Formalisation of a novel design methodology of virtual shopping environments using emotional engineering and consumer experience

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Formalisation of a novel design methodology of virtual shopping environments using emotional engineering and consumer experience.

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Glossary

Terminology	Definition
VR (Virtual **R**eality**)**	The electronic simulation of environments, filled with computer-generated images displayed through head-mounted displays, to respond to human movements enabling interactive immersive experience.
SEO (Search **E**ngine **O**ptimisation**)**	The process of improving a website's ranking within a search engine result page
Brick-and-mortars	Retailers that do business through physical stores
V-Commerce	Virtual reality e-commerce
E-commerce	Platform for purchasing/selling products and services over the internet
BSA (Behavioural **S**oftware **A**ssistance**)**	Elements, that aid the user to navigate and interact within the virtual environment
Atmospherics	Ambiances that trigger specific emotions matching with a product's brand to promote purchasing using personalisation.
Psychographics	The qualitative study of personality, value and motivation attributes

General Introduction

Online shopping has become the predominant method of accessing a wide range of products to find the best deals. The prevalence of e-commerce sites has caused the global market to rapidly rise to an estimated 2 trillion dollars in 2016. However, major retailers like Amazon contribute to 49% of the US e-commerce market leaving a narrow margin to other e-commerce merchant. The intense competition amongst e-commerce merchants forces to continually innovate and search for alternatives to retain consumers longer, improve the consumer experience and augment the conversion rates. However, the constraints of web-technology limit e-tailors to only use pictures and videos on websites to woo customers.

The advances in ubiquitous computing and big data drive multi-channel e-commerce strategies, which provide a competitive advantage to online stores over brick-and-mortars. E-commerce represents only 13% of retail sales worldwide. Despite the opportunity for obtaining better bargains and access to a wide-range of products instantaneously online, which e-commerce platform provides, consumers opt for a brick-and-mortar shopping experience. Research in consumer behaviour identifies, that the main driver of purchase intentions during a shopping activity within brick-and-mortar is associated to the emotional experience, an experience that is hardly replicated on e-commerce websites. The desire of an emotional experience outweighs the associated constraints of physical shopping through brick-and-mortars (i.e.: limited opening hours, inventory insufficiency, rent, etc.). E-commerce today represents a major potential channel of income for merchants and a major lens in which consumers view brands. E-commerce provides a shopping platform that can

understand and determine in real-time the preferences (a subjective factor) of consumers to propose the right product for the right consumer. However, the inability to provide an emotionally engaging experience and the limitations of web-technology that provide similar looking websites offers brick-and-mortars the lead. That is why DIAKSE developed a solution to uplift e-commerce standards using virtual reality. Throughout this study, we investigate the possibility and advantages of using virtual reality to aid e-commerce sites in leveraging consumer behaviour data to offer the right product at the right time, whilst providing an emotionally engaging shopping experience.

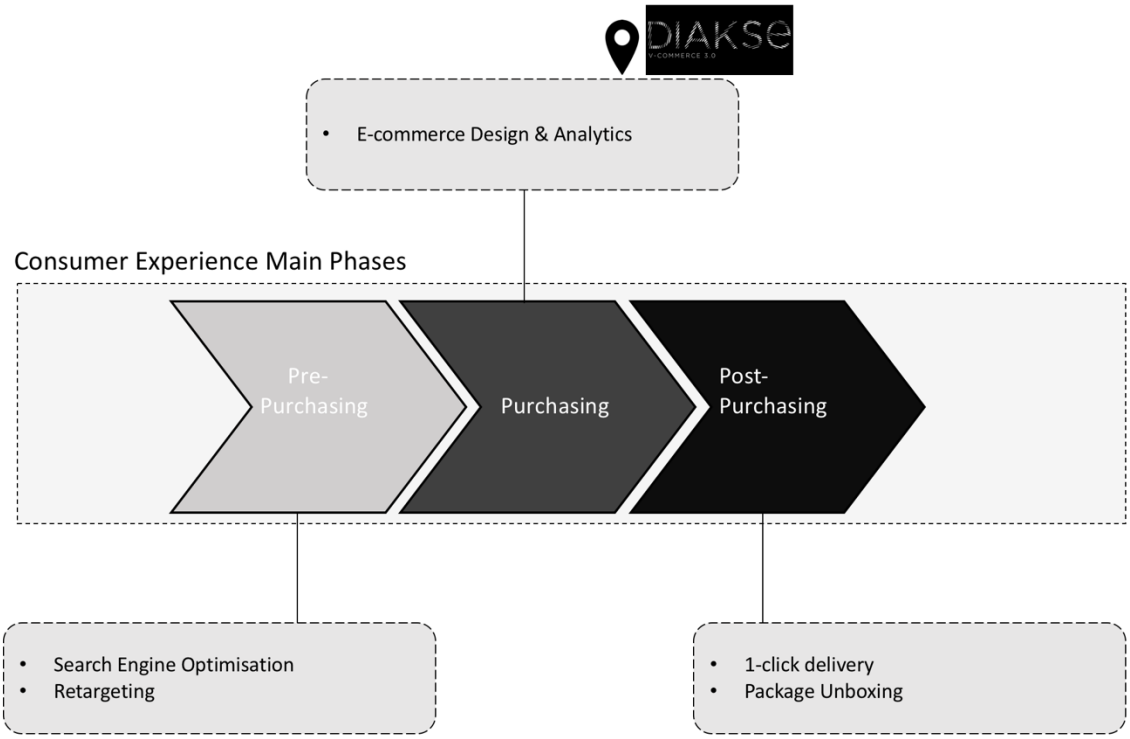


Figure 1. DIAKSE position in the e-commerce market

The use of virtual reality technology to uplift the standards of online e-commerce (a process known as v-commerce) is not novel, various researches are being undertaken into analysing and understanding the dynamics of purchasing behaviour. Virtual reality proves to be a powerfully engaging tool to personalise the consumer experience and reduce cart abandonment rate. However, by integrating virtual reality as an experience medium, the conventional e-commerce bilinear product/user coupling would be further complexified into identifying the right product to be placed in the most adequate environment for the right consumer. The undertook research aims to discover the dynamics of the tryptic phenomena

(consumer, staging environment and product) that arises in v-commerce. This research investigates the main characteristics of the consumer entity (consumer behaviour) to identify motivational drivers that trigger purchase intentions. We investigate the product entity (product characteristics) to identify how the consumer interacts with the product to identify how the consumer preferences can be detected and determine the elements to be transcribed in a VR shop environment. We seek to identify through this research the main attributes that constitute a product from a consumer's perspective. We investigate the environment entity (the virtual staging environment) to identify product staging insights and decrypt the factors that match with consumer preferences, resulting with a triggered purchase intention.

Academic context

This PhD work is undertaken in the 432 Engineering Sciences (SMI) doctoral school. This doctoral school brings together almost 500 PhD students in 30 research units. The PhD is conducted in the Laboratory Design Products and Innovation (LCPI) Arts et Métiers. The PhD is supervised by Professor Améziane AOUSSAT, who is a director at LCPI. This thesis is co-supervised by Dr. Fabrice MANTELET, who is a researcher at LCPI and lecturer at Arts et Metiers.

The thesis work is carried out under a CIFRE agreement (Industrial Conventions of Training by Research). This agreement, implemented by ANRT (National Association of Research and Technology) and funded by the Ministry of Higher Education and Research, promotes public-private collaboration by subsidising the hiring of a doctoral employee to conduct a research mission with a public laboratory. The industrial partner of this research project is DIAKSE, represented by Julien Berthomier (Chief Executive Officer) and Florian Leray (Chief Technology Officer) who serve as the industrial advisors. This research partnership associates an academic actor (LCPI) and an industrial player (DIAKSE) to develop a research strategy that drives innovation and development of new products to provide DIAKSE with a competitive advantage.

The LCPI is a renowned leader in the industrial engineering field that has accompanied countless international companies in their design, optimisation and the development of

human centred complex system within an economic and technological aspect. The methodologies developed and the tools designed the laboratory provide valuable insight throughout the product lifecycle ranging from the need analysis to the product prototyping stage.

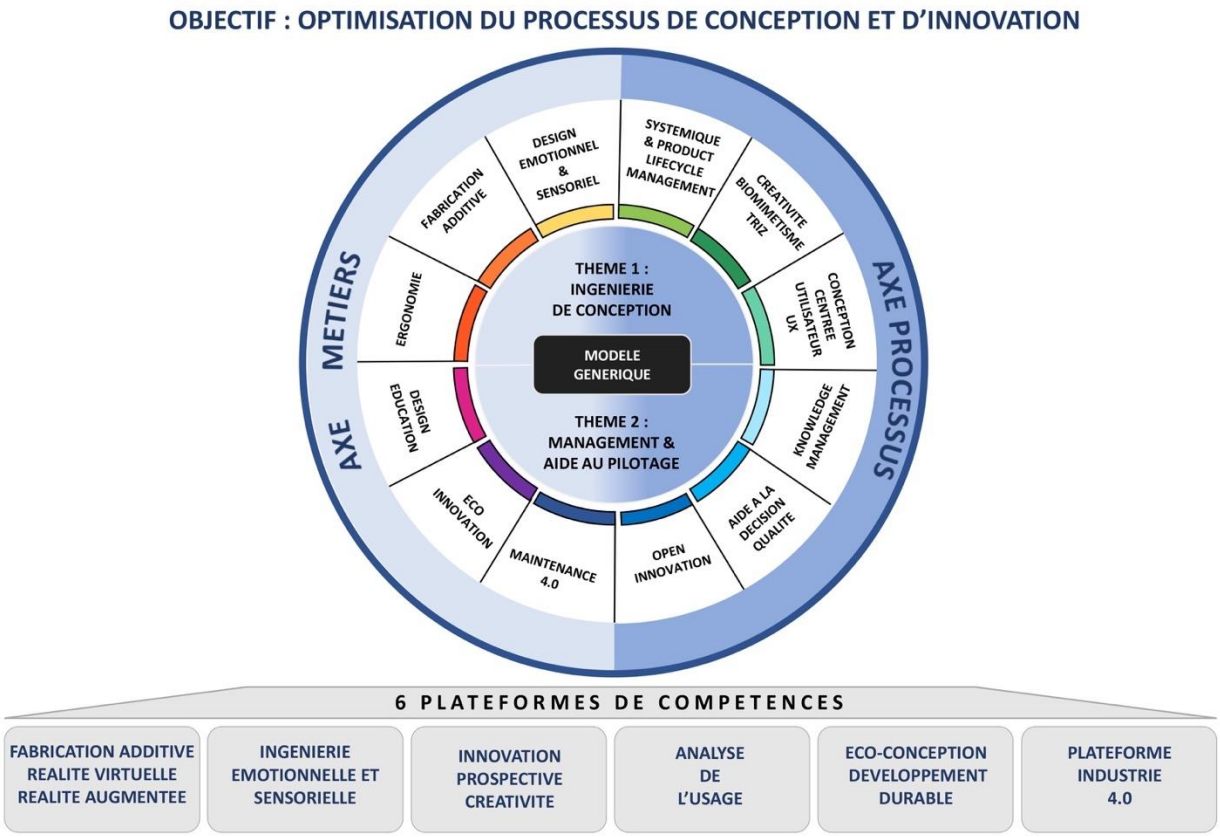


Figure 2. Representation of LCPI fields of research[1]

The LCPI laboratory aims to integrate human factors at early design stages to optimise and improve the process stage. Various research projects have been undertaken within this field through the works of Dr. Carole Bouchard, whose research thesis [Bouchard, 1997] was centred on stylistic awareness modelling for the automobile industry. Her pioneering work in including the sensory and emotional design methods to the industrial engineering process has given birth to various tools such as the Conjoint Trends Analysis (CTA) method the TRENDS System with the aid of Dr. Jean-Francois Omhover [Bouchard, C., Omhover, J., Mougenot, C., & Aoussat, A., 2007]. These powerful tools help model human cognitive and affective needs to identify current trends at an early design stage and determine essential key attributes for the product solution. The work undertaken by Dr. Fabrice Mantelet

[1] http://lcpi.ensam.eu/thematiques-de-recherche-114295.kjsp?RH=6600224935547&RF=1446136676020

[Mantelet, 2006] have furthered this research field in identifying developing tools to quantify the emotional representation of products to integrate the emotional and semantic perception during the design process. Finally, with the current advances in technology the research work of Dr. Vincent Rieuf [Vincent Rieuf, 2013] have explored the impact of virtual reality technology on mood-boards in the early product design process on a cognitive, behavioural and physiological level. The purpose of this research is to develop tools to model human factors, identify design elements to optimise and attain desired behaviour using virtual reality instruments.

This research aims to formalise a methodology to develop personalised virtual shopping experience by considering the behavioural consumer data within a v-commerce (VR e-commerce) system. As a result, the LCPI laboratory expertise provides the perfect platform to cultivate this research work. With virtual reality being at its early stages, the methodology will serve as a process guideline that helps uncover best-practices to improve the consumer experience.

Industrial context

DIAKSE is a Paris based company that specialises in creating v-commerce websites for luxury brands. DIAKSE offers brands a realistic, immersive and interactive e-commerce omnichannel solution in VR. Customers are immersed in a dynamic and interactive universe in which they can remotely wonder freely and discover various products to purchase. This innovative solution arose from a misalignment between current online shopping experiences and retail shopping experiences. E-commerce websites are unable to reproduce the brick-and-mortar shopping experience due to web-technology constraints but are quicker to adapt to customer needs. Whereas brick-and-mortars provide customers an emotionally engaging shopping experience, that is not adaptable to different customers. Therefore, DIAKSE uses VR to bridge the gap between online e-commerce websites and brick-and-mortars. As a result, v-commerce systems provide a powerful solution that benefit of the synergy between e-commerce and brick-and-mortars.

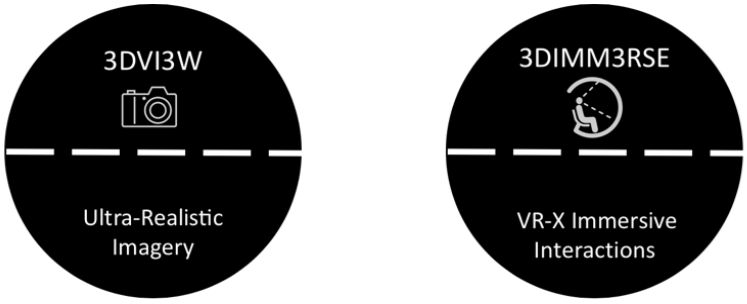


Figure 3. DIAKSE Technology

The v-commerce solution provided by DIAKSE is composed of two in-house built solutions. DIAKSE uses 360° computer processed photography images to provide ultra-realistic renderings. With the development of its 3DVI3W technology it can insert any product images within 360° environment providing the capability of alternating different backgrounds for various products. To interact with the 360° environment, DIAKSE uses an existing WebVR (Web Virtual Reality) technology to provide an immersive experience that powers its' 3DIMM3RSE solution through website browsers. The 3DIMM3RSE solution provides a fluid and smooth experience that aid consumers navigate during immersion. The developed v-commerce solution provides a lightweight immersive web-based solution that does not suffer from the constraints (computer-heavy processing requirements) of current VR in web-technology. This provides DIAKSE with a competitive advantage over existing WebVR solutions, by being able to dynamically adapt the product background to match with the customer's preferences all through a lightweight web application. The DIAKSE VR consumer journey is simple and requires no specific application download. This allows consumers to experience immersion in VR shop using any computer, tablet or smartphone. Upon commencing the VR shopping experience, consumers have the possibility to view the staged products in a VR environment that best reflects the brand image and matches the consumer preferences. Upon triggering purchase intentions, consumers may directly add the product to their basket and purchase the product, whilst in immersion.

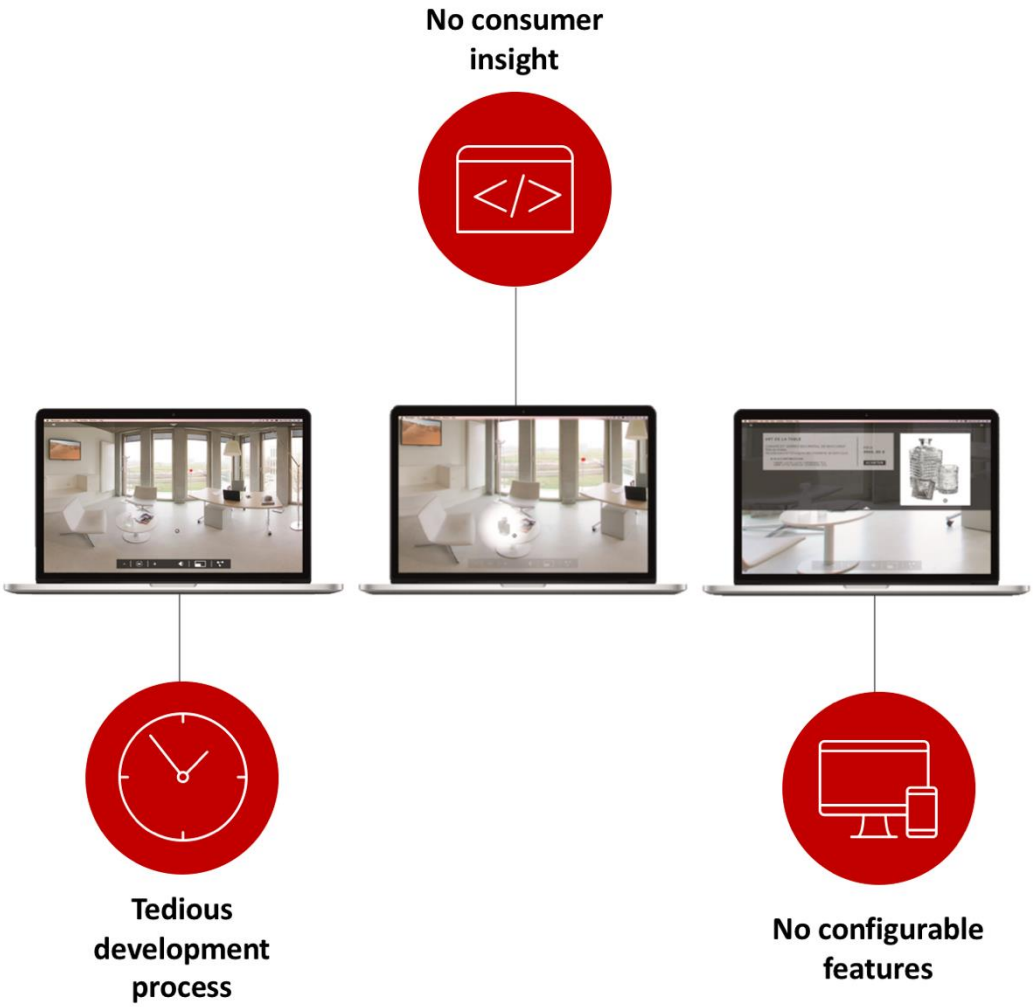


Figure 4. Industrial challenge

In order to improve the consumer experience and promote purchase behaviour the current v-commerce system should adapt to consumer preferences in real-time and recommend the right product to be staged in the most adequate environment for the right consumer. However, the current design process of each v-commerce boutique is subjective and not data-driven. There exists no database to observe, extract and analyse consumer behaviour and infer consumer insights. The architecture of the v-commerce system requires a tedious repetitive development for each new VR shop or modification to be implemented. Furthermore, the current system does not accommodate configurable features that allow for a scalable development and a personalised experience for each brand. These challenges require a research analysis on the different components that constitute a v-commerce

system to identify a method on how to uplift the v-commerce system with a data-driven design approach.

The objective DIAKSE aims to attain throughout this research project is to shed light onto the consumer experience in immersion and understand how to promote purchase behaviour. For this reason, we wish to develop and formalise a methodology to dynamically design VR environments based on consumer behaviour analysis. The industrial ambition is to formalise the fundamental framework of DIAKSE's third technology pillar– 3DR3CO technology. The purpose of the 3DR3CO technology is to coordinate a suite of tools that uncover insight about consumer preferences in real-time to promote purchasing for various set of products.

The following document is structured as such:

Chapter 1: Literature Review

This chapter will cover the literature review that has been undertaken to understand the scientific work that has been undertaken in the field of v-commerce. This chapter uncovers the minimal characteristics that contribute to a v-commerce system. We commence this chapter by defining the different influential factors on consumer behaviour. We also investigate the different factors that contribute to purchase intentions. Given the industrial context of this research work an analysis on the determinant factors that define immersion and its' impact on purchasing behaviour is assessed. We also research the different techniques used by online and brick-and-mortar stores and how they leverage influential factors to promote purchase behaviours. This allows to identify the pain points in each mode and how virtual reality instruments can provide a synergy to overcome the limitations of each channel. This state of art provides us with 2 main findings that provide a clearer perspective of the main rules to consider during the design process of a v-commerce solution.

Chapter 2: Research Question and Methodology

Given the industrial challenge of this research project, the previously undertook state of art has allowed to develop an understanding of the key issues main to consider during the development of a v-commerce system. The 2 findings that result from the state of art allow to formalise the following research question of the industrial challenge as:

> **Research Question:** How to incorporate consumer behaviour analysis to optimise the v-commerce design process and promote purchase behaviour?

The research question above is composed of two main sections that leads towards the development of two hypothesis**:**

> **Hypothesis 1:** The navigation data of a consumer in a virtual reality (VR) shop allows to observe design elements for the VR shop.
> **Hypothesis 2:** The aggregated consumer navigation (H2.1), interaction (H2.2), and affect (H2.3) data improves the dynamics of the tryptic relationship to personalises the shopping experience and increases purchase intentions.

To validate the hypotheses, we developed the 3DR3CO methodology to determine how to incorporate consumer behaviour in the v-commerce design process.

Chapter 3: Experimental Development

To execute the formalised 3DR3CO methodology described in the previous, this chapter will dive into the working processes of the 3DR3CO technology. Throughout this chapter we explore how to observe consumer navigation data, by describing the developed eye-tracking solution and how it contributes to the construction of a descriptive model. The modes of interaction with the product are described by presenting the developed productsheet tool and BSAs that aid in the virtual staging environment exploration. Finally, the modes of evaluating the consumer's perception

and satisfaction by presenting the developed VR survey and VR rating tool help infer consumer affective insight and reinforce the quality of the descriptive model. This chapter describes how the descriptive model is used to derive a data-driven design process of the VR shop by extracting real-time consumer insight and personalising the shopping experience. The validity of the elaborated hypothesis was verified by the implementation of the 3DR3CO technology on real-life consumers providing 2 case studies and how it was used to promote customer experience on v-commerce. The results are analysed and discussed to identify areas of improvements.

