for the user. It has been specially designed to be portable and to be used in situations where the user is on the move, while maintaining excellent signal quality (Park et al., 2012). The system directly computes from the brain activity four variables available to the experimenters. These variables are computed using different information captured by the headset, mainly the position of each of the 12 electrodes and the frequencies of the brain signals. Table 6 details the four variables and gives references explaining how these are computed.

Table 6: The four variables computed using the data from the EEG headset.

| **Name** | **Definition** | **References** |
|---|---|---|
| Engagement | The degree of connection between the participant and the task. | • Pope et al., 1995<br>• Mikulka et al., 2002<br>• Freeman et al., 1999<br>• Stikic et al., 2014 |
| Valence | The degree of attraction experienced in response to a stimulus or situation. | • Harmon-Jones et al., 2010<br>• Allen et al., 2004<br>• Davidson, 1992 |
| Memorization | The intensity of cognitive processes related to the formation of future memories. | • Klimesch et al., 1997<br>• Sederberg et al., 2003<br>• Klimesch et al., 1996<br>• Long et al., 2014 |
| Workload | The focus or concentration of a participant during the experience. | • Gevins et al., 1998<br>• Klimesch, 1999<br>• Stikic et al., 2014<br>• Brouwer et al., 2012 |

It should be noted that all the values of these variables depend on each participant as everyone has a different physiological response to a situation. In order to measure these responses as metrics, the EEG used in this study starts every session with a calibration phase assessing the low and the high cognitive activity of each participant. The data provided is therefore presented mainly between 0 and 100, with the possibility of going beyond in the event of particularly intense brain activity.

As part of this work, we focus on the cognitive and affective dimensions of the experience. We pay particular attention to the immersive quality of the experience (Novak et al., 2000 ; Nakamura & Csikszentmihalyi, 2014.), the playfulness (Kuts, 2009 ; van Beurden et al., 2012), pleasure, arousal and dominance (Mehrabian, 1995). We are also interested in the engagement as a consequence of the experience, and the valence. Regarding the cognitive dimensions of the experience, we are interested in the perceived ergonomics (ISO 9241), ease of use (Davis, 1989), ease of learning (Dix et al., 2003), memorization effort and workload. We therefore formulate the following 12 hypotheses available in Table 7. We expect that, when using gestural interaction instead of a classical user interface:

Table 7: Hypotheses comparing gestural interaction to classical user interfaces.

| | | |
|---|---|---|
| *Tested with self-reported scales* | H1: The playfulness increases<br>H2: The level of immersion is deeper<br>H3: The pleasure increases<br>H4: The level of arousal increases | H5: The dominance decreases<br>H6: The perceived ergonomics decreases<br>H7: The ease-of-use decreases<br>H8: The learnability decreases |
| *Tested with the EEG* | H9: The engagement increases<br>H10: The valence increases | H11: The memorization effort increases<br>H12: The workload increases |

### *4.2.Methodology*

This study was carried out with 39 non-students' participants ($M_{age}$ = 36, 46% female). The experimenters install a computer screen on a desk, as well as the LeapMotion controller and a mouse. During this time, the participants complete the consent form and answer the same questions as in the first study. Once this is done, the participants are installed on a chair, in front of the computer screen, and the electroencephalographic (EEG) headset is installed on their head. After that, a calibration phase lasting a total of fifteen minutes is carried out. During this process, the participant goes through phases of high cognitive intensity and periods of rest.

Once the installation and calibration of the EEG has been completed, the experimentation can begin. The particularity of this study is that it directly compares the gestural interface to a classical user interface with a mouse. Even if only one modality (gesture or mouse) is used at a time, each participant tests the interface in both modalities. The order is random, so some participants started with the mouse and ended with gestures, and others the opposite.

The participants begin with a video tutorial explaining how to use the catalog with a mouse or gestures. They then have to perform two tasks: (1) to go to the "videos" application and to choose a video to watch, and (2) to place three items of their choice in their shopping basket. In order to ensure that the participants selected items that they really wanted, they were informed that they had a chance to win one of the articles they had liked. Once these three steps (tutorial, video and shopping) were completed, the participants fill out a short questionnaire about their immediate experience. The same procedure was then repeated for the second mode of interaction (gesture or mouse). As compensation, all the participants received a voucher worth €40 to redeem in an IKEA store.

### *4.3.Analyses and results*

This study uses two methods to cross-analyze subjective and objective data. A first interest of this approach is the comparison of the results, enabling to observe a possible convergence or complementarity when comparing the results (Poncin & Derbaix, 2004). Secondly, this approach makes it possible to affirm with more robustness the differences in terms of the consumer experience provided by gestural interaction compared to a classical user interface (Van Camp et al., 2019 ; Zaki & Islam, 2021).

*Self-reported scales*

In this study we adopt a within subject approach, which means that each individual participates in both conditions. Given our small sample size, our dataset does not follow a normal distribution. We therefore performed, in SPSS, a Wilcoxon signed-rank test to compare mouse and gestures, with the data of the questionnaires. Since we formulated hypotheses, the results are presented in 1-tailed. Full results are available in Table 8.

Table 8: Comparison of mouse and gestures using the questionnaire (Wilcoxon signed-rank test).

| Variable | Interaction | Mean | Std. Deviation | Z | df | Sig. (1-tailed) | Decision |
|---|---|---|---|---|---|---|---|
| Playfulness | Mouse | 4.13 | 1.24 | -2.751 | 38 | .003 | H1 accepted |
| | Gesture | 5.11 | 1.24 | | | | |
| Immersion | Mouse | 4.16 | 1.22 | -2.108 | 38 | .017 | H2 accepted |
| | Gesture | 4.63 | 1.36 | | | | |
| Pleasure | Mouse | 5.06 | 1.32 | -0.735 | 38 | .231 | H3 rejected |
| | Gesture | 4.84 | 1.39 | | | | |
| Arousal | Mouse | 3.65 | 1.29 | -3.693 | 38 | <.001 | H4 accepted |
| | Gesture | 4.94 | 1.19 | | | | |
| Dominance | Mouse | 5.37 | 1.31 | -1.889 | 38 | .028 | H5 accepted |
| | Gesture | 4.83 | 1.27 | | | | |
| Ergonomics | Mouse | 5.83 | 1.40 | -3.716 | 38 | <.001 | H6 accepted |
| | Gesture | 4.21 | 1.76 | | | | |
| Ease-of-use | Mouse | 5.96 | 1.38 | -3.950 | 38 | <.001 | H7 accepted |
| | Gesture | 4.22 | 1.59 | | | | |
| Learnability | Mouse | 6.41 | 0.99 | -3.377 | 38 | <.001 | H8 accepted |
| | Gesture | 5.32 | 1.44 | | | | |

Based on these results, we know that using gestural interaction rather than a classical user interface significantly improves the playfulness, enables a deeper level of immersion, and provides a higher arousal. In return for these gains in experience quality, we have to pay attention to the ergonomics, ease of use, ease of learning and feeling of control, all of which decrease significantly when adopting gestural interaction. It is especially important as consumers desire to exercise control at all stages of the service process (Bateson, 1985; Van Raaij & Pruyn, 1998).

We also observe that there is no significant effect on the pleasure dimension of the emotional state. When analyzing the data, we notice individual disparities in the difference in pleasure between gestural and mouse interaction. This could be explained by the different nature of these two methods of interaction, the gesture being new while the mouse has been known and used by many people for a longer time. There could therefore be an impact of the participant's ease with technologies, itself correlated with the age, on their level of pleasure after having interacted with this new technology. In order to verify this, we performed a correlation analysis using the Spearman's coefficient in SPSS. As expected, there is no correlation between the age of the participant and the level of pleasure with the mouse interaction. However, there is a negative correlation between the age of the participant and the level of pleasure with the gestural interaction, $r_s(37) = -.409$, $p = .005$. Therefore, the older the person interacting with gestures, the lower their level of pleasure. This can be interpreted by a greater difficulty for older people to use this new mode of interaction, or simply the initial expectation that it will be more difficult, which can also impact the level of pleasure (Mehrabian, 1996).

The main risk of this type of technology is therefore to give consumers the feeling of being rather controlled by the system (Coutrix & Mandran, 2012), which tends to provide a poorer experience. This is particularly problematic in the case where pleasure is absent and the arousal high, which is a situation where a feeling of anxiety may appear (Mehrabian, 1996). To avoid this situation, consumers should not be left on their own when discovering such interfaces, and especially older ones. The integration of this type of technology in an e-commerce situation should therefore go hand in hand with an easy and effective learning process.

*EEG data - Exploration*

The first step in the approach we chose is the data exploration. This was done by first visualizing the data individually, as illustrated in Figure 13. We try to compare gesture and mouse signals for the same variables and individuals. Our goal is to see if it is possible to see any differences in these data with the human eye. We also visualized the aggregate distribution of these data (cf. Figure 14), which allowed us to see the major values and potential outliers. Note that all the steps in the following parts were done in Python, via JupyterLab. The complete code is available in Appendix 5.

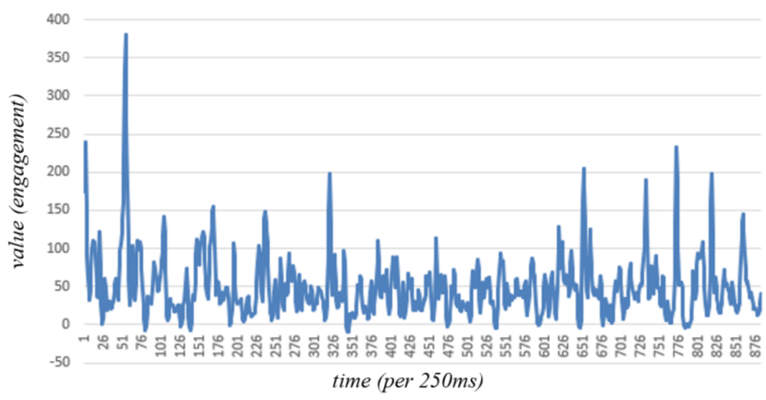



Figure 13: Example of EEG data visualization for one individual and one variable.

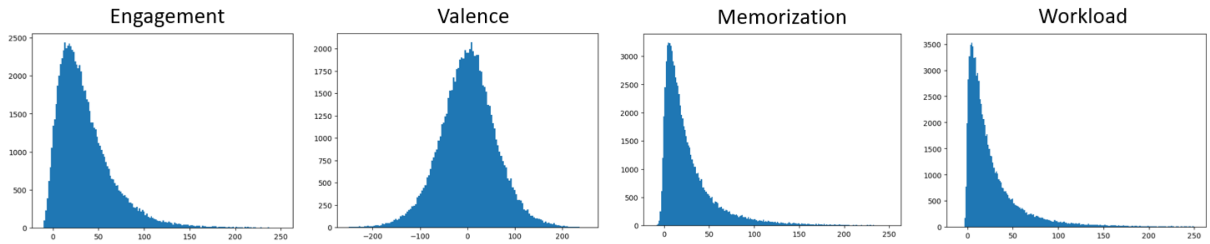



Figure 14: Distribution of the four variables of the EEG.

In addition to this, we computed summary statistics of the dataset (cf. Table 9) as well as specific metrics such as the mean during specific moments of the interaction (cf. Table 10). The objective is again to note if it is possible to see with the human eye potential elements allowing to differentiate the gestural interaction from the classical user interface.

Table 9: Summary statistics of the dataset.

| **Variable** | **Median** of mouse | **Median** of gestures | **Mean** of mouse | **Mean** of gestures | **Std**. of mouse | **Std**. of gestures |
|---|---|---|---|---|---|---|
| Engagement | 29.6 | 28.6 | 35.4 | 35.3 | 6.3 | 5.4 |
| Memorization | 17.7 | 18.1 | 24.4 | 26.7 | 5.3 | 4.7 |
| Valence | 0.1 | 2.5 | -0.1 | 2.1 | 7.5 | 7.4 |
| Workload | 17.4 | 17.3 | 24.7 | 27.5 | 4.7 | 4.4 |

Table 10: Part of participants where the brain activity increases when switching from mouse to gestures.

| **Variable** | **Mean** of the whole interaction | **Max** peak | Mean of the **first second** of interaction | Mean of the **first ten seconds** of interaction | Mean of the **last second** of interaction | Mean of the **last ten seconds** of interaction |
|---|---|---|---|---|---|---|
| Engagement | 46% | 56% | 28% | 46% | 41% | 38% |
| Memorization | 54% | 64% | 59% | 36% | 44% | 49% |
| Valence | 59% | 69% | 54% | 49% | 46% | 56% |
| Workload | 46% | 62% | 62% | 41% | 38% | 41% |

Based on the peak-end rule (Do et al., 2008), we know that the most important moments of interaction impacting the experience are the most intense and last moments of interaction. In our experimental design, looking at the first and last moment is irrelevant as participant take part in both conditions and stay with the interface in front of them. We also found that computing means and medians of the whole interaction smooths the data and gives no result. The most significant observations we made were by looking at the peaks of activity. We therefore decided to focus on the most intense moment of interaction in two different ways: by looking at (1) the highest peak of brain activity and at (2) the proportion of high brain activity, for each participant, interaction session and variable.

A final observation that allowed us to make this exploratory analysis is to notice that we have 61% of the total interaction time with gestures (39% with the mouse). Since no time constraint was given to the participants, they tended to use the interface longer using gestures rather than the mouse. This is an important aspect that will be considered when computing metrics.

*EEG data - Pre-processing*

Before analyzing the data, we have to perform some pre-processing. The EEG headset records brain activity throughout the duration of the experiment, even when the tasks have not yet started or when the participants answer the questionnaires. Therefore, we filter the data to keep only the times when the participant interacts with the interface for the shopping task. Then, in order to avoid noise, we apply an "interquartile range" filter technique to detect outliers (Tukey, 1977 ; Vinutha et al., 2018). This technique is particularly relevant when the distribution of the data is skewed on one side (Walfish, 2006). As the data distribution in Figure 14 shows, this is mostly the case in our dataset. Since we are interested in the highest peak of activity of individuals, we are particularly sensitive to noise, and we must therefore manage the outliers. In addition, these results will then be used following a classical statistical approach, where it is traditionally required to consider outliers.

The interquartile range technique computes the distance between the 25$^{th}$ percentile (Q1) and 75$^{th}$ percentile (Q3) and defines two boundaries based on this distance. If a value is outside these boundaries, it is considered an outlier:

- InterQuartile Range (IQR) = Q3 – Q1
- Lower Boundary = Q1 – (1.5 * IQR)
- Upper Boundary = Q3 + (1.5 * IQR)

However, if the outliers show extreme deviation in comparison to the boundary, as shown in Table 11, we should replace the inner boundaries by the outer boundaries (Schwertman et al., 2004). To do so, we must replace the "1.5" with "3" in the formulas, and therefore only consider strong outliers (Santhanam & Padmavathi, 2014):

- Lower Boundary = Q1 – (3 * IQR)
- Upper Boundary = Q3 + (3 * IQR)

Table 11: Highest values compared to the inner and outer upper boundaries.

| Variable | Mean **highest value** when keeping outliers | Mean inner **boundary** value (with **1.5** in formula) | Mean outer **boundary** value (with **3** in formula) |
|---|---|---|---|
| Engagement | 269 | 101 | 152 |
| Memorization | 288 | **77** | 118 |
| Valence | 215 | 149 | 259 |
| Workload | 497 | **79** | 121 |

This is particularly relevant in our case because by using "1.5" we often establish an upper boundary of less than 100. This leads us to consider perfectly plausible values as outliers, which is not the case when using "3" instead. However, for the sake of making our results more robust, we carried out the same procedure which will follow also using "1.5". This enabled us to see that our results were similar, and that the choice of technique does not significantly impact the performance of our model.

Once outliers are detected, they must be managed. For this, we have two main options: delete them, which is not recommended for small datasets like ours, or impute them, i.e. replace them with other values (Toka & Çetin, 2014 ; Santhanam & Padmavathi, 2014). We favored this second method, also called trimming in machine learning literature. Therefore, when a value crosses a boundary, it is replaced by the value of the boundary.

*EEG Data - Computation of the metrics*

In order to base our choice of features on our intuition, we focus on two main metrics: (1) the highest peak of brain activity and (2) the proportion of high brain activity during an interaction session. Since we have more interaction time with the gestures than with the mouse, we first have to take that into account as it can be problematic. Since we are interested in the maximum peak of brain activity, we assume that interacting longer increases the probability of seeing a high activity peak appear. To account for this, we correct the dataset by randomly removing data points from longer sessions so that the durations are equal for each participant. Once this is done, we store, for each participant and each variable, the value of the peak of activity for the gestures and the mouse. Given the random aspect of this technique, we repeat this process 5,000 times (corresponding to the stabilization of the results) and compute an average of these peaks. This average is the first measure that we will use in the following analyses.

For our second metric, the proportion of high brain activity, it is not necessary to correct the durations of the sessions as we are interested in a proportion of time. The main challenge is to choose an objective threshold defining what constitutes a high activity. We have therefore chosen to consider that any value exceeding 100, which is the threshold defined by Bitbrain for this EEG headset, can be considered as a particularly high brain activity for the individual.

*EEG Data - Supervised classification approach*

We could ask ourselves why opting for this method rather than a simple discriminant analysis. The main problem is that this type of analysis of classical statistics requires respecting many statistical conditions. In the case of small samples like ours, it becomes difficult to respect all these conditions to carry out this type of test. In our case, the sample does not follow a normal distribution. We therefore favor the less restrictive machine learning approach.

Our approach consists in training a model to interpret a series of variables, called "features", in order to classify an observation with a given label. In our case, we have 8 features, namely the 4 variables of the EEG headset all having the computation of their highest peak and the proportion of high values. Our goal here is to know whether an interaction session was performed using gestures or a mouse, which are our two classification labels. Finally, our dataset is composed of 78 observations, namely the 39 participants who all had a session with gestures and another with the mouse.

We prefer to compute a single model including all aspects of our variables rather than 4 separate models including the 2 features per variable. By doing so, we increase our chances of creating a performing model that will allow us to say whether it is relevant to be interested in this aspect of the data. Moreover, it will give us a first indication of the relative importance of these different variables compared to each other.

We first have to choose a classification model, which is the method that will classify an interaction as gesture or mouse. In our case, we are in a supervised machine learning problem, and we want to be able to understand how the model takes its classification decisions (Kotsiantis et al., 2007). We therefore focus on an untuned random forest model (Svetnik et al., 2003), considered as a relevant tradeoff between its performances (Hasan et al., 2014) and the explanatory abilities. This model works with multiple decision trees, each constructed by a different bootstrap sample from the dataset. When a new observation arrives, it cycles through each of the trees and receives a vote that indicates the tree's decision. The model then chooses the decision with the most votes.

Concretely, the system first randomly splits the dataset into 2 parts, one used to train the model and another to test its performances. In our case, we have 80% of the dataset that becomes the training set and the remaining 20% the test set. Once it is trained on the first set, the model reads the values of the features of a new observation coming from the test set and gives a classification prediction. Once all the test set is completed, we compare the classification predictions with the actual values, which allows us to compute model performance metrics. Regarding the hyperparameters of the random forest model, we left the default values without trying to fine-tune them since our dataset is relatively small.

In order to stabilize the results, given the randomness of the sampling method and of the random forest model, we repeat this process 100,000 times. This corresponds to the stabilization of the results, namely that their values did not deviate more than 0.1% during 5 computations. This allows us to obtain models with an accuracy of 72%, which is the number of correct predictions divided by the total number of predictions. The full confusion matrix is available in Table 12.

Table 12: Confusion matrix of our model.

| | | **Actual values** | |
|---|---|---|---|
| | | **Gesture** | **Mouse** |
| **Predicted values** | **Gesture** | 35.2% | 13.2% |
| | **Mouse** | 14.8% | 36.8% |

This means that, when the system receives new brain activity data from a person, it can tell while being 72% right whether that person used gestures or the mouse. These results are a significant improve from a random model that would have 50% accuracy. Another baseline model to compare with is the model using the means or medians of the EEG signal, that each have approximately 51% accuracy. This allows us to affirm that the two metrics relating to high brain activity contain relevant information to differentiate gestures and mouse.

Another advantage of the machine learning approach is that we can now ask the random forest model the relative importance of the features it used to make its classification decisions. These are detailed in Table 13. We can see that the most useful variable for the model to make its classification decision is the workload, and more specifically the proportion of high workload. It is followed by the memorization, also placing more importance on the proportion rather than the highest peak. The trend is reversed for the valence and engagement, where the highest peak of activity is considered more important than the proportion of high activity throughout the session. It should also be noted that the engagement only accounts for 18.2% of the weight of the decision, which means that it is either less useful or harder for the model to interpret it. In total, the highest activity peaks represent 40.3% of the weight of the decision against 59.7% for the proportion of high activity.