Chapter 4: Conclusion, contributions and perspectives

This chapter recapitulates the findings from the undertaken literature review. The research problem that arose from the industrial challenge of DIAKSE is re-stated. The objective of this research is to understand the dynamics of the tryptic phenomena of v-commerce systems. This scientific contribution of this research allowed to formalise a 3DR3CO methodology that tests the validity of the hypothesis. The scientific contribution of the developed 3DR3CO methodology overcomes the industrial challenges by bridging the typical laboratory analytic methodologies found in laboratories directly to consumers. This chapter illustrates the undertaken time plan and the scientific communications published throughout this research project. Finally, the perspectives of this research are discussed to describe how to overcome the challenges faced during this research project and further our work.

"Why shouldn't people be able to teleport wherever they want?"

– **Plamer Luckey**

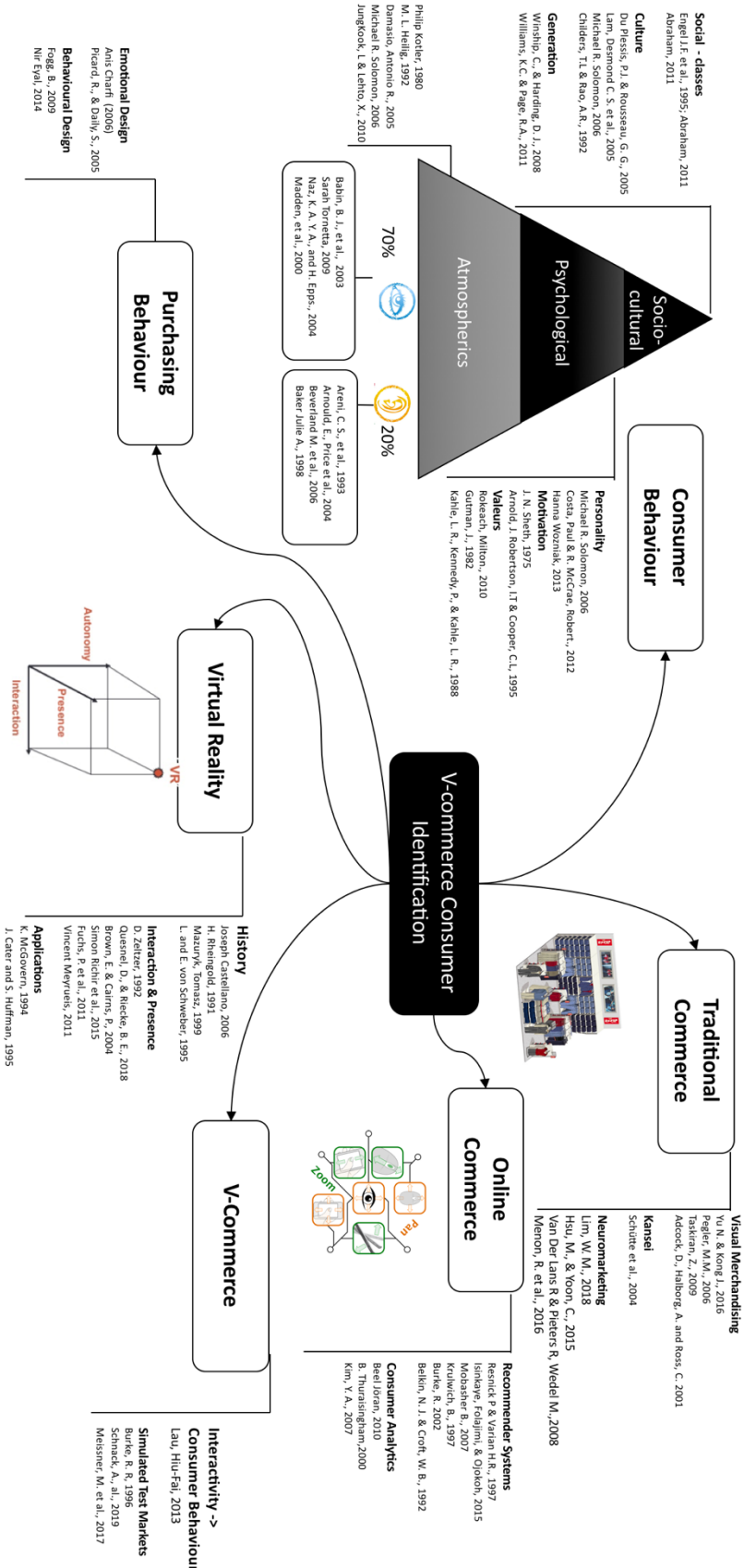
oculus

Chapter I

Literature Review

This chapter will cover the literature review that has been undertaken to understand the scientific work that has been undertaken in the field of v-commerce. This chapter uncovers the minimal characteristics that contribute to a v-commerce system. We commence this chapter by defining the different influential factors on consumer behaviour. We also investigate the different factors that contribute to purchase intentions. Given the industrial context of this research work an analysis on the determinant factors that define immersion and its' impact on purchasing behaviour is assessed. We also research the different techniques used by online and brick-and-mortar stores and how they leverage influential factors to promote purchase behaviours. This allows to identify the pain points in each mode and how virtual reality instruments can provide a synergy to overcome the limitations of each channel. This state of art provides us with 2 main findings that provide a clearer perspective of the main rules to consider during the design process of a v-commerce solution.

I.I Literature Review Mind-map



I.II What is E-commerce?

E-commerce defines an act of transactions over the internet [Oliviera T. et al. 2017] that requires the selling/buying of a product or service. There exist 6 types of e-commerce forms: business-to-consumer, business-to-business, consumer-to-consumer, consumer-to-business, consumer-to-administration, business-to-administration [Rayport, J.F. & Jaworski, B.J 2017][2]. E-commerce has allowed for conventional commerce methods to break out from the physical and temporal constraints, allowing for the different entities of each type of e-commerce to reach out to a global market. E-commerce has contributed to an increased productivity and competitiveness by reshaping the product distribution chain in order to bring suppliers closer to consumers, sometimes at the expense of removing middle tiers. Due to the ease of access of internet online shopping has become the third most popular activity, following instant messaging and web-browsing/streaming [Harlan Lebo, 2016]. Online shopping has become the predominant method of accessing a wide range of products to find the best deals. As a result, the e-commerce market is estimated at 2 trillion US dollars at 2016 [eMarketers Worldwide Retail estimation, 2017] orienting the cutting-edge technology into taking interest in developing solutions to promote, facilitate and optimise purchasing. To put things in perspective, e-commerce giants such as Alibaba Group have stated an estimated revenue of 23 billion US dollars in the 2017 fiscal year. The evolution of ubiquitous computing has contributed to a digitalisation of the previous face-to-face modes of consumer interaction to augment the number of transactions. As a result, e-commerce platforms continually develop user-centric solutions that extend and augment the consumer retail experience to the homes of consumers. Consumers can now shop for a product manufactured and stored at the other side of the world through a few clicks on a smartphone or a computer. However, despite the integration of these technologies onto our daily lives, the limitations of accessing e-commerce websites only through tangible user interfaces does not allow to recreate the same consumer shopping experience that is felt in brick-and-mortars. The consumer views the product through the perspective of a web-browser window, which provides a tabular design, inhibiting consumers to plunge inside the business owner's environment and embrace the brand identity. These limitations create a barrier

[2] Defined and detailed in ANNEX

between the consumer and the retail store leading to a brand disassociation (distance between the buyers and sellers), which obstructs the consumer's trust [Yoon, 2002].

Major e-commerce platforms like Amazon contribute to 49% of the US e-commerce market leaving a narrow margin to other e-commerce merchant. The intense competition for the remaining e-commerce merchants (e-merchants) forces for a continual search of alternative solutions that retain consumer longer and augment the conversion rates. However, e-merchants often find themselves constrained due to current web-technology constraints and can only use a tabular structure of text, pictures and videos of the product to woo the customers.

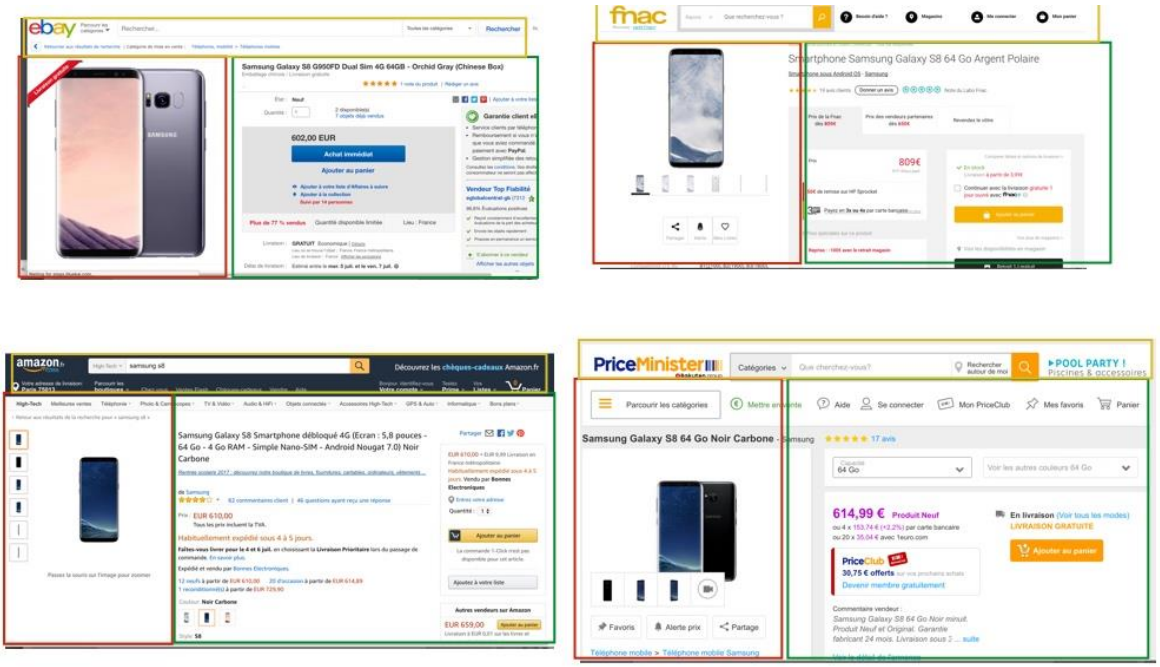


Figure 5. Leading e-commerce sites tabular design

The figure above displays some of the leading e-commerce sites in France for consumer electronics. The factor that stands out the most is the similar tabular design amongst competitors. For instance, each site contains a product description section that is composed of descriptive text, a set of photos at different angles and an advertisement video staging the qualities of the product. E-commerce sites rely on media content to submerge consumers within their brand identity and augment purchase intentions [Li, M. Wang, 2014]. However, these modes of brand perception are limited to the conventional 2D grids and blocks found

in web-content technology. As a result, e-commerce utilises alternative strategies like SEO, retargeting and e-marketing to attract retain and convince consumers to purchase items.

The success for e-commerce solution is driven by its' ease of access to information. It is essential for e-commerce websites to present to the consumers the right information in the most intuitive manner. However, the efficiency of browsing through a website and spending time on it heavily relies on the user experience and the affordance of the user-interface [Yu, N. & Kong, J., 2016]. For instance, the e-commerce platforms illustrated in *Figure 5* above contains minimal information for the consumer to spend the least amount of time on the website and proceed to purchasing.

Search Engine Optimisation and Retargeting

Search engines such as Google, Bling or Quantz have become the entry point of consumers to internet. Therefore, e-commerce websites rely highly on the visibility and order of the results in which they are displayed. Due to the rapid growth of websites on internet, especially e-commerce [Sunda, G. K., & Prof V. Vaidhehi, 2017] the dependability on search engines for information retrieval has increased. As a result, the competition has become fiercer to be amongst the first in a search engine result page (SERP). The improvement of such a process is known as search engine optimisation (SEO) [Beel Jöran, 2010]. For instance, given a search query for a product in a search engine, which of the e-commerce platforms exhibited above are displayed first? Websites that are ranked higher on a search engine result, inspire more trust and are most likely to be clicked [Agarwal, Hosanagar, & Smith, 2011]. Search engines use software bots (known as crawlers) that browse the world wide web and caches a partial or the full content of the webpage within the search engine's database. This crawler then schedules for another bot known as an indexer to extract keywords and the full content of the downloaded page to be ranked. The scoring of the webpage is based on the trustworthiness of content, information about website ownership, quality of content and reputation of website. The algorithm used determines a ranking based on relevancy and the best web-page results are displayed amongst the first results of search queries. Hence, for a given search query the user is effectively searching the database of

what the search engine indexed and its evaluation of the website across the aforementioned factors.

One of the factors that contribute greatly to the SEO ranking of a webpage is the textual quality of the content. That is why websites prevent crawling on specific webpages, using meta-tags, to only index specific content of a website and thus increases its' relevancy for a specific content. Therefore, good content makes the website relevant for a specific audience and thus increases its' ranking. An alternative technique known as cloaking, which consists in a website displaying a highly SEO optimised but not user-friendly version of the website to the search engine and another to human users. In doing so the website misleads the search engines into ranking it higher than it deserves [Berman,R. & Katona, Z., 2013]. Moreover, websites sometimes market through different channels to make it more accessible using a technique known as link-building. By increasing the number of high-quality websites that point to a specific website, the latter will have its' rank get improved and be listed amongst top results.

Often online consumers are not impulsive buyers, and do not purchase an item upon their first visit. Therefore, the e-commerce has long served as an informative tool that may have created purchase intention, but often not strong enough to purchase promptly. That is why e-commerce platforms take advantage of retargeting solutions to tag consumers to extend the shopping experience, whilst undertaking another internet activity to augment the chances of purchasing.

It is important to note that the order in which shops are displayed is critical to its' success. Moreover, the quality of the textual description defines the order in which a site is referenced by search engines, which inspire trustworthiness.

E-commerce platforms seek retargeting techniques to help re-direct users towards their websites after having left without making a purchase. Retargeting solutions benefit from high traffic service platforms (i.e.: social media, news sites, etc…) to display targeted advertisements, which redirect the user to the previously visited e-commerce platform. To

describe the scale of such solutions, the social network Facebook has a reported in 2016 a revenue of 8.8 billion US dollars from advertisement and retargeting. Retargeting solutions operate by providing e-commerce solutions the possibility to tag visitors using cookies. Cookies are a set of data that are sent from a website and stored onto a user's computer with a unique identification key. The main purpose of cookies is to mark the current website visitor and log the useful information (i.e. user activity, items added to cart, authentication details, etc..). The cookies can store specific set of user-data that remembers past user-behaviour and inferred preferences for better advertisement targeting on high-traffic. Logging what a consumer has viewed in a past e-commerce website and the browsing activity is fundamental to targeting users that share similar preferences and provide a personalised consumer experience. [Jose Kantola, 2014].

E-commerce use e-marketing strategies, a process in which digital media communications (i.e.: e-mails, SMS messaging and notifications) are used to convey time-sensitive offers and re-attract consumers to the online stores. E-marketing uplifts the e-commerce visibility by: providing relevant information to customers, raising credibility of the brand, leading users back to shopping experience [Hudák, M., Kianičková, E., & Madleňák, R., 2017]. Platforms such as Amazon were found to re-invest as much as 5.5% of the revenue into automating laborious processes of retargeting [Dobbs, R. et al., 2013] as it was found to augment the conversion rate up to 5-6%. The conversion rate is a key e-commerce performance metric, which refers to ratio of visitors who perform a desired task (i.e purchasing for e-commerce sites) on a specific website [Ayanso, A., & Yoogalingam, R., 2009].

Cookies represent a mode of storing user-browsing activity on web-browsers for a personalised consumer web-experience and augment conversion rates.

To promote purchasing, e-commerce has also focused on developing solutions to fasten the online shopping experience. The once inputted personal and bank details are automatically pre-filled for future purchases. This functionality improves customer loyalty by facilitating repeated purchasing [Dreyfuss, 2000] and provide a convenient solution for consumers who have higher time valuation. Such modes of online consumer behaviour have inspired the

development of solutions like Amazon's one-click buy and dash buttons for instantaneous purchasing. The one-click buy patented solution by Amazon, revealed the severity and impact of frictional costs e-commerce conversion rates. The frictional costs refer to difficulties and obstacles that a consumer faces on their path to purchase [Osterwalder, A., 2003]. Hence by reducing the amount of difficulties or inconvenient experiences throughout the shopping experience augments conversion rates. However as aforementioned earlier, the highest conversion rates rarely exceed 5-6%. It was identified on a marketplace site that 23% of transactions ended up in failure due to the e-commerce's poor user experience design [Silverman, B. G. et al., 2001]. Hence it can be induced that an optimised consumer experience design is critical to conversion rates. In order to optimise the online consumer experience, this research dives into the mechanical drivers of a consumer behaviour in the following section.

The e-commerce industry has focused greatly on the development of solutions that detect the needs of consumers to attract and retain them on their website. Once the right product has been proposed identified, solutions to fasten the purchasing process has been developed so that the e-commerce transaction requires minimal effort and goes as smooth as possible. However, it can be noticed that there exists in the industry few solutions that uplift e-commerce consumer experience, by creating an engaging, emotional experience. That is why, this work explores the application of immersive WebVR to overcome the constraints of e-commerce platforms and provide consumers with the realism of brick-and-mortar shopping experience online. In a recent study undertook by Walkers Sands Communications on 1,433 consumers in the United States in 2016, 62% are interested in trying shopping in virtual reality [Dave Parro et al. 2016]. It was concluded in the study that the future of e-commerce is not to replace the physical stores, but furthering physical shopping experiences onto online. The potential of simulating life-like experiences in-store shopping experiences through VR can be brought to work in tandem with e-commerce techniques to differentiate a brand's value proposition.

62% are interested in trying shopping in virtual reality as an uplifting e-commerce experience. However, it is important to study the VR shopping experience to reduce frictional costs.

I.II Consumer Behaviour

To identify the effectiveness of e-commerce solutions it is important to understand the main factors that trigger purchasing. This section uncovers how and why brick-and-mortar and e-commerce techniques influence consumer. This section focuses on the cognitive decision-making process of a consumer to understand what drives a consumer to purchase. We will also discuss about the various categories of stimuli that influence and shapes a consumer's perception during the purchasing process.

Consumer behaviour can take various forms (digital or physical) to purchase various objects/services. However, it was identified that the consumer decision-making process is broken down to 5 general phases (Figure 6) [Michael R. Solomon, 2006; Shahrzad J. et al., 2013]. Furthermore, 95% of the purchase-decision behaviour is a subconscious experience that influences their cognitive process. In other words, a consumer's decision process is an originally emotional fuelled reaction, that is cognitively rationalised [Zaltman, G., 2003].

The cognitive conscious purchasing decision process initially starts with a consumer subconsciously identifying a lag between a desired situation and the current one, which is categorised as the *problem recognition*. The consumer then moves onto the *information search* process, which requires the consumer to identify the possible solutions to their "problem". Once a solution has been identified, the consumer evaluates the possible alternatives, which is a stage called *evaluation of alternatives*. This stage is critical to business owners since it represents the opportunity for their products/services to match with the solution of the consumer. Once the consumer identifies the best between solution and a chosen alternative, they proceed onto the *purchasing act*. Upon purchasing, the consumer enters the *post-purchasing* evaluation phase, this phase defines the consumer's level of satisfaction or dissatisfaction of the purchase. This is critical as it represents the impression of the consumer's purchase and re-define the future decision-making process. Overall, the consumer decision making process is a set of phases that results into a purchasing behaviour. Like any other human decision, the neuroscientist Antonio Damasio asserted that the

purchasing behaviour is highly influenced by emotions [Damasio A., 2005; Eser, Z., Isin, F. B., & Tolon, M. 2011]:

> *Emotion: a conscious mental reaction (as anger or fear) subjectively experienced as strong feeling usually directed toward a specific object and typically accompanied by physiological and behavioural changes in the body*
>
> *[Plutchik, R., 2001]*

Robert Plutchnik, an American psychologist, studied the human response and its' dependence on emotions. Throughout his research he argued that each emotion is the trigger of human behaviour and not simply a feeling. Emotions, according to Robert Plutchnik is a collection of connected events initiated with a stimulus and includes feelings, psychological changes, impulses to attain a specific goal. He suggested that there exist 4 primary bi-polar emotions: ecstasy-grief, vigilance-amazement, rage-terror, loathing-admiration [Plutchik, R., 2001]. The 8 fundamental emotions represent the first set of emotions at a survival level. The understanding of human emotions helps understand the nature of human response to external stimuli environments.

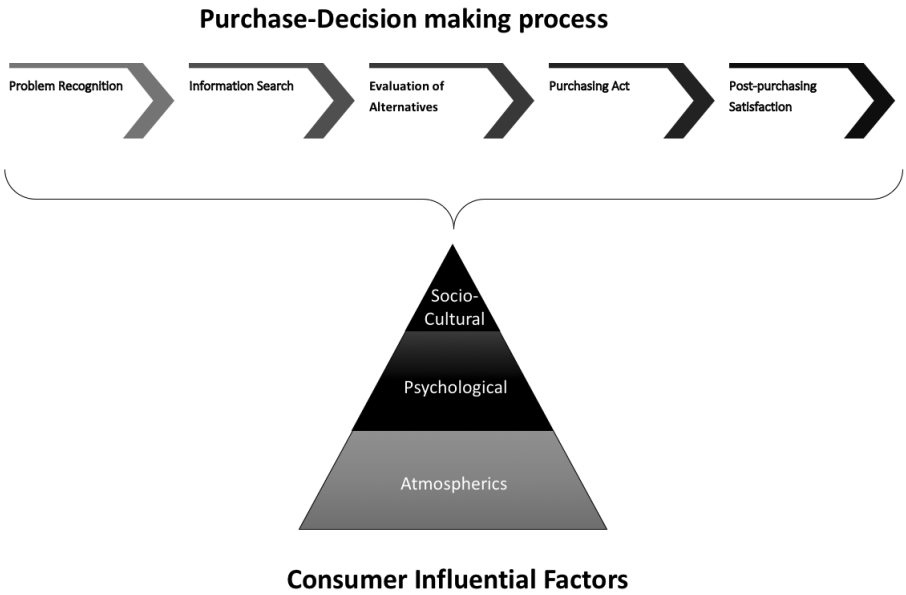


Figure 6. Consumer decision process and influences

The identification of the mental reaction provoked from an external stimulus, exposes how the same stimuli could be used as a trigger to ignite specific behaviours with little conscious awareness. There exist diverse variables of influences that trigger purchasing behaviour, which can be grouped in 3 general categories: atmospherics, psychological and sociocultural influences. Appropriately coordinating such influences on the most susceptible consumer during the evaluation of alternatives, e-tailors and business owners could distinguish themselves from the competition and promote purchasing.

The consumer purchasing decision is an emotionally experience, that can be stimulated through various cues.

Atmospheric Drivers

Atmospherics are defined as ambiances that trigger specific emotions matching with a product's brand to promote purchasing using personalisation [JungKook, L & Lehto, X., 2010]. This refers to elements that are felt by the consumer's physical surroundings and are in contact with the human five senses of the consumer [Philip Kotler, 1980]. The following literature review dives into understanding how each of the five human senses contributes to the information processing of external stimuli. Throughout this section we focus on identifying how retailers tune key characteristics of the human senses to personalise the atmospherics of the consumer's shopping experience, trigger pleasant emotions and augment purchase intentions. The e-personalisation of the shopping experience allows for the usage of atmospherics that are relevant to the user, which are most prone to increasing purchasing behaviour. The research undertook by Morton Heilig [M. L. Heilig, 1992] on the impact of each sense onto the human information processing helped categorise the importance of each atmospheric, which guided our state of art. Along with the industrial scope (v-commerce) of this research it was identified that the visual sense contributed the most to the information and decision-making process. The contribution of each sense was listed as the following:

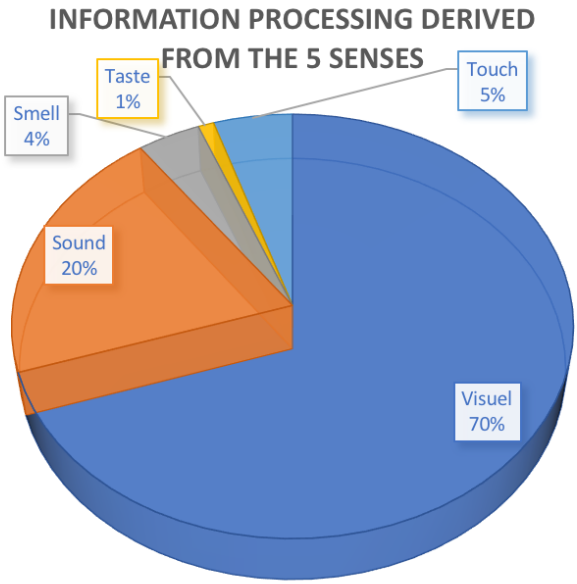


Figure 7. Distribution of the information of each of the five senses [M. L. Heilig., 1992]

Controlling what consumers see and hear uncovers 90% of the consumer's information processing, to anticipate triggered emotions and consumer behaviour. VR technology uses the visual dimension to immerse users in non-real environment content. Although the other senses are currently marginalised due to their poor impact on human perception, the level of immersion could be amplified by developing and embedding equipment to stimulate all five senses.

The visual and auditive sense correspond to 90% of the consumer's information processing.

Visual sense

One of the most important and first dimension that influences consumer behaviour is the human visual sense. The visual dimension represents the first channel of processing information that portrays the physical/digital surroundings of consumers, due to its weak dependence on proximity. Throughout this literature review, we focus on of the critical factors that portrays the visual influence on consumer behaviour: *colour*. Colour refers to

the property of light that is reflected off an object and perceived by humans. The colour factor is characterised by the *hue*, *value* and *saturation* [Sarah Tornetta, 2009]. The hue represents the varying wavelength of light, which is perceived by humans as colour. The value determines the brightness of the colour, while the saturation refers to the colour intensity of light. Hence by altering different hue, value and saturations the human eye can perceive different colours.

Goethe, Johann W, a German poet, first published in 1810 an essay on "Theory of Colours", in which he described each colour on the visual spectrum triggers different emotional states [Goethe, Johann W., 1971]. Goethe formulated a psychological approach to the human perception of colour, which contradicted the Newtonian perspective. Although most of his works was largely dismissed, when stating that the darkness is a necessary component that contributes to the colour spectrum, Goethe's theory on the emotional influences of colours remained inspiring for various philosophers and physicists. Several years later, researchers [Naz, K. A. Y. A., and H. Epps., 2004] undertook a study to understand the colour–emotion relationship amongst college students. This was attained by asking students to provide emotional responses associated to a set of different colours. It was found that the colour conventions and emotional associations varied amongst societies and was prone to evolve throughout time. This was since colours are highly dependent on how an individual associate's colours to personal preferences and past experiences. Furthering Goethe's intuition, Goldstein [Goldstein K., 1942] stated that colour stimulate physiological reactions that manifest as emotional experience, cognitive orientation (cognitive attention), and overt action (such as forceful behaviour). Studies undertook by Saito [Saito, M., 1996], identified that the emotional perception of colours is impacted with cultural attributes. For instance, the colour black was perceived as a colour associated to mourning in certain cultures, while other regions associated it to weddings and festivities [Linton, H., 1991].

Emotional states being a main driver to decision-making, which lead to purchase behaviour, the colour choice for merchants represents a critical key-strategy to influence consumer behaviour. Other researchers undertaken by Thomas J. Madden [Madden, T. J., Hewett, K., & Roth, M. S., 2000) investigated into how different colours could emit brand perceptions and define images onto the consumer's mind. This study identified patterns in cross-cultural

behaviour, by asking consumers to match colour preferences with product logos. Therefore, the product design, product logo or packaging consider the affective association of colours of each targeted cultural cluster, which impact the global marketing and branding strategies.

Color	China	Japan	Egypt	France	U.S.A.
	Happiness, Luck	Anger, Danger	Death	Aristocracy	Danger, Stop
	Heavens, clouds	Villainy	Virtue,Faith, Truth	Freedom, Peace	Masculine, Corporate
	Heavens	Future, Youth, Energy	Fertility, Strength	Criminality	Safety,Go
	Birth, Wealth, Power	Grace, Nobility	Happiness, Prosperity	Temporary	Cowardice, Temporary
	Death, Purity	Death	Joy	Neutrality	Purity

Table 1. Emotional State Comparision Between Studies (Sarah Tornetta, 2009)

The studies undertook by Sarah Tornetta (2009), confirmed that colour is used as a marketing strategy to transmit the brand's image onto the consumer's mind. This work displayed how brands such as McDonalds, an American fast-food chain, used the colours red and yellow to convey urgency and efficiency impressions, which was compelling to hungry people. The colour yellow is associated with happiness and is the most visible colour during daylight. However, the colour red is associated with being active, increases heart rate, which drives an appetite. Hence by appropriately, using the right colours on products or within stores (i.e: design, sales panels) the consumer behaviour could be stimulated to favour purchasing. Her researches concluded that there is no universal scheme of colour, due to its' diverse generalised representations amongst cultures.

Barry J. Babin [Babin, B. J., Hardesty, D. M., & Suter, T. A., 2003], investigated the impacts of colour within retail environments and how it impacts purchasing. He assessed the impacts of the colours red and blue backgrounds in electronic stores and found that subjects in blue coloured stores browsed and purchased more products. This inspired his postulate that colours of shorter wavelengths, triggered happier emotions, which made consumers shop more. Therefore, by altering the background colour of shopping stores, different emotions could be triggered to improve the shopping experience and increase purchasing behaviour.

Virtual reality provides the possibility to identify, study and tune a user's preferred visual characteristics for a product or environment to promote emotional triggers that could lead to purchasing behaviour. The flexibility of easily modifying the colouring of VR backgrounds or products, allows to personalise the shopping experience to each consumer and stimulate purchasing behaviour.

The colour characteristic represents a visual cue e-tailors & brick-and-mortars to trigger desired emotions that promote purchase intentions. However, the colour perception varies amongst different cultures.

Auditive sense

The auditive sense is considered as an atmospheric that is used as background music by retail stores and e-commerce platforms to create a link between the customer's experience and the emotional perception of a product. The consumer's auditive perception of music is characterised by tempo, genre and playing method (volume, transition and looping) [Ding, Cherng & Lin, Chien-Hung., 2011; Arnould, E., Price, L. and Zinkhan, G., 2004]. Background music serves as an invisible language that stimulate emotions and differences to promote purchase intentions. Matching music characteristics to the preferences of targeted consumers, is a persuasive marketing strategy that promotes purchasing behaviour. For instance, it was found that music with a lower tempo decreased the consumer arousal and slowed down the consumers in brick-and-mortars, prolonging the shopping experience to expose more products, which resulted in increased purchasing behaviour. Conversely, faster tempo music background, impacted the behaviour of consumers causing them to quickly browse through the aisles and often resulted in less exposure to products, which resulted in increased impulsive purchasing. It was also found that low volume in background music gave consumers the impression of obligation to interact with salespeople, while loud music inhibited the interaction with salespeople. Each consumer has different preferences, which restricts brick-and-mortars to target a specific segment of consumers through the auditive sense.

Another study conducted research to investigate the influence of a consumer's time perception when exposed to familiar music, such as: common, commercial ambient music genre [*Yalch, R. F., & Spangenberg, E. R., 2000*]. This research displayed that when younger consumers are exposed to adult-oriented background music had the impression of spending more time in the store compared to older consumers. This impacted negatively the consumer experience and reduced purchase intentions. Matching the appropriate background music to the appropriate age group prolongs the time the consumer spends within a store, furthering the exposure to purchasing cues and resulting with a higher chance of undertaking a purchase. Moreover, the evaluation of products was higher (correlated to pleasurable emotions) when exposed to familiar music background, compared to unfamiliar music [Cameron, M. A., et al., 2003]. It could therefore be assumed that tuning the ambient sound in such a way to improve a consumer's mood, renders them favourably disposed to products. This indicates the necessity of personalising ambient store music to each consumer to improve product perception and promote purchasing.

Baker Julie (Baker Julie A., 1998) investigated how ambient store elements (of which music is a critical factor) is used by consumers for a brand image quality inference. Achieving a "fit" between the ambient music and in-store variables resulted in consumer-brand reinforcement. This triggered positive emotions (elevated valence and positive overall in-store experience). The perceived consumer impressions resulted in the following favourable purchasing behaviour: increased amount spent in-store, greater satisfaction, increased willingness to pay, and increased purchasing intentions [Beverland M. et al., 2006]. However, ambient music can be perceived as noise when its' characteristics are mismatched with the consumer's profile and preferences.

Charles S. Areni and David Kim [Areni, C. S., & Kim, D., 1993] undertook a study on the impact of classical music and soft lighting on wine brand perception. This research highlighted how the combination of in-store variables along with classical music created a prestigious perception of the store, which incited consumers to perceive the store with a higher rating. Interestingly it was found that classical music influenced the price perception, resulting with people more likely to purchase expensive products with the presence of ambient classical

music. The prestigious ambiance created by the in-store atmospherics and bolstered by classical music impacts the perceived quality of the product and justified the costly pricing.

Retail stores face the challenge of being unable to personalise and fit the ambient sound to each consumer. Throughout this research we will investigate and develop a methodology that uses immersive VR to identify each consumer's auditive preferences to personalise the shopping experience. Tuning the ambient sound to create a personalised VR shopping experience, reinforces the purchasing cues that trigger consumer behaviour.

Ambient music that match consumer preferences is an auditive cue used by e-tailors & brick-and-mortars to convey a brand perception, trigger hedonic emotions and promote purchase intentions.

Psychographic Drivers

In the following section above, we discuss how the atmospherics are interpreted to trigger consumer behaviour. Througghout this section we will explore how atmospherics influence the cognitive process of consumers by stimulating and influencing the consumer's psychological drivers.

Human needs

The consumer purchase decision process initially starts with a current mismatch of the consumer's situation and a desired state, a need. The need drivers of human behaviour have long been a main research interest in attempting to understand what motivates consumers to behave in a specific way. For instance, the graph below, known as Maslow's pyramid of needs, has long been used to describe the 5 levels of needs that drive human behaviour. [Hoffman Edward, 1988].

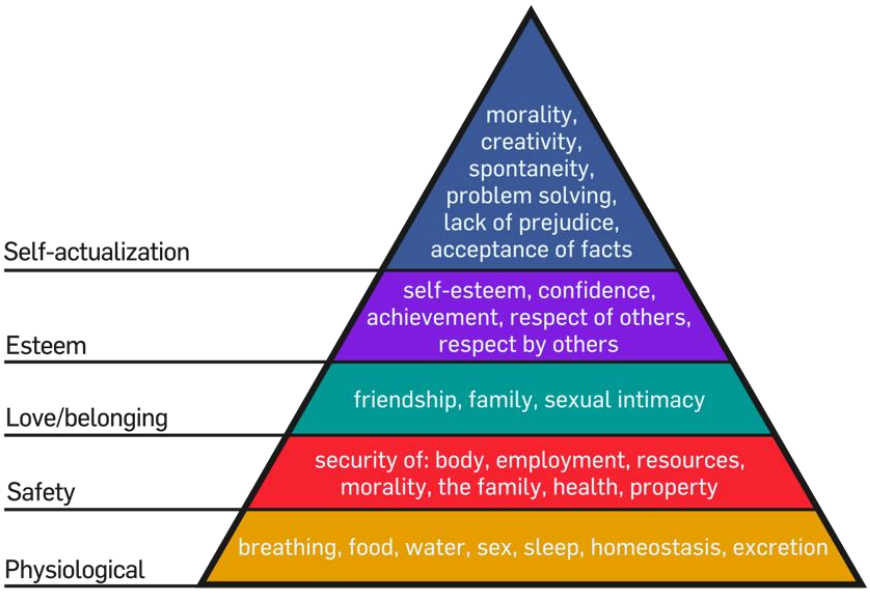


Figure 8. Abraham Maslow's pyramid hierarchy of needs[3]

Maslow's pyramid illustrates that human are driven by fulfilling hierarchically innate needs, in which they attempt to do so through behaviour. The Maslow hierarchy of needs is organised in the following order of priority; Physiological, Safety, Love/belonging, Esteem and Self-actualisation. This means that a current need must be satisfied before considering a higher level of needs. Therefore, a purchasing behaviour may be promoted by identifying the motivational drivers of the consumer and matching the product/service to satisfy such needs.

The motivational needs reflect the current state of the consumer and what drivers motivates promote a purchasing behaviour. The motivation represents the force that triggers specific behaviour given a person's context. The motivation is composed of three factors: *Direction, Effort (or intensity) and Persistence [Arnold, J. Robertson, I.T & Cooper, C.L, 1995].* The direction refers to the objective a person aims to attain in a specific environment. The effort corresponds to the amount of energy an individual is willing to invest in order to attain their objective. Finally, the persistence indicates how long one can maintain the effort for a direction (objective). The motivational driver of a consumer starts at the *problem recognition*

[3] https://uxdesign.cc/persuasive-design-advanced-psychology-9f5bdc7d48db

stage (when there is a difference between a consumer's state and a desired state). The higher the difference at this stage, the higher the intensity of the motivation leading to a purchasing behaviour. Although, purchase behaviour is a common objective-oriented process, its' a subjective factor of influence. Simply put, whilst the objective of a consumer behaviour is to purchase an item/service is common amongst individuals, the motivational drivers are personal and vary amongst individuals, triggering different behaviours.

A study undertook by Jagdish N. Sheth [J. N. Sheth, 1975] defined 5 utility needs emanating from Maslow's pyramid that an item may satisfy to trigger a purchasing intention. As a result, a product's utility need may be used as a reference to identify the consumer's current need state and motivational drivers. The following product utility needs are presented in a hierarchical order of needs, respectively referring to the 5 levels of Maslow:

Product Utility Needs	Definition
Functional	Refers to the perceived utility of a product associated to its functionalities.
Aesthetic/Emotional	Associated with the fundamental emotive values of the user, characterised by style luxury and comfort of a product.
Social Organisational	Associated with the demographics and socioeconomics of the consumer (i.e.: status and prestige).
Situational	The perceived utility of a mode due to the circumstance surrounding its availability (price discounts, availability).
Curiosity	Associated with the innovativeness of the product, which triggers impulsive purchasing.

Table 2. Product utility needs (Sheth 1975)

Showcasing an item's utility along the levels in the table above is a strategy of probing the consumer's current state of needs determining what the motivational drivers are. Once the motivational drive has intensified enough to trigger a purchasing behaviour to fulfil the need, the following behaviour will depend on how the consumers perceives the environment they are in.

The motivational force of a consumer is characterised by the objective, the effort and how long a person is willing to put an effort to attain the goal. It is

important to study the consumer's willingness to put an effort along with the motivational needs.

Perception

The following section investigates the role of perception in consumer behaviour, to better understand how atmospherics and motivational forces may be showcased to promote purchase behaviour. Perception refers to the process of selecting, organising and interpreting sensations into a meaningful whole [Hanna Wozniak, 2013]. Due to the continual exposure to external stimuli, the human brain is constantly making sense of and interpret its' surroundings as a representation. The perception is constituted of 3 key factors:

- **Exposure**: The instant of an individual with external stimuli.
- **Attention:** The allocation of mental memory to the stimuli.
- **Sensation:** The response of the human sensory receptors and the transfer of the information to the brain.

Marketers ensure the targeted consumer audience are continuously exposed to the brand image they aim to portray. The attention span of the consumer to the brand image is measured to control a consumer's perception. That is why analysing the consumer's attention helps segment the psychographics (the qualitative study of personality attributes [Peterson, R.A., 1972]) of a consumer to better understand the factors that elicit purchase intentions. For instance, the attention span to price, quality and risk factor of products was used to segment consumers and identify common consumer behaviour. Consumers with low income are more price conscious and give further attention to the product's price perception. This resulted with an observed increase purchase of products whose value is greater than that perceived price [Thu Ha, N. & Ayda G., 2014].

Consumers only become aware of atmospherics and allocate attention if it relates to an anticipated event. Simply put, a stimulus can reach the consciousness of a consumer and be effective as an influencer if the information satisfies a present need. The exposure to a stimulus leads to either selective distortion or retention of the perception. The selective distortion refers to individual's ability to alter the stimuli and make it align its' conformity with internal beliefs or feelings of an individual. The selective retention refers to the

capability of the individual to filter stimuli that is in mismatch of their beliefs. Once the stimuli information retained, the information is categorised and organised for an interpretation process to infer cognitive meanings.

To further our comprehension of how visual atmospherics may be used to convey specific representations, influencing the design of e-commerce and brick and mortar stores, we investigate the Gestalt theory of perception. Gestalt is a German term that refers to a pattern/configuration. The principle of gestalt states that a stimulus is interpreted holistically and independent of its individual parts [Yu-Ping Chiu et al., 2017]. This principle states when a consumer is developing a perception of a product, a consumer does not perceive its' individual parts separately but as a whole and considers the context of its situation. The gestalt principle is composed of the following 5 rules:

Gestalt Principles	Definition
Proximity	Products/objects that are close to each other appear as groups, despite physical (shape) differences
Similarity	Products /objects that share similar features (i.e.: colour, shading, etc…) in a collection are often perceived as a group.
Continuity	Refers that although there might be intersections in a product/object individual perceive it as a whole.
Closure	This refers to the capability of the mind to see complete figures, even if a picture may be incomplete.
Connectedness	This refers to the capability of an individual being able to perceive as a group element that are connected by a consistent visual property (i.e: word tags within a circle)

Table 3. Gestalt Principles

The way in which the human senses interpret a stimulus, formulates the perception. Perception takes place when the stimuli activates sensory receptors and the information is processed by the brain. The perception is characterised by the cognitive structure of each individual, which is determined by their individual experiences, beliefs and attitudes. Hence, the individual associates a perception to a set of stimuli. As it was discussed in the atmospherics section, the colour stimuli triggers emotions within individuals/consumers.

This colour stimuli are used to quickly capture the attention of consumers. The brightness and saturation levels are determinant factors, compared to hue levels, in generating stimulus-driven attention [Camgöz, N., Yener, C., & Güvenç, D., 2003]. The visual contrast of two elements (distinctive colour difference between the background and foreground) directs the visual attention of a consumer. This concept is used extensively in package design to control the consumer's sight towards their regions of the product where influential information is placed.

Visual stimulus is used as a cue to attract the attention. The quantification of a consumer's attention indicates the exposure level to a perception. During the development of a perception representation, the consumer does not perceive an item's individual parts separately but as a whole and considers the context of its situation.

Personality

The effectiveness of an exposure stimuli relies on an individual's current drivers to promote selective distortion, which relies highly on the individual's personal beliefs. Throughout the next section we investigate the role of personality and values that shape an individual's personal beliefs.

Sigmund Freud, a renowned psychologist on the modes of operation of human psyche, states that the main driver behind human behaviour relies on subconsciousness. His work postulated that the psyche of subconsciousness is composed of three essential parts: *Id, Ego and Super Ego.* The *Id* refers to the human instinctual desires and the need to satisfy basic urges. The *Ego* refers to the reasonable aspect of a human psyche that is moderated by the external world and considering social norms, etiquette, etc. The *Super Ego* aims to balance between impulsive desires of *Id* all whilst satisfying the principles of *Ego.* The factors that constitute the Freudian human psyche are determined at an early age (during childhood) and through embedded values. The three aforementioned factors control the personality and motivational drivers of consumers. Despite the uniqueness of every individual, individuals can be segmented using personality. Personality refers to the set of characteristic traits that shape an individual's character. From a marketer's perspective, personality can be

defined as a set of pattern behaviour amongst a group of individuals in response to specific external stimuli [Michael R. Solomon, 2006].

Katharine Cook Briggs and Isabel Briggs Myers (daughter) published in 1956 the Myer-Briggs Type Indicator (MBTI) to characterise human personality types [Gardner, William L; Martinko, Mark J., 2016] and understand how people make decisions. The MBTI is based on the following four principles that contain two gradual extremities:

MBTI Principles	Definition
Extroversion VS Introversion	How a person directs their attention, energy and learning. The introvert prefers to derive energy from their inner world and prefers to be alone.
Seeing VS Intuition	Refers to what does a person direct their attention to. The sensing types of people focus on more concrete concepts, while intuitive types focus on abstract notions.
Thinking VS Feeling	How a person prefers to make decisions. The thinkers prefer to make decision logically and impersonal to outside influences. The feelings types consider personal opinions and external point of views when making decisions
Judging VS Perceiving	Describes a person's orientation to the external world and what the world tends to see. The judging type is seen as organised people who prefer to have control over their lives. The perceiving type is seen as flexible and spontaneous people that are easily adaptable.