Table 13: Importance of the features used in the random forest model (with 8 features).

| **Feature** | **Importance** | **Aggregated importance** |
|---|---|---|
| Highest engagement peak | 9.5% | 18.3% |
| Proportion of high engagement | 8.8% | |
| Highest valence peak | 12.3% | 23.1% |
| Proportion of high valence | 10.8% | |
| Highest memorization peak | 9.5% | 26.1% |
| Proportion of high memorization | 16.6% | |
| Highest workload peak | 9.0% | 32.5% |
| Proportion of high workload | 23.5% | |

The next and final step is the simplification of the model. It will make it possible to gain even more in accuracy and to choose among these 8 features which ones to keep for the classic statistical approach. To do this, we remove the least important feature from the model and compute it again. We then systematically repeat the same procedure until only one feature remains. In order to preserve as much as possible the information of the 4 variables, if two less important features have a similar score, we prefer to keep the one allowing to guarantee at least one feature per variable. The performance metrics of all these simplified models are detailed in Table 14.

Table 14: Performance metrics of the simplified models.

| **Nb. of features** | **Accuracy** | **Precision** | **Recall** | **F-score** |
|---|---|---|---|---|
| 8 features | 72.1% | 73.9% | 72.0% | 70,1% |
| 7 features | 72.6% | 74.2% | 72.2% | 71,4% |
| 6 features | 72.7% | 74.5% | 71.8% | 71,3% |
| 5 features | 74.5% | 76.1% | 73.6% | 73,2% |
| **4 features** | **77.4%** | **78.5%** | **76.8%** | **76,3%** |
| 3 features | 75.7% | 76.0% | 77.0% | 75,1% |
| **2 features** | **77.1%** | **78.5%** | **76.1%** | **75,8%** |
| 1 feature | 60.8% | 62.8% | 60.4% | 58,7% |

The most efficient model is therefore the one with 4 features. The level of importance of these features is detailed in Table 15. In addition to being more precise, this allows us to identify the most important aspect of each of the 4 variables.

Table 15: Importance of the features used in the random forest model.

| **Feature** | **Importance** (4-features model) | **Importance** (2-features model) |
|---|---|---|
| Highest engagement peak | 17.0% | - |
| Proportion of high engagement | - | - |
| Highest valence peak | 22.0% | 43,7% |
| Proportion of high valence | - | - |
| Highest memorization peak | - | - |
| Proportion of high memorization | 24.7% | - |
| Highest workload peak | - | - |
| Proportion of high workload | 36.3% | 56,3% |

It should also be noted that the model comprising 2 features also obtains high-performance scores. What is particularly interesting is the fact that it is a combination of a highest peak and a high activity. We might therefore ask ourselves if the most important aspect is to combine workload and valence, or if any combination of highest peak and high activity would work equally well. To verify this, we tested the 16 possible combinations of models including 2 features (with a combination of max peak and proportion of high activity). The accuracy of each of these models is detailed in Table 16.

Table 16: Accuracy of the 16 combinations of 2-features models.

| | | **Proportion of high activity** | | | |
|---|---|---|---|---|---|
| | | Engagement | Valence | Memorization | Workload |
| **Max peak** | Engagement | 48% | 51% | 66% | 70% |
| | Valence | 45% | 50% | 65% | 77% |
| | Memorization | 42% | 49% | 61% | 63% |
| | Workload | 51% | 50% | 62% | 68% |

It turns out that the variables play an important role. Using the proportion of high engagement or valence only gives poor accuracy scores. The best score that stands out in particular is the one that had been previously identified, namely the proportion of high workload combined with the highest valence peak.

*EEG Data - Classic statistical approach*

The metrics we used were exported into SPSS to perform Wilcoxon signed-rank test to compare gestures and the mouse. As with the questionnaires, since we formulated hypotheses, the results are presented in 1-tailed. Table 17 gives the results using the average highest peaks of brain activity.

Table 17: Comparison of mouse and gestures using the highest brain activity peaks.

| **Variable** | **Interaction** | **Mean** | **Std. Deviation** | **Z** | **df** | **Sig. (1-tailed)** | **Decision** |
|---|---|---|---|---|---|---|---|
| Engagement | Mouse | 142.8 | 23.3 | -3.866 | 38 | <.001 | H9 accepted |
| | Gesture | 150.0 | 21.3 | | | | |
| Valence | Mouse | 192.3 | 31.4 | -2.819 | 38 | .002 | H10 accepted |
| | Gesture | 211.1 | 38.2 | | | | |
| Memorization | Mouse | 114.1 | 22.4 | -5.442 | 38 | <.001 | H11 accepted |
| | Gesture | 118.4 | 23.7 | | | | |
| Workload | Mouse | 117.7 | 22.5 | -5.442 | 38 | <.001 | H12 accepted |
| | Gesture | 120.9 | 23.0 | | | | |

These results go in the direction of the validation of our last four hypotheses. However, we also have to perform the same analyses using the second metric, the proportion of high brain activity. The results are presented in table 18.

Table 18: Comparison of mouse and gestures using the proportion of high brain activity.

| **Variable** | **Interaction** | **Mean** | **Std. Deviation** | **Z** | **df** | **Sig. (1-tailed)** | **Decision** |
|---|---|---|---|---|---|---|---|
| Engagement | Mouse | .0365 | .0247 | -0.339 | 38 | .367 | H9 rejected |
| | Gesture | .0409 | .0268 | | | | |
| Valence | Mouse | .0446 | .0168 | -1.912 | 38 | .028 | H10 accepted |
| | Gesture | .0514 | .0181 | | | | |
| Memorization | Mouse | .0163 | .0168 | -3.925 | 38 | <.001 | H11 accepted |
| | Gesture | .0337 | .0244 | | | | |
| Workload | Mouse | .0180 | .0156 | -4.664 | 38 | <.001 | H12 accepted |
| | Gesture | .0433 | .0280 | | | | |

In this case, the hypotheses H10, H11 and H12 are still accepted, but H9 is not anymore. The difference in engagement is no longer statistically significant. We can interpret this by the fact that there are individual differences in terms of engagement with the task, especially since our dataset is relatively small. Yet, when we look at the most impactful event causing the peak of engagement, the difference is statistically significant. This is consistent with the results of the random forest model, which placed more importance on the highest peak of engagement rather than the proportion of high engagement throughout the session. According to the peak-end rule (Do et al., 2008) and the results of our machine learning approach, we could put more importance on the peak of activity rather than the proportion throughout the session. In this case, we could conclude that the engagement is significantly higher using gestures rather than the mouse, and therefore validate H9. However, this choice is debatable and above all shows that the effect on the engagement requires further investigation in future work.

Regarding the other three variables, the results converge between the analyses with the two different metrics. When we interact with a gestural interface rather than a classical user interface, our valence increases significantly, meaning that we are more connected with the task. On the other hand, the memorization effort and the cognitive workload each are significantly more intense. This also converges with the results obtained with the self-reported scales. There are therefore affective experiential gains offset by an increase in the cognitive difficulty of controlling this type of new technology.

## 5. Discussion and conclusion

To understand the impact of gestural interaction technologies on the consumer experience, we first answered our research question “what are the key aspects to consider when designing gestural interaction interfaces?”. To do so, we highlighted the important variables to take into account when building an interface based on gestural interaction, and then built a conceptual model. In order to test it, we set up two studies in which participants interact with an IKEA-like digital catalog fully controllable with gestures. This enabled us to cross-analyze our data and multiply the contexts of use. In the first study, we put people in a situation similar to using an in-store kiosk and we evaluate the discovery of the interface. In the second study, we put the participants in a situation similar to shopping online from a personal computer. The analyzes were then carried out using SmartPLS, a qualitative approach, SPSS and a machine learning approach. Doing so enabled us to answer our second question “how does the gestural interaction impact the consumer experience?”.

We observed the importance of the naturalness of the interaction which, despite being subjective, is explained by several factors more objective and specific to the gestures. This naturalness itself has an impact on the perceived intuitiveness of the interaction, the stimulation of the customer and the feeling of being in control of the situation. Moreover, we can directly observe the impact of this interaction on retailing, with a positive impact on the time spent shopping and the number of products added to the basket. For the designers of such interfaces, we therefore recommend paying particular attention to the naturalness of the gestures implemented. For this, it seems relevant to go through a gesture elicitation study. Another important element is the need to set up easy and complete learning of the interface, for example via a tutorial as in this data collection or via personalized support.

We have seen that practitioners can use gestural interaction to provide a more playful, immersive and stimulating consumer experience. On the other hand, we must not neglect the loss in user's feeling of control, which will directly influence the consumption and the experience. This is especially the case for older people. We therefore recommend setting up a complete and easy learning of the interface, for example via a tutorial as in this study. Finally, we have shown that the participants' subjective declarations in terms of their experiences correspond to the objective measures observed through the EEG (Van Camp et al., 2018).

It should be kept in mind that these studies present limitations. As a first one, the samples remain relatively small, and particularly for the structural equation modeling. As another limitation, we adopt a diachronic point of view. In a future work, it would be particularly interesting to study the impact over time, to observe a potential learning or novelty effect. It would also be the opportunity to study the experience through multiple touchpoints of the customer journey. Finally, we performed both studies in a controlled lab environment. In order to observe the experience in a real context, il would be relevant to test the same setup in a shop or when completing real online purchases.

This work contributes to the current literature by providing understanding of the impact of new technologies in retailing, and particularly in the case of 3D gestural interaction. From a managerial point of view, we provide guidelines for the use of this type of new technology and its impact on the consumer experience. More specifically, we study how this type of technology can improve the experience, in an environment where it is crucial to stay one click ahead of the competition.

## Essay 4: Definition and Application of a Method for Evaluating the Gestural Interaction Experience

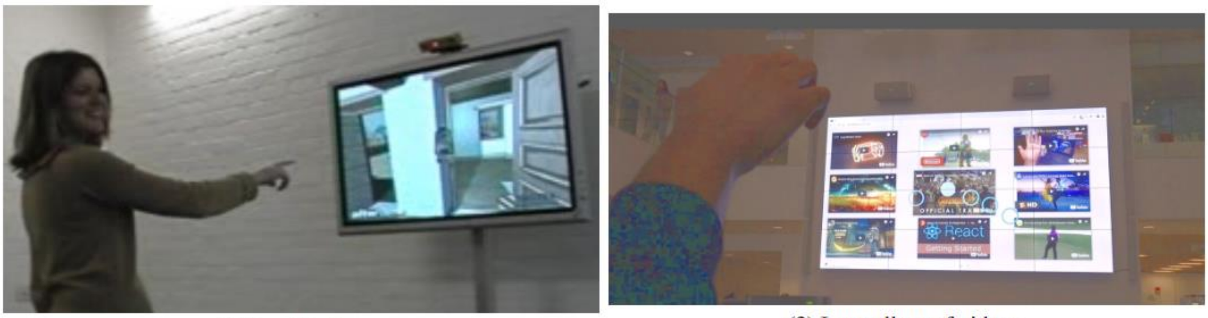
Part of this work was used in another research with another PhD student. This resulted in a presentation at a conference and a publication in a journal:

*Parthiban, Vik ; Maes, Pattie ; Sellier, Quentin ; Sluÿters, Arthur ; Vanderdonckt, Jean. Gestural-Vocal Coordinated Interaction on Large Displays. ACM SIGCHI Symposium on Engineering Interactive Computing Systems (EICS '22) (Sophia Antipolis, France, 21/06/2022 to 24/06/2022). doi:10.1145/3531706.3536457.*

*Sluÿters, Arthur ; Sellier, Quentin ; Vanderdonckt, Jean ; Parthiban, Vik ; Maes, Pattie. Consistent, Continuous, and Customizable Mid-Air Gesture Interaction for Browsing Multimedia Objects on Large Displays. International Journal of Human-Computer Interaction, Vol. 38, no.15, p. 32 (2022). doi:10.1080/10447318.2022.2078464.*

## 1. Introduction

Many methods exist for evaluating the quality of a user interface (UI) in general (Vermeeren et al, 2010), but not that many specifically tailored to gesture UIs, a UI that brings into play the rich palette of all human movements for interacting with a system. For example, Figure 15 depicts a gesture UI for browsing a virtual reality 3D scene and a gallery of videos. Given the particularities of gestural interaction compared to traditional user interfaces, some authors have already put forward the need for more advanced evaluation method for gestural interaction (Wickeroth et al., 2009), capturing the multi-faced perspective of the richness of interaction (Xia et al., 2022). Rohrer (2014)'s classification distinguishes between methods producing qualitative measures capturing attitudinal UI quality attributes, such as preference, and methods producing quantitative measures expressing behavioral UI quality attributes, such as performance. This distinction is important since attitudinal measures represent end users' self-reported measure when interacting with the UI while behavioral measures report what end users really do when interacting. End users may report a preference that is radically different from what they actually do: this expresses the eternal divergence between the end users' preference (what they say) and their performance (what they actually do).




(1) In a 3D Scene. (2) In a gallery of videos.

Figure 15: Gesture user interfaces for multimedia browsing.

Most UI evaluation methods (Vermeeren et al., 2010) target *usability*, one of the main software quality factors (ISO, 2019), that is decomposed into three sub-factors (ISO, 2018): *effectiveness* refers to task performance by expressing how accurately and completely did the user achieve the goals (for example measured by task completion rate and error rate), *efficiency* refers to the amount of effort that is required to achieve the level of effectiveness when achieving the goals (for example measured by task completion time and fatigue), *satisfaction* refers to how comfortable the user feels while using the system (for example assessed by a questionnaire for subjective satisfaction). There is thus an absence of subjective and affective measures, which are essential to human nature.

But currently the evaluation of user experience (UX) (Hassenzahl, 2008) goes beyond usability (van Beurden et al.,2012) because it is influenced by both the UI and its context of use (Calvary et al., 2003), which itself includes the user and the tasks, the platforms and devices, and the environment. The ISO (2018) 9241 standard defines UX as a "user's perceptions and responses that result from the use and/or anticipated use of a system, product or service". According to this definition, UX could include all the users' emotions, beliefs, preferences, perceptions, physical and psychological responses, behaviors and accomplishments that occur before, during, and after use. The decisive benefits of gesture UI are not just revealed through usability, but much more through the UX, which encompasses a broader class of quality factors, such as enjoyment, stimulation, and identification (van Beurden et al., 2012).

Frequently, gestures are modelled in a laboratory setting where usability testing should be carried out to evaluate the extent to which the gesture interface can be used by specified users in a specified context of use (Calvary et al., 2003) to achieve specified goals with effectiveness, efficiency, and satisfaction. However, the wide diversity of gesture UIs makes it difficult to decide which quality factors should be taken into account in a usability test (Xia et al., 2022). This observation also holds for methods evaluating the UX of gesture UIs. A thorough evaluation of a gesture UI should go beyond than merely assessing its usability, namely by evaluating its UX.

In principle, these evaluation methods apply to any interface, whatever their modality, since they have been designed and presented as such. However, it is clear that these methods have been applied, tested and validated on corpora of graphical UI, even if this has been done on a wide variety of contexts of use. The same is true for their interpretation: the results of the evaluation are mainly mapped to graphical interfaces. Therefore, reusing classical evaluation methods, whether for usability or user experience, is not sufficient to account for all the richness of the possibilities offered by a gesture interface and does not specifically account for the quality factors specific to this interface (Xia et al., 2022). Such an evaluation may be incomplete, partial or even inadequate.

Therefore, we benefit from several possibilities: (1) to redefine an evaluation method and its measures within the strict framework of a gesture interface; (2) to extend an existing method to take into account new aspects not previously covered; (3) to create a new method entirely devoted to a gesture interface. This last option seems to be utopian, because of the complexity that such an activity would entail and because it would mean forgetting all the knowledge acquired in the field of evaluation. A combination of these options therefore seems more realistic, based on what has already been learned. This essay aims at the following contributions: to propose a method for evaluating a gesture interface by revisiting (1), extending (2), and introducing (3) qualitative and quantitative measures for such an interface. Then, to apply them on an operational interactive system with a gesture interface intended for a general public (i.e., a system for multimedia browsing on a wide variety of displays, such as large displays), to analyze these results in a detailed way and to see how these measures account for the quality of a gesture interface. In particular, we take advantage of the complementarity and convergence of approaches allowing us to capture objective and subjective measurements.

The remainder of this essay is structured as follows: Section 2 reviews the literature pertaining to UI evaluation methods with a focus on their application to gesture UIs. Section 3 states the research hypothesis of this essay and justifies why a gesture UI for multimedia browsing has been selected for conducting the evaluation. For this purpose, this section explains the design and the development of LUI, a gesture-based interactive application for multimedia browsing in multiple contexts of use. Section 4 defines and justifies our method for evaluating the user experience of a gesture UI, applies it on the LUI system, and discusses its detailed results. Section 5 synthesizes the results in terms of implications for evaluating a gesture UI by highlighting the methodological aspects of the proposed method. Section 6 concludes this essay and discusses some future avenues to this work.

## 2. Literature review

In this section, we review the literature related to UI evaluation methods as soon as they have some links with gesture interaction. Then, we discuss work related to gesture UI for multimedia browsing, since our LUI application belongs to this domain.

### *2.1. Methods for evaluating gesture user interfaces*

In the area of questionnaire-based evaluation, the System Usability Scale (SUS) (Brooke, 1996) became a classical usability questionnaire consisting of ten 5-point Likert scales with questions like Q1 = "I think that I would like to use this system frequently". Lewis and Sauro (2009) showed that SUS actually has two factors: *usability* covered by eight items and *learnability* covered by items 4 and 10. Since they have a reasonable reliability (Cronbach's $\alpha$ = .91 and

.70, respectively) and they correlate with the overall SUS and with one another, they can be used separately. Wickeroth et al. (2009) extended SUS into a Gesture Usability Scale (GUS) by adding five items related to the gesture UI to evaluate the perceived reliability (G1 and G4), performance (G3 and G5), and compliance with the user's expectations (G2):

- G1 = "The system recognized the gestures reliably"
- G2 = "The system followed the movements as expected"
- G3 = "The reaction time of the system is satisfactory"
- G4 = "The system aborted movements unexpectedly often"
- G5 = "The system reacted to my movements too slowly"

Although the GUS score was lower than the SUS score, a correlation existed between them. This method involves only self-reported items and does not compute any quality model. To overcome these shortcomings, Barclay et al. (2011) defined a quality model for evaluating a gesture UI as follows: accuracy, fatigue, and duration are objectively measured and naturalness is assessed by a 5-point Likert scale; their values are repeated for each gesture, normalized, averaged, and aggregated into a model where weights of the factors are determined by participants. This results into a quantitative, yet simple, model for evaluating a gesture UI.

In order to compare a gesture UI with respect to a touch-based UI in a driving scenario, Graichen et al. (2019) combined questionnaire-based evaluation (in this case, a 12-point rating scale for trust, a driver distraction questionnaire, the NASA TLX questionnaire (Hart & Staveland, 1988) and the AttrakDiff questionnaire (Hassenzahl, 2008)) with quantitative data (in this case, glance points and duration). The questionnaires used are, again, widely applicable, therefore not targeting any particular modality such as gesture interaction. van Beurden et al. (2012) compared a gesture UI to a pointer-based UI, both in terms of their usability and UX through two experiments, one in a near-field context and one in a far-field context of use. Whereas pointer-based UIs scored higher on perceived performance, and the mouse scored higher on ease of learning and pragmatic quality, gesture UIs scored higher in terms of hedonic quality and fun, which demonstrates the need to evaluate a gesture UI beyond usability.

In the area of heuristic evaluation, Norman and Nielsen (2010), regretting that no valid usability guidelines exist yet for guidelines review, recommend the use of several heuristics, i.e., visibility, feedback, consistency, discoverability, scalability, and reliability, but without going any further. Similarly, Wachs et al. (2011) expressed eight heuristics specifically tailored for hand gestures, i.e., price, responsiveness, user adaptability and feedback, learnability, accuracy, low mental load, intuitiveness, and comfort, each associated to a challenge. For example, accuracy poses challenges for the detection of gestures, its continuous tracking, and its real-time recognition, which are all complex problems to solve.

Later on, Chuan et al. (2014) proposed four general heuristics for evaluating a gesture UI: gesture learnability (to be evaluated before producing gestures), gesture cognitive workload (to be evaluated when producing gestures), gesture adaptability (to be evaluated after producing gestures), and gesture ergonomics (to be evaluated when the interaction is prolonged over time). For example, gesture ergonomics should be assessed through comfort, fatigue, and physical ergonomics. Chuan et al. (2015) report that five evaluators discovered significantly more defects for a gesture UI with these heuristics than without. While performing a heuristic evaluation based on these heuristics in addition to classical heuristics (Nielsen, 1994) is certainly desirable, no guidance is provided on how to effectively assess them, therefore basing the quality of this evaluation entirely on the expertise of the evaluators themselves and the knowledge they have of the domain. Moreover, the potential overlapping of these heuristics, taken together, could pose some problems of conflict (two different heuristics cover the same factor, but in a different way) or redundancy (two different heuristics cover the same factor in the same way).