Table 4. The Myer-Briggs Type Indicator Principles

Kotler, P., & Keller, K.L. (2009) applied the trait theory to study the impact of consumer behaviour in response to a given stimuli. People who share similar personality traits respond with similar behaviour, formulate consistent perceptions and emotions to a given external stimuli. The modelling of the behavioural pattern responses to an external stimulus for various personalities, could be used as a framework for predictive modelling. For instance, the OCEAN model (also known as the five-factor model) is widely used for personality and trait identification developed by McCrae and Costa in 1987 Costa, Paul & R. McCrae, Robert., 2012]. This model is composed of the following five elements:

OCEAN Model	Definition
Openness to experience	The tendency to appreciate new ideas, values and behaviours. People with high openness to experience are referred to as curious and willing to try new things.
Conscientiousness	The tendency to be careful, vigilant and hard working.
Extroversion	The tendency to attain pleasure and derive energy from the outside world. An extrovert consumer is one who is outgoing and displays what they have purchased through social media.
Agreeableness	The tendency to be kind-hearted and compassionate. This trait describes a person's trusting nature and temperament.
Neuroticism	The tendency to be emotional unstable, easily experience psychological stress and prone to interpersonal problems.

Table 5. The big-five personality traits.

During the write-up of this thesis a scandal involving the biggest social network, Facebook and the USA presidential elections. The scandal surfaced, when evidence showed links between the Trump administration (45th president of the USA) and the company Cambridge Analytica to micro-target American voters with personalised messages about democratic candidates. Michal Konsiki, a Cambridge researcher, developed a Facebook application based on the OCEAN model to assess a user's personality fit. The Facebook application requested access to publicly available data of each Facebook user to determine factors that correlate best with the personality type. The OCEAN model was used to identify personality characteristics US voters and predict behaviour when exposed to politically shaped stimuli and influence elections [Kosinski, M., & Lambiotte, R., 2014].

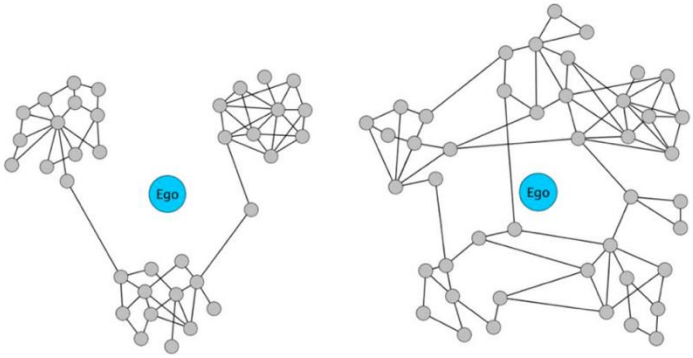


Figure 9. Example of introvert (Left) and extrovert (Right) Facebook user connections [Kosinski, M., & Lambiotte, R., 2014]

As a result, the user's personality traits were modelled and the anticipated behaviour could be predicted. The figure above displays how an analysis on a Facebook user (blue) and their relationship with communities and groups (grey) help extrapolate their extroversion trait. Michal Kosinski identified that introvert people belong to smaller communities but denser communities, while extrovert people act as bridges between smaller and more frequent communities. Michel Kosinski stated that this proved that the Facebook digital footprint and other social networks to infer personality types and eventually influence behaviour. With the usage of semantic analysis and machine learning to extract sentiments from public status and music tastes, Michal Kosinski was able to model a user's personality as a function of the 5 personality traits.

Personality can be used to classify behavioural patterns and reactions to stimuli amongst different individuals, for optimised targeting and predictive behaviour inference.

Values

Human personal values represent the beliefs that define human identities. Human personal values represent another factor that marketers use to assess the motivational forces of consumers to understand their behaviour. The human personal values represent the decision-making standards that affect preferences and are embedded into humans at a very early stage.

Milton Rokeach, stated in 1973 that values share many of the human work-related behaviours. He stated that values represent a specific mode of conduct (described by a set of instrumental values) in order to achieve an end of state mode (described by a set of terminal values) socially preferable to each individual [Rokeach, Milton., 2010]. The Rokeach values describe a belief that represents how a group of people view a desired perspective, defining a common perception amongst a group of people. People with the same socioeconomic scale share similar goals (terminal values) and live their lives with a set of instrumental values to achieve those goals. The Rokeach value survey (detailed in annex) are socially oriented and best describe a human's personal beliefs on society. In 1992, Shalom Swartz developed a set of human values referred to as the circular continuum of values [Schwartz, Shalom H., 1992]. Unlike Rokeach, who considers each value to be independent of the other, Schwartz mapped out the circular continuum of values in such a way the relative positioning of each value represents a distance from another value, hence illustrating their dependence. Each of the 10 values are driven by the 4 opposing quadrants: openness to change vs conservation (along the x-axis) and self-enhancement vs self-transcendence (along the y-axis).

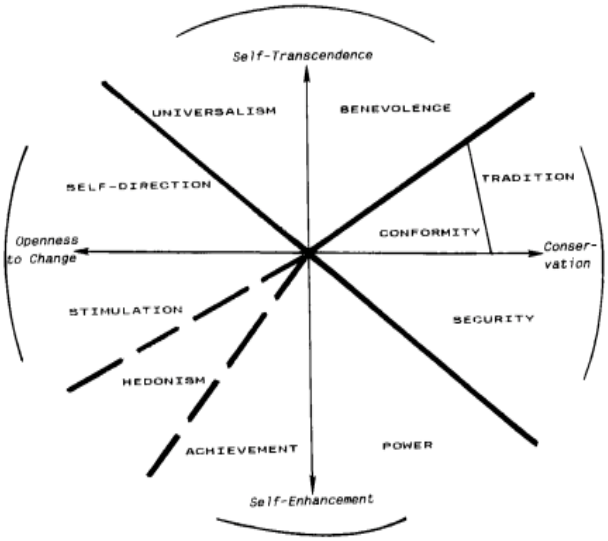


Figure 9. Schwartz Circular Continuum of Values [Schwartz, Shalom H., 1992]

Similarily, Lynn Kahle – an American psychologist, furthered the work undertaken by Rokeach and Schwartz to further simplify the human personal values and reduce the number of dimensions. His works were based on the social adaptation theory that an "individual actively filters societal and cultural demands, refining and redefining values in the process,

in order to enhance their adaptive worth" [Kahle, L. R., Kennedy, P., & Kahle, L. R., 1988]. As a result, developed the following 9 core terminal values as: *sense of belonging, need for excitement, fun and enjoyment of life, warm-relationships, self-fulfilment, self-respect, security, sense of accomplishment and well-respect*. The works of Lynn Kahle highlight the importance of social interaction in order to attain desired values. Therefore, consumer behaviour is a social behaviour that could be understood and anticipated. For instance, people who are constantly driven by the *sense of belonging* could be motivated to undertake a purchasing of an item because their peers/friends have a similar item. As a result, value identification and its' effective matching to consumers have been critical in marketing.

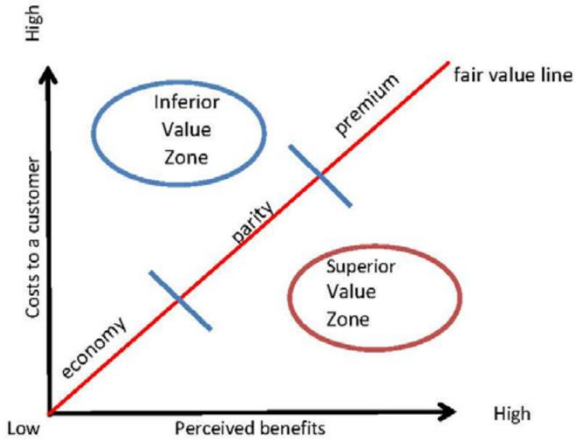


Figure 10. Consumer value proposition [Woodruff, R. B., and S., Gardial., 1996]

A product's value is perceived by the consumer as the expectation and matching of its' benefits to attain personal value [Woodruff, R. B., and S., Gardial., 1996]. The product's perceived benefits may be characterised using the means-end approach, which associates the products attributes (i.e.: service, quality reliability, performance, safety, ease of use, durability, economy, convenience) to the consumer's values attributes [Gutman, J., 1982]. The perceived benefits and a product's relative cost define its' value, which in return determines the consumer's loyalty [Lobasenko, V., 2017].

Values refer to the lifegoals a consumer is determined to attain, by undertaking specific behaviour to accomplish it.

Socio-cultural Drivers

The section above investigated how individuals have distinguishable psychographics that shape preferences, when matched to make an impact on consumer behaviour. The psychological characteristics that shape the cognitive thinking of consumers are defined by socio-cultural factors. Throughout this section, we will investigate the role of the socio-cultural characteristics and investigate how they can be leveraged to drive the consumer behaviour.

Culture is defined as an adaptive, dynamic and patterned blueprints that characterise a set of implicit beliefs, norms costumes and values that prescribe conduct in a socially acceptable manner to other members of the same culture [Du Plessis, P.J. & Rousseau, G. G., 2005; Arnould, E., Price, L. and Zinkhan, G., 2004]. Similarities in consumer behaviour were observed by individuals who share similar cultural dimensions (using Hofstede's 4 cultural dimensions) [Lam, Desmond C. S. et al., 2005]:

Cultural Dimension	Definition
Individualism VS Collectivism	This refers to the degree of interest an individual has for themselves over that of a group within a society. This refers to the extent an individual is integrated in a group. In individualist cultures, people often look after themselves, while in collectivist cultures there is a notion of a group protection and loyalty.
Masculinity VS Femininity	This cultural dimension refers to the distribution of gender roles in a society. Masculine cultures value and associate male characteristics to assertiveness and success. Feminine cultures tend to have preferences for modesty and caring.
Uncertainty avoidance	This refers to the degree a culture is risk avert and its tolerance for the unknown. Cultures with higher levels of uncertainty avoidance are known to minimise ambiguousness and uncertainty by being conform. Conversely people are more comfortable with opinions that differ from their own.
Power Distance	This refers to the level of acceptability of unequal power distribution of throughout society. Cultures that have a higher power distance index accept the idea of a hierarchical power. Conversely cultures with that are evaluated as being low on a power

	distance dimension tend to question authority and demand for an equally distributed power.

Table 6. Hofstede's cultural dimensions

The four cultural dimensions above represent the minimum factors required to characterise social culture, which displayed common behaviour amongst a group of people. For instance, individualist and masculine cultures are less exposed to marketing influences due to their desire to gain more control and independence. Whereas, cultures with high uncertainty avoidance remain brand loyal, as they are more resistant to changes. Cultures with an elevated power distance are more susceptible to reference group influences and are not brand loyal [Wiedmann, K., Hennigs, N., & Siebels, A., 2007]. Reference groups (also referred to as peer influences) refers to a group of people that have significant relevance on a consumer's evaluation, aspirations and (consumer) behaviours [Michael R. Solomon, 2006]. Reference influence, which rely on social bonds to affect the consumer behaviour, is defined into 3 sub-group influences of consumer behaviour:

- **Informational:** When an individual seeks information from those who have already had an experience with the purchase (i.e.: customer review).
- **Utilitarian:** When a consumer's decision to purchase a specific brand, is defined by the product's functional congruity.
- **Value-expressive:** The thought that the purchase will enhance their social entourage image.

Different levels of the social bond for the reference groups determined the type of impact on consumer behaviour. For instance, it was noticed that consumers were more affected by family reference groups in the choice of purchasing privately consumed luxuries (i.e.: mattresses) rather than public consumed luxuries (i.e.: wristwatch) [Childers, T.L & Rao, A.R., 1992]. The choice of public consumed luxuries was influenced by social and non-family referrals.

In addition to social relationships, the social classes correspond to an essential factor that contributes to the consumer behaviour [Engel J.F. et al., 1995; Abraham, 2011]. Social classes refer to the grouping of people with similar behaviour, values and ways of thinking based on

their economic status. It was noticed that consumers from lower social classes preferred face to face interaction with salespersons and shops with a sense of familiarity. While upper class consumers preferred innovative new shops where there are few interactions with salespeople and more independence.

Generation corresponds to a socio-cultural influential factor, which significantly impacts consumer behaviour. The generation refers to a group of people who share a common worldview after experiencing similar life cohorts. This is often predicted by age and country of residence throughout the consumer's life [Winship, C., & Harding, D. J., 2008]. By sharing a common experience and knowledge, consumers of similar generations display similar patterns of purchasing preferences and behaviours [Williams, K.C. & Page, R.A., 2011]. Valuable insight about an individual's outlook and attitude can be determined by identifying to what generation group a consumer belongs to. Therefore, by identifying personal socio-cultural information of a consumer, they could be appropriately classified in segments which display what influences are most relevant and effective given to promote purchasing.

The socio-cultural factors describe a common cohort of consumers who share similar psychographic reaction trends to atmospherics.

I.III Leveraging Consumer Behaviour Drivers

The continuing research in understanding consumer behaviour has allowed marketers to elaborate effective techniques that increase purchasing behaviour, often without the consumer's awareness. The continual growth of the commerce market has allowed for retail shops, brick-and-mortars, to evolve from a simple shop with a counter to a location that proposes an emotional experience.

Merchandising

Visual merchandising is a strategy used by business owners to attract and retain customers within their shop. This refers to the presentation of merchandise at its' best scenario, ensuring a colouring harmonisation, integration of accessories in a self-explanatory way to

capture attention [Taskiran, Z., 2009]. Visual merchandising is characterised by the following elements [Pegler, M.M., 2006]:

Visual Merchandising elements	Definition
Window Displays	Refers to the first contact point that converts a passer-by into a potential consumer. This includes a theme composed of impactful products that create a welcoming ambiance.
Colours	This element refers to the use of trends analysis to identify trending palettes of colours to combine and contrast. The goal of this element is attracting the attention of by-passers and trigger a desired emotion for an audience that will make them enter and stay inside the shop.
Lightning	The use of lightings to direct the consumer's attention to visible product attributes. It was noticed that the temperature of lighting (warm or cool) influenced the emotional and arousal responses of the consumers [Lin, Y.-F., & Yoon, S.-Y., 2015]. Cool lighting tends to trigger higher level of arousal for customers and higher levels of approach intention in contrast lighting.
Signage	This factor refers to the conveyed message that helps create the awareness of the product/service being sold, generally in the form of text, images and videos. Cognitive signage (text) provide decision-helping experiences while affective signage (images / videos) provide aesthetically pleasing sensory-affective experiences. The latter is effective in increasing purchasing intentions [Alamanos, E., Brakus, J. J., & Dennis, C., 2014].
Shop Interior	This factor refers to the interior design and in-store layout. The store interior is composed of the aisle design experience, which aims to provide a personal space for comfort and guidance (grid, freeform or racetrack) [Turley, L. W., & Milliman, R. E., 2000] and shelves design, which provides structure to the shopping experience by considering vertical and horizontal product placement [Raghubir, Priya & Ana Valenzuela.,2008] and product categorisation [Mogilner, C., Rudnick, T., & Iyengar, S. S., 2008].

Table 7. Visual merchandise elements

The adjustment and personalising of the elements above to the consumer's preferences help capture and retain consumer attention. The store design elements lure the consumers inside and use atmospherics to trigger purchasing intentions. However, different consumers in different market segments have diverse mental biases and cognitive structures that eventually trigger various responses for the same store design. As a result, due to the physical inability of retail stores to tailor merchandising elements for each consumer's cognitive structure and preferences, retailers often aim to find compromises in terms of store design choices and customer audience.

The professor Mitsuo Nagamachi coined the term *Kansei*, which refers to the study of cognitive and affective evaluation during an experience. This has given rise to the discipline of exploring methods to quantifying user's subjective impressions, for product development/design using a semantic differential approach [Schütte et al., 2004]. Osgood's research on the measurement of meaning stated that every artefact can be described within a semantic vector space. Thus, semantic descriptors maybe be applied onto product properties to represent features from a user's impression. By decomposing a product into several attributes labelled by semantic descriptors, we can identify which product characteristics fit a consumer's preferences. The incorporation of Kansei design into merchandising strategies provides a user-centric process to match consumer preferences and promote purchase intentions.

The matching of the merchandising elements with a consumer's semantic preferences provides a user-centred approach that promotes a hedonic experience, leading to increased purchase intentions.

Market Analysis

Marketers often use tools to determine the right product/service proposition. One of the commonly used market strategies is known as the *marketing mix*. The marketing mix refers to a tool that retailers/companies use to sell products or services. This tool is also known as

the 7-P's: **p**roduct, **p**lace, **p**rice, **p**romotion, **p**rocess, **p**eople and **p**hysical evidence (*definitions detailed in annex)*. The marketing mix is widely used in the industry to design the right product/service for the right consumer at the right place and at the right time [Adcock, D., Halborg, A. and Ross, C. 2001]. This tool is effective in ensuring that a product continuously matches the need of the consumer's needs and is up to the standards of the market. However, the issue of such marketing strategies is that there is no direct method of evaluating its' effectiveness in real-time for optimisation.

Companies occasionally choose the path of neuromarketing to better understand the effect of marketing onto consumer behaviour. Neuromarketing is referred to as the study of the cerebral mechanism to understand consumer behaviour in order to improve marketing strategies [Lim, W. M., 2018]. Neuroscientific methods help measure, quantify, map and record brain and neuronal behaviour when exposed to a set of stimuli to generate a neuronal representation of the human cognitive process. As a result, neuromarketing uses neuroscience techniques in order to understand the consumer expectations and behaviour.

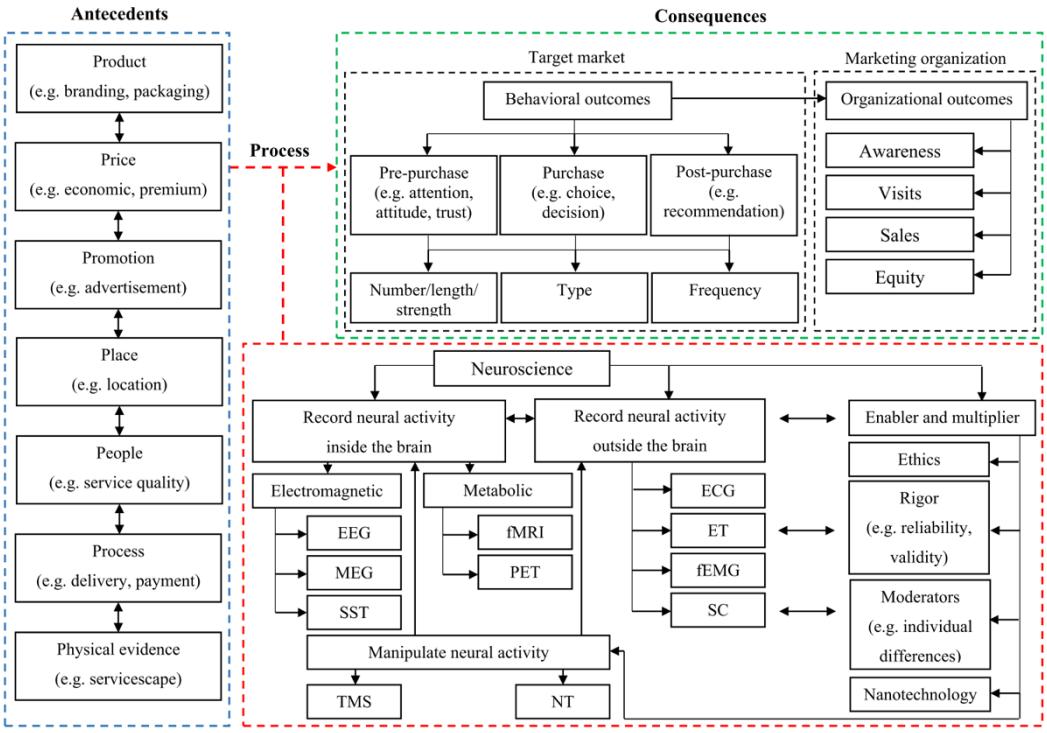


Figure 11. Systematic Overview of neuromarketing research [Lim, W. M., 2018]

The figure above depicts the embedding of neuroscience processes (highlighted in red) with respect to the marketing stimuli of a company (highlighted in blue) and the resulting consumer behaviours (highlighted in green). The neuroscience process dissects the links between the antecedents and the consequences tos understand why certain consumer behaviours take place. As a result, this process shed light on specific neuro-cognitive consumer behaviour and re-evaluate the marketing strategies used in the antecedents.

The effectiveness of neuroscience techniques requires invasive researches and tests, which are undertaken in laboratory environments. For instance, a laboratory assessment of choice preferences between similar unbranded drinks (Pepsi and Coca-Cola), found that brand knowledge biased people's choices. The tests were taken under a functional magnetic resonance imaging (fMRI) and displayed that choice preferences were correlated to activity in the ventromedial prefrontal cortex [Hsu, M., & Yoon, C., 2015]. The use of neuromarketing techniques help understand the impact of external stimuli and their influence on memory, attention and valuation process during purchasing decision making.

One of the commonly used techniques in understanding the influence of stimuli on attention is eye-tracking analysis in laboratory environments. This often requires the re-creation of a sample of the physical store to simulate a realistic shopping experience and an eye-tracking camera (often in head-mounted sets). The eye-tracking camera measures the eye movements and patterns of subjects when exposed to a set of products [Pieters, R., and Wedel, M., 2004] to identify the stimuli factors that impact the saccades and fixation of an eye. The saccades refer to the movement of the eye between a point of interest to another. The saccades process refers to a rapid (~20-40 milliseconds) visual search in which a person aims to reduce location uncertainties [Van Der Lans R & Pieters R, Wedel M.,2008]. During the saccades process the vision is suppressed and no visual information is processed. Conversely fixations refer to longer times (~50-600 milliseconds) and refer to points in which the eye rests at a point of interest and visual information is cognitively processed [Menon, R. et al., 2016]. Hence, during fixation periods, longer attention is recorded and consumer perception leading to preference choice is formed. As a result, the attention of a consumer can be modelled [Yang, L. Cathy et al., 2015] by associating product attributes and their utility to consumer derived utilities. However, the information of the processing of a consumer

relies on both attention and memory and may be more complex to infer as the consumer does not necessarily visually process all the product's attribute during the fixation time [Hsu, M., & Yoon, C., 2015]. As a result, visual information processing laboratory models may be misleading.

Neuromarketing techniques, such as eye-tracking, are effective in modelling consumer cognitive processes. For instance, the saccades and fixation periods define the consumer's cognitive processed information enabling to model perception. The modelled systems allow to develop predictive behavioural systems.

Neuromarketing techniques relies on neuroscience fundamentals to help optimise the marketing effectiveness often used by brick-and-mortars. Despite the value of such strategies, they are often invasive and require laboratory environments that only partially simulates the real-life circumstances. Consequently, e-commerce outperforms brick-and-mortar shops due to the latter's inability to acquire real-time consumer data to personalise their store to every individual's preferences. The ability to identify in real-time the needs of every consumer and provide the consumer with best choice of alternatives increases purchase intentions. As it was mentioned before, despite the inability for e-commerce to recreate the emotional shopping experience due to its technological limitations, it is proving to be a gradually increasing method of business transactions. The following section will explore how e-commerce makes use of recommender systems to entice purchasing behaviour.

The invasiveness of the laboratory environments in which neuromarketing tests are conducted does not allow brick-and-mortars to benefit in real-time of the insights to personalise the consumer experience and promote purchase intentions.

Recommender Systems

Recommender systems serve as a filtering system to avoid information overload, by selecting and predicting pertinent information to display according to user's preferences, interests and behaviour. These systems identify a set of online customers whose purchased/rated items overlap other user's rated items, aggregates these items, and elimenates previously purchased products to prorpose new ones [Resnick, Paul, and Hal R. Varian, 1997]. Recommender systems contribute greatly to the increase in revenue for e-commerce solutions when there is insufficient personal knowledge about consumers or products. Various techniques have been developed to build recommender systems, which included *collaborative filtering, content-based, demographic* and *hybrid* approaches. For instance, how many times have users accessed video-content (i.e: YouTube) to view a specific video and often find themselves having watched more videos than anticipated. How many times someone access social network websites (i.e: Facebook) for a quick break and often lose the notion of time when scrolling for new content. The increase of user engagement on online systems is due to the efficiency of recommender systems. Throughout this section we will see the different types of recommender systems and the different types of scenarios they are used on. More specifically we will also explore their drawbacks and learn about methods to overcome the challenges encountered.

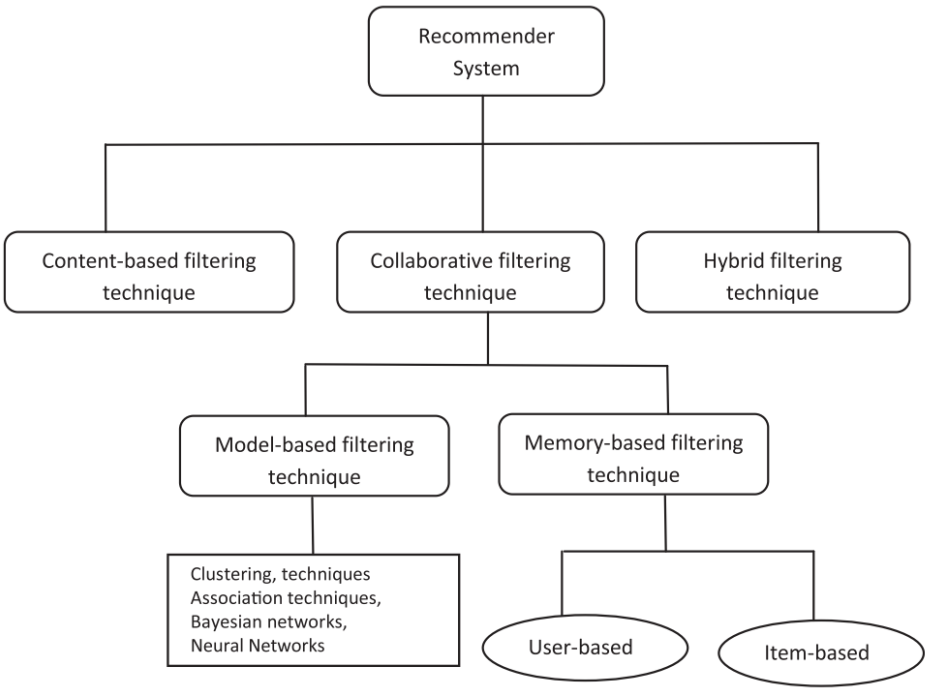


Figure 11. Ontology of recommender systems (Isinkaye, Folajimi, & Ojokoh, 2015)

Collaborative filtering is the first technique that was used to build recommender systems and is nowadays the most mature and commonly used approach. This technique recommends items to active users by identifying other users with similar taste. A typical user profile in a collaborative system consists of a vector of items and their ratings, that is continuously populated as the user interacts with the system throughout time. Collaborative filtering can be achieved by directly using correlations between users and directly comparing the item/user coupling similarities, a process known as memory-based filtering. Despite their simplicity, memory-based suffer from matrix sparsity, which refers to the insufficiency of observed users who share similar preferences to the active user. An alternative to overcome this issue is by comparing the active user with a statistical model derived from the historical rating and purchasing data to make predictions. This can be achieved using variety learning techniques such as neuronal networks, association techniques, clustering techniques, etc. under a process called model-based filtering. The success of collaborative filtering systems was due to the independence of representations of items, where variations in taste affect preferences [Mobasher B., 2007].

Some recent collaborative filtering approaches have been developed to *overcome cold start issues, scalability* and *sparsity* issues. The *cold start* issue refers to when there is few information about the active user to make accurate recommendations. *Scalability* refers to the fact that in order to make accurate recommendations extensive data about the user and the item is required, hence increasing the complexity of computations. The *sparsity* issue arises when there is huge number of items in a database and only a small subset of these items is consumed/rated.

One of the approaches is known as demographic filtering, where the demographic data of the active user is obtained from surveys to form people-to-people correlations. This helps classify the active user within a similar group to extrapolate preferences [Krulwich, B., 1997] and promote diversity and discover niches. Another approach, known as the knowledge-based filtering, is to identify and the needs of the user and infer how an item meets the needs

of the active user, and can therefore reason about the relationship between a need and a possible recommendation. Lastly, another popular system is the utility-based approach, where the user profile is used as a utility function to represent the constraints of the recommenders. The advantage of such a system is that it factors in non-product attributes, such as vendor reliability and product availability, into the utility computation, which allows to trade off price against delivery schedule for a user who has an immediate need [Guttman, Robert H., 1998].

In *Content-based filtering* systems, the object of interest is the associated attribute/features of the item. This system composes the user-specific classification or regression modelling using the item description and attributes labelled with ratings as training data [Belkin, N. J. & Croft, W. B., 1992]. These systems have the advantage of making recommendations for new items, whose attributes are not yet rated if the active user already rated similar attributes using supervised models. However, content-based systems are highly dependent on the descriptive data, which can be subjective and biasing the recommendations. Although they are effective for new items, content-based recommender systems are not efficient for new users because the training model for the target user needs to use the history of their ratings, an issue known as the *ramp-up* problem. This system reduces diversification of recommended items, since it will recommend items containing the same attributes the user has consumed, therefore items whose attributes are not known to the user has no chance of being recommended.

Collaborative, and content-based filtering suffer from plasticity issues, where user's preferences change (i.e.: steak-eater turning into a vegetarian) and the active use will continue getting recommendations based on historical data until new data restructures their profile. This can be overcome by implementin temporal weighting discounts on the user-profile data, but this is associated to a risk with a loss of user data.

Recommender Systems	Advantages	Disadvantages
Collaborative Filtering	A. Can identify cross-genre niches. (Recommendations outside preferences) B. Domain knowledge not needed. C. Adaptive: quality improves over time. D. Sufficient implicit feedback	I. New user ramp-up problem J. New item ramp-up problem K. "Grey sheep" problem (*No correlation amongst u*) L. Quality dependent on large historical data set. M. Stability vs. plasticity problem (carnivore->Vegan)
Content-based Filtering	B, C, D	I, L, M
Demographic	A, B, C	I, K, L, M N. Must gather demographic information
Utility-based	E. No ramp-up required F. Sensitive to changes of preference G. Can include non-product features (vendor reliability, urgency, etc…)	O. User must input utility function (a burden of interactions) P. Suggestion ability static (does not learn)
Knowledge-based	E, F, G H. Can map from user needs to products	P Q. Knowledge engineering required.

Table 8. Recommender System Types [Burke, R. 2002]

Each recommender system technique has its strength and weaknesses, which makes each technique favourable depending on its' application. Luckily there exist a hybrid approach, which allows the development of customised recommender systems, by combining two or more techniques to gain in performance and have each one compensates of the drawbacks of the other. The recommender system can be hybridised using the following techniques:

Hybrid Recommender System Techniques	Definition
Weighted	Corresponds to the score of a recommended item is computed from the result of all recommendation techniques of the system.
Switching	The system switches between recommendation techniques depending on confidence level thresholds to make the best recommendations
Mixed	The recommendations presented are obtained from various recommendation techniques at the same time.
Feature Combination	This technique uses the collaborative data as an additional feature to content-based approach to create a single recommendation algorithm.
Cascade	This is a sequential technique, where the output of a recommender system will serve as the input of another to be refined future.
Feature Augmentation	This a sequential technique where the features of the first recommender systems are added onto the second recommender system to improve the performance of the core system.
Meta-level	The learning model of one recommender system will be used as inputs of another recommender system.

Table 9. Hybrid recommender system modes of operations

The choice of a recommender systems depends on the desired predictive recommendations and the given datasets. Nevertheless, it is possible to merge different models for operational synergies. It is therefore important to consider a semantic context approach when tagging v-commerce elements.

Consumer Data Mining

The accuracy of recommender systems depends greatly on the data quality and the ability of the e-commerce to retrieve the right data. Various e-commerce solutions have been developed to retrieve real-time consumer data and extract inferences. E-commerce solutions attempt to analyse large volume of data (databases) retrieved from different channels to generate new insights through a process known as data mining. The data mining processes involves exploring, searching and modelling large amounts of data to disclose previously unknown patterns deemed to be useful comprehensible information. This is done through machine learning methods in which a computer agent is trained on a set of

algorithms and statistical models to undertake autonomous tasks using patters and interferences to attain a specific goal. Machine learning techniques such as: statistical analysis, decision trees, neuronal networks, rule induction and refinement and finally data visualisations [B. Thuraisingham,2000], help make sense of senseless raw data to provide actionable insightful recommendations. Depending on a specific result (i.e.: increasing purchasing, or consumer loyalty, brand visibility, etc…) different e-commerce employ several data-mining techniques to develop optimal marketing strategies [Astudillo, C.A., Bardeen, M., & Cerpa, N., 2014; [M.J. Zaki and M. Ogihara., 1998].

Different data-mining methods[4] are used to infer consumer insights from various channels using basic and easily retrieved data. Depending on what e-commerce wish to find various methods could be used in parallel to better display a consumer's preferences and current situation. Moreover, due to ubiquitous computing and various online tracking solutions (i.e.: retargeting solutions) e-commerce are capable of building of a holistic view of the consumer's profile to identify their preferences and needs. As it could be seen from the figure below, basic data such as location, device type and purchasing history could lead to insightful inferences by correlating the basic data with real-time information (weather, device-type owners and even pollution count). The contextual deductions help e-commerce systems transform basic raw data into meaningful insight that powers recommender systems for predictive modelling.

[4] See Annex

Figure 12. Contextual View of Consumers [Ovum, Retrieved Online][5]

In order to make accurate recommendations and provide a personalised experience, recommender systems depend on qualitative data. This qualitative data is achieved by filtering out unnecessary user data, using the techniques mentioned above. In order to obtain qualitative inferences e-commerce systems, rely on third party social network API's (Application Programming Interfaces) such as Facebook, Instagram and Twitter to acquire semantic personal information. As a result, recommendation systems could interpret social semantic data due to a better consumer profiling.

Modern social networking analysis methods, with the aid of existing e-commerce (API's [Kim, Y. A., 2007] personal information and individual's interests could help determine the strength of bonds amongst communities and portray their socio-cultural segments [Wasserman, S. & Faus, K., 1994]. Current e-commerce systems can link their solutions to social networking API's to identify socio-cultural segments and study their market to optimise the impact of their marketing strategies. E-commerce solutions benefit from their capability to track in real-time the development of consumer preferences across their behaviour online and decision-making process to continually seek insight for better

[5] https://viuz.com/2016/04/19/panorama-de-le-commerce-et-de-la-distribution-en-2026/

targeting. Online solutions such as Google Analytics and Hotjar are widely used in the e-commerce industry to better understand audience preferences. These analytics solutions help get a clearer understanding of the consumer audience by providing: reporting features (audience, behaviour, conversion reports, etc…), data and visualisation features (filtering, funnel analysis, heatmaps, etc…), user-tagging management systems and predictive analysis through audience demographics and segmentations. As a result these solutions provides a wide a set of tools that aid e-commerce owners obtain valuable insight and be constantly up-to-date to with the market dynamics.

It is possible to extract significant consumer data during an online shopping experience, to provide a 360 contextual view of preferences/traits. Moreover, the accuracy of recommender systems depends on the quality of the descriptive data of a consumer. Therefore, it is important to consider the method in which data is retrieved, stored and structured descriptive models.

Behavioural & Emotional Design

Online platforms, such as e-commerce platforms, marketplaces and social network platforms, benefit from advertisement as an indirect revenue. As a result, variety of research is undertaken to identify methods of increasing user's retention in online platforms. In order to anticipate the preferences of users, their current behaviours must be understood. Bj Foggs, a researcher in Stanford's Persuasive Technology Laboratory coined the Bj Foggs Model (*BFM*) [Fogg, B., 2009] which is represented as: $B=M \cdot A \cdot T$. The **B** refers to the behaviour, which represents the action someone does.

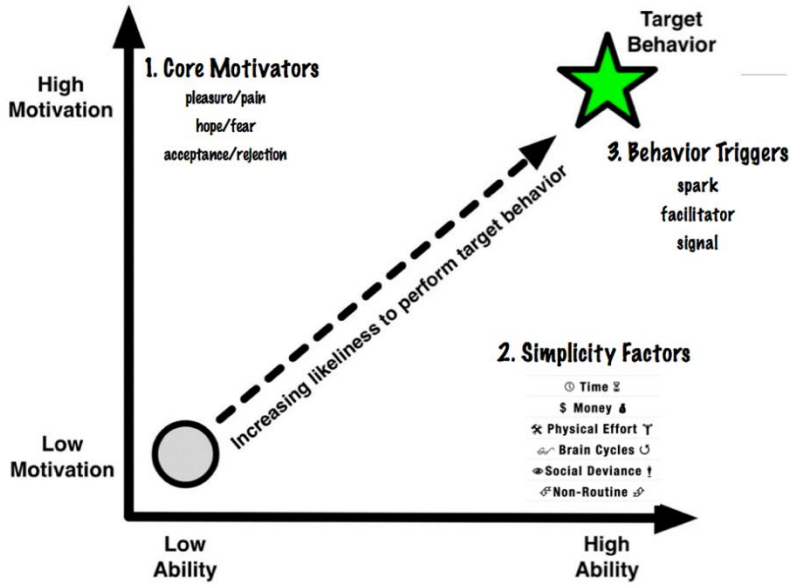


Figure 13. BFM Model [BJ. Fogg, 2009]

The **M** refers to the motivation of users and represents the underlying sensation, anticipation and belonging drivers of users. Bj Fogg states that it's composed of three levels: *sensation, anticipation and belonging.* The sensation refers to the physical/tangible level of motivation that corresponds to a person's motivation to seek pleasure and avoid pain and has an immediate result. A concrete example of this is the usage of gamification when attempting to direct users towards a goal. By offering incentives to encourage a behaviour, people's motivation for such a behaviour intensifies. The anticipation level corresponds to the emotions of hope and fear, which are characterised by the expectations of an outcome. The feeling of hope is the anticipation of a positive outcome, while fear is the anticipation of something bad. The anticipation is a powerful motivator and at times tends to overcome the sensation motivator. For instance, accepting the pain of flu shots and overcoming its' fear for a greater outcome. Finally, the third motivator corresponds to the social dimension of acceptance and rejection, providing a sense of belonging. This motivator defines the behaviour of people (clothing, language, choices, etc…) in order to continually feel part of a community.

The **A** refers to the element of ability, that corresponds to the simplicity to perform a desired behaviour and is characterised by six factors: *time, money, physical effort, mental cycles,*

social deviance and non-routine. BJ Fogg identified that humans are fundamentally resistant to training and learning as it requires effort. Hence in order to increase the element of ability and the simplicity, a behaviour must be simplified. The *time* factor defines the simplicity level of a target behaviour. For instance, if prior to making a purchase various information is required to be input, the target behaviour (purchasing) is made difficult. Thus, modes such as Amazon's one-click buy option, simplify and fasten the buying process by overcoming the time factor. The *money* factor represents a boundary that hinders cost-associated target behaviours for people with limited financial resources. Hence, any target-behaviour that costs too much money is not made simple and is be cost-prohibitive. The third factor of simplicity represents the amount of physical effort a person requires to achieve a targeted behaviour. People are less likely to undertake and achieve target behaviours that require too much physical effort and energy. The *brain cycles* factor corresponds to the complexity of a targeted behaviour and make users/customers abandon a target behaviour. As a result, clear instructions describing the expectations facilitate the achievement of a targeted behaviour. The *social deviance* factor corresponds to the conformity of a target behaviour with social norms. The less conform a behaviour is, the less simple it becomes. Finally, the *non-routine* factor refers to the familiarity of a target-behaviour. People engage more with behaviours they are used to and perceive a behaviour they are not familiar with to not be simple (i.e: shopping in virtual reality). As a result, by replicating familiar behaviours through novel platforms (familiar online shopping experience through VR) increases the simplicity of achieving targeted behaviours.

The **T** refers to the calls to actions or prompts that incite a target behaviour to take place and is characterised by the following types of triggers: *Facilitator, Signal and Spark.* The *spark* type of trigger prompts for people who lack motivation and high ability. Spark triggers contain motivational elements that demonstrate the value concisely such as the use of texts or videos that highlight hope or fear. The *facilitator* trigger is used for people who have high ability and low motivation. Facilitators simplify the process of achieving targeted behaviours by convincing users that the targeted behaviour is easy to do with no extra resources. This type of trigger takes the form of videos and instructional texts. Finally *signal* triggers, are used when a person has high motivation and a high ability and serves as a reminder to undertake the desired behaviour. Triggers are powerful in the era of interactive media

increase impulsive behaviours (i.e.: clicking on sales advertisement and immediately redirected to the product sheet with the product already added to the basket).

Consumer behaviour can be triggered by continuously tuning the <u>motivators</u> (sensations, anticipations and belongings), <u>ability</u> (time, money, physical effort, mental cycles, social deviance and non-routine) and <u>triggers</u> (facilitator, signal and spark). It is important to consider the configurability of the aforementioned factors during the design of an experience to trigger desired behaviours.

The BFM helps understand the various factors that contribute to altering and manipulating human behaviour by tuning each element to resonate with the specific state of each person/user/consumer. The BFM model describes how technology solutions could be more persuasive and alter human behaviour. Nir Eyal, elaborated in his novel the *Hooked,* of how a user's needs problems could be connected to a company's solution with enough frequency to transform a targeted behaviour into a habit [Eyal, N., 2014]. By transforming the desired behaviours into habit, online platforms can increase their attention, retention and eventually conversion rates.

Figure 14. Hook Model [Nir Eyal, 2014]

The hook model starts off with the trigger phase that is composed of external and internal triggers. As it was mentioned in the BFM model earlier, the external triggers correspond to prompts and external cues that provide information to a user and engage users to act. The

internal triggers originate from the user and correspond to the association a user has to external triggers (i.e: feeling bored and checking e-mails or social network platforms). The objective of the trigger is to demonstrate a reward and how to achieve it. The action phase corresponds to the desired user-behaviour. As it was described above in the BFM behaviour is an action that anticipates a reward and depends greatly on motivation and ability. Thus, simplifying the actions to become delightful and with little or no thought to become a habit. This takes different forms (i.e.: browsing on Amazon for deals or searching on google). The variable reward phase refers to the user obtaining what they desire after undertaking the action. More specifically throughout this phase the *nucleus accumbens* region in the user's brain is stimulated in anticipation of a reward with an element of uncertainty and unknown. The variable rewards are composed of three types: reward of the tribe, reward of the hunt and reward of the self. The reward of the tribe refers to rewards that have an element of variability whilst seeking empathetic joy through social interactions (i.e.: social variability associated by accessing social media platforms and not knowing what to see.). The reward of the hunt refers to the search of resources that contribute to survival (i.e.: the search of products that match preferences in flash sales on Amazon). The reward of the self refers to the search of intrinsic rewards of completion (i.e.: reading unread e-mails, finishing to-do lists or validating an e-commerce purchase basket). The purpose of these rewards is to satisfy the desires of the users with an element of unknown and frequency to form a habit. Finally, the investment phase contributes to increasing the likelihood of looping around the hook model again. This is achieved by making users store value into the service and anticipating a future reward (in contrast with the action phase in which an immediate gratification is achieved). By adding more content and personal data in a service, the better it becomes as a mode of usage (i.e.: the more search criteria input in e-commerce sites the better the recommendations displayed). A common example of this is the impact of the "*Like*" feature in social networks. Liking a content is one of the easiest forms of interactions in social networks that displays to someone that you liked their content. However, the social importance of the like button allowed people to post content and receive immediate gratification and enjoy short-term boosts of social affirmation [Eranti, V., & Lonkila, M., 2015] encouraging them to publish more content. Meanwhile the social networking site in the investment phase of the hooked model provides a platform for the user in which they are continually attempting to get more "likes" social recognition and harvest valuable data about

user preferences and suggest more accurate content. However, it can be noticed that by limiting user's options (i.e: YouTube's video autoplay) excluding the choice of whether to watch another video or not the attention of a user is fully captured and controlled.

By designing solutions that make users loop through the hook model's, a behaviour is converted into habits and the solution is associated with a mood/need regulator [Nir Eyal, 2014]. Thus, identifying in real-time the current emotions and needs of users is critical into providing quality triggers that facilitate a desired consumer behaviour. Rosalind Picard, coined the term affective computing throughout her research in MIT Media Labs by exploring fields computer systems that recognise, interpret and stimulate human affective empathy. A study published by the social network leader Facebook identified that emotions could be triggered through contagion [Kramer, Adam et al., 2014]. Since consumer behaviour is an emotionally driven behaviour, to better anticipate and trigger desired behaviours, online solutions should be able to interpret and process emotions. By considering the emotional variability, online solutions can respond adequately to human needs [Picard, R., & Daily, S., 2005]. The issue of affective computing is that the current solutions are not capable of reading human minds and the commonly used method of assessing emotions is through cognitive self-reporting. Cognitive self-report methods (i.e.: responding to surveys) are good in measuring the subjective dimension of the emotional experience during product evaluations. However, these methods fail to record in real-time the affect during evaluations, and as a result the reported feelings may be drawn from a biased memory [Ahn, H. Il, & Picard, R. W., 2014]. As a result, affective computing depends on behavioural and physiological modes of measurements to gain a full representation of the consumer emotional experience. The behavioural modes measurements rely on capturing external variances in the body. The behavioural modes of emotion recognition are classified in five groups: physical appearance, vocal, facial, eye and gesture [Guerrero L., DeVito J. & Hecht M., 1999; Jacob-Dazarola, R., et al., 2016]. Whereas the physiological modes of measurements attempt to detect internal body variances in response to a stimulus. This is achieved by recording internal body activity, such as; autonomic nervous system (ANS) measures using skin responses or brain activity using functional magnetic resonance imaging (fMRI) or electroencephalography (EEG) [Whang, M., & Lim, J., 2012; Picard, R. W., Vyzas, E. & Healey, J., 2001]. Physiological responses are less subjective than behavioural responses,

therefore provide an unbiased mode of emotional recognition. Using multimodal modes of measurements (cognitive, behavioural and physiological) provides an accurate emotional representation can be quantified. Solutions such as *Affectiva*[6] use behavioural modes of measurements (facial tracking) using image recognition and computer vision systems to identify moments in videos that are emotionally stimulating and arousing for each user. This solution is useful in advertisement as it shed lights on characteristics companies should emphasise on to trigger specific emotions and brand placement when viewers are emotionally aroused. Hence, the advertisement reinforces the association of an emotion to the company's brand.