In the area of guidelines review, few usability guidelines are suggested to evaluate a gesture UI. For instance, Yee (2009) recommends usability guidelines such as "achieve high effectiveness", "Minimize learning among users and increase differentiation among gestures", and "Design efficient gestures to increase user adoption". Again, these guidelines are hardly measurable per se and their sound evaluation is based on the seriousness of the evaluators and their experience. For example, how can we decide that two gestures are distinguishable enough if we cannot rely on a sound measure or a guideline that is empirically valid, with a strength of evidence and an importance level?

In the area of user testing, Brandao et al. (2019) evaluated a gesture UI for a tele-rehabilitation system in virtual reality by relying on a functional magnetic resonance imaging (fMRI) protocol. By monitoring correlation maps between a region of interest in the primary motor cortex and brain voxels, they evaluated how brain connectivity changes over time before and after producing gestures. While this evaluation method is quantitative, it is sophisticated, requires a specific setup and is tied to brain activities, thus making it challenging to transpose to any gesture UI outside the area of tele-rehabilitation. Neca and Duarte (2011) measured the average reflection time to manipulate images: in the “table of images” scenario, the average reflection time was larger in the gesture UI condition (M = 2.23 msec) than in the gesture and vocal UI condition (M = 1.21 msec), whereas in the “wall of images” scenario, times were comparable (M = 0.58 msec vs. M = 0.61 msec).

### *2.2.Gesture interaction for multimedia browsing*

More specifically for mid-air gesture interaction with multimedia objects, less work can be found and usually focus on one media type or two at a time but not as a whole (Steinmetz & Nahrstedt, 2004): images (Neca & Duarte, 2011 ; Koutsabasis & Domouzis, 2016), videos (Zigelbaum et al., 2010), virtual objects (Ortega et al., 2017), and images with videos (Drossis et al., 2013).

For example, Ackad et al. (2015) designed and evaluated a “media ribbon”, a large public display that shows information about events for theaters and concerts. Designing an intuitive and easy-to-learn gesture interface is more critical for such displays, as people are less inclined to take time to learn how to interact. They came up with four gestures (swipe left/right and move the hand up/down then hold briefly) that could trigger five different commands. To evaluate the interface, they let passers-by interact freely with the large display and interviewed them afterward. They concluded to keep gesture sets small and easy-to-learn, for instance by always showing the most important gestures on the display and by providing context-dependent tutorials for additional gestures.

Zigelbaum et al. (2010)’s G-stalt is a chirocentric gesture interface for manipulating videos in a 3D graphical space. It featured an extensive gesture set of 21 gestures based on g-speak and relied on a Vicon motion capture system to track passive IR retro-reflective dots placed on the hands for gesture recognition, which created 3D point clouds. The actual interface consisted of a cubical arrangement of media such as photos and videos, which the user could sort through, play, and reorganize the structure into meaningful arrangement.

## 3. Conceptual framework

This section defines our general research model for evaluating a gesture UI and describes LUI, a gesture UI selected to apply this model.

### *3.1.Definition of the method*

The evaluation session begins with a free discovery phase, allowing to assess the discoverability of the gestures implemented. The interface must be divided into tasks each corresponding to a gesture. These are then shown to the participants for them to learn. After a break, the participant is invited, in a testing phase, to perform the requested actions. In order to test long-term memory, it is suggested to organize another session later with the same participants and the same tasks. At the end of each session, a questionnaire containing the relevant scales is given to the participant.

The research model for evaluating a gestural user interface consists of quantitative and qualitative variables. The first part of the model is calculated objectively during the experiment and consists of the following dependent variables:

- *Gesture task success rate*: a real variable between 0 and 100 that measures the percentage between the number of successful gesture tasks (i.e., the gesture is correctly remembered, produced, and recognized) and the total number of executed gesture tasks.
- *Number of gesture trials*: a positive variable that measures the total number of gestures executed for a given task, whether successful, incorrectly recalled, incorrectly executed or incorrectly recognized by the gesture UI.
- *Gesture thinking time*: a positive real variable that measures in seconds the time needed by a participant to remember a gesture for a given task.
- *Gesture average thinking time*: a positive real variable that averages thinking times for all participants for a gesture task.
- *Gesture memorability rate*: a real variable between 0 and 100 that measures the percentage between the number of correctly remembered gestures and the total number of gestures produced.
- *Gesture recognition rate*: a real variable between 0 and 100 that measures the percentage between the number of correctly recognized gestures and the total number of gestures produced. Note that a gesture could be properly remembered by a participant, but not accurately recognized by the gesture UI or could be inadequately remembered, but accurately recognized. It is the system’s “fault”, the participant’s “fault”, respectively.

The second part of the model is composed of *gesture evaluation scale*: any scale $Si$, $\forall i \in \{1, ... , n\}$ decomposed in $mi$ subscales $SCij$ , $\forall j \in \{1, ... , mi\}$ or items to be evaluated (for instance the scale *attractiveness* of UEQ+ is decomposed in four subscales: annoying vs. enjoyable, bad vs. good, unpleasant vs. pleasant, and unfriendly vs. friendly), each subscale $SCij$ being a differential scale with 7 points between items of each pair (annoying o o o o o o o enjoyable). We measure each subscale $SCij$ employing a 7-point Likert scale with response categories "Strongly disagree" (= 1) to "Strongly agree" (= 7). For each $Si$, we have in addition:

- *Subscale Score* (SS): an ordinal variable that measures the score for each subscale $SCij$ of a scale $Si$, ranging from 1 = "Strongly disagree" to 7 = "Strongly agree".
- *Subscale Importance* (SI): an ordinal variable that measures the weight for each subscale $SCij$ of a scale $Si$, ranging from 1 = "Least important" to 7 = "Most important".
- *Scale Mean Score* (SMS): a real variable that measures the average score obtained on all subscales $SCij$ of a scale $SCi$ for all participants, ranging from -3 = "Mostly negative" to +3 = "Mostly positive", computed as follows: SMS($SCi$) = $(\sum_{j=1}^{n} SS(SCij\ ) \ / \ n) - 4$, $\forall i \in \{1, ... , n\}$, where 4 is the scale median.
- *Scale Mean Importance* (SMI): a real variable that measures the average weight of importance of all subscales $SCij$ of a scale $SCi$ for all participants, ranging from -3 = "Mostly negative" to +3 = "Mostly positive", computed as follows: SMI($SCi$) = $(\sum_{j=1}^{n} SS(SIij\ ) \ / \ n)$ – 4, $\forall i \in \{1, ... , n\}$, where 4 is the scale median.

For each evaluation scale, practitioners should identify important variables applying to their interface and select established questionnaires provided that are empirically validated. For instance, each evaluation scale could be any scale defined in UEQ+ (Schrepp & Thomaschewski, 2019), a flexible and modular method for evaluating the UX of any UI.

Based on these definitions, the usability could be evaluated through its three subfactors as follows: Effectiveness is covered by the gesture task success rate and gesture recognition rate variables; Efficiency is covered by the number of gesture trials, gesture (average) thinking time, gesture memorability rate and the discoverability and learnability scales; Subjective satisfaction is covered by the social acceptability scale and by any relevant gesture evaluation scale. Any such scale could of course supplement any of the three subfactors. UX could be covered by any gesture evaluation scale and its related measures, such as those factors proposed by UEQ+ (Schrepp & Thomaschewski, 2019) or the Pragmatic Quality (PQ), Hedonic Quality

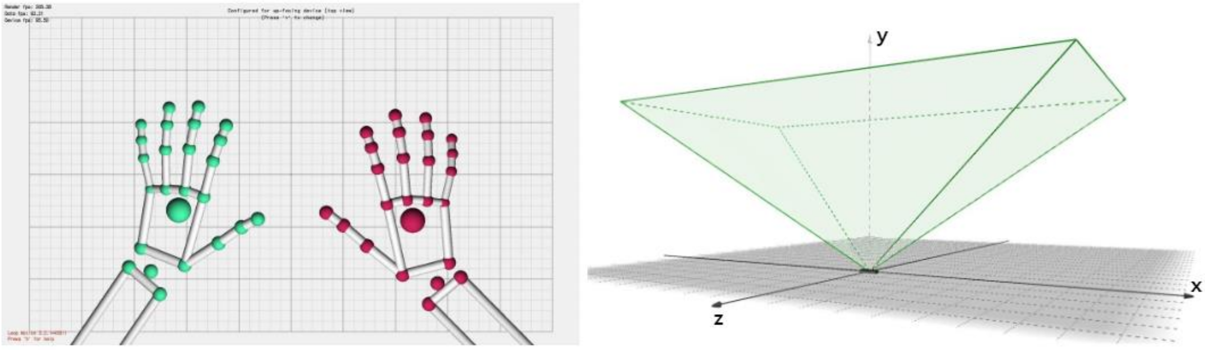
Stimulation (HQS), and Hedonic Quality Identification (HQI), as defined by Hassenzahl (2008).

### *3.2.Designing a gesture user interface for multimedia browsing*

Large User Interface (LUI) is a gesture-based interactive application that enables the manipulation of multimedia objects (i.e., photos, videos, documents, and maps) on any display, such as a video wall, a TV screen, a tabletop, or a video projector. It implements a wide set of multimedia actions, including zooming in/out a picture, rotating a document, and playing a video (Sluÿters et al., 2022). LUI and its gesture set are designed to be highly learnable and intuitive to use, as well as to impose as little constraints as possible to the user. As such, the system relies on an affordable and non-intrusive off-the-shelf device, the Leap Motion Controller (LMC), for capturing users' motion (Bachmann et al., 2018). In addition, LUI is able to automatically extract gestures from the continuous stream of motion data without additional input from the user.

The LMC plugs into a computer with USB. Using its two cameras and three infrared LEDs, it is able to accurately reconstruct a 3D skeleton of the user's hands, including the position of finger joints and hand palms within its 0.6 m wide × 0.6 m long × 0.6 m deep pyramid-shaped interaction space (cf. Figure 16). With the Leap Motion API, developers can retrieve this skeleton and use it in their application, for example to perform hand gesture recognition. Three versions of LUI were iteratively developed:

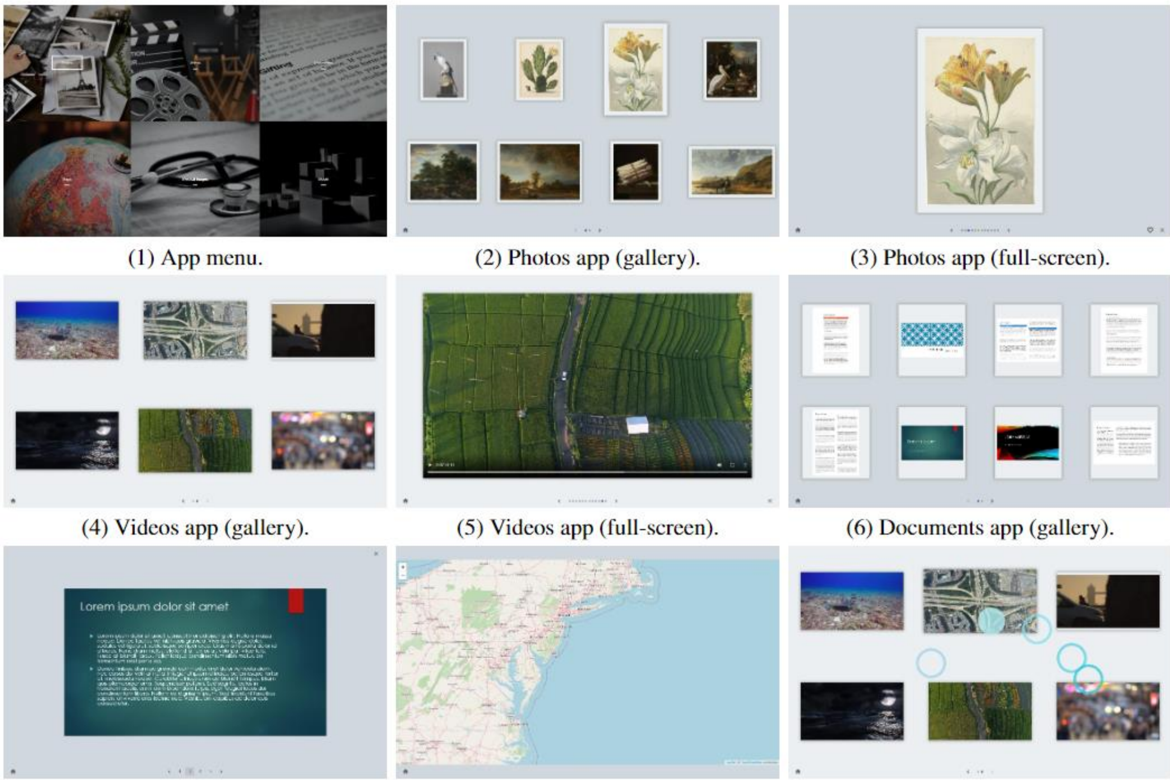
- First iteration: it featured two applications for browsing photos and videos and a limited set of gestures, such as play/pause a video, going to the next/previous item, and toggling full-screen mode.
- Second iteration: it was developed by taking into account the results of a usability testing with 20 potential end-users which highlighted some issues regarding the learning curve, accuracy of gesture recognition, and user fatigue. This version introduced simpler gestures to replace the problematic ones.
- Third iteration: it introduced many changes, including new Maps and Videos applications and gestures for manipulating content with direct feedback (for instance zooming out of a picture by pinching the fingers). A gesture elicitation study was conducted with 23 participants to help design a highly memorable and intuitive gesture set.




(1) Hand skeleton.
(2) Interaction space.

Figure 16: Illustrations of the LMC hand skeleton (1) and interaction space (2).

LUI is entirely written in JavaScript and consists of four applications (namely Photos, Videos, Documents, and Maps) that can be accessed through an App menu (cf. Figure 17). Its implementation is divided into two main parts: a ReactJS frontend (Boduch, 2019) and a backend for gesture recognition. The backend connects to the LMC and processes the continuous flow of data from the LMC to identify user gestures. It applies filtering to the raw LMC data, performs gesture segmentation and recognition, and triggers changes in the frontend (for instance the rotation of a picture by a couple of degrees) when relevant gestures are recognized.




(1) App menu.
(2) Photos app (gallery).
(3) Photos app (full-screen).
(4) Videos app (gallery).
(5) Videos app (full-screen).
(6) Documents app (gallery).
(7) Documents app (full-screen).
(8) Maps app.
(9) User's fingers.

Figure 17: Screenshots of the last version of the LUI application.

## 4. Evaluating the gesture user interface of LUI

An experiment was conducted following a procedure inspired by Vogiatzidakis and Koutsabasis (2022) to evaluate the usability of LUI, as well as the short- and long-term memorability of its gesture set. This section details the design of the experiment and reports its results.

### *4.1.Participants*

Seventeen participants (8 female, 9 male, and 0 identified as gender variant/non-conforming) aged between 22 and 65 years old (M = 37.5 years, SD = 15.3 years) were randomly selected from a list of volunteers using stratified sampling to balance between gender, background, and age (see bottom line of Table 19). All 17 participants used smartphones multiple times every day, and 16 participants (16/17 = 94.1%) used computers weekly, with 15 of them (15/17 = 88.2%) using computers multiple times per day. Two participants (2/17 = 11.8%) used gesture interaction multiple times a week. Participants' occupations included student, researcher, employee, computer scientist, physiotherapist, professor, and accountant. All participants were right-handed.

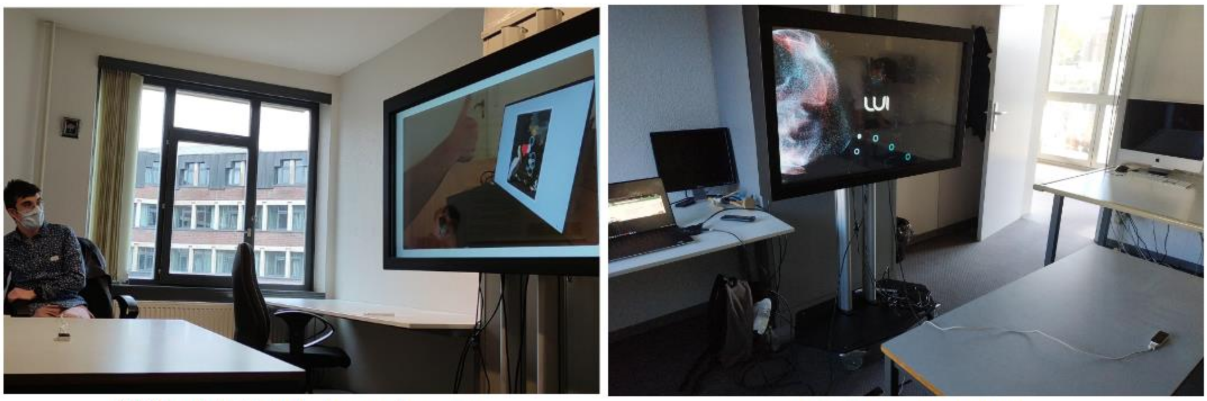
Table 19: Distribution of the population sampling used in the experiment.

| Id | Age (≤ or >30 y.) | Gender | Occupation (tech. *vs.* non-tech.) | Smartphone | Computer | Gesture Int. | Digital Skills |
|---|---|---|---|---|---|---|---|
| P1 | 34 (>) | F | Computer scientist (tech.) | 7 | 7 | 1 | 5.75 |
| P2 | 24 (≤) | M | Student (non-tech.) | 7 | 7 | 1 | 7 |
| P3 | 23 (≤) | M | Student (non-tech.) | 7 | 7 | 2 | 6.5 |
| P4 | 25 (≤) | F | PhD student (tech.) | 7 | 7 | 1 | 5.5 |
| P5 | 58 (>) | M | Accountant (non-tech.) | 7 | 7 | 1 | 3.5 |
| P6 | 22 (≤) | F | Student (non-tech.) | 7 | 7 | 2 | 5.25 |
| P7 | 55 (>) | M | Professor (tech.) | 7 | 7 | 2 | 6.5 |
| P8 | 30 (≤) | F | Communication manager (non-tech.) | 7 | 7 | 1 | 6 |
| P9 | 46 (>) | F | Computer scientist (tech.) | 7 | 7 | 1 | 7 |
| P10 | 57 (>) | F | Lab technician (non-tech.) | 7 | 7 | 1 | 5 |
| P11 | 22 (≤) | M | Student (tech.) | 7 | 3 | 1 | 1.25 |
| P12 | 23 (≤) | M | PhD student (tech.) | 7 | 7 | 5 | 5.5 |
| P13 | 36 (>) | M | Researcher (tech.) | 7 | 7 | 6 | 6.75 |
| P14 | 26 (≤) | F | PhD student (tech.) | 7 | 7 | 1 | 3.5 |
| P15 | 56 (>) | F | Civil servant (non-tech.) | 7 | 7 | 1 | 1 |
| P16 | 65 (>) | M | Physiotherapist (non-tech.) | 7 | 4 | 1 | 2 |
| P17 | 35 (>) | M | Researcher (non-tech.) | 7 | 7 | 1 | 4.5 |
| Mean | 37.5 (8≤, 9>30 y.) | 8F, 9M | 8 tech., 9 non-tech | 7 | 6.6 | 1.7 | 4.8 |

### *4.2.Apparatus*

Participants were seated at a desk and faced a large TV screen situated approximately two meters away, which displayed the LUI application and tutorial videos. An LMC was placed on the desk to capture their gestures. A laptop computer served to run the LUI application and control the experiment using a custom software (for example to play a tutorial video - see Figure

18). In addition, a camera recorded both the screen and the participant's hands, and logs of the LUI application were saved on the system.




(1) Tutorial video playing on the screen.　　(2) Physical configuration.

Figure 18: The setup of the experiment.

### *4.3.Protocol*

The experiment was divided into two sessions to properly evaluate the discoverability, as well as the short- and long-term memorability of the gesture set. The interval between two sessions was 7 days on average, ranging from 3 to 14 days (SD = 2.2 days).

*Session 1 (Discoverability and Short-term Memorability)*

The objective of the first session was to introduce participants to LUI and to evaluate its discoverability, usability, as well as the short-term memorability of its gesture set. It consisted of six phases:

1. Consent form and demographic information. The participants were introduced to the procedure and informed that they could choose to leave the experiment at any time. They were then invited to sign a GDPR-compliant consent form and fill in a demographic survey with information such as their age, gender, level of education, occupation, digital skills (Rose et al., 2012), and previous experience with technologies such as smartphones, computers, and gesture interaction.
2. Discovery phase. Participants interacted freely with the LUI for three minutes, starting from the App menu. They did not receive any specific instructions or information about the interface. The only explanation given to them is that it was controllable using the movements of the right hand above the sensor, without touching any surface. This phase served to assess the discoverability of the gesture interface.
3. Learning phase. This phase served to teach the gestures to the participants and let them familiarize with the system. The participants were given 17 tasks in a random order (cf.

Table 20). Each task was read aloud by the experimenter, who then played a short tutorial video of the associated gesture (cf. Figure 19). The use of videos ensured that all participants received the same instructions. Once the tutorial finished playing, the experimenter loaded the associated page of the LUI application and prompted the participants to perform the gesture in order to complete the task. Participants could re-watch the tutorial videos as many times as necessary. If a participant accidentally left the current page, for example by performing the wrong gesture, the experimenter informed them and re-loaded the correct page.

4. Resting phase. Participants were given five minutes to rest in a separate room.
5. Testing phase. This phase aimed to evaluate the short-term memorability of the gesture set by asking participants to perform 20 tasks with no external help. The participants first completed 17 atomic tasks (cf. Table 20) in a random order, following a similar procedure to the learning phase: the experimenter first read the task aloud, loaded the associated page of the LUI application, and prompted the participants to perform the gesture. The target content was randomly selected for each task (for instance, for the "zoom in" task, the target could be a picture, a document, or a map) and the tasks were grouped by target content. The participants then performed three compound tasks (cf. Table 21). For each compound task, the experimenter read the task aloud, loaded the application menu, and prompted the participants to perform the task. Participants could request the experimenter to repeat the instructions or to go back to the application menu.
6. Interview and questionnaires. After completing the testing phase, participants were interviewed to collect their feedback about the LUI application. The interview consisted of three open-ended questions: (1) "What is the first positive thing that comes to mind regarding your experience with the LUI application?", (2) "What is the first negative thing that comes to mind regarding your experience with the LUI application?", and (3) "Do you have any other comments?". Then, they were asked to complete a questionnaire consisting of seven evaluation scales selected from the UEQ+ method and the three aforementioned scales targeting the *discoverability*, *learnability*, and *social acceptability* of the LUI application.

Table 20: The 17 atomic tasks, potential target content, and associated gestures.

| Id | Task | Target(s) | Gestures |
|---|---|---|---|
| A1 | Previous | Photo/video/document/page | Flick right |
| A2 | Next | Photo/video/document/page | Flick left |
| A3 | Enable fullscreen | Photo/video/document/app | Tap |
| A4 | Disable fullscreen | Photo/video/document/app | Flick up |
| A5 | Zoom in | Photo/document/map | Pinch out |
| A6 | Zoom out | Photo/document/map | Pinch in |
| A7 | Volume up | Video | Swipe up |
| A8 | Volume down | Video | Swipe down |
| A9 | Rotate clockwise | Photo/document | Rotate a knob clockwise |
| A10 | Rotate anti-clockwise | Photo/document | Rotate a knob anti-clockwise |
| A11 | Play | Video | Tap |
| A12 | Pause | Video | Tap |
| A13 | Like | Photo | Thumbs up |
| A14 | Dislike | Photo | Thumbs down |
| A15 | Fast-forward | Video | Swipe left |
| A16 | Rewind | Video | Swipe right |
| A17 | Pan | Map | Move hand while pointing index |

Table 21: The three compound tasks and the minimum set of actions required to complete a task.

| Id | Task | Instructions | Required actions |
|---|---|---|---|
| C1 | Maps | In the Maps app, move and enlarge the map so that the two blue markers are situated at the left and right sides of the screen. | Enable fullscreen, zoom in, pan |
| C2 | Photos | In the Photos app, manipulate the windmill painting so that the author's name is the right way up and large enough to be easily readable. | Enable fullscreen, next, zoom in, rotate clockwise and/or anticlockwise |
| C3 | Videos | In the Videos app, find the words pronounced halfway through the "sea turtles" video. Fast-forward through the video to get to the right part. | Enable fullscreen, next, play, fast-forward |

*Session 2 (Long-term Memorability)*

The second session was much shorter than the first session and consisted of only three phases:

1. Introduction. Participants were welcomed and reminded of the procedure, in particular that they could leave the experiment at any time.
2. Testing phase. This second testing phase served to evaluate the long-term memorability of the LUI gesture set. We followed the same procedure as in the testing phase of the first session.
3. Questionnaire. At the end of the session, participants were asked to fill out the same scales selected from UEQ+ (Schrepp & Thomaschewski, 2019) and the *learnability* and *social acceptability* scales as they did in the first session, but not the *discoverability*, which is no longer considered relevant.

### *4.4.Quantitative measures and qualitative scales*

We collected a set of quantitative measures for the learning and testing phases of both sessions to give us insight into the user experience of the gesture UI:

- The *number of gesture trials*, as defined in our research model, measures the total number of gestures executed for each task, whether successful, incorrectly recalled, incorrectly executed or incorrectly recognized by the gesture UI.
- The *gesture task success rate*, as defined in our research model. An atomic task was considered successful if it was correctly executed within a maximum of four gesture trials. Regarding compound tasks, the number of gesture trials was not limited since they required participants to perform several gestures in an undefined order. We thus considered a compound task unsuccessful only if it was skipped by the participant.
- The *gesture thinking time*, as defined in our research model, measures the time, in seconds, needed by participants to remember a gesture for a given task.

In addition to these measures, we collected demographic information from the participants at the start of the first session. Participants were instructed to fill in at the end of each session a UEQ+ questionnaire (User Experience Questionnaire) (Schrepp et al., 2017), a modular extension of UEQ in which we selected 7 relevant scales (i.e., attractiveness, efficiency, perspicuity, dependability, stimulation, usefulness, and intuitive use) among 20 scales to focus on evaluating the user experience of participants interacting by gestures with LUI.

In order to include these dimensions not present in UEQ+ but particularly important in the case of gesture interaction, we have created 3 ad hoc scales. These scales, created for the framework of gesture interaction, gave very satisfactory results in a previous exploratory study, both in terms of validity, with dimensionality, and internal consistency (Cronbach's $\alpha$ of .914 for discoverability, .726 for learnability and .941 for social acceptability). We define these scales as follows:

- *Discoverability*: the ability to make the gestures straightforward for the end user to locate, observe, and discover how they work (Wobbrock et al., 2009). It is an important aspect as it enables to quickly navigate in a UI without going through a complete training. Nacenta et al. (2013) argue that "[...] for users to leverage gestures in the first place, they have to discover and learn how to apply them effectively". Since gestures are by nature performed by a human movement captured outside the UI but in the physical environment, the UI should reflect in some way that these gestures exist to execute the commands they are looking for. The effect of the action associated to a gesture is of course a minimal feedback. Different mechanisms, such as based on feedup and feedforward, could let the end user discover the existence of these gestures and how to operate them. The agreement score (Vatavu & Wobbrock, 2015), expressed as the common agreement between pairs of participants, can be also considered as an indicator of discoverability. It is sometimes called guessability or approachability (Xia et al., 2022). This scale is decomposed in three subscales:

    - D1 = "I could easily guess how to use the gesture interface".
    - D2 = "It was not complicated to find out how to control the gesture interface".
    - D3 = "The gestures to control the gesture interface were easy to discover".

- *Learnability*: the ease with which a new user can learn to use the interface and achieve maximal performance gestures (Dix et al., 2004). This factor is one of the most popular in the literature (Xia et al., 2022). It is linked to the intuitiveness as it is easier to learn how to use an interface based on intuitive gesture. The ISO (2019) 25010 standard on software quality defines learnability as the "degree to which a product or system can be used by specified users to achieve specified goals of learning to use the product or system with effectiveness, efficiency, freedom from risk and satisfaction in a specified context of use". This scale is decomposed in three subscales:
    - L1 = "It was easy to learn how the gesture interface works".
    - L2 = "The mastery of the gesture interface was not complex to acquire".
    - L3 = "I felt a progression in my ability to control the gesture interface".

  This learnability scale is specifically adapted to disruptive modes of interaction, and in particular gestural interaction. It should indeed be noted that the 3rd item refers to a progression and is therefore no longer relevant when the individual has mastered the method of interaction perfectly.
- *Social acceptability*: refers to the UI ability to provide end users with gestures that are acceptable to be issued in a particular context of use. It depends on the social (Rico & Brewster, 2009) and cultural factors (Archer, 1997) that affect the experience when a gesture is performed. It can be influenced by the place where the interaction occurs, the potential audience, the age of the user, the gestures produced, and so on (Williamson, 2012). It "is determined when the motivations to use technology compete with the restrictions of social settings" (Rico & Brewster,

2009), therefore being influenced by the context of use, i.e., user and tasks, platforms, and environments (Calvary et al., 2003). This scale is decomposed in three subscales:

- SA1 = "I would feel comfortable interacting with the gesture interface in the presence of strangers".
- SA2 = "I would have no problem using this gesture interface in the middle of a store".
- SA3 = "I would not feel embarrassed to use this gesture interface in the presence of others".

Regarding the interviews, all the session were conducted by the same interviewer to ensure consistency (Riedel et al., 2018). Once the data collection phase was over, we used thematic analysis to analyze and interpret the corpus of data, via the NVivo 11 software. Thematic analysis is a method that identifies, analyzes, and reports patterns (themes) within data to obtain a rich and detailed description of it (Boyatzis, 1998 ; Braun & Clarke, 2006). The analysis was both deductive and inductive (Valos et al., 2017) by adopting a "theory-driven" approach, with themes and codes identified in prior literature and a "data-driven approach" with other codes emerging from the data (Braun & Clarke, 2006). Finally, we captured video footage of the discovery, learning, and testing phases of the experiment.

## 5. Results and discussion

### *5.1.Gesture task success rate*

Table 22 gives the success rate for the atomic and compound tasks. Only two atomic tasks have a success rate below 80% in the learning phase: tasks A4 (disable full screen) and A9 (rotate clockwise). In the first testing phase, only task A9 has a success rate below 80%, while in the second testing phase, the overall success rate decreases slightly, and three tasks have a success rate lower than 80%: tasks A9, A10 (rotate anticlockwise), and A16 (rewind). Overall, the lower success rate of the rotating (anti-)clockwise tasks can be explained by the high sensitivity of the system to the users' hand pose. For instance, if the users' fingers were too far apart when performing the "grab" gesture, it was not recognized by the system. To a lesser extent, this high sensitivity may have affected the recognition of other static gestures, such as in the "fast-forward", "rewind", and "pan" tasks.

Table 22: Success rate for the 17 atomic and 3 compound tasks.

| Id | Task | Learning phase | Testing phase 1 | Testing phase 2 |
|---|---|---|---|---|
| A1 | Previous | 100% | 100% | 100% |
| A2 | Next | 100% | 94% | 94% |
| A3 | Enable fullscreen | 88% | 82% | 100% |
| A4 | Disable fullscreen | 76% | 88% | 100% |
| A5 | Zoom in | 100% | 88% | 94% |
| A6 | Zoom out | 94% | 94% | 82% |
| A7 | Volume up | 94% | 88% | 82% |
| A8 | Volume down | 82% | 100% | 94% |
| A9 | Rotate clockwise | 71% | 71% | 71% |
| A10 | Rotate anti-clockwise | 82% | 82% | 71% |
| A11 | Play | 82% | 88% | 100% |
| A12 | Pause | 94% | 88% | 82% |
| A13 | Like | 100% | 100% | 100% |
| A14 | Dislike | 100% | 100% | 94% |
| A15 | Fast-forward | 88% | 88% | 88% |
| A16 | Rewind | 82% | 82% | 71% |
| A17 | Pan | 88% | 88% | 88% |
| C1 | Photo | – | 100% | 94% |
| C2 | Video | – | 82% | 94% |
| C3 | Map | – | 76% | 65% |

Regarding compound tasks, tasks C1 (photo) and C2 (video) had a higher success rate than task C3 (map) in both the first and second testing phases. The “pan” gesture used in the Maps application was not elicited, which may have impacted the usability of the application. In addition, this task required more precision than the other two, as it required participants to accurately manipulate the map so that two markers were situated on each side of the screen.

### *5.2.Number of trials*

Table 23 gives the average and median number of tries needed to successfully complete the atomic tasks. These metrics are presented for the learning session and the two testing sessions, allowing in particular to study the memorability of gestures.

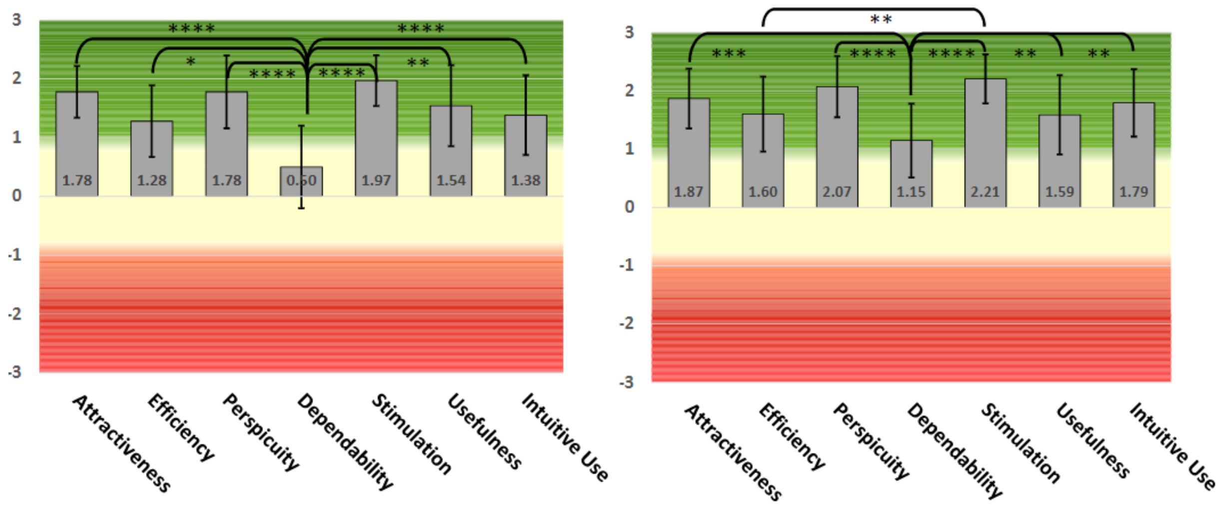
As presented, most tasks were completed with a single trial. The most problematic tasks were the rotations, whether clockwise or anticlockwise. We can also observe that more attempts were needed to pass the tasks in session 2, especially for A1 (previous), A2 (next), A12 (pause) and A15 (fast forward). On the contrary, the tasks of increasing or decreasing the volume (A7 and A8) required fewer tries over time.

Table 23: Number of trials for successful completion of each atomic task.

| Id | Task | Learning phase | | Testing phase 1 | | Testing phase 2 | |
|---|---|---|---|---|---|---|---|
| | | Average | Median | Average | Median | Average | Median |
| A1 | Previous | 1,2 | 1 | 1,6 | 1 | 1,7 | 1 |
| A2 | Next | 1,1 | 1 | 1,3 | 1 | 1,6 | 2 |
| A3 | Enable fullscreen | 1,5 | 1 | 1,5 | 1 | 1,1 | 1 |
| A4 | Disable fullscreen | 1,2 | 1 | 1,7 | 2 | 1,5 | 1 |
| A5 | Zoom in | 1,4 | 1 | 1,3 | 1 | 1,5 | 1 |
| A6 | Zoom out | 1,4 | 1 | 1,1 | 1 | 1,2 | 1 |
| A7 | Volume up | 1,3 | 1 | 1,3 | 1 | 1,1 | 1 |
| A8 | Volume down | 2,0 | 2 | 1,5 | 1 | 1,3 | 1 |
| A9 | Rotate clockwise | 2,1 | 1,5 | 1,6 | 1,5 | 1,9 | 1,5 |
| A10 | Rotate anti-clockwise | 1,8 | 1,5 | 2,1 | 1,5 | 2,4 | 2,5 |
| A11 | Play | 1,3 | 1 | 2,0 | 1 | 1,6 | 1 |
| A12 | Pause | 1,4 | 1 | 1,5 | 1 | 1,8 | 1,5 |
| A13 | Like | 1,0 | 1 | 1,2 | 1 | 1,3 | 1 |
| A14 | Dislike | 1,0 | 1 | 1,1 | 1 | 1,0 | 1 |
| A15 | Fast-forward | 1,7 | 1 | 1,7 | 1 | 1,9 | 2 |
| A16 | Rewind | 1,4 | 1 | 1,7 | 1 | 1,4 | 1 |
| A17 | Pan | 1,3 | 1 | 1,3 | 1 | 1,5 | 1 |

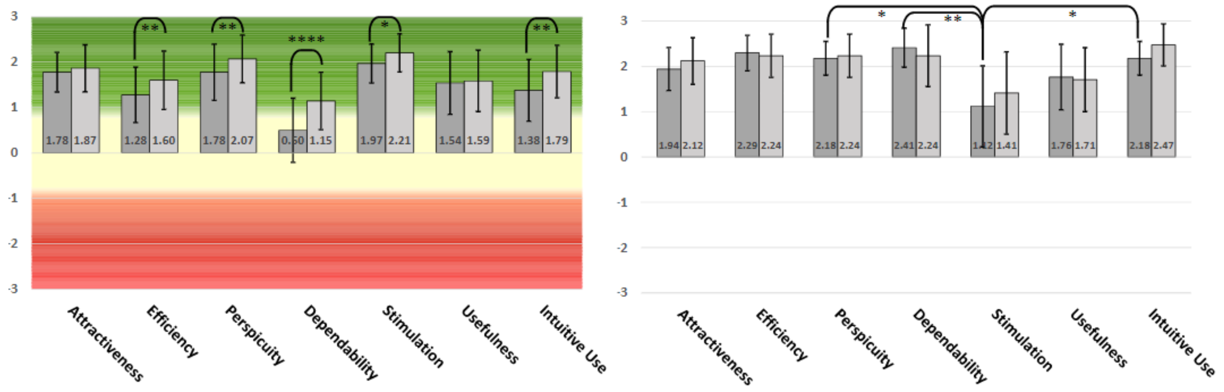
### *5.3.UEQ+ questionnaire*

Users' answers to the seven scales selected for this study were encoded and interpreted with the UEQ data analysis tool to obtain the mean scores for the first session (cf. Figure 19-1), for the second session (cf. Figure 19-2), and for their comparison (cf. Figure 20-1). The mean score for each selected scale belongs to an interval [-3,...,+3], where a score of -3 expresses the weakest value of the scale and +3 expresses the strongest value of the scale.




(1) Session 1. (2) Session 2.

Figure 19: Mean score for each selected scale of the UEQ+ questionnaire. Error bars show a confidence interval of 95%.




(1) Mean scores. (2) Importance ratings.

Figure 20: Comparison of mean scores and importance ratings for each selected scale of the UEQ+ questionnaire across sessions (S1 = left in dark grey, S2 = right in light grey). Error bars show a confidence interval of 95%.

Table 24 reports the reliability of the seven scales with respect to consistency and interrating. Overall, all scales are well consistent ($\alpha \geq 0.70$) for the first session and very well consistent ($\alpha \geq 0.80$) for the second and all values increased from the first session to the second one. Interrater reliability ranges from very weak for five scales to strong for one of them (*efficiency*). Little or no variations were observed after the second session.

Table 24: Consistency reliability (Cronbach's $\alpha$: G = good, V = very good, E = excellent) and interrater reliability ((Kendall & Smith, 1939)'s W : V = very weak, W = weak, M = moderate, S = strong) of mean scores (UEQ+ scales and ad hoc scales).

| Scale | Cronbach's $\alpha$ (inter.) | | Kendall's $W$ ($p$-value, inter.) | |
|---|---|---|---|---|
| | S1 | S2 | S1 | S2 |
| Attractiveness | 0.82 (V) | 0.96 (E) | 0.01 (0.92, V) | 0.039 (0.59, W) |
| Efficiency | 0.82 (V) | 0.93 (E) | 0.42 (<0.0001, S) | 0.25 (0.0066, M) |
| Perspicuity | 0.89 (V) | 0.84 (V) | 0.04 (0.61, V) | 0.054 (0.45, W) |
| Dependability | 0.85 (V) | 0.92 (E) | 0.08 (0.28, V) | 0.21 (0.017, M) |
| Stimulation | 0.81 (V) | 0.93 (E) | 0.09 (0.19, V) | 0.010 (0.16, V) |
| Usefulness | 0.92 (E) | 0.97 (E) | 0.17 (0.033, W) | 0.048 (0.50, V) |
| Intuitive Use | 0.77 (G) | 0.89 (V) | 0.04 (0.55, V) | 0.041 (0.57, V) |
| Discoverability | 0.90 (E) | – | 0.03 (0.56, V) | – |
| Learnability | 0.84 (V) | 0.95 (E) | 0.15 (0.08, W) | 0.04 (0.53, W) |
| Social acceptability | 0.74 (G) | 0.95 (E) | 0.08 (0.25, V) | 0.02 (0.73, V) |

We ran a series of Kolmogorov-Smirnov tests to check the normality of these scales. None of them passed the normality test. For example, *attractiveness* for both the first session (S1, KS distance = 0.24) and the second session (S2, KS distance = 0.28) did not pass the normality test ($\alpha$ = 0.05, $p < 0.0001$****). A series of Shapiro-Wilk tests confirmed the same results. For example, *attractiveness* for both the first session (S1, W = 0.87) and the second session (S2, W

= 0.79) did not pass the normality test ($\alpha = 0.05$, $p < 0.0001****$). Consequently, we performed a series of Wilcoxon matched-pairs signed rank tests (two-tailed) for all scales within each session (S1, S2) and across sessions (S1 vs. S2) to investigate any potential difference among them. When appropriate, we also computed Spearman's rank order correlation $rs$(N = 17).