The capability of computer systems to acquire, process and interpret imagery [David A. Forsyth & Jean Ponce, 2002] to semantically understand their environments ergo develop perceptions for emotional recognition is a form of artificial intelligence known as computer vision. Artificial intelligence (AI) refers to machine actions displaying some sort of intelligence. John McCarthy [J McCarthy et al., 1956] who was dubbed the father of AI, defined it as the science of making intelligent machines that perform tasks associated with intelligence and learning. Artificial intelligence is attained through 3 main approaches of learning: supervised, unsupervised and reinforcement learning [Peter Norvig & Stuart Russel, 1995]. Supervised learning algorithms pre-analyse data (training data) to reasonably learn and infer classification functions. This method bases its learning on model relationships and dependencies between input features and a desired prediction output. Some of the techniques used in supervised learning methods are the regression and classification. Conversely, unsupervised learning approaches infer functions that characterise and describe an unlabelled structure of data without pre-trained data. This method is used in descriptive modelling and useful when the human expert is not sure of what to look for. Some of the techniques used in unsupervised learning methods are the pattern detection, clustering and association rules. Finally, reinforcement methods correspond to systems learning from consequences of its actions and continually attempts to maximise rewards. Reinforcement learning (RL) agents select actions based on exploitation and exploration (trial and error) and is widely used in areas of characterising optimal solutions. Artificial Intelligence provides

[6] An MIT media lab spin off (https://www.affectiva.com/)

online solutions and effectively, e-commerce platforms, the capability to extract and process an overwhelming amount of user data, in order to identify and seek patterns to create better experiences and better prediction tools to match dynamic market environments [Milgrom, P. R., & Tadelis, S., 2018]. AI provides customers with personalised experience that match their preferences [Linlin Liu, Haijun Zhang, Yuzhu Ji, Q.M. Jonathan Wu, 2019]. This discipline has allowed the development of solutions (analytics, chatbot, etc…) that serve help leverage large volumes of data into actionable insights.

As it was defined by John McCarthy, the objective of artificial intelligence is to simulate natural intelligence found in living organisms. However, artificial intelligent systems incorporate statistical inferences to simulate rational cognitive thinking. Whilst throughout our research we have identified the importance of emotions in determining human behaviour. As a result, humans are emotionally driven, and artificial intelligent systems must be capable of taking into consideration the affective situations of users to anticipate and predict future behaviour.

Unlike retail stores, e-commerce systems provide access to all ranges of products that matches consumer preferences instantaneously, without having to switch stores or specific inventory issues. However, despite providing the consumer with the right information (most adequate product suggestion) at the right time (satisfying the current motivation drivers), e-commerce systems are unable to recreate the potency of emotions subjected during a shopping experience. Although e-commerce websites are incapable of re-creating the emotional impact of the shopping experience, they are capable to retrieve key behavioural data shedding light of current emotional states. By integrating social network solutions to gain access to consumer data and the AI powered solutions to infer insight on consumer current states, accurate recommendations could be made to provide the consumer with the right product at the right time. In order to recreate life-like shopping experiences we will investigate the immersive technology of virtual reality to reinforce the emotional impact of a shopping experience. The bilinear product/user coupling relationship.

The integration of virtual reality as a shopping medium converts the previous product and consumer coupling into a tryptic challenge and consider an optimal staging environment that

matches the consumer's preferences and best showcases the product. The use of virtual reality allows to bring together the synergy of recommender systems to personalise, target and optimise the impact of visual merchandising techniques. Hence, identifying right descriptive model inputs that help construct the user 3D vector profiles in a virtual reality environment is critical to recommending the right product, to the right user, within the right environment.

I.IV Virtual Reality

Visual display units have first appeared as cathode ray tubes evolving from plasma displays, vacuum fluorescent displays to the current LCD (Liquid-Crystal Displays) and LEDs (Light Emitting diodes). In 1965, Ivan E. Sutherland, has predicted that the ultimate display would be display unit that mimics the physical properties of the world enough for the user to be immerged within [H. Rheingold, 1991]. Although this definition was something compared to fiction (comparing it himself to Alice in Wonderland in his article), this description of such a device today seems unsurprising and quite common. This created a hype of research and was coined Virtual Reality in 1989. Therefore, a VR experience is defined as an experience in which the user is immersed in a responsive and interactive virtual world [F.P. Brooks, J., 1999]. There exist three types of virtual reality [Mazuryk, Tomasz, 1999] levels of immersion:

Modes of VR	Definition
Desktop VR	This type of immersion is also referred to as Window on World (WoW) systems. Using a conventional screen to display a monoscopic vision of the visual content.
Fish Tank VR	This system is an improvement of the Desktop VR system by incorporating stereoscopic vision to augment the perception of depth. Moreover, this system uses head trackers and data gloves to increase sensory feedback and interactive immersion [C. Ware, Arthur K., 1993].
Immersive VR	This represents the ultimate VR experience using head mounted displays (HMD) and controllers. These systems enhance the level of immersion using various sensory interfaces, of which the most common today is: audio, visual and haptic These devices help give a reference point for the users to localise them in the virtual environment and immersive navigate within.

Table 10. Evolution of VR immersions

Virtual reality is defined in the current literature as the electronic simulation of environments filled with computer-generated images displayed through head-mounted displays (Figure 2). These simulations respond to human movements enabling the end user to interact in realistic three-dimensional situations [Fuchs, P. et al., 2011; M. Gigante,1993; L. and E. von Schweber, 1995]. Virtual reality is an interactive immersive experience, whose current advances and levels of immersion are measured with is measured as the level of presence (depth perception), interactivity (modes of interactions) and autonomy (quality of content) [D. Zeltzer, 1992]. This aids the users bypass the complex non-intuitive user interfaces and generates life-like genuine response behaviours from the users. Immersion refers to the sense of being in the virtual environment due the presence factor and the multisensory cues.

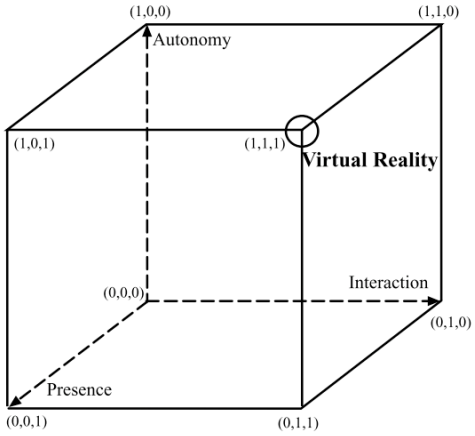


Figure 15. The 3-dimension factors in VR Immersion factors [Mazuryk, T. et al., 2014]

The potential of virtual reality allowed it to rapidly develop in sectors in training (i.e: medical and aerospatial) sectors [K. McGovern, 1994; J. Cater and S. Huffman, 1995], modelling and designing (i.e: 3D CAD models) and entertainment areas (i.e: HTC Steam Game Engine & Sony Playstation) [O'Brolcháin et al. 2016]. The goal of virtual reality devices is to simulate the real world and teleport its' users into a virtual environment by fooling their senses [R. Holloway & A. Lastra, 1995], where they can undertake tasks as they would in the real world. Moreover, it has been noticed that the use of immersive experiences intensified the emotional experience. Vincent Rieuf throughout his Phd research identified that immersive moodboards triggered more intense emotions (emotions with higher arousal levels) than

when using traditional moodboards during the early design [Rieuf, V., 2013]. As a result, virtual reality could be used as a magnifying loop that amplifies the emotional triggers encoded in product design attributes. Not only is virtual reality capable of magnifying emotional empathy from a user or consumer's perspective, but it can be used as a medium to virtually induce emotions such as awe [Quesnel, D., & Riecke, B. E., 2018]. Individuals in awe often do not understand the grandeur of the moment and make changes to their mental model to understand the scale of the situation afterward. Awe-inspiring experiences provide positive feelings, increased pro-sociality, well-being and self-transcendence. For instance, individuals are sometimes willing to pay the price in time, effort and cost to watch a movie in the cinema rather than watch the movie at home, which would have cost less.

The awe experience could be induced when participants are emotionally affected [Bouchard, S. et al., 2008]. The intensity of the experience strengthened for self-selected virtual reality environments. As a result, the narrative and aesthetic use of virtual reality technology provides the perfect platform to harness awe-inspiring user-experiences. For instance, a person who is watching a movie in the cinema, whose narrative they are not interested in, are not immersed in the experience. Therefore, the level of interest of a participant in the narrative determines the attention given and impacting their level of immersion. Immersion is composed of three levels: *engagement, engrossment and total immersion* [*Brown, E. & Cairns, P., 2004*]. The engagement refers to the lowest level of involvement and the first door to immersion. Throughout this stage an individual invests time, effort and attention that are determined by preferences. For instance, in gaming, the engagement level is attained if the gamer is interested enough in a style of game to invest time, effort and attention. Once the individual becomes engaged their experience requires an emotional experience to achieve the engrossment level. The engrossment level refers to when the experience's features imapct the individuals affect. This refers to the quality of images, realism of tasks and comprehension of the plot. At this level the individual is less aware of their surroundings and emotionally invested with all their attention onto the experience. Finally, the total immersion level refers to when individuals are cut off from reality and the experience is the only thing that matters. During this stage the individuals feel a high level of empathy to the attributes (i.e.: characters) in the immersive experience and relevance of the atmosphere realism.

The level of immersion is defined by the level of interactions, autonomy and presence. The level of immersion can be improved by incorporating relevant and realistic atmospheres that individuals can navigate easily within through natural interactions. Increasing the level of immersion augments the level of empathy and bolsters the emotional experience.

Currently, there are 6 levels of interaction in immersive VR. The first level corresponds to the level of *no interaction* where the user is placed in a pre-recorded VR experience and consumes the content by looking around. The next level refers to the interaction with the VR content achieved through gaze. This type of interaction is currently the simplest mode of interaction in VR and requires no additional devices. The VR experience contains interactive elements upon which a gaze that exceeds a given time would represent a VR click. This level of interaction is easy to learn but restricts the physical movement of the user and hinders the immersion. The next level of interaction corresponds to a device-assisted interaction, in which the interaction occurs through controllers. The head mounted displays (HMD) are often equipped with sensors to be able to see the controllers in the immersive VR environment. However, certain technical difficulties (i.e.: controller lagging, and need to be in line of sight of sensors) hinder the immersive experience. The fourth level of interaction in an immersive VR experience corresponds to the unassisted experience. This type of interaction makes use of object detectors that recognise natural user hand gestures to interact with the VR experience. Although this experience is a more natural way to interact with the immersive environment the lack of feedback hinders the degree of presence. The fifth level of interaction in immersive VR makes use of feedback devices (i.e: haptic gloves) to recreate the physical sensations experience in the VR experience. Although this mode of interaction is still new and at a laboratory level, displays the importance of gesture feedback into immersion. Finally, the last level corresponds to brain interaction [Guger, Christoph et al., 2009] in which brain computer interactions are used to control the VR experience. This mode of interaction is still in its prototype phase and as it requires invasive modes of data acquisition (EEGs) and a training period. Overall, virtual reality provides a new platform that has the potential to change market research and to uplift the standards of interacting with

digital content [Markowitz, D., & Bailenson, J.N., 2019] and better bridging the current gap between brick-and mortar and e-commerce platforms.

VR advances in shopping

Researchers have long employed simulated test-market (STM) services. This refers to a simulated controlled laboratory experiment that investigate consumer behaviour. This method is costly, lacks flexibility (requires normative data to calibrate to compensate for the consumer's stated purchase intentions) and is often employed at the end stages of market planning (requires a final products). Therefore, the recent advances in virtual reality promises to solve STM challenges by testing new concepts before incurring manufacturing costs and determine how to design retail space that matches consumer preferences [Burke, R. R, 1996]. Companies such as Proctor & Gamble and Kimberly Clarke are currently exploiting virtual reality as a channel as computer simulated stores [Byron E., 2007]. The operational advantages of virtual laboratory stores encouraged various researches in investigating the potential bias between computer simulated stores and physical laboratory stores [Campo, K et al., 1999; Desmet, P., Bordenave, R., & Traynor, J., 2013]. It was noted that the quality of the virtual representation created little differences between virtual and physical laboratory stores. Moreover, it was noted that the naturalness of interactions and realistic rendering of the representations augmented the degree of immersion and telepresence in virtual laboratory stores [Schnack, A., al., 2019] The literature review on VR shopping displayed that VR is currently mostly used to investigate consumer choice in simulated laboratory environments. Current research integrates eye-tracking technology onto VR headsets to investigate the consumer's perspective during shopping [Meissner, M. et al., 2017]. However, the invasiveness of such technology (eye-tracking detectors) allow for such a solution to be used only in laboratory settings.

I.V V-commerce

Throughout this research project we develop a v-commerce system that brings together, the realism of brick-and-mortar shopping, data analytics of e-commerce and the configurability of virtual reality.

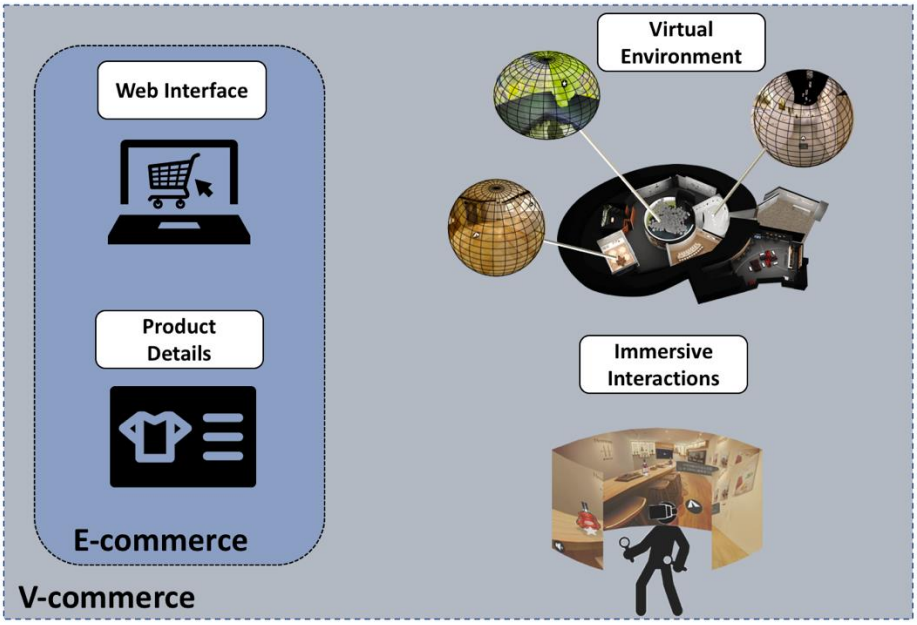


Figure 16. V-commerce fundamental blocks

The figure above illustrates that an e-commerce (highlighted in blue) is constituted of a web-interface that enables consumers to access and interact with the brand's universe. The e-commerce site is exposing the different products sold with along with its' details serving as different cues to the consumer. A v-commerce system is composed of the e-commerce block and uplifts it by incorporating a virtual environment and immersive interactions. The virtual environment refers to an environment that fully recreates an artificial or real (using panoramic images) environment that engulfs the user's field of view (heading), in which the user can freely interact. The virtual environment is composed of multiple scenes (illustrated by different spherical panoramic), which refer to different points of a VR shops a consumer may explore. The virtual environment contains of behavioural software assistance (BSA) elements, that aid the user to navigate and interact within the virtual environment [Simon Richir et al., 2015; Vincent Meyrueis, 2011]. The consumer may navigate and interact with the virtual environment using the device's native modes of interaction (mouse for computers, touches for tactile interfaces) or in an immersive mode (using a head-mounted display).

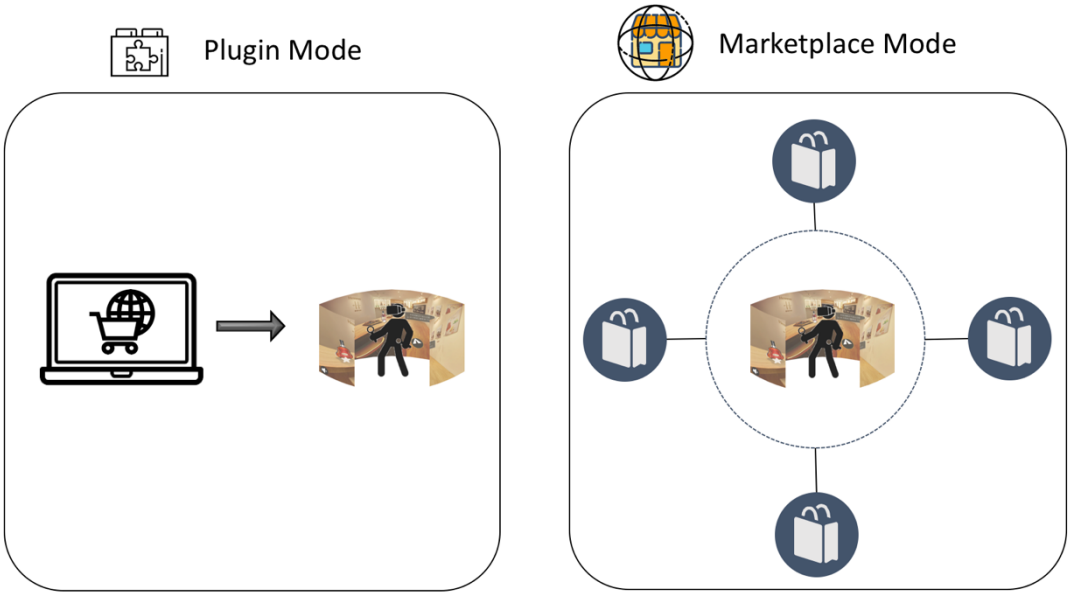


Figure 17. Two modes of DIAKSE V-Commerce Experience

There exist two modes to access the DIAKSE v-commerce experience. The plugin mode refers to a solution that depends on an existing e-commerce platform and relies on an e-merchant's traffic. Consumers originating from the plugin mode of v-commerce are presented only the e-merchant's products and therefore depend highly on the e-merchant's SEO performances. Upon purchasing items, the consumers are re-directed towards the e-merchant's purchase validation page for payment. The purpose of this solution is to perform real-time behaviour analysis on the consumer in an immersive environment and improve the consumer experience, such that to promote purchase intentions. The marketplace mode provides consumers access to a variety of categories of VR shops. This solution is designed to be part of a remote seat placed in high traffic areas (i.e.: hotels, malls, car centres, etc…). The consumer is immersed in each shop, where they may browse and purchase products. Upon validating their purchases, they are re-directed to the DIAKSE payment page, where an in-built distributed solution has been developed.

Prior to the development of the marketplace mode, the v-commerce was 1-client oriented. This means that each client had a specific version of a VR shop plugged to their e-commerce and tailored to their needs. The design of a marketplace mode quickly displayed the limitations of this development process and required a reorganisation of the solution architecture. As a result, the core DIAKSE solutions were centralised allowing for rapid

updates and better code versioning. This re-designed v-commerce accommodates for both modes of v-commerce experience and offered a scalable, rapid and homogenous architecture solution across all VR shops. Web-based monitoring solutions were developed to assess inactivaties and rapid intervention during system failures.

To better understand how a VR shop is created, an equirectangular image is taken by a 360 cameras or a by assembling basic images from a normal camera of a specific viewpoint. A simple example of an equirectangular resembles to the following figure:

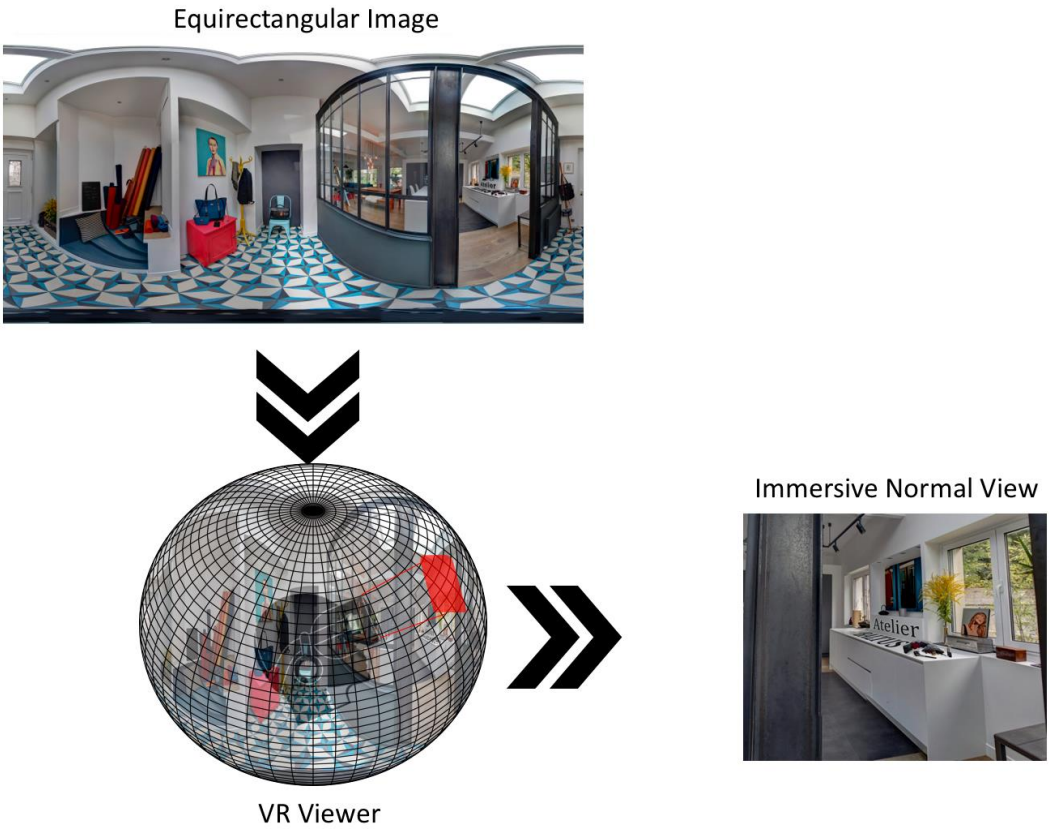


Figure 18. Equirectangular Projection example

The equirectangular image is reconstructed as a sphere's texture using the 3DVI3W technology. The VR viewer is simply a camera that represents the user's perspective, which is placed at the centre of the sphere. With the aid of sensors on head-mounted displays, the user's head motions control the projection of a field view providing an immersive experience and a sense of presence. Dynamic modes of interaction and buttons are placed in the VR viewer allowing the user to interact with the VR environment.