*Intra-session Mean Scores*

If we stick to the original interpretation that a mean score greater than or equal to 0.8 represents a positive evaluation (Schrepp & Thomaschewski, 2019), then all mean scores for the first session are considered positive (ranging from M = 1.28 for *efficiency* to M = 1.97 for *stimulation*), except *dependability* (M = 0.50, SD = 2.22) considered as a neutral value. This low value can be explained by the cognitive destabilization of participants producing these kinds of gestures for the first time of their life, and being puzzled by them. However, this phenomenon is observed transiently insofar as the gestures, initially felt to be difficult to produce because they are unknown, then become easier to produce. If we interpret the mean scores according to the partial benchmarking (cf. Table 1 in Schrepp et al. (2017)), then *attractiveness* is assessed as "excellent" (M = 1.78 ≥ 1.75), *efficiency* is assessed as "above average" (M=1.28 ≥ 0.98), *perspicuity* is assessed as "good" (M = 1.78 ≥ 1.56), *dependability* is assessed as "bad" (M = 0.50 < 0.78), and *stimulation* is assessed as "excellent" (M = 1.97 ≥ 1.55), as depicted in Figure 21. A Friedman test with multiple comparisons reveals that *dependability* is significantly lower than other scales during the same session (cf. Figure 19–1), for example with respect to *attractiveness* ($F$ =146.5, $p < 0.0001****$).

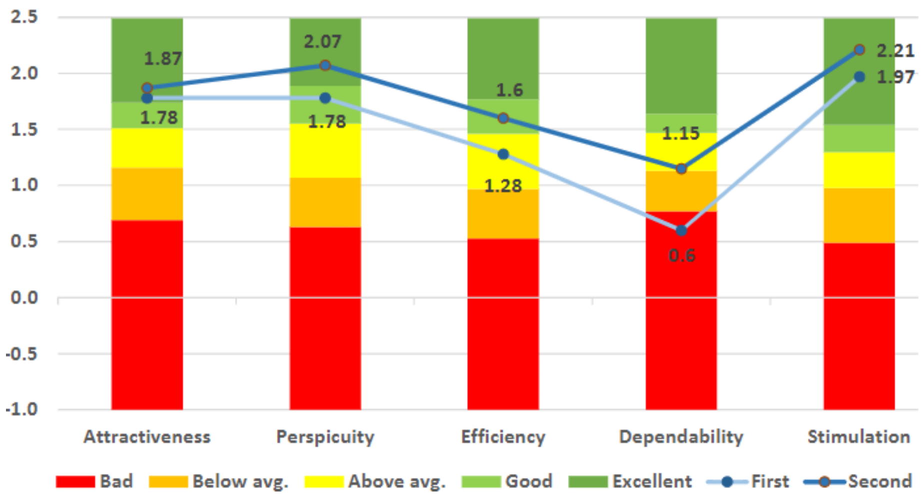



Figure 21: Benchmarking of scales for the two sessions.

Regarding the second session, all mean scores are again above the threshold of 0.8 (Schrepp & Thomaschewski, 2019), ranging from a minimum for *dependability* (M = 1.15, SD = 1.33) to a maximum for simulation (M = 2.21, SD = 0.79). Mean scores resulting from this second session have all improved according to the benchmarking (Table 1 in Schrepp et al. (2017), see Figure 21): *attractiveness* is assessed as “excellent” (M = 1.87 ≥ 1.75), *efficiency* is assessed as “good” (M = 1.60 ≥ 1.60), *perspicuity* is assessed as “excellent” (M = 2.07 ≥ 1.90), *dependability* is assessed as “above average” (M = 1.15 ≥ 1.14), and *stimulation* is assessed as “excellent” (M = 2.21 ≥ 1.55). Although *dependability* increased since the first session, another Friedman test with multiple comparisons reveals that *dependability* is again significantly lower than other scales during the same session, apart from *efficiency* ($F = 72$, $p = 0.089$, n.s.). However, this scale now appears to be significantly lower than *stimulation* ($F = -90$, $p = 0.0074{**}$), thereby suggesting that participants felt more stimulated than efficient by the gesture interaction.

*Inter-session Mean Scores*

Although *dependability* knew a negative mean score during the first session, it experienced a positive increase of 130% (M = 1.15, SD = 1.80) in the second session, which leads it to a positive evaluation. Mean scores for S2 are all superior to those obtained for S1 and range from M = 1.15 for *dependability* to M = 2.21 for *stimulation*. The mean score for some scales even largely increased, such as *efficiency* (from M = 1.28 to M = 1.60), *perspicuity* (from M = 1.78 to M = 2.07), and *intuitive use* (from M = 1.38 to M = 1.79)).

We found a statistically significant difference for five scales among the seven used, which denotes a real progress across sessions. Such a difference was found for *efficiency* (W = 332, $p = .0089{**}$), thus suggesting that participants felt more efficient in producing the gestures during the second session than during the first one. We also found a strong positive correlation ($rs = 0.62$, $p < 0.0001{****}$): the more a participant passes a new session, the more efficient it becomes. If we had conducted still other sessions, it is likely to observe an increase in *efficiency* until reaching an asymptote.

A statistically significant difference across sessions was found for *perspicuity* across sessions (W = 263, $p = 0.0094{**}$) with a strong positive relationship ($rs = 0.69$, $p < .0001{****}$), thus suggesting that participants felt more familiar with LUI after the second session than after the first one; for *dependability* (W = 633, $p < .0001{****}$), thus suggesting that participants felt more in control of the LUI after the second session than after the first one; for stimulation (W = 249, $p = .011{*}$) with a strong positive relationship ($rs = 0.62$, $p < .0001{****}$), thus suggesting that participants felt excited and motivated to use LUI in the future more after the second session than after the first one; and for *intuitive use* (W = 385, $p$ = .011$**$) with a moderate positive relationship ($rs$ = 0.58, $p$ < .0001$****$), thus suggesting that participants thought that LUI could be of immediate use more after the second session than after the first one.

No significant difference was found for *attractiveness* (W = 114, $p$ = .49, n.s.) and *usefulness* (W = 52, $p$ = .62, n.s.). All in all, we see the benefits of a positive learning effect: during the first session, some participants felt unsafe or unsure on how to correctly produce gestures mainly because they never did it before. But after the second session, they felt more safe and sure about reproducing and reusing the gestures they learnt. A similar phenomenon was observed when 2D stroke gestures were introduced for the first time on Apple's iPhone: people were unsure about what gestures to do when using the interface but when they realized them, they felt more safe and able to reproduce the gestures quite efficiently.

The KPI (Key Performance Indicator) computed by UEQ+ (Hinderks et al., 2019) started from M = 1.44 (SD = 0.80) for session 1 to M = 1.74 (SD = 0.94) for session 2, which confirms the overall positive evolution.

*Intra-session Importance Ratings*

With regard to the first session, all importance ratings are very well consistent: the global Cronbach's $\alpha$ = 0.85 ≥ 0.80, all individual $\alpha$ are above 0.80, except *dependability* ($\alpha$ = 0.79 ≤ 0.80). However, the interrater reliability is very weak (Kendall & Babington Smith (1939)'s W = 0.081, $p$ = 0.21). All importance ratings are significantly higher than the median value Md = 4, ranging from *stimulation* (W = 74, $p$ = 0.033$*$) to *attractiveness* (W = 148, $p$ < 0.0001$****$). The *stimulation* (M = 5.1) was rated significantly (W = −25, $p$ = 0.046$*$) less important than *perspicuity* (M = 6.2) and significantly (W = −55, $p$ = 0.0020$**$) less important than *dependability* (M = 6.4). The *usefulness* was rated significantly (W = −28, $p$ = 0.015$*$) less important than *dependability*. The *intuitive use* was rated significantly more important (W = 25, $p$ = 0.046$*$) than *stimulation*.

With regard to the second session, all importance ratings are very well consistent: the global Cronbach's $\alpha$ = 0.85 ≥ 0.80, all individual $\alpha$ are above 0.80, ranging from *usefulness* ($\alpha$ = 0.80) to *intuitive use* ($\alpha$ = 0.85). The interrater reliability is again very weak (Kendall's W = 0.057, $p$ = 0.44). All importance ratings are significantly higher than the median value Md = 4, ranging from *stimulation* (W = 84, $p$ = 0.014$*$) to attractiveness (W = 148, $p$ < 0.0001$****$). A Friedman test with multiple comparisons reveals that the importance was not rated differently depending on the scale ($F$ = 10.69, $p$ = 0.098, n.s.).

*Inter-session Importance Ratings*

No significant difference was found between the importance of scales across sessions (all Wilcoxon tests returned a $p > 0.05$), thus suggesting that participants did not attach more or less importance to the scales during the first session than during the second.

### 5.4. *Ad hoc questionnaire*

Three ad hoc scales, i.e., *discoverability*, *learnability*, and *social acceptability*, were added to extend the evaluation beyond the current UEQ+ scope and to cover gesture interaction. The last rows of Table 24 show that their Cronbach's $\alpha$ coefficient was excellent since the beginning for *discoverability* ($\alpha$ = .90) until the end for *learnability* and *social acceptability* ($\alpha$ = .95), thus suggesting that participants responded in a consistent way that is very reliable. The coefficient of consistency reliability is approximately the same for all scales in the end of session S2. The values of Kendall's W coefficient of concordance are interpreted mostly as "weak" or "very weak", thus indicating that there was no particular agreement among participants in the way they assessed the three scales. This is pretty much justified by the three types of profiles: participants having very diverse profiles have assessed the device in their own way that is not necessarily in agreement with other participants.

Figure 22 shows how the participants' answers to the items of these three scales are distributed. Since the distribution of the answers to the 9 questions does not follow a normal distribution (all Kolmogorov-Smirnov normality tests did not pass with $\alpha$ = 0.05), we computed a series of Wilcoxon signed-rank tests for a single sample with ties and continuity correction (with 10,000 iterations) to determine whether the items would significantly depart from the median value M$d$ = 4, either above or below. Indeed, an item could receive an average answer above the median value, but not significantly. None of the three items of *discoverability* were significantly different D1 = "I could easily guess how to use the interface" (M = 3.76, $SD$ = 1.83, M$d$ = 4, $p$ = .23, n.s.), D2 = "It was not complicated to find out how to control the interface" (M = 3.59, $S$D = 1.78, M$d$ = 3, $p$ = .18, n.s.), and D3 = "The gestures to control the interface were easy to discover" (M = 4.06, $S$D = 1.55, M$d$ = 5, $p$ = .47, n.s.). All other items of *learnability* and *social acceptability* were significantly above the median during both sessions, except for the item SA2 (M = 4.71, $S$D = 1.74, M$d$ = 5, $p$ = .067, n.s.). For instance, L1 (M = 5.88, $S$D = 0.90, M$d$ = 6) is significantly ($p \leq .001{*}{*}{*}$) above the median with a large effect size ($r$ = .86). We believe that *discoverability* was rated low due to the new interaction modality that participants were not used to, which induced a disruptive nature and a cognitive destabilization in the beginning. We captured this scale only once since gestures need to be discovered the first time participants are confronted to. It is likely that this scale would be rated differently during a subsequent session. Fortunately, both *learnability* and *social acceptability* were assessed very positively by participants: not only the items were almost very positively assessed but significantly better during the second session with respect to the first one.

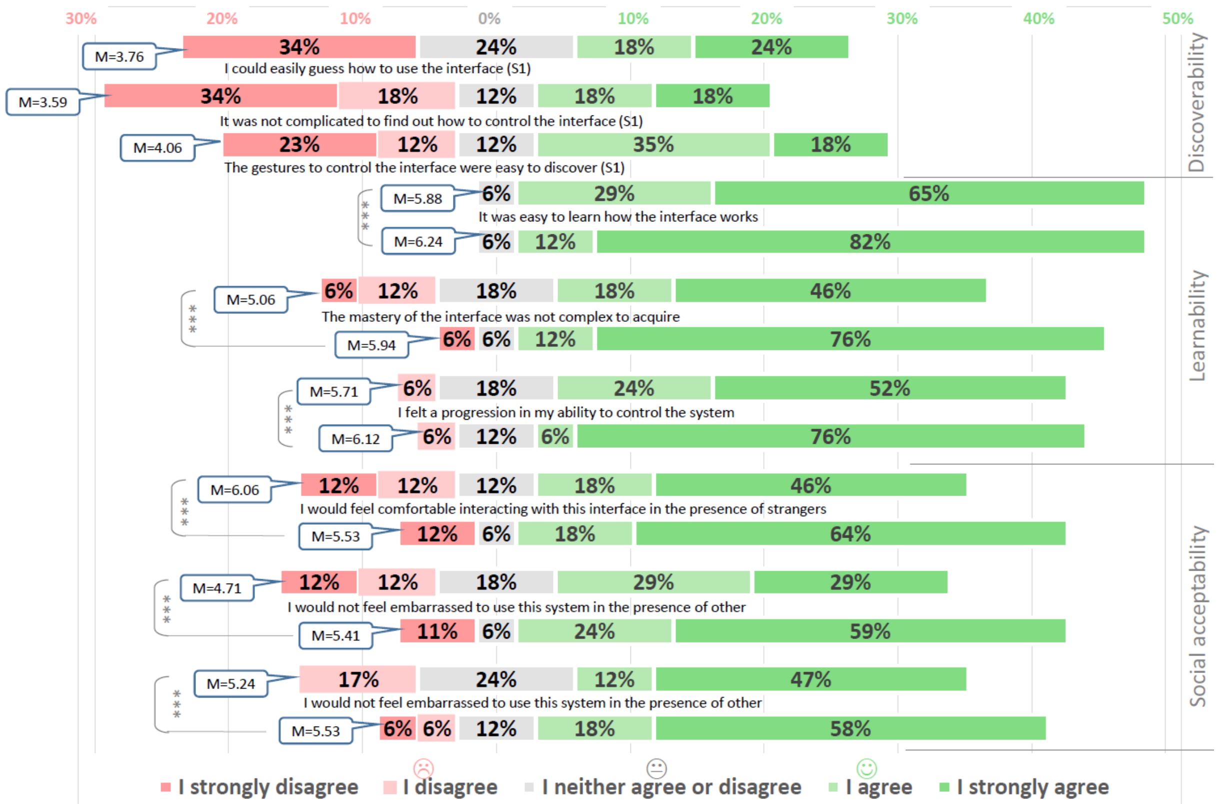



Figure 22: Distribution of participant's answers to the three new scales: discoverability (only during the first session S1), learnability (for both sessions: S1 above and S2 below), and social acceptability (for both sessions as well) (M = mean, $p < .001{*}{*}{*}$).

Indeed, we finally computed another series of Wilcoxon signed-rank tests to investigate whether participants answered in a different way to the items during the second session with respect to the first one. All six items were assessed significantly better during S2 than during S1, which denotes a real progression of the answers, even after only one session. For instance, item SA3 during S1 (M = 5.24) is different than during S2 (M = 5.53) in a significant way ($z$-$score$ = 3.62, $p$ = .00014$***$) with a large effect size ($r$ = .87), thus indicating that participants felt significantly less embarrassed with the gesture-based UI during the second session that during the first one.

### *5.5.Interviews*

The use of interviews allows us to confirm certain results but also to reveal others, given the more free and open nature of the questions asked. As for the advantages of this type of interface, intuitiveness was mentioned by 9 of the 17 participants in a positive way.

> "If I compare it to a computer, it's true that it's just gestures and it's easier to remember than shortcuts. That I think is a bit the basis of the gesture." P3 | M | 23

Other arguments in favor of this type of interface are its innovative and original side, as well as its usefulness and practicality perceived as superior. Finally, the fun provided by using this system is also an argument that emerged for some participants. It is of particular interest as it is considered one of the fundamental pillars providing a rich consumer experience (Holbrook & Hirschman, 1982).

Regarding the first negative point that came to the minds of the participants, the sensitivity of the system, linked to the performance of the recognizer, emerged in the interview of 15 of the 17 participants. This problem can even lead to frustration and is often linked to the users' feeling that they may be the cause of the problem, speaking for example of poor control on their part.

> "It is frustrating when it confuses gestures. For example, when I want to turn up the volume and it changes my video, it's a bit scary." P6 | F | 22

Another problem, which emerged in 10 interviews, is the direction of movement to move forward or backward in the video, considered to be reversed. It should also be noted that the 7 people who did not mention this in their interview just did not bring this subject up on their own. It therefore does not mean that they consider the gesture to be correct in the way which it is currently implemented. The fact of making a movement to the right to go back in the video and to the left to go forward was chosen during the gesture elicitation study. However, now that the gesture has been implemented in a real application, participants actually feel like they are grabbing the cursor and moving it. In this logic, it would be necessary to make a movement to the right to move forward and to the left to move back. This is an example of the difference that can be created between an elicitation study and a real implementation. It thus seems necessary to carry out a systematic evaluation of each system, even if it was built by users, and also to leave the possibility to the participants to freely approach any subject that they wish. It also shows the advantage of organizing interviews, as this problem would have been invisible if we had just focused on the other evaluation methods.

Finally, some other negative points were cited to a lesser extent. Three older participants found the gesture interaction to be unintuitive and to take a long time to get used to. Another point is muscle fatigue, mentioned by 4 participants, and finally problems understanding how the interface works. This last problem is however related to this data collection since we initially left the participants to discover for themselves without any help. In order to ensure a correct understanding and use of this type of interface, it is therefore necessary to be particularly attentive to the learning of users, for example via a video tutorial and even personal support.

## 6. Implications for the evaluation of gesture interfaces

We recommend practitioners to identify the relevant scales that could apply to the assessed interface. To do so, we advise to first look at UEQ+ (Schrepp & Thomaschewski, 2019), an evaluation method consisting of several scales decomposed into four items each. This method, by its modularity and flexibility, represents a suitable candidate for its extension with three new scales relevant for gesture interaction, that we define as follows: the scale *discoverability* is covered by the items "I could easily guess how to use the gesture interface", "It was not complicated to find out how to control the gesture interface", "The gestures to control the interface were easy to discover", and "I did not need help to know how to use the gesture interface"; the scale *learnability* is covered by the items "It was easy to learn how the gesture interface works", "The mastery of the gesture interface was not complex to acquire", "I felt a progression in my ability to control the gesture interface", and "Learning the gesture interface went well"; the scale *social acceptability* is covered by the items "I would feel comfortable interacting with this gesture interface in the presence of strangers", "I would have no problem using this gesture interface in the middle of a store", "I would not feel embarrassed to use this gesture interface in the presence of others", and "I would not feel judged by using this gesture interface with other people". Based on these definitions, we have updated the UEQ+ calculation tool to select these three additional scales on demand and to incorporate them into the UEQ+ method in the same way as the other scales. However, the UEQ+ calculation tool was only intended for one evaluation session, which represents only a snapshot in time. On the contrary, we need several evaluation points, especially for *learnability*. That is why we have also implemented a multi-session extension in the calculation tool as reported in this essay.

This concrete evaluation allows us to show the advantages of this method, first in combining different types of measurements. On the one hand, the task success rate remains relatively high and the median number of gesture successes is mostly 1, which attests to the quality of the interface. This result is confirmed by our questionnaires, where the majority of UEQ+ scales are considered excellent or good. However, we also observe a divergence in these data. In atomic tasks, the situation is slightly better in the first session rather than the second. However, when we look at the questionnaires, the experience is considered to be better in session 2. So even though users on average had more difficulty a week later, they were more comfortable and satisfied with the interface. Another advantage of this interface is the division between atomic and compound tasks. Focusing on the gestures themselves, we could see the weakness of the rotation movements, which is not apparent in the compound task of the photos. On the other hand, the Maps application stands out as clearly weaker, which would have been invisible by just looking at the atomic tasks. Finally, the debriefing interviews make it possible to confirm the overall quality of the interface, particularly in terms of intuitiveness, which also emerges from the questionnaires. Apart from that, they allowed us to highlight a problem unknown to the experimenters, which would not have been discovered if we had limited ourselves to the objective measurements and the questionnaires.

## 7. Conclusion and future work

In this essay, we have detailed a new method for evaluating gestural interfaces, dividing the analysis by gesture, use case and overall subjective experience. This method combines quantitative measures, particularly specific to memorability, qualitative scales and interviews. In particular, we have detailed 3 new scales that are particularly relevant in the context of gestural interaction, namely learnability, discoverability and social acceptability. We then applied and validated this method with LUI, a free-hand gestural interaction interface. We then discussed our results and gave key takeaways.

The added scales provide a more comprehensive assessment of gestural interfaces by including subjective user experiences and perceptions that are critical to evaluating the quality of the interface. Secondly, we propose a novel approach to gestural interface evaluation that combines quantitative measures, qualitative scales, and debriefing interviews to obtain a holistic view of the experience. This approach recognizes the importance of both objective and subjective evaluation methods. We highlight the importance of multi-session evaluation, particularly for measuring the learnability of gestural interfaces. This is important as gestural interfaces are often more complex than traditional graphical user interfaces and require users to learn new interaction paradigms. By obtaining a more complete understanding of the experience, designers and developers can make informed decisions about how to improve their interfaces and make them more user-friendly and efficient (Grandhi et al., 2011).

This work also presents limitations and avenues for future work. The first important point is the use of our 3 ad hoc scales, which had been chosen thanks to their good validity results in other studies. It would however be interesting to change their format in order to match the one used in UEQ+, therefore functioning as an extension of the latter. In order to increase the representativeness of this evaluation method, it should be applied to other interfaces and contexts. This would also allow to refine the method, for instance in term of the scales used. Another future research would be to adapt this method to other contexts and interaction mediums.

# General Conclusion

The central goals of this thesis were to (1) understand deeply the notion of experience, (2) explore the use of gesture interaction technologies in a consumption context, and (3) define a model and a method in order to evaluate the overall quality of the experience when using gestural-interaction technologies. In this concluding part, we will summarize the findings of the four essays, focus on our five research questions, develop our main contributions, and explore future work possibilities.

## 1. Summary of findings

Through a systematic literature review, the first essay aimed to clarify the constructs of the experience. The second essay focused on the importance of the affective consumer response in the gestural interaction experience. The third essay's goal was to understand the impact of gestural interaction technologies on the experience. The fourth essay aimed to develop a method for evaluating the gestural interaction experience. Table 25 presents an overview of this thesis and the main findings, divided by essay and research question.

*Essay 1: Systematic literature review of the user, customer and consumer experience*

This essay aimed to show the complementarity between the fields of human-computer interaction and marketing, and more particularly to unify the constructs of experience. We first exposed the peculiarities of the different constructs of the experience. The user experience tends to be specific to one human-product interaction in a given context while the customer experience includes several interactions during the customer journey. The consumer experience is more holistic and aims to understand consumers as non-rational beings. Despite these peculiarities, these constructs capture different aspects of the same overall holistic experience and thus influence each other. It is therefore important to enable effective communication between the fields of human-computer interaction and marketing. Some studies are starting to move in this direction, but some work is still necessary.

We then looked at the articles developing several constructs in the same paper and highlighted the heterogeneity in the literature. To identify these references, we went through the PRISMA methodology via four different research scenarios. At the end of the four stages of the process - identification, screening, eligibility and inclusion - we ended up with 78 articles. It appears that the majority of the articles of our corpus do not differentiate the constructs. Rather, these are articles focusing on a particular construct, or even none, and sometimes using other terms as synonyms. Only the scenario where we were looking for articles mentioning both user experience and customer experience revealed references that properly develop these constructs together. These variabilities were explained via several analyses. First, we saw that the theoretical foundations are disparate, sometimes within the same constructs. Moreover, there is neither reference definitions nor dimensions widely used for each of the constructs, which shows that the theory is not stabilized yet. However, even if there are some minor particularities, the topics are strongly linked.

Finally, we formulated some suggestions to researchers and practitioners working with the constructs of the experience. First, we suggested opting for a multi-constructs approach whenever possible, to benefit from the complementarity of points of view. We also advised to first link the user experience to the customer experience, without taking into account the consumer experience, as these two first constructs are naturally closer (Lee et al., 2018). When using the constructs of experience, we suggested limiting to a few popular works that are already well established, such as Pine and Gilmore (1998), Lemon and Verhoef (2016), Hassenzahl et al. (2003) and ISO 9241-210 (2018). Lastly, we advised specialists to familiarize themselves with these other constructs even if it is outside the scope of their initial discipline.

*Essay 2: Affective consumer responses and gestural interaction experience*

In this essay, we first were able to observe a link between the perceived usefulness and the quality of the experience (Davis, 1989). Regarding the other factor pairing with the usefulness, the ease of use (Davis, 1989), we saw that the gestural interaction has the advantage of being more intuitive and therefore makes easier to interact with an interface. However, this feeling was not shared by everyone, and mainly for participants less comfortable with technology. Some people see new technologies as a loss of control on their part, thus increasing the feeling of being rather controlled by the system (Coutrix & Mandran, 2012), which tends to provide a poorer experience. These participants are those with a tendency to experience anxiety, characterized by an absence of pleasure, a feeling of not being in control and a high arousal. They also less easily give their trust, unlike some others who have a high brand confidence and therefore perceive the websites as more reliable (Rose et al., 2012; Sauro, 2015), positively impacting their overall experience.

One statement that was common to all participants was that the tasks were actually easy, although some had a lot of difficulty. For those people, the fact of carrying out these tasks serves as training and improves their knowledge in terms of interaction, which has a positive impact on the feeling of intuitiveness of the interaction. This then has a positive impact on the feeling of perceived control, which is a dimension to which we have often come back in this thesis. All these affective dimensions enable us to explain a lot of observations we made and have a clear and direct impact on the gestural interaction experience.

We found that a factor that made it possible to quickly assess the quality of the experience was the traits specific to the perceived immersion of the participants, observed through the inattention to time and circumstances surrounding the individual. Participants having a good experience were more likely to leave blanks, keep their eyes on their smartphones or start sentences without finishing them. Some authors even consider immersion to be the "heart of the experience" (Charfi & Volle, 2011; Poncin et al., 2015). We have seen that this state is particularly relevant to address in the context of gestural interaction. In the first appropriation step of the immersion process, the users relate what they experience to what is familiar to them (Poncin & Garnier, 2012). Since the gestural interaction is natural (Baudel & Beaudouin-Lafon, 1993), it makes it possible to reach this stage of immersion more quickly. Another explanation is via the high intuitiveness of the gestural interaction, also having a positive impact on the immersion (Poncin et Garnier, 2010).

In this essay, we have placed our interviews and observations sessions under the theme of purchasing, allowing us to consider the context of use. An important phenomenon that we have observed during our sessions is the link between the gestural interaction experience and impulse buying, in particular via the example of the participant scrolling for hours to buy things that she does not need. We have also seen a connection between these purchases and the intuitive nature of gestural interaction. The latter was explained through the local presence (Ning Shen & Khalifa, 2012; Vonkeman et al., 2017) which would be increased within the framework of this gestural interaction, but also via the perceived ownership which increases the perceived valuation of an object by touching it virtually (Peck & Shu, 2009; Peck et al., 2013; Brasel & Gips, 2014).

*Essay 3: Definition of a model, and impact of the gestural interaction technologies on the experience*

To understand the impact of gestural interaction technologies on the experience, we first highlighted the key aspects to consider when designing gestural interaction interfaces. To do so, we uncovered the important variables to take into account when building an interface based on gestural interaction, and then built a conceptual model. In order to test it, we set up two studies in which participants interact with an IKEA-like digital catalog fully controllable with 3D hand gestures. This enabled us to cross-analyze the research methods and multiply the contexts of use. In the first study, we put people in a situation similar to using an in-store kiosk and we evaluate the discovery of the interface. In the second study, we put the participants in a situation similar to shopping online from a personal computer. The analyzes were then carried out using SmartPLS, a qualitative approach, SPSS and a machine learning approach. Doing so enabled us to study the impact of gestural interaction on the experience.

We observed the importance of the naturalness of the interaction which, despite being subjective, is explained by several factors more objective and specific to the gestures. This naturalness itself has an impact on the perceived intuitiveness of the interaction, the stimulation of the customer and the feeling of being in control of the situation. Moreover, we can directly observe the impact of this interaction on retailing, with a positive impact on the time spent shopping and the number of products added to the basket. For the designers of such interfaces, we therefore recommend paying particular attention to the naturalness of the gestures implemented. For this, it seems relevant to go through a gesture elicitation study (Wobbrock et al., 2009).

We have seen that practitioners can use gestural interaction to provide a more playful, immersive and stimulating consumer experience. On the other hand, we must not neglect the loss in user's feeling of control, which can directly influence the consumption and the experience. This is especially the case for older people. We therefore recommend setting up a complete and easy learning of the interface, for example via a tutorial as in these studies. Finally, we have shown that the participants' subjective declarations in terms of their experiences correspond to the objective measures observed through the EEG (Van Camp et al., 2018).

*Essay 4: Method for evaluating the gestural interaction experience*

In this essay, we have detailed a new method for evaluating gestural interfaces, dividing the analysis by gesture, use case and overall subjective experience. This method combines quantitative measures, particularly specific to memorability, qualitative scales and interviews. In particular, we have detailed 3 new scales that are particularly relevant in the context of gestural interaction, namely learnability, discoverability and social acceptability. We then applied this method to evaluate a gesture-based interface.

We first have updated the UEQ+ calculation tool to select three additional scales on demand and to incorporate them into the UEQ+ method in the same way as the other scales. However, the UEQ+ calculation tool was only intended for one evaluation session, which represents only a snapshot in time. On the contrary, we need several evaluation points, especially for the learnability. That is why we have also implemented a multi-session extension in the calculation tool.

When applying our method to a concrete interface, we were able to show the advantages of the method, first in combining different types of measurements. On the one hand, the task success rate remained relatively high, and the median number of gesture successes is mostly 1, which attests to the quality of the interface. This result was confirmed by the questionnaires, where the majority of UEQ+ scales are considered excellent or good. However, we also observed a divergence in these data. In atomic tasks, the situation was slightly better in the first session rather than the second. However, when we looked at the questionnaires, the experience was considered to be better in session 2. Therefore, even though users tended to have more difficulty a week later, they were more comfortable and happier with the interface.

Another advantage of this method is the division between atomic and compound tasks. Focusing on the gestures themselves, we could see the weakness of the rotation movements, which was not apparent in the compound task of the photos. On the other hand, the Maps application stands out as weaker, which would have been invisible by just looking at the atomic tasks. Finally, the debriefing interviews made it possible to confirm the overall quality of the interface, particularly in terms of intuitiveness, which also emerges from the questionnaires. Apart from that, they allowed us to highlight a problem unknown to the experimenters, which would not have been discovered if we had been satisfied with our objective measurements and the questionnaires.

Table 25: Summary of the four essays of this thesis.

| Essay | Research Questions | Research methods | Key concepts | Key findings |
|---|---|---|---|---|
| Essay 1 | RQ1 & RQ2 | • Systematic literature review (PRISMA) | • User experience<br>• Customer experience<br>• Consumer experience | • Each construct of the experience has particularities and should be differentiated<br>• The majority of the articles currently do not differentiate the constructs<br>• Suggest to opt for a multi-constructs approach, and limit to a few popular definitions |
| Essay 2 | RQ2 | • Qualitative (interviews and observations) | • Intuitiveness<br>• Impulse buying<br>• Perceived control<br>• Immersion | • Intuitiveness plays a central role and has a link with impulse buying<br>• The immersion is the heart of the experience<br>• Highlight of the role of perceived control in the interaction<br>• Highlight of the impact of trust, anxiety and perceived reliability |
| Essay 3 | RQ2, RQ3 & RQ4 | • Targeted literature review<br>• Conceptual model<br>• Quantitative (SmartPLS, SPSS, machine learning)<br>• Qualitative (interviews and observations) | • Naturalness<br>• Intuitiveness<br>• Immersion<br>• EEG<br>• Supervised learning | • Highlight of the important variables and relations for gestural interaction experience<br>• Importance of the naturalness of the interaction, itself impacting the intuitiveness, stimulation and perceived control<br>• We can use gestural interaction to provide a more playful, immersive and stimulating experience<br>• The subjective declarations in terms of experiences correspond to the objective measures |

Table 25: Summary of the four essays of this thesis (continued).

| | | | | |
|---|---|---|---|---|
| Essay 4 | RQ5 | • Methodolo-gical | • Complementarity<br>• Convergence | • Interest of dividing the analysis by gesture, use case and overall subjective experience<br>• Interest of combining quantitative measures, qualitative scales and interviews<br>• Enables to show convergence or complementarity of the data |

## 2. Contributions

The different essays of this thesis provide several answers to our research questions. These insights together form the contributions that we will present below, divided between theoretical, methodological, managerial and societal parts. A summary of the main contributions is available in Table 26.

*Theoretical contributions*

The present work makes several theoretical contributions to the fields of human-computer interaction and marketing. First, we extend on the literature of the constructs of the experience, and we highlight the need for their unification. We first clarify the peculiarities of the different constructs of the experience, namely the user experience, customer experience, and consumer experience. Through a systematic literature review, we also highlight the current heterogeneity in the literature. We show that the majority of the articles combining the constructs of the experience do not differentiate them. We also uncover that there is a lack of widely used definitions and dimensions for each of the constructs. This finding indicates that the theory is not yet stabilized, and it underscores the need for further research to create a certain homogeneity in the literature. In order to overcome this problem, we suggest a multi-constructs approach to benefit from the complementarity of points of view. We also advise linking the user experience to the customer experience before taking into account the consumer experience and limiting the use of definitions and dimensions to a few popular works that are already well established to avoid confusion, such as Pine and Gilmore (1998), Lemon and Verhoef (2016), Hassenzahl et al. (2003) and ISO 9241-210 (2018).

During our qualitative approach with consumer's interviews, we highlight the importance of including affective responses when evaluating the experience, and particularly when using gestural interaction. We show the importance of intuitiveness, perceived control, and perceived reliability in the consumption process with gestural interaction technologies. We also identify the immersion as a particularly relevant factor to consider in order to assess the experience. We provide insights into the impact of the gestural interaction in the first appropriation step of the immersion process, which enables users to reach a deeper immersion level more quickly. To go further, this thesis provides insights into the impact of intuitiveness and immersion on impulse buying, showing how immersion, and particularly gestural interaction, can lead to impulse buying in some cases. This can be due particularly to the increased feelings of presence and perceived ownership.

Based on these first findings, we complete our research to get an extensive view of the factors impacting the experience. We extend on the work of Xia et al., 2022, who identify important aspect to consider when designing gestural interaction interfaces. However, this work does not include social and affective aspects of the interaction. In order to complete it, we conduct a targeted literature review, enabling us to identify the key aspects to consider in order to evaluate the gestural interaction experience. As a next step, we build an extensive conceptual model, based on the literature of human-computer interaction and marketing. Based on this conceptual model, we conduct two studies aiming to provide a better understanding of how gestural interaction impacts the experience, especially in a consumption context. This enables us to highlight the importance of naturalness in gestural interactions and its impact on perceived intuitiveness, stimulation, and the feeling of control. Overall, we contribute to the marketing literature by providing a better understanding of how the use of gestural interaction can improve the consumer experience by making it more playful, immersive, and stimulating. We also highlight the importance of providing complete and easy learning of the interface to maximize the effectiveness of gestural interaction in a consumption environment.

In the final essay of this thesis, we introduce a new approach for evaluating gestural interfaces, answering to the last of our main goals in this thesis. Firstly, we add three new scales to the existing UEQ+ evaluation method, which were specifically designed to measure the learnability, discoverability, and social acceptability of gestural interfaces. These scales provide a more comprehensive assessment of gestural interfaces by including subjective user experiences and perceptions that are critical to evaluating the quality of the interface. Secondly, this thesis proposes a novel approach to gestural interface evaluation that combines quantitative measures, qualitative scales, and debriefing interviews to obtain a holistic view of the experience. This approach recognizes the importance of both objective and subjective evaluation methods. Finally, we highlight the interests of conducting multi-session evaluation, particularly for measuring the learnability of gestural interfaces. This is important as gestural interfaces are often more complex than traditional graphical user interfaces and require users to learn new interaction paradigms.

In conclusion, this thesis presents a number of theoretical contributions to the field of human-computer interaction and marketing. Through a multi-method approach, we identify the important aspects to consider when studying gestural interaction technologies, and the experience resulting from their use We also highlight the need for an effective communication between marketing and human-computer interaction, identify the importance of affective responses in evaluating the gestural interaction experience, and emphasize the impact of immersion on impulse buying. Furthermore, this thesis provides a better understanding of how gestural interaction can improve the consumer experience by making it more playful, immersive, and stimulating. Additionally, we propose a novel approach to evaluating gestural interfaces, which includes both subjective and objective evaluation approaches.

*Methodological contributions*

This thesis also makes several methodological contributions to the fields of human-computer interaction and marketing. At multiple occasion, we take advantage of the systematic and targeted literature methodologies. In the first essay, we use the PRISMA methodologies not to have an overview of a specific literature but to identify papers crossing multiple literatures. This approach enables us to highlight heterogeneity in these papers through a multidisciplinary approach.

In terms of qualitative approaches, we show the interest of combining techniques and context, making the results even more robust. In the 2$^{nd}$ essay, we combine consumer interviews with observations of 2D gestural interaction. In particular, we increase the representativeness of the results by simulating a real consumption situation using the participants' smartphones. In the 3$^{rd}$ essay, we focus on interviews with people who just completed a 3D interaction session with a digital catalog. The particularity of this study is also its laboratory-controlled character.

Regarding quantitative research methods, we also employ different methods to cross-analyze the data and increase the validity of the results. The first study of essay 3 is a laboratory experiment that simulates the experience of using an in-store kiosk, while the second study simulates shopping online from a personal computer. By using different contexts, we show the complementarity of such methods, enabling to generalize the findings and make the results even more robust.

These studies also employ multiple data analysis techniques and tools, including SmartPLS, SPSS, and a machine learning approach. By using different techniques, we were able to show a complementarity between data collection and analysis methods. As a consequence, we were able to provide a more comprehensive and nuanced understanding of the impact of gestural interaction on the experience. In the second study of essay 3, we also used EEG to objectively measure the participants' experiences, which provides another measure of the impact of gestural interaction on the experience. This methodological contribution is particularly important as it allows researchers to verify the validity of the subjective declarations made by the participants in the questionnaires, showing a complementarity with the subjective measures. To use this data, we introduce a new method enabling to use Bitbrain-style EEG headset in social science studies, and without requiring extensive teams with neuroscience skills. This method starts with a machine learning approach enabling to highlight the important aspect of the data to consider for the analysis. This enables to move to a more classic statistical approach, offering higher interpretability power.

Finally, we propose a new evaluation method for gestural interfaces based on techniques not necessary present in the field of human-computer interaction. To do so, we update the UEQ+ calculation tool to include the three new scales introduced in this thesis. This tool is available as an open science supplemental material, which provides researchers with a more comprehensive evaluation method for gestural interfaces. Secondly, this thesis shows the importance of having a multi-session evaluation approach to measure the learnability of gestural interfaces. This approach involves testing users on multiple occasions, which provides a more accurate measure of the long-term experience with the interface. Finally, we show the usefulness of debriefing interviews as a complementary method to questionnaires and objective measures. Debriefing interviews can help identify issues with the interface that may not be apparent from other evaluation methods and can provide researchers with valuable feedbacks for improving the interface.

In conclusion, this thesis shows the advantage of combining multiple approaches, enabling to cross-analyze the results and make the findings even more robust. These approaches include a systematic and targeted literature review methodology, a qualitative approach that combines consumer interviews with observations of gestural interaction, a laboratory-controlled approach for conducting interviews, and the use of various quantitative research methods such as SmartPLS, SPSS, and a machine learning approach. Moreover, we introduce a method to objectively measure participants' experiences using EEG, without requiring extensive neuroscience skills. This thesis also proposes a new evaluation method for gestural interfaces and emphasizes the importance of a multi-session evaluation approach and debriefing interviews. This multi-methods and -contexts approach can provide researchers with a comprehensive and nuanced understanding of the impact of gestural interaction on the experience, as well as new evaluation methods that can improve the design of interfaces.

*Managerial contribution*

This thesis presents contributions that can be useful for researchers, practitioners, and managers in the fields of human-computer interaction and marketing. Firstly, we highlight the importance of effective communication and collaboration between these two fields. We first identify and clarify the differences and peculiarities of the constructs of user experience, customer experience, and consumer experience, which are essential components of the overall holistic experience. Based on this, we suggest adopting a multi-constructs approach for researchers and practitioners working with the experience. The complementarity of points of view can benefit from a managerial perspective, leading to an increased level of experience provided to the user, customer or consumers. We also suggest to first link the user experience to the customer experience, without taking into account the consumer experience, which is harder to measure.

By combining qualitative and quantitative research methods, we provide insights into the factors that influence the gestural interaction experience. We started from variables to use when designing gestures and go further to social and emotional aspects important in the experience resulting from the interaction. In particular, we emphasize the importance of perceived usefulness and ease of use in the gestural interaction experience. Designers should also ensure that the gestural interaction is intuitive and easy to use, particularly for users less comfortable with technology, to enhance the experience. We also provide insights into the impact of intuitiveness and immersion on impulse buying, showing how gestural interaction can lead to impulse buying in some cases. It is an essential aspect to consider in order to create immersive experiences while maintaining ethical practices.