The VR shop is composed of multiple viewpoints (equirectangular images) named denoted as *scenes* scattered throughout the store.

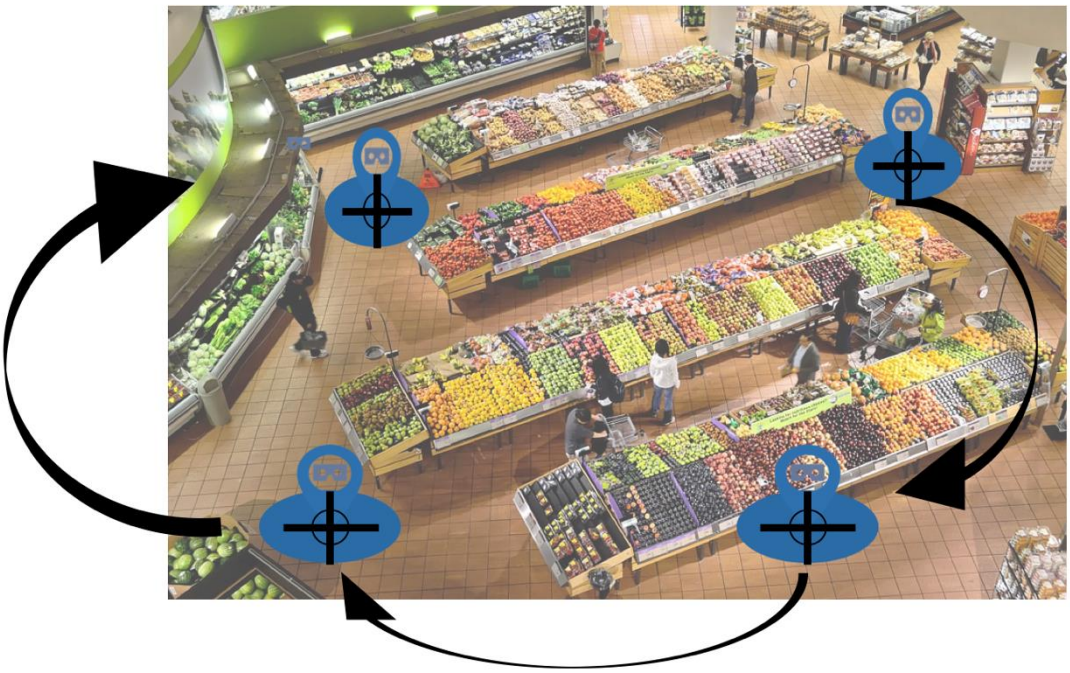


Figure 19. Multi-scene VR Shop

With the aid of BSA's from the 3DIMM3RSE solution, consumers can move freely from a scene to another and explore products.

Icon	DIAKSE V-Commerce Nomenclature	Definition/Purpose
	Product Sheet Star	A call to action (button) that that indicates an interactive item in the virtual environment.
	Displacement Hotspots	A button that is anchored in a specific coordinate of the virtual environment. This enables consumers to explore the virtual environment move through scenes.
	Displacement Layers	A button that is anchored onto the web-browser and **not** in a specific coordinate of the virtual environment. This enables consumers to explore the virtual environment move through scenes.
	Progress Bar Layers	A progress bar that is anchored onto the web-browser and allows consumers to monitor the level of exploration of the VR shop.

Table 12. DIAKSE v-commerce behavioural software assistants.

Throughout this research we will focus on the consumer behaviour in VR immersion and attempt to formalise a methodology that considers consumer affect by assessing the user-experience and emotional engineering. This methodology will serve as the foundations that constitutes the 3DR3CO technology and contribute to the continual optimisation of 3DIMM3RSE and 3DVI3W technology.

I.VI Summary

The literature review above shed light on the consumer behaviour process decision that is highly influenced by three levels of influence. The objective of the literature review is to identify the minimum determinant factors that characterise a v-commerce experience. It was noticed that the atmospheric level of influence corresponded to the external stimuli a consumer initially comes in contact with. The psychological level of influence corresponds to the way in which consumer's interpret different stimuli and develop emotions. The socio-cultural level of influence corresponds to the most abstract level of influence which corresponds to cultural norms societies abide by, which define a trend of psychological preferences. A literature review in behaviour design highlighted elements to consider when designing solutions to convince individuals to undertake a specific behaviour (consumer behaviour). The undertook state of art on consumer behaviour highlighted the first finding as the following:

Finding 1

The consumer decision process is influenced by motivational factors that vary amongst different consumer profiles. The motivational factors during a VR shopping experience may be quantified to investigate preferences

Given the industrial nature of the project's scope, various strategies used by brick-and-mortar shops and e-commerce were explored to improve the consumer experience by matching preferences. The undertook literature review uncovers how various strategies value consumer data (merchandising, eye-tracking, recommender systems and social network analysis) to personalise the experience for a diverse target audience.

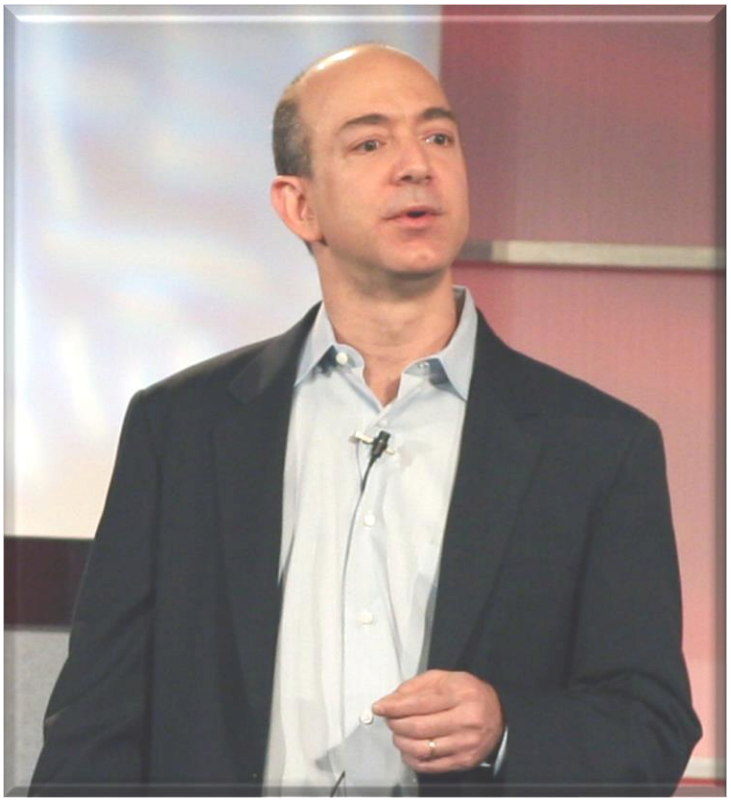
The originality of this study is to investigate how a VR shopping experience can be personalised based on consumer behaviour. More specifically how can the VR immersive experience trigger positive emotions that lead to purchase intentions. The major role of emotions in anticipating consumer preferences and the purchase decision process lead us to explore modes of acquiring and incorporating qualitative behavioural data into product development.

Finding 2

The consumer behaviour data collected in a VR shopping experience can provide valuable insight into consumer preferences. Hence it is important to study a continuous integration of consumer behaviour data in VR shopping design for personalised experiences.

"If we have 72 million customers, we should have 72 million shops"

– **Jeff Bezos**



amazon

Chapter II

Research Question & Methodology

On the basis of the industrial challenge of this research project, the previously undertook state of art has allowed to develop an understanding of the key issues main to consider during the development of a v-commerce system. The 2 findings that result from the state allows to formalise the research question of the industrial challenge. The research question is formalised as:

> ***Research Question:*** *How to incorporate consumer behaviour analysis to optimise the v-commerce design process and promote purchase behaviour?*

The research question above is composed of two main sections that leads towards the development of two hypothesis.

> ***Hypothesis 1:*** *The navigation data of a consumer in a virtual reality (VR) shop allows to observe design elements for the VR shop.*
>
> ***Hypothesis 2:*** *The aggregated consumer navigation (H2.1), interaction (H2.2), and affect (H2.3) data improves the dynamics of the tryptic relationship to personalises the shopping experience and increases purchase intentions.*

To validate the hypotheses, we develop a methodology to determine how to incorporate consumer behaviour in the v-commerce design process.

III.I Research problem statement

The previously carried literature review of this research work displayed findings that argument how virtual reality can be a solution that uplifts e-commerce by re-enforcing and providing personalised awe-inspiring experiences. This is due to the emotion's critical role in consumer's purchase decision. However, in order to provide a personalised shopping experience, the various preferences of each user must be identified in a non-invasive method that will provide the necessary behavioural and cognitive data to adapt each environment to consumer preferences. The complexity of this research project consists in identifying a methodology that incorporates the consumer behaviour into the design of a user-centred v-commerce solution.

Considering in real-time consumer's affect in a v-commerce environment is complex due to the multidimensional nature of the tryptic. The subjectivity of each consumer's preferences, and the multi-varying nature of the product and virtual environment staging settings complexifies the modelling of the tryptic dynamics. As a result, throughout our research we aim to determine the most critical sensory factors and interactions that influence a consumer's purchasing decision to personalise a shopping experience.

Currently diverse methods are used to assess consumer insight to promote the business proposition. Studies carried out in brick-and-mortars often focused on one dimension (i.e.: light, colour, messages, etc…) to assess its impact on consumer behaviour due to the inability retrieve the results in real-time without being invasive (i.e: eye-tracking, FMRI, etc…). Moreover, due to the physical inability of tailoring each store to each consumer, it is not possible to assess the impact of atmospherics on each product and its' influence on the consumer's perception. Whereas e-commerce sites can extract real-time insight about a user's interactions and digitally manipulating web-atmospherics, they are not capable of determining *how*, *which* and *what* factors caused a specific behaviour. The lack of standardisation makes it difficult to compare the results of these studies and thus improve the understanding of the tryptic. In addition to evaluate sensory and emotional consumer

responses to changes in products and environments also requires real-time and invasive solutions.

It appears necessary to develop a tool to evaluate the perception of consumers along the varying dimensions of products and environments. The formalisation of this tryptic phenomena would require the consideration of the diverse inter-dependant relationships of the factors within each entity. Moreover, this tool will aid in determining the minimal (most crucial) characteristics of each factors that contribute to a descriptive model of the tryptic phenomena. The current industrial limitations do not allow to identify different consumer groups and what motivational drivers are most impactful during a v-commerce experience. Since each consumer profile is susceptible, we seek to understand what motivation drivers (situational, psychological and socio-cultural) define a consumer profile's preferences We also aim to understand which product and staging environment attributes correspond to which influential factor. It has been displayed throughout the undertook literature that to identify consumer preferences, various laboratory experiments are conducted in simulated environments to extract behavioural models for brick-and-mortars. E-commerce on the other hand benefits from the advantage of online analytics data, which allow each online experience to be personalised.

In order to improve and personalise the consumer shopping experience, the developed tool should provide industrial professionals and researchers the ability to analyse in real-time consumer behavioural data in v-commerce platforms to better apprehend new shopping interaction insights. This leads us to express our research question as:

Research Question

How to incorporate consumer behaviour analysis to optimise the v-commerce design process and promote purchase behaviour?

III.II Formalisation of hypothesis

Based on the findings of the undertook literature review, we have formulated two hypotheses based to answer our research question. The undertook state of art displays that the consumer perception is a multidimensional concept that is not characterised by one factor, but rather an aggregation of various influences that are extremely subjective. Therefore, it seems appropriate to combine several measures to assess the influence of product and environment attributes on a consumer's perception. As a result, the challenge of such a strategy is to identify what are the most influential interactions undertook during an act of purchasing behaviour. We will attempt to model the dynamics of the V-commerce tryptic and build a descriptive database model. The descriptive model will serve as input data to construct a predictive system coordinating recommender systems to optimise the design of VR shops and promote purchase behaviour.

As it was stated in the first findings of the literature review, consumers are influenced by various motivational factors that differ amongst consumer profiles. In order to obtain the relevant data on the varying attributes that contribute to the construction of a consumer's perception that trigger purchasing decisions, it is possible to use the observed consumer behaviours throughout their shopping experience. The observed elements indicate a how a

consumer explores a v-commerce shop and allows to extract merchandising strategies. As it was displayed in the undertook literature review, the matching of the merchandising elements with a consumer's semantic preferences provides a user-centred approach that promotes a hedonic experience, leading to increased purchase intentions. An optimised merchandising strategy is only achieved by conducting laboratory research tests using neuromarketing techniques to model consumer perceptions. The modelled systems allow to develop a predictive behavioural system and identify optimal merchandising strategies that correspond to different consumer behaviour. We can therefore formalise the first hypothesis as:

Hypothesis 1

The navigation data of a consumer in a virtual reality (VR) shop allows to observe design elements for the VR shop.

By observing and understanding the overall VR consumer behaviour, insights on v-commerce elements that trigger a desired behaviour (i.e.: purchasing behaviour) could be uncovered and promoted. The design elements we refer to correspond to features and attributes that compose the v-commerce experience. This may range from the physical placement of the products, the number of scenes a VR shop, the assortment of products, the time spent browsing each product and each scene, what attributes retained the most attention and modes of navigation. The study of this hypothesis describes the VR shopping experience as a learning platform that continually provides personalised shopping experiences insight for each consumer behaviour. The validation of such a hypothesis allows us to evaluate in further details the consumer behaviour and build a descriptive model.

The second finding of the literature review highlight the importance of investigating and integration of consumer preferences in a v-commerce shop to personalise the shopping experience. It becomes necessary to investigate the interactions between the main entities of the v-commerce system (the consumer, the product and the VR staging environment) and the personalisation of the consumer experience. As it was noted in the literature review, the accuracy of the recommended personalisation depends on the quality of the descriptive model. The appropriate tuning of the VR staging environment attributes, behavioural system assistants, and product attribute display modes promotes desired purchasing behaviour. This highlights the importance of investigating consumer interaction with the virtual staging environment and the products in the VR shop. The configurability of such factors allows to leverage the descriptive model and personalise the consumer experience. Moreover, the consumer behaviour, being emotionally driven displays the importance of understanding consumer affect to determine accurate preferences. The data flow amongst each coupling in the main v-commerce system is to be investigated, which allow us to formalise the second hypothesis as:

Hypothesis 2

The aggregated consumer navigation (H2.1), interaction (H2.2), and affect (H2.3) data improves the dynamics of the tryptic relationship to personalises the shopping experience and increases purchase intentions.

The study of such a hypothesis requires the development of a methodology (that we name throughout this research work: **3DR3CO**) that models the tryptic relationship and formalises a descriptive model of each VR shop. The validation of the second hypothesis will result in a successful development of a methodology that allows to uncover in real-time design elements

that optimise the shopping experience using consumer affect, interaction and navigation data.

III.III 3DR3CO methodology

In order to respond to the scientific question, we will introduce throughout this section the undertaken methodology that helped verify the validity of the hypothesis.

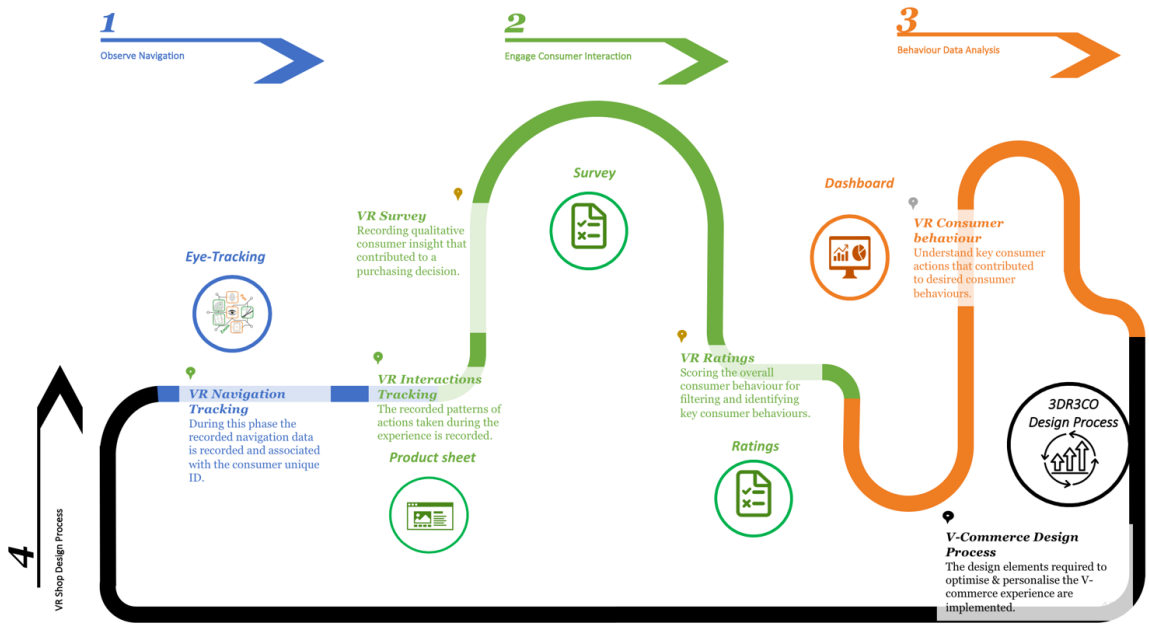


Figure 20. 3DR3CO Methodology

The first phase consists in developing *behaviour tracking tools* within virtual reality shops. These tools record the main consumer actions (i.e. time spent in each virtual environment, products seen, basket overview, etc..). Moreover, these tools allow to recreate the consumer journey and re-live their shopping experience. This tool allows to identify and study consumer behaviour patterns that have led to a purchasing or any desired consumer behaviour in an informative and non-intrusive mode [Ayanso, A., & Yoogalingam, R., 2009].

The second phase consists in developing a *qualitative and explicit logging tool* to identify consumer-types and understanding consumer behaviour. These tools take the form of end-of-experience surveys and rating requests to obtain user-feedback. These feedbacks help in

understanding the reasons behind the consumer behaviour, by providing data that could not be obtained implicitly by consumer behaviour tracking.

The third phase consists in *interpreting data* obtained from phase 1 and phase 2. Due to a high traffic, the previous phases will generate a massive amount of data that cannot be humanely read. Therefore phase 3 consists in developing data analysis tools that determine consumer behaviour insights (consumer types and associated behaviour, top-ranked products, virtual environments, etc…). The tools developed took the form of an analytic dashboard that displays in a synthetically visual method the key characteristics of the tryptic (consumer profiles/behaviour, product details and environment influences). Eventually this phase would result in the creation of a descriptive model that describes the tryptic relationship.

Finally, the fourth phase consists in developing the descriptive model, generated in phase three, to build *predictive tools*. The purpose of this phase is to identify tryptic associations rules. For instance, identify for a given consumer behaviour/type the most adequate virtual shopping environment in which to place a product that will trigger a purchase intention. These predictive tools will take the form of conditional algorithms that will be applied based on past consumer behaviour (looping back into phase 1). Based on the tracked consumer behaviour, the consumer shopping experience can be personalised to the consumer to promote purchasing.

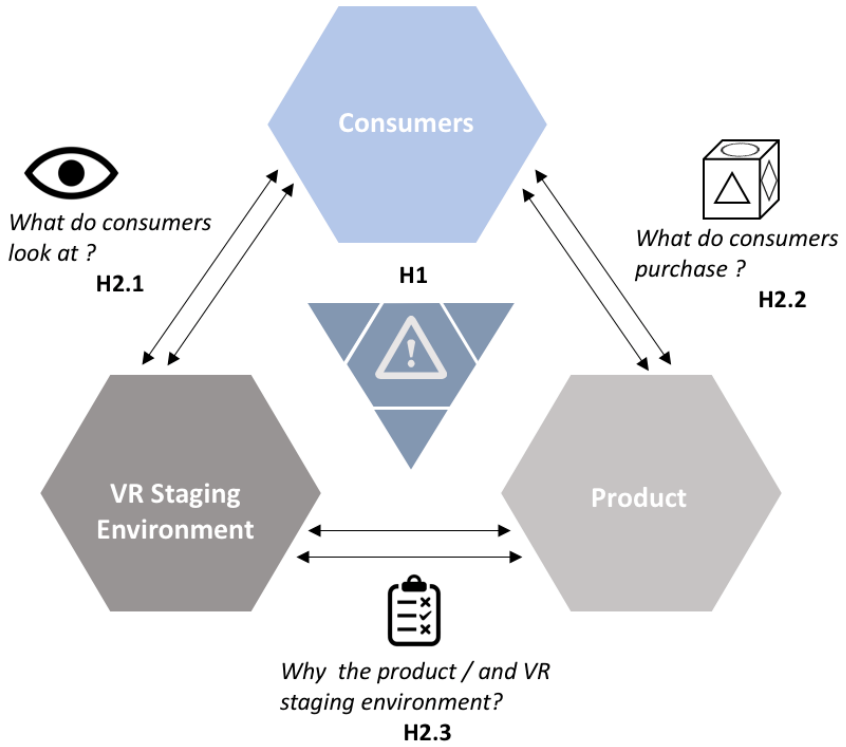


Figure 21. V-commerce tryptic

The tryptic figure displays how the elaborated hypothesis intervene in with the fundamental scope of this research. The first phase of the experiment consists in identifying a methodology to observe consumer experience during a VR shopping experience. This requires the study of the tryptic dynamics. This is described as the heart of the tryptic. The second hypothesis describes the interaction amongst each entity of the tryptic. The investigation of the consumer and VR staging environment entity help uncover and understand what the consumer is looking at. The investigation of the consumer and product relationship uncovers insight into identifying the modes of interaction with the product during a VR shopping experience. Finally, the study of the product and VR staging environment relation, consists in understanding what VR staging environment attributes best show case a given product from a consumer's perspective. The investigation of this relationships requires a semantic analysis of both entities during the VR shopping experience.