Lastly, we provide guidelines on how to design gestural interaction interfaces that are natural and intuitive for customers, enhancing the experience and leading to a competitive advantage (Pine & Gilmore, 1998; Verhoef et al., 2009; Lemon & Verhoef, 2016). We also highlight the importance of designing interfaces that are easy to learn and discover. These qualities are critical to the success of gestural interfaces, as users may experience difficulties to adopt new interaction paradigms.

When assessing interfaces, we demonstrate the importance of evaluating gestural interfaces using a variety of methods, including subjective evaluations such as questionnaires and debriefing interviews. This should enable practitioners to benefit from complementary points of view and have a better understanding and control of the experience they offer.

*Societal contribution*

As developed before, we provide insights into how gestural interaction technologies can enhance the experience. This is particularly relevant given that we live in a world where virtual reality applications are increasingly present. Even more than that, it is more and more common to hear about the future metaverse. As the popularization of this concept is rather recent, it is still too early to give an exact definition. There is however one major feature that everyone agrees on: the use of immersion technologies.

For many people, the metaverse will take place in an entirely virtual world. To access it, there are many candidate technologies, virtual reality being just one of many. Since the metaverse aims to connect different universes, it is likely that a combination of technologies will be necessary in order to take full advantage of its possibilities. Among all these possibilities, gestural interaction interfaces, or their future evolutions, will probably have an essential role to play. Gestural interaction therefore seems to be a key subject to master. This is all the more important for certain categories of the population. In this thesis, we have repeatedly highlighted the impact of these technologies on older people and on their feeling of control. However, it is essential to deepen research on this impact and extend it to other categories of the population, such as people with disabilities.

In conclusion, this thesis provides a comprehensive set of contributions that can benefit researchers, practitioners, managers and the society. These contributions highlight the importance of effective communication and collaboration between different fields, as well as the significance of designing interfaces that are intuitive, natural, and easy to learn. By providing a multi-constructs approach to understanding the experience, we offer insights into how businesses can create engaging and immersive experiences that could provide a competitive advantage. We also emphasize the importance of evaluating interfaces using a variety of methods to gain a comprehensive understanding of the experience.

Table 26: Summary of the main contributions of this thesis.

| Type | What we had | What we did | What is left to do |
|---|---|---|---|
| *Theoretical contributions* | • Different constructs of the experience separated in multiple literatures. | • Highlighted the constructs of experience and their complementarity.<br>• Highlighted the heterogeneity in the literature. | • Create and validate a model unifying the constructs of the experience.<br>• Build homogeneity in the literature. |
| | • Important IT factors to consider when designing gesture vocabularies. | • Identified the important aspects to consider when studying gestural interaction technologies. | • Validate a more extensive model with a large sample. |
| | • Promising technology (without knowing its concrete impact on the experience). | • Identified the importance of affective responses when evaluating the gestural interaction experience.<br>• Emphasized the impact of immersion on impulse buying.<br>• Provided a better understanding of how gestural interaction can improve the experience. | • Study and deepen these aspects in order to make them more common in the literature.<br>• Conduct a quantitative study to measure this effect.<br>• Conduct complementary studies in different contexts. |

Table 26: Summary of the main contributions of this thesis (continued).

| | | | |
|---|---|---|---|
| *Methodological contributions* | • Some research methods remaining mainly compartmentalized in their original disciplines. | • Showed the complementarity of combining: Systematic and targeted literature reviews across multiple disciplines ; Quantitative research methods to provide a comprehensive understanding of the gestural interaction experience ; Qualitative approaches in IT to cross-analyze results and increase the robustness of findings. | • Continue to conduct in-depth literature reviews in specific areas (as Becker & Jaakkola) <br>• Replicate and refine the triangulation of these research methods. |
| | • EEG methods requiring larger teams with extensive neuroscience knowledge. | • Introduced a method to objectively measure participants' experiences using EEG. | • Apply and adapt this method to other contexts and with other EEG headsets. |
| | • Restrictive evaluation methods not adapted to gestural interfaces. | • Developed a new evaluation method for gestural interfaces (including subjective and objective measures, multi-session evaluation and interviews). | • Apply this method to other interfaces and contexts, and validate it. |

Table 26: Summary of the main contributions of this thesis (continued).

| | | | |
|---|---|---|---|
| *Managerial contributions* | • Separate disciplines | • Emphasized the importance of collaboration between multiple fields of research. | • Generalize the communication between different fields. |
| | • Some studies tending to limit to a single point of view. | • Recommended a multi-fields approach to benefit from the complementarity of the points of view. | |
| | • Guidelines tending to limit to objective aspects of the individual. | • Provided insights into the factors influencing the gestural interaction experience.<br>• Offered guidelines for designing and implementing gestural interfaces, enhancing the experience. | • Testing these technologies in real consumption contexts (representative design). |
| | • Restrictive evaluation methods not particularly adapted to gestural interfaces. | • Provided a comprehensive evaluation method of gestural interfaces. | • Refining and using this method with different technologies and in other contexts. |
| *Societal contributions* | • Arrival of the metaverse. | • Provided insights into the use of technologies that may be used in the metaverse. | • Study gestural interaction in a fully or partially virtual environment. |
| | • Certain parts of the population to be protected. | • Showed some impact of gestural interaction on older people. | • Deepen the study of the impact and extend it to other categories of the population. |

## 3. Limitations and future research

Despite the multiplication of methods, techniques and measurements, some limitations to our work persist that may be addressed in future research. Table 27 outlines the future research agenda.

Most of the studies we conducted during this thesis were realized with a diachronic point of view, therefore without multiple observations over time. Only the evaluation conducted in essay 4 organised two sessions spaced one week apart. However, the goal of this study was to apply our evaluation method to an interface, and it did not focus on the consumer experience. This would be an interesting work to carry in a future study. For instance, we could study a potential learning effect in gestural interaction, making it easier over time and impacting our findings about perceived control. Another possible outcome would be to observe a novelty effect, which could impact affective dimensions resulting from the experience. It would also be the opportunity to study gestural interaction technologies through multiple touchpoints of the customer journey and therefore have a more holistic understanding of the impact on the experience.

Regarding the evaluation method for gesture-based interfaces that we introduced in essay 4, we have only applied it to one interface and context. In order to increase its representativeness, it should be applied to other interfaces and contexts. This would also allow to refine the method, for instance in term of the scales used. Another important point is the use of our three ad hoc scales, which had been chosen thanks to their good validity results in other studies. It would however be interesting to change their format in order to match the one used in UEQ+, therefore functioning as an extension of the latter.

In this thesis, we focused on hand gestures as these are used most often (Santiago et al., 2020). However, by definition, gestural interaction can apply to any part of the body. There are therefore many other possibilities, focusing on other parts of the body or even taking into account the body as a whole. Santiago et al. (2020) provide an overview of the current research in gestural interaction and identify the most used body parts based on 216 gesture elicitation studies. This study could be a good starting point to explore different parts of the body as interaction mediums. Moreover, we focused on two types of hand gestural interaction, 2D and 3D, with a focus on 3D interaction for the quantitative studies. We also decided to oppose gestural interaction to the classical interaction with a mouse. It would be relevant to explore the combination of these two modes of interaction in order to combine the advantages of each. In another aspect, all quantitative experiments were performed with a LeapMotion. The company producing this product has since launched the ultrahaptic, a sensor similar to the LeapMotion recognizing gestures, but also providing haptic feedback. In this way, the person interacting with the interface can get feedback on the interaction, which adds a new sense to the interaction. This is a major development in gestural interaction that would be particularly relevant to study as it provides even more feedback to the users.

When studying the constructs of the experience in essay 1, we had to make choices in the keywords used during the identification of articles in order not to disperse. For example, we carried out research with the "consumer experience" but not the "consumption experience". We also had to put aside other concepts that could potentially be considered as constructs of experience but without specifically mentioning the term "experience" in their name. In addition, this work mainly focuses on papers at the crossroads between several constructs of the experience. It would be relevant to focus on all the papers specific to each single construct, as for example Becker and Jaakkola (2020) did for the customer experience. This work would be particularly relevant in order to have a global view of the experience, further facilitating its multidisciplinary use and its unification.

During our qualitative approaches, we had to focus on two specific gestural interaction contexts, namely 2D gestures on smartphone touch surfaces (essay 2), and 3D gestures to control a digital catalog in a lab (essay 3). In order to generalize even more our results, it would be interesting to carry out more studies with different contexts. More specifically, it would be particularly relevant to conduct an in-store study using 3D gestural interaction technologies, such as a kiosk. It would be the opportunity to study the consumption in real settings and make our findings even more representative of the reality. The situation is similar for the quantitative studies, all performed in controlled lab environments. In order to observe the experience in a real consumption context, il would be relevant to test the same setup in a shop or when completing real online purchases. This would make it possible to quantify whether using interaction technologies has a financial impact, in addition to an experiential one.

In conclusion, this thesis provides a first approach for understanding the impact of gestural interaction on the experience and provides guidelines for designers and practitioners to improve the experience through gestural interaction technologies. However, there are still many unanswered questions and areas for future research that could further expand on the findings of this thesis.

Table 27: Future research agenda.

| Topic | Research gap | Research questions | Expected contributions |
|---|---|---|---|
| Repeat observations over time | We mostly opted a diachronic point of view, while multiple observations over time would bring even more perspectives. | • Is there a learning effect when using gestural interaction technologies? | • Investigate the long-term effect of gestural interaction on the perceived control and other variables specific to the use of gestural interfaces. |
| | | • Is there a novelty effect when using gestural interaction technologies? | • Investigate the long-term effect on the playfulness, immersion and other experiential variables when using gestural interaction. |
| | | • What would be the impact of gestural interaction technologies when used at different touchpoints of the customer journey? | • Study different touchpoints of the customer journey in order to understand the impact of gestural interaction in a broader picture. |
| Apply our evaluation method to other contexts | Need to refine and validate this method over time in order to make it more robust. | • Is our method adapted to different types of gestural interaction technologies and contexts? | • Validate our evaluation method and make it more robust to the general use for all gestural interaction technologies. |
| | | • Could this method be generalized to other kind of interfaces? | • Explore the adaptation of our method to other types of interfaces and assess its relevance. |

Table 27: Future research agenda (continued).

| | | | |
|---|---|---|---|
| Variations in gestural interaction | The gestural interaction is a wide subject constantly evolving and many aspects have yet to be studied. | • Are the results still valid when considering other parts of the body as an interaction medium? | • Explore the impact of gestural interaction with different parts of the body on the experience and the consumption in general. |
| | | • Could we combine gestural interaction to classical user interfaces in order to enhance the experience? | • Understand the effect of combining different modalities of interaction and explore how it could be used in order to enhance the experience. |
| | | • What would be the effect of a haptic feedback when using gestural interaction technologies? | • Investigate the effect of including an haptic feedback functionality in the interaction. |
| | | • Are the results similar with consumers with different (dis)abilities? | • Explore the use of gestural interaction technologies for consumers with different abilities. |
| Unification of the constructs of the experience | Need to identify and unify all the constructs of experience across multiple literatures. | • How to unify in the same model every construct of the experience? | • Better understand the different constructs of the experience, their underlying relations, and their role in the same holistic experience. |

Table 27: Future research agenda (continued).

| | | | |
|---|---|---|---|
| Improve even further the representativeness of our results | The impact of 3D gestural interaction in a real consumption context has still to be studied. | • What is the impact of gestural interaction technologies when in a real consumption context? | • Confront our results to a real consumption context with other factors impacting the experience. |
| | | • Is there another impact not only experiential? | • Identify the impact of gestural interaction technologies on other aspects not necessarily directly linked to the experience. |

# Appendices

## Appendix 1: List of the 78 papers retained in the final corpus (Essay 1)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## Appendix 2: Interview guide (Essay 2)

NB: questions in grey are not necessarily asked.

**Presentations – getting to know each other**

1) Presentation of the experimenter and the research

“Thank you for your time. First of all, do you give me the authorization to record this interview? To introduce myself, my name is Quentin Sellier, I am a PhD student at UCLouvain, and as part of my thesis I need to understand your feelings as a user / consumer in general. There is therefore no wrong answer given that I am asking your personal opinion and feeling."

2) General question about the interviewee

Ask to introduce yourself in a few words (name & first name, age, occupation, location, situation)

**Purchases**

3) General purchases questions

- Can you describe for me the way you usually shop?
    - How / Why do you decide to do your shopping?
    - How do you choose your stores? What about your products?
- What about other product categories? (Example: food, clothing, furniture / decoration, books, electronics, etc.)
- What do you like or dislike about going shopping?
    - Example: contact with sellers, choice available, etc.

4) Experiences

- Could you describe the last good or bad experience that comes to your mind?
- What do you think makes a good / bad experience?
- Do these experiences have consequences for future choices?

**Technologies**

5) Develop more the technologies, specific to shopping and in general

- What do you think of technologies for shopping?
    - Example: Online sites, applications, virtual vouchers, targeted communication and promotions, etc.
- Do certain technologies seem particularly interesting to you? Which ones and why?
    - Do you ever use apps or sites that could help you with your errands? Why?

**Gestures**

6) IKEA smartphone scenarios: ask people to do a search directly on the IKEA website and describe in detail what they are doing (especially their actions). Ask them to look for a particular product, look at the photos, give the dimensions of the product.

7) Debrief: How was the difficulty? What did you think of the website?

**Conclusion**: thank again for the time, sum up the interview and ask if they want to add something.

## Appendix 3: List of the 270 papers retained in the final corpus (Essay 3)


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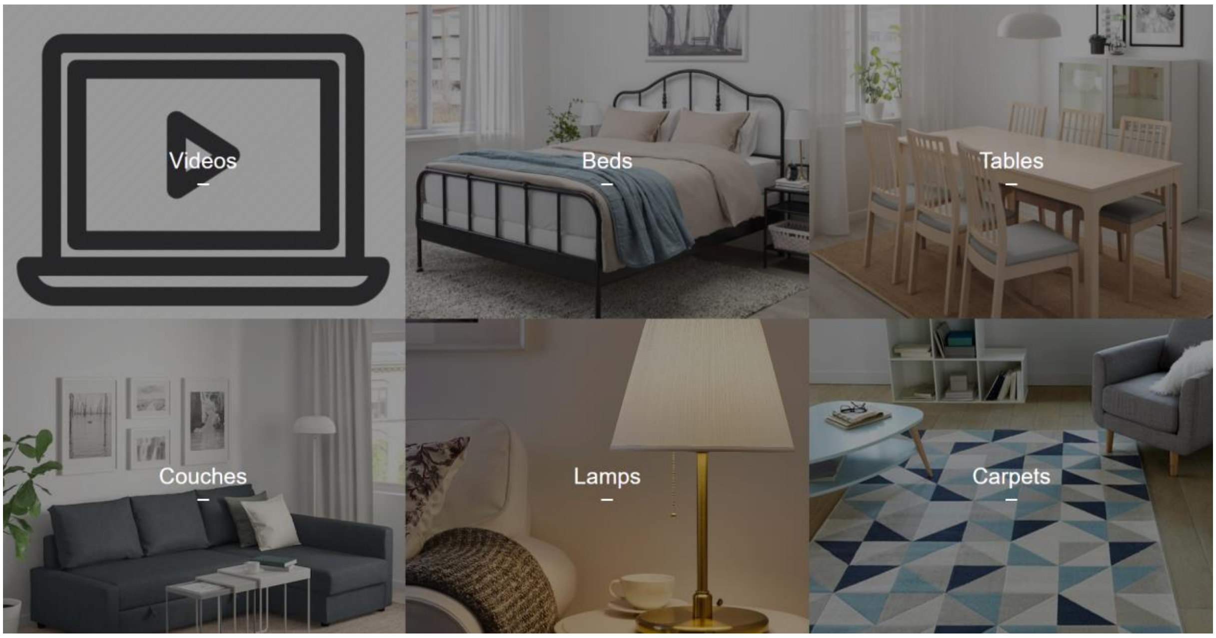
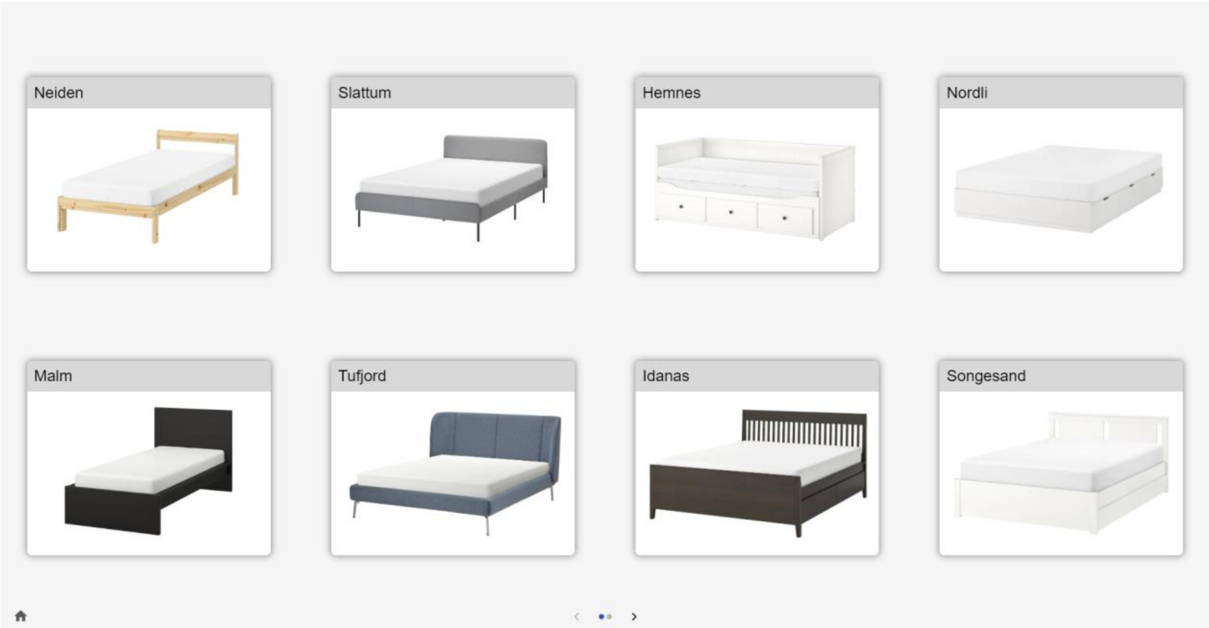
## Appendix 4: Screenshots of the IKEA-like digital catalog (Essay 3)

Main menu of the catalog (which is also the home screen):




Menu of the "Beds" category:

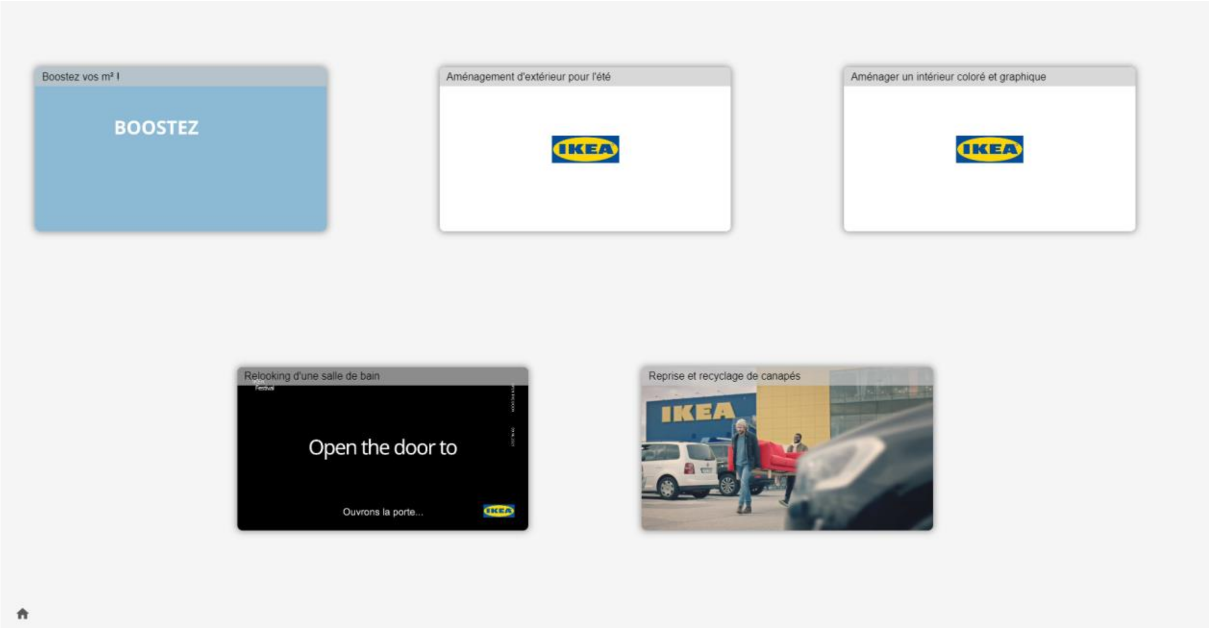



NB: All the other 4 product categories (Tables, Couches, Lamps and Carpets) have similar menus featuring 8 products per page, with two content pages.

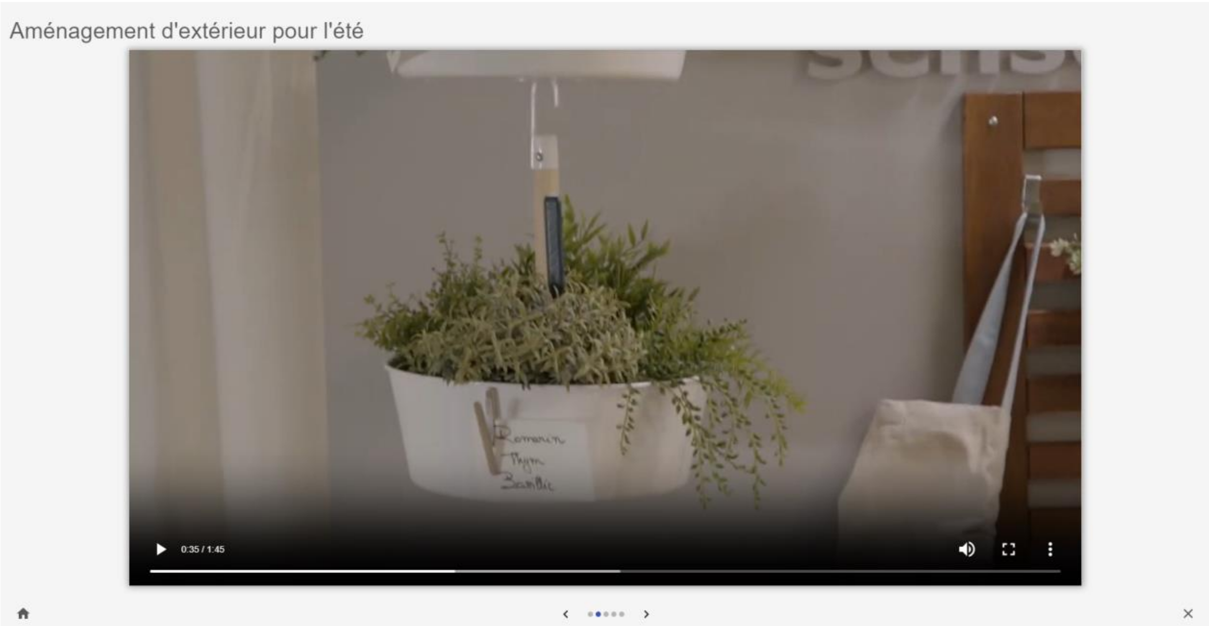
A product page, including a title, a price, a description and several navigable photos by clicking on the arrows or making a Swipe gesture:


The “add to favorites” animation, triggered by clicking on the heart at the bottom right or by making the Like gesture:

Menu of the "Videos" category:




A video page, including a title, and the video player (enabling to play, pause, fast forward and rewind):



## Appendix 5: Python code of the machine learning approach (Essay 3)

```
# Reading of the Excel files, small filtering of the data and store it in a 3D table
import pandas as pd
import numpy as np

EEGCleanedData =
[[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[ ],[]],[[],[],[],[],[],
[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[], [],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],
[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[ ],[],[],[],[],[],[],[]
],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[]
,[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[], [],[],[],[],[]],[[],[]
,[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[ ],[],[
]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[] ,[],[]]] #
Creation of the lists that will contain the filtered data of every participant (used after to compute the peaks)

# Small block to define the xlsx documents
belgian_base_id = 1000
n_participants = 39
filenames = [f'individual_upv_{i}.xlsx' for i in range(belgian_base_id+1,belgian_base_id+n_participants+1)]
tab_names = ['t01  Test_gestures', 't02  Test_mouse']

# Read the file and only keep the relevant columns
idpart = 0
for filename in filenames:
    idvar = 0
    print("Participant "+str(idpart+1)+" out of "+ str(n_participants), end='\r', flush=True)
    for tab_name in tab_names:
        df = pd.read_excel(f'data/{filename}', sheet_name=tab_name, header=2) # Open the right xlsx file

        # Deletion of lines where the person does not interact with the catalog (we are only interested in the
shopping session)
        df = df.loc[df['CatalogInteraction'] == 1]
        # Suppression des lignes ou la qualité des données n'est pas bonne
        df = df.loc[df['quality'] == 1]

        # Remove the "time" column (repeated for each variable)
        time_columns = [col for col in df if col.startswith('time')]
        time_columns = time_columns[1:]
        filtered_columns = [column for column in df if column not in time_columns]

        # Remove the columns not used
        filtered_columns = [column for column in filtered_columns if not(column.startswith('quality'))]
        filtered_columns = [column for column in filtered_columns if not(column.startswith('Tutorial'))]
        filtered_columns = [column for column in filtered_columns if not(column.startswith('VideoInteraction'))]
        filtered_columns = [column for column in filtered_columns if not(column.startswith('CatalogInteraction'))]
        filtered_columns = [column for column in filtered_columns if not(column.startswith('User marker'))]
        filtered_columns = [column for column in filtered_columns if not(column.startswith('x'))]
        filtered_columns = [column for column in filtered_columns if not(column.startswith('y'))]
        filtered_columns = [column for column in filtered_columns if not(column.startswith('click'))]
        df = df.loc[:, filtered_columns]
        df.columns = ['time', 'engagement', 'memorization', 'valence', 'workload']
```

```
        # Removing the non-integer values
        for column in df.columns:
            if column != 'time':

                NbBadValues = 0
                for value in df[column]:
                    try:
                        a = int(value)
                    except:
                        NbBadValues+=1

                FilteredValues=np.zeros(df[column].count()-NbBadValues)
                i=0
                for value in df[column]:
                    try:
                        a = int(value)
                        FilteredValues[i]=value
                        i+=1
                    except:
                        pass

                EEGCleanedData[idpart][idvar] = FilteredValues

                idvar += 1
    idpart += 1

print("Completed                              ")



# Function changing the outliers in the data with the max accepted values
def outlierschange(EEGData):
    EEGfiltered =
[[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[ ],[]],[[],[],[],[],[],
[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[ ],[],[],[],[]],[[],[],
[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[ ],[],[],[],[]],[[],[],[],[],[],[],[],[]
],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[], [],[]],[[],[],[],[],[]
,[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[], [],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[]
,[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[ [],[],[],[],[],[],[],[
]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]]] #
Creation of the lists that will contain the filtered data of every participant (used after to compute the peaks)

    idvar = 0
    while idvar < 4: # For each variable in gesture interaction (that will be compared to the 4 other mouse
variables)
        idpart = 0
        meanRangeInf=0
        meanRangeSup=0
        while idpart < n_participants: # For each participant
            # Compute the quartiles & the range where the data is acceptable
            Q1 = np.percentile(np.concatenate((EEGData[idpart][idvar],EEGData[idpart][idvar+4]), axis = None),
25)
```

```
        Q3 = np.percentile(np.concatenate((EEGData[idpart][idvar],EEGData[idpart][idvar+4]), axis = None),
75)
        rangeInf = Q1-(3*(Q3-Q1))
        rangeSup = Q3+(3*(Q3-Q1))

        # --------------- Gesture --------------

        # Creates a list with the accepted data
        AcceptedValues=np.zeros(len(EEGData[idpart][idvar]))
        i=0
        for value in EEGData[idpart][idvar]:
            if value >= rangeInf and value <= rangeSup:
                AcceptedValues[i]=value
            if value > rangeSup:
                AcceptedValues[i]=rangeSup
            if value < rangeInf:
                AcceptedValues[i]=rangeInf
            i+=1

        EEGfiltered[idpart][idvar]=AcceptedValues

        # --------------- Mouse --------------
        # Compute the number of values out of the range
        NbBadValues = 0
        for value in EEGData[idpart][idvar+4]:
            if value < rangeInf:
                NbBadValues+=1
            if value > rangeSup:
                NbBadValues+=1

        # Creates a list with the accepted data (excluding values out of range)
        AcceptedValues=np.zeros(len(EEGData[idpart][idvar+4])-NbBadValues)
        i=0
        for value in EEGData[idpart][idvar+4]:
            if value >= rangeInf and value <= rangeSup:
                AcceptedValues[i]=value
                i+=1

        EEGfiltered[idpart][idvar+4]=AcceptedValues

        idpart += 1
    meanRangeInf/=n_participants
    meanRangeSup/=n_participants

    idvar+=1

  return(EEGfiltered)
```

```
# Function correcting the duration of the sessions (no more longer gesture sessions, or the opposite), for each
variable and each participant
import random

def durationcorrectionIndividualRemoval(EEGData):
   EEGDurationCorrection =
[[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[ ],[]],[[],[],[],[],[],
[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],
[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[ ],[],[],[],[],[],[],[]
],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[], [],[]],[[],[],[],[],[]
,[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[], [],[]],[[],[],[],[],[],[],[],[]],[[],[]
,[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[ [],[],[],[],[],[],[],[
]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[ ],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]]] #
Creation of the lists that will contain the filtered data of every participant (used after to compute the peaks)

   # Create a copy of the EEG data, that will then delete random values
   l = 0
   while l < n_participants:
      j=0
      while j < 8:
         EEGDurationCorrection[l][j]=EEGData[l][j]
         j+=1
      l += 1

   idvar = 0
   while idvar < 4: # For each variable in gesture interaction (that will be compare to the 4 other mouse
variables)
      idpart = 0
      while idpart < n_participants: # For each participant
         NbToRemove = 0
         if len(EEGData[idpart][idvar]) > len(EEGData[idpart][idvar+4]):
            NbToRemove = len(EEGData[idpart][idvar]) - len(EEGData[idpart][idvar+4])
            while NbToRemove > 0:
               EEGDurationCorrection[idpart][idvar] = np.delete(EEGDurationCorrection[idpart][idvar],
random.randrange(len(EEGDurationCorrection[idpart][idvar])-1))
               NbToRemove -= 1

         if len(EEGData[idpart][idvar]) < len(EEGData[idpart][idvar+4]):
            NbToRemove = len(EEGData[idpart][idvar+4]) - len(EEGData[idpart][idvar])
            while NbToRemove > 0:
               EEGDurationCorrection[idpart][idvar+4] = np.delete(EEGDurationCorrection[idpart][idvar+4],
random.randrange(len(EEGDurationCorrection[idpart][idvar+4])-1))
               NbToRemove -= 1
         else:
            pass
         idpart += 1
      idvar+=1
   return EEGDurationCorrection
```

```
# Computation of the "average" max peak for each variable and participant (taking into account the duration
correction with multiple simulations)
import numpy as np

NumberSimulations = 2000 # Number of simulations
averagemaxpeak = np.zeros((n_participants, 8))
temporarydata =
[[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[ ],[]],[[],[],[],[],[],
[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[ ],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],
[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[ ],[],[],[],[],[],[],[]
],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[]
,[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[], [],[],[],[],[]],[[],[]
,[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[] ,[],[
]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[],[],[]],[[],[],[],[],[],[] ,[],[]]]

# Create the excel file where the data will be stored
import xlsxwriter
workbook = xlsxwriter.Workbook('AverageCorrectedMaxPeak.xlsx')
worksheet = workbook.add_worksheet()
worksheet.write(0, 0, 'Nb. of simulations: '+str(NumberSimulations))
for i in range(1,n_participants+1):
    worksheet.write(i, 0, belgian_base_id+i)
worksheet.write(0, 1, 'EngaGest')
worksheet.write(0, 2, 'MemoGest')
worksheet.write(0, 3, 'ValeGest')
worksheet.write(0, 4, 'WorkGest')
worksheet.write(0, 5, 'EngaMous')
worksheet.write(0, 6, 'MemoMous')
worksheet.write(0, 7, 'ValeMous')
worksheet.write(0, 8, 'WorkMous')

EEGFilteredData = outlierschange(EEGCleanedData)

i = 0 # Look at the max peak for a given simulation (for each variale and each participant) & add it to the
variable that will compute the average
while i < NumberSimulations:
    temporarydata = durationcorrectionIndividualRemoval(EEGFilteredData)
    l = 0
    while l < n_participants:
        j=0
        while j < 8:
            averagemaxpeak[l][j] += max(temporarydata[l][j])
            j += 1
        l += 1
    i += 1
    print("Simulation "+str(i)+" out of "+str(NumberSimulations), end='\r', flush=True)

idpart = 0 # End of computation of the average max peak for each participant and each variable
while idpart < n_participants:
    idvar=0
    while idvar < 8:
        averagemaxpeak[idpart][idvar] /= NumberSimulations
        worksheet.write(idpart+1, idvar+1, averagemaxpeak[idpart][idvar])
```

```
        idvar += 1
    idpart += 1

print("Completed "+str(NumberSimulations)+" simulations successfully")
workbook.close()



# Compute the % of data above 100
import xlsxwriter
workbook = xlsxwriter.Workbook('%above100.xlsx')

worksheet1 = workbook.add_worksheet()
worksheet1.write(0, 0, 'With outliers changed, every value above 100')
for i in range(1,n_participants+1):
    worksheet1.write(i, 0, belgian_base_id+i)
worksheet1.write(0, 1, 'EngaGest')
worksheet1.write(0, 2, 'MemoGest')
worksheet1.write(0, 3, 'ValeGest')
worksheet1.write(0, 4, 'WorkGest')
worksheet1.write(0, 5, 'EngaMous')
worksheet1.write(0, 6, 'MemoMous')
worksheet1.write(0, 7, 'ValeMous')
worksheet1.write(0, 8, 'WorkMous')

proportionabovehundred = np.zeros((n_participants, 8))

EEGFilteredData = outlierschange(EEGCleanedData)

idpart = 0
while idpart < n_participants:
    idvar=0
    while idvar < 8:
        NbHundred = 0
        for m in EEGFilteredData[idpart][idvar]:
            if m > 100:
                NbHundred += 1
        proportionabovehundred[idpart][idvar] = NbHundred/len(EEGFilteredData[idpart][idvar])
        worksheet1.write(idpart+1, idvar+1, NbHundred/len(EEGFilteredData[idpart][idvar]))
        idvar += 1
    idpart += 1

print('Completed')
workbook.close()
```

```
# Compute the means and medians
import numpy as np
import xlsxwriter
workbook = xlsxwriter.Workbook('mean.xlsx')

worksheet1 = workbook.add_worksheet()
worksheet1.write(0, 0, 'With outliers changed')
for i in range(1,n_participants+1):
    worksheet1.write(i, 0, belgian_base_id+i)
worksheet1.write(0, 1, 'EngaGest')
worksheet1.write(0, 2, 'MemoGest')
worksheet1.write(0, 3, 'ValeGest')
worksheet1.write(0, 4, 'WorkGest')
worksheet1.write(0, 5, 'EngaMous')
worksheet1.write(0, 6, 'MemoMous')
worksheet1.write(0, 7, 'ValeMous')
worksheet1.write(0, 8, 'WorkMous')

mean = np.zeros((n_participants, 8))

EEGFilteredData = outlierschange(EEGCleanedData)

idpart = 0
while idpart < n_participants:
    idvar=0
    while idvar < 8:
        mean[idpart][idvar] = np.mean(EEGFilteredData[idpart][idvar])
        worksheet1.write(idpart+1, idvar+1, mean[idpart][idvar])
        idvar += 1
    idpart += 1

print('Completed')
workbook.close()
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegressionCV
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix
from sklearn.model_selection import train_test_split
import numpy as np

workbook = xlsxwriter.Workbook('DiscriminantAnalysis.xlsx')

worksheet1 = workbook.add_worksheet()
worksheet1.write(0, 0, 'Gesture')
worksheet1.write(0, 1, 'MaxPeakEngagement')
worksheet1.write(0, 2, 'MaxPeakMemorization')
worksheet1.write(0, 3, 'MaxPeakValence')
worksheet1.write(0, 4, 'MaxPeakWorkload')
worksheet1.write(0, 5, 'ProportionHighEngagement')
worksheet1.write(0, 6, 'ProportionHighMemorization')
worksheet1.write(0, 7, 'ProportionHighValence')
worksheet1.write(0, 8, 'ProportionHighWorkload')
number_format = workbook.add_format({'num_format': '#,##0.00'})

NumberSimulations = 1000 # Number of simulations

AccuracyRF = 0
PrecisionRF = 0
RecallRF = 0
FoneRF = 0
tnRF = 0
fpRF = 0
fnRF = 0
tpRF = 0

feature_importances_rf = np.zeros(2)

i = 0
while i < NumberSimulations:
    X_gest = []
    X_mouse = []

    # Prepare the data
    # Extract the relevant features and the target variable for gestures
    X_gest = np.column_stack((averagemaxpeak[:,[3]], proportionabovehundred[:,[3]]))
    y_gest = np.ones((n_participants,))

    # Extract the relevant features and the target variable for mouse
    X_mouse = np.column_stack((averagemaxpeak[:,[7]], proportionabovehundred[:,[7]]))
    y_mouse = np.zeros((n_participants,))

    X = []
    y = []

    # concatenate the data of gestures and mouse
    X = np.concatenate((X_gest, X_mouse))
    y = np.concatenate((y_gest, y_mouse))
```

```
    # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

    # Train and test the Random Forest model
    clf_rf = RandomForestClassifier()
    clf_rf.fit(X_train, y_train)
    y_pred_rf = clf_rf.predict(X_test)

    # Evaluation metrics for the Random Forest model
    AccuracyRF += accuracy_score(y_test, y_pred_rf)
    PrecisionRF += precision_score(y_test, y_pred_rf)
    RecallRF += recall_score(y_test, y_pred_rf)
    FoneRF += f1_score(y_test, y_pred_rf)

    # Confusion matrix
    #print(confusion_matrix(y_test, y_pred_rf))
    [tn, fp], [fn, tp] = confusion_matrix(y_test, y_pred_rf)
    tnRF += tn
    fpRF += fp
    fnRF += fn
    tpRF += tp

    # Importance of the features for the Random Forest model
    importances_rf = clf_rf.feature_importances_
    feature_importances_rf += importances_rf

    i += 1
    print("Simulation "+str(i)+" out of "+str(NumberSimulations), end='\r', flush=True)

print("Completed "+str(NumberSimulations)+" simulations successfully")
print("")

print("Random Forest Model Evaluation Metrics")
print("Accuracy:", AccuracyRF/i)
print("Precision:", PrecisionRF/i)
print("Recall:", RecallRF/i)
print("F1-score:", FoneRF/i)
print("")

# Normalize the feature importances
feature_importances_rf /= i

# Names of the features
features = ["MaxPeakEngagement", "MaxPeakMemorization", "MaxPeakValence", "MaxPeakWorkload",
"ProportionHighEngagement", "ProportionHighMemorization", "ProportionHighValence",
"ProportionHighWorkload"]

# Create dataframe of feature importances
importances = pd.DataFrame(feature_importances_rf, index = features[:feature_importances_rf.shape[0]],
columns=['importance'])
```

```
# Sort by importance & print
importances = importances.sort_values(by='importance', ascending=False)
print(importances)
print("")

# Print the confusion matrix
print("Confusion matrix")
somme=tnRF+fpRF+fnRF+tpRF
print("True Negative: "+str(tnRF/somme))
print("False Positive: "+str(fpRF/somme))
print("False Negative: "+str(fnRF/somme))
print("True Positive: "+str(tpRF/somme))

workbook.close()
```

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## Louvain School of Management
Doctoral Thesis

# Exploring the Impact of Gestural Interaction Technologies on the Experience: A Marketing and HCI Perspective

Quentin SELLIER

It is now essential for businesses to provide the best experience to their customers to ensure their competitiveness. As a result, technologies are continuously evolving to offer more immersive, rich, and comprehensive experiences. Notably, some of these technologies, originally rooted in the realm of video games known for their captivating immersion, have found new applications in e-commerce and are poised to play a significant role in the future metaverse. Among these technologies is gestural interaction, which leverages meaningful human body movements to control computer-based information systems. However, from a marketing perspective, the impact of gestural interaction on the consumer experience remains largely unexplored. A deeper understanding of this relationship could empower practitioners to effectively integrate gestural interaction technology and identify crucial considerations during its development and implementation in interfaces. Moreover, from a human-computer interaction perspective, there is a pressing need to establish comprehensive methods for evaluating the user experience associated with gestural interaction technologies. Therefore, this doctoral thesis addresses three principal objectives. Firstly, it delves into the notion of experience and its various facets as presented in different literatures. Secondly, it investigates the application of gestural interaction technologies in the context of consumption to evaluate its effects on the overall consumer experience. Lastly, this thesis proposes and defines a model and method for assessing the holistic quality of the experience when employing gestural interaction technologies.

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