"Your most unhappy customers are your greatest source of learning"

– Bill Gates

Microsoft

Chapter III

Experimental Development

To execute the formalised 3DR3CO methodology described in the previous, this chapter will dive into the working processes of the 3DR3CO technology. Throughout this chapter we explore how to observe consumer navigation data, by describing the developed eye-tracking solution and how it contributes to the construction of a descriptive model. The modes of interaction with the product are described by presenting the developed productsheet tool and BSAs that aid in the virtual staging environment exploration. Finally, the modes of evaluating the consumer's perception and satisfaction by presenting the developed VR survey and VR rating tool help infer consumer affective insight and reinforce the quality of the descriptive model. This chapter describes how the descriptive model is used to derive a data-driven design process of the VR shop by extracting real-time consumer insight and personalising the shopping experience. The validity of the elaborated hypothesis was verified by the implementation of the 3DR3CO technology on real-life consumers providing 2 case studies and how it was used to promote customer experience on v-commerce. The results are analysed and discussed to identify areas of improvements.

III.I Seeing through a customer's eyes

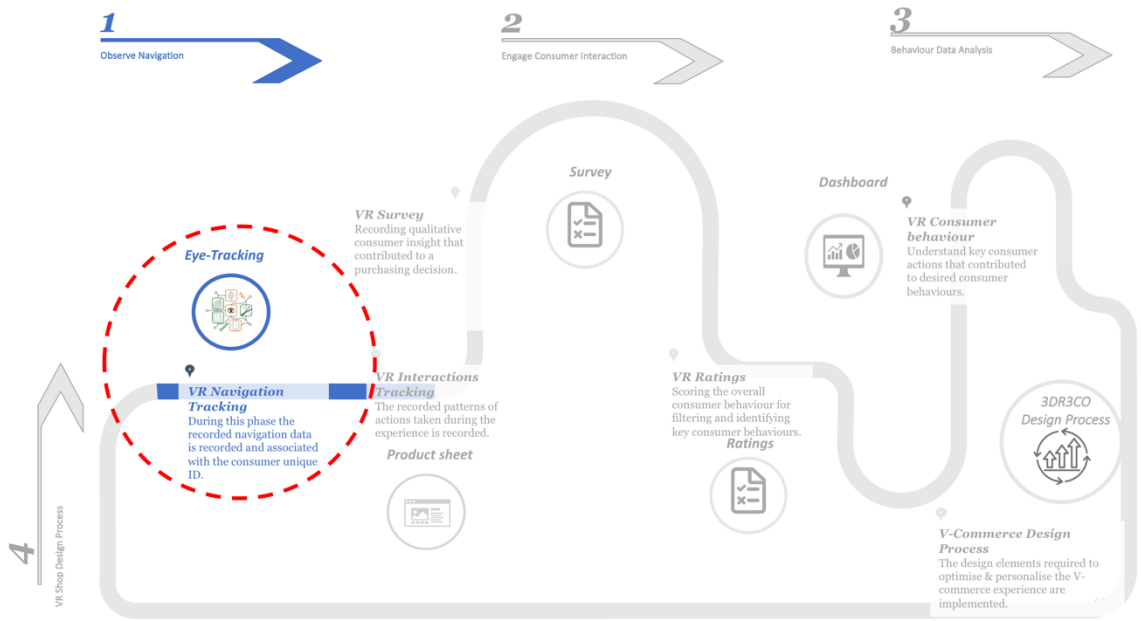


Figure 22. 3DR3CO methodology - observing consumer navigation

The undertook state of art displayed that the visual information contributes to 70% of the information processing a consumer's perception. This underlaid the importance of tracking what the consumer is looking at throughout their VR shopping experience. More specifically, we have investigated modes of identifying the product and environment attributes that retained a consumer's attention and whose visual stimuli contributed to a consumer's perception.

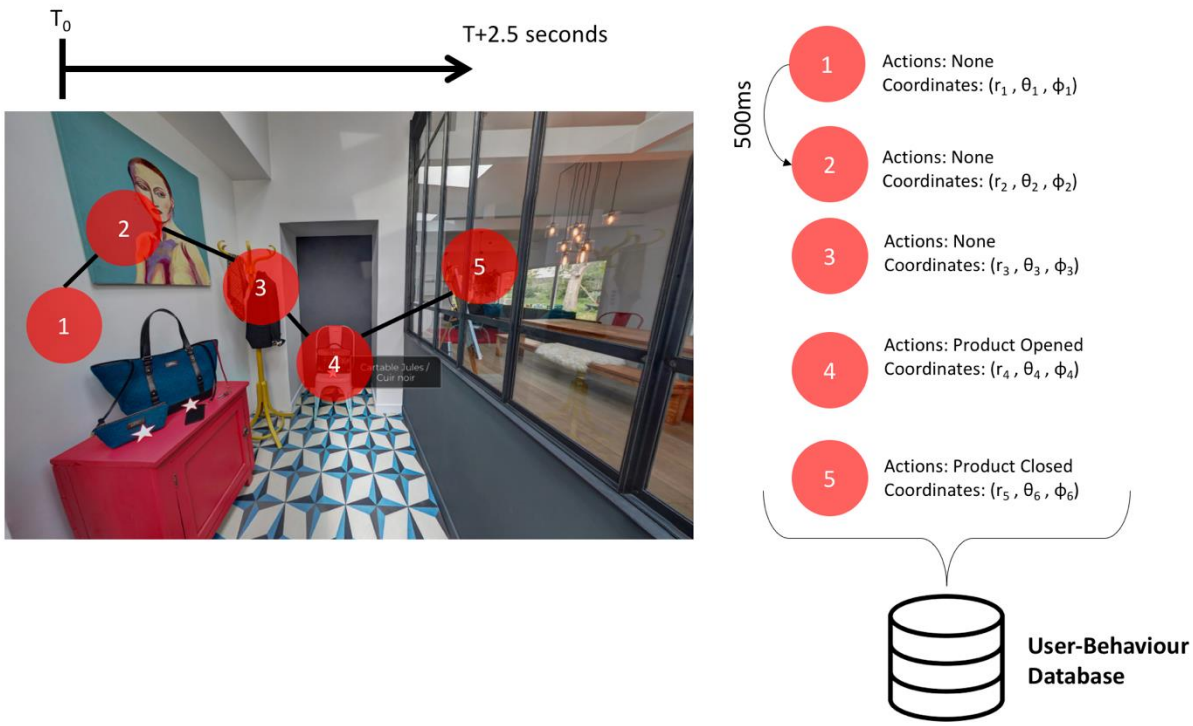


Figure 23. A 2.5 second glimpse of a VR behaviour tracking process

The figure above displays how an eye-tracking functionality can be incorporated onto a v-commerce experience. Moreover, this functionality proves to be a non-invasive and inexpensive method of understanding a consumer's affect. This is achieved by recording activity timestamps in cookies at a defined frequency for the consumer's heading. What this means is that the physical coordinates of a consumers' sights are recorded each 500 ms [Menon, R. et al., 2016]. The frequency of the time-space stamp recording was determined from the literature review above to record average fixation periods be between (~ 50 - 600ms). This represents the necessary consumer perception time to form preference.

Figure 24. DIAKSE eye tracking player platform

In order to visualise the recorded consumer-behaviour an eye-tracking player was developed to re-simulate customer journey. This platform allows e-merchants to study what the consumer has visualised during a purchase-decision process in a detailed manner. It was noticed that re-simulating the heading of the consumer was not informative, as the undertaken interaction was not recorded. Therefore, an improved version was developed to consider the interactions (gaze per clicks) executed during the consumer experience. Each consumer journey was classified with a unique ID, to facilitate the analysis of the virtual environment and product characteristics on to the consumer decision making process. The eye-tracking player contained a pre-programmed filtering feature to display the most meaningful consumer journeys (i.e.: longest journeys, most purchased products, most seen scenes, etc..).

Analysing the consumer journeys on an individual level provides an opportunity to dive into the details of how the virtual environment impacts each consumer behaviour. However, this mode of analysis is trivial and non-scalable for an e-commerce site with high traffic. The eye-tracking player solution above does not portray a big picture of the overall consumer behaviour to extract trends. Moreover, due to the subjective nature of the consumer behaviour, the eye-tracking player platform does not provide e-merchants with a rapid recommendation of the overall consumer behaviour. For this reason, a heatmap solution was

developed to complement the eye-tracking platform into highlighting main regions of interest of in the virtual environment.

Figure 25. DIAKSE heatmap platform

The heatmap feature depicted in the figure above leverages the recorded time-space consumer behaviour data to provide a heat signature of the overall consumer behaviour in each scene. The heatmap highlights what regions the virtual environment attracted the most attention. This solution indicates new potential regions of interests that retained the most of the consumer's attention and would represent an opportunistic product placement location. This solution enables the e-merchants to vary the product placement and study its' influence on the consumer behaviour. The heatmap above displays a colour coding that displays the "warmest" regions with the colour red and "least warm" regions with the colour blue to no colour. The warmth of the region is determined by the frequency of the recorded spherical coordinates. As a result, the most common recorded spherical coordinates are the red-coloured regions. This solution has also proven that the attention of consumer can be controlled by placing interactive call to actions (i.e.: buttons, products, signs etc…), since the overall attention is concentrated at the centre of the virtual environment. The heatmap allows to observe the variation of the consumer behaviour through time by filtering through different dates and different scenes. Overall, the eye-tracking platform leverages the

implicitly recorded navigation data (saccades and fixation periods less than 500ms that do not contribute to clicks per gaze) to provide actionable insights to consumers.

III.II V-Commerce Mode of Navigation

Due to the nature of the v-commerce solution, the autonomy level of the consumer's and naturalness of the interactions were critical to improving the level of presence, which bolsters the emotional experience. Various focus groups were carried to study the different modes of interactions and ensure an intuitive v-commerce experience. Due to the novelty of VR technology, we are often confronted to difficulties, where potential consumers have never had a VR experience and their inability to navigate autonomously becomes frustrating and hinders any purchasing opportunities. This displayed the need to develop an explanatory welcome tutorial, that describes the various modes of interactions in VR to improve the consumer's VR experience.

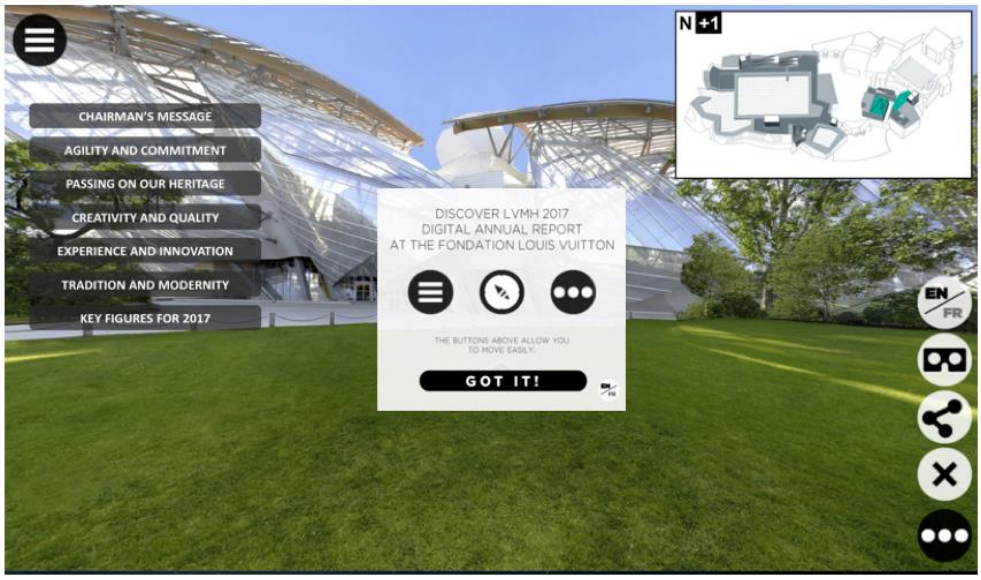


Figure 26. DIAKSE Welcome Tutorial

The tutorial displayed at the centre of the figure above helps reduce learning-related interactions and minimise perceived biased consumer behaviours seen through the eye-tracking solution. This is done by walking first time consumers throughout the necessary functionalities to be autonomous during a v-commerce experience. A study was undertaken

to identify modes of detecting first-time consumers (using IP geo-location) to avoid repetitive welcome tutorials and allow for recurring consumers to quickly dive into the v-commerce experience. A second study was undertaken to identify the most used functionalities of the logged user-behaviour to determine which functionalities new-time comers require explanatory assistance with. The difficulty of this solution was to explain the use of the VR shop minimal text to avoid information overload. Inspired from the undertaken literature review to improve affordance, familiar buttons were used to focus users' attention on the buying experience instead of learning [Norman, D. A., 1990]. The objective of this work is to fundamentally record interactions that represent desired actions of the consumers and reduce false manipulations that may pollute the user-behaviour database and introduce bias to the predictive recommender systems.

The welcome tutorial provides a sense of autonomy and serves as a help me mode for users to understand the purpose of a button before clicking it. This increases autonomy and favours navigation, which results in a higher level of presence, eventually intensifying immersion. In the context of facilitating and improving consumer interactive in immersion, a VR-based version of the menu was developed.

Figure 27. DIAKSE VR Interactive Menu

To avoid overflowing the immersive v-commerce experience with information a VR menu BSA was developed that triggers the necessary information upon looking downwards. The trigger of the interactive menu was designed to overcome the phenomena when a user in VR is not sure of how to navigate throughout the VR experience and has a “lost” sensation. Whenever

there is discrepancy between the real world and the virtual world (giving rise to a lost sensation) users tend to look down in the VR environment to locate their body and identify a position of reference [Yao, R., Heath, T et al., 2014]. This interactive menu, is configurable but contains the necessary functionalities (quit the virtual shop, empty the basket, and validate shopping cart) for a complete v-commerce experience. To further improve the consumer experience in VR mode, a shopping cart icon that follows the consumer's eye that indicates the number of items on the basket. The challenge of this feature was to design an affordant icon to reduce explanatory texts that hinder the VR experience. Inspired by the reward sensation of the hooks model users get when ticking off a notification, this icon contains red indicator to attracts attention and increase the intention to validate the basket. With the aid of the behaviour tracking solution and the rated experience, the time taken to undertake each action is studied to evaluate the consumer's comprehension and continually improve the v-commerce experience.

Consumers need to constantly geolocate themselves for presence (Simon Richir et al., 2015) to know of the whereabouts in a virtual environment and an increased. To this end, a navigation map is used as an imported behaviour schema (IBS) serves the purpose of a frame of reference and allow the consumer to have a bird-eye view of the VR shop. The map allows consumers to skip a defined consumer journey and directly 'teleport' to a scene of interest. This helps us to study the impact of self-localisation on consumer behaviour and the improvement of virtual shops.

Figure 28. Modes of navigation

To study the consumer's preferred methods of interaction in v-commerce we alternate amongst various modes of navigation to identify the most accepted method. The figure above displays. The figure above illustrates 3 modes of navigations used during a v-commerce experience. More precisely, we aim to seek what mode of interaction facilitates navigation throughout the visit and retains consumers. The longer consumers are exposed to virtual environment and product characteristics, that trigger purchase intentions the more likely they are to purchase an item. The progress bar layer (highlighted in orange) is developed to evaluate the impact of a consumer's self-actualisation onto consumer behaviours. Each circle of the percentage bar represents a scene, indicating a level of completeness. The circles in the progress bar are initially white and filled upon each scene visit. Therefore, we seek to study if the intrinsic factor to tick off all the remaining scenes drive consumers to longer onto longer explorations during a v-commerce experience. Another mode of exploration corresponds to the displacement layers and hotspots (highlighted blue and red, respectively). The displacement hotspots correspond to embedded BSAs that contains a fixed position in the virtual environment and only visible when in the user's field of view. The displacement layer BSAs correspond to elements fixed to device's web-browser and is constantly displayed regardless of the consumer's heading.

III.III Product sheet system

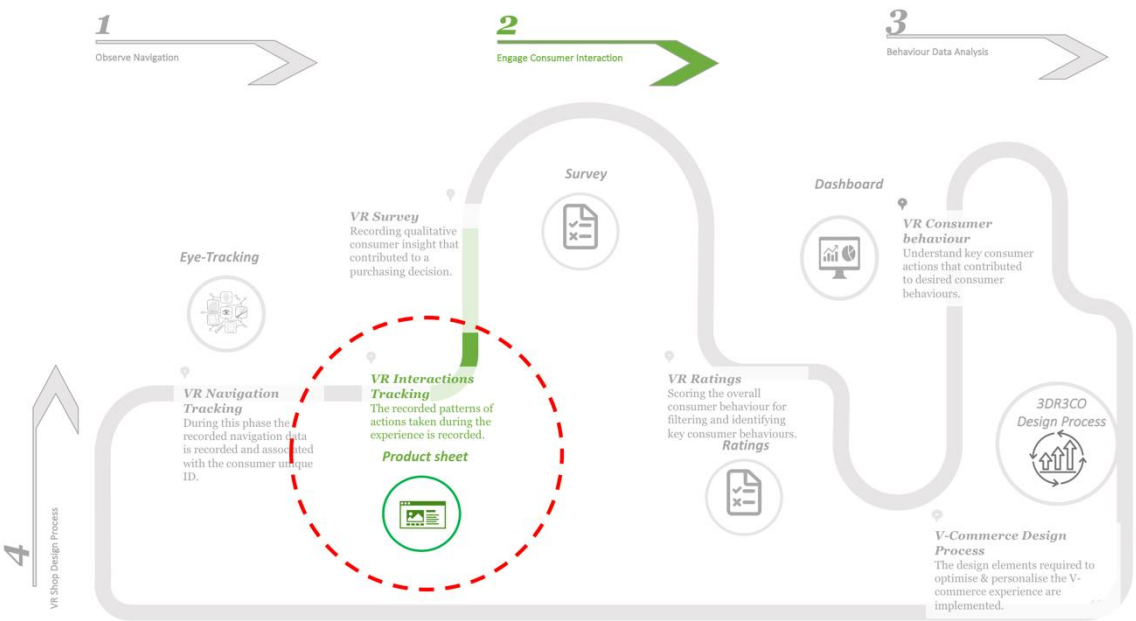


Figure 29. 3DR3CO methodology – engage product interaction

The conveyed product information is critical to the construction of the consumer's perception construction. Throughout this section we will explore how the product sheet solution was developed to establish a communication channel between the consumer and product entity. We will also explore, how this solution plays a fundamental role in the construction of the 3DR3CO technology, which aims to push upfront product attributes that match consumer attributes within a given virtual environment. The development of a product sheet was initially designed in a repetitive, non-configurable, and manual process, for every product type. This mode has proven to be non-scalable and time-consuming and inhibited the speed of v-commerce developments. Hence, a study was undertaken to re-design the product sheet as a system that, identifies and push forwards product attributes that resonated with a consumer's preferences and psychographics in real-time.

The first feature of the product sheet required a study in how to convey to the consumer that a placed product in the virtual environment is interactive (for sale) and not a décor. Therefore, a configurable BSA was developed to convey interactivity and incite clicks. A star icon is transposed in front of the available products to be purchased. The product sheet star BSA is used as an interactive element that attracts attention using colour contrasting and pulsations. Once the consumer's field of view is attracted towards the region within the virtual environment where the product sheet star is anchored, a product name tag is displayed to bolster the consumer's curiosity to open and browse the product sheet.

Figure 30. DIAKSE VR Product Sheet

The figure above displays the product sheet that is displayed upon clicking the product sheet star. The product sheet is used to convey product attributes that aim to promote purchase intentions and study their impact on consumer behaviour. The novelty of this product sheet is the modular and automated design process in which it is constructed. This modular process allowed to rapidly personalise the product sheet attributes to each virtual environment (virtual boutique). The development of this product sheet system allowed to dynamically create, rename, update and delete product detail information and study its' impact on the consumer's perception. As a result, the product sheet provided rapid automatic modifications

to various product attributes with 1-click and in real-time. For instance, the dynamic updating of the product prices to study the price perception with different virtual environments and atmospherics. The product sheet system allowed to vary and adapt the semantics and modes (auditive or textual) in which the descriptive texts was used to motivate the consumer's purchase intentions to each consumer types, cultures and generations. The product sheet's descriptive text can be adapted based on the consumer's logged IP address and web-browser settings to identify and study the influence of culture and origins on v-commerce behaviour. The configurability of the product sheet layout design allowed to study the consumer's attention to different product attributes during a purchase-decision making process. The consolidation of the product database allows to dynamically verify and update and account for the stock of each product. Overall, the product sheet along with the developed eye-tracking solution provides the possibility to gain insight in real-time of what product attributes attracted the most attention and were most impactful during a decision-making process.

The development of the product sheet system allowed for a rapid roll out to various e-merchants whose products/services ranged from insurance, décor, luxury cosmetics leather goods, etc… This quickly underlined the need to have to display the product under different angles. The angles and the contextual scenarios are chosen such that they bring out different attributes of the product that may match a consumer's motivational drivers, values and personality. This allowed to push forward the different attributes of the product to shape the consumer's perception representation of the product to allow for the consumers to project themselves. The product sheet system was therefore optimised to incorporate minified thumbnails, that would display a zoomed version in the product sheet's top left main image section.

Figure 31. Product Sheet Thumbnails (product aspects variations)

The development of the thumbnails makes it possible to highlight various aspects of the products that could trigger and motivate consumer purchasing intentions. With the aid of the recorded user-behaviour, this allows to study the product attributes that shed light on a consumer's motivational drivers defined in chapter 2 (functional, aesthetic, social, situational, curiosity) [Sheth, 1975]. For instance, consumers who gave peculiar attention to the glamour fabric during the purchase decision making process were driven by a social and prestige motivation. Studying a consumer's way of browsing a product sheet thumbnail along with the semantic meta data associated to each component allows to provide psychographic insight to complement the navigation data. The recorded user-behaviour database can be used in developing predictive models (discussed in the next section) to personalise the v-commerce experience and promote purchasing behaviour.

Figure 32. Product Sheet Thumbnails (product colour variations)

Following the carried literature review, it was noticed that hedonic emotions driving consumer preferences are shaped by the colour atmospheric. Therefore, the product sheet thumbnail system was optimised to allow consumers to browse and purchase different colour models of the product. This allowed to study the influence of colour contrasts (virtual environment and product) on purchase intentions. Overall, the thumbnail feature provides a method to collect in real-time the influence of the different product characteristics onto the consumer behaviour.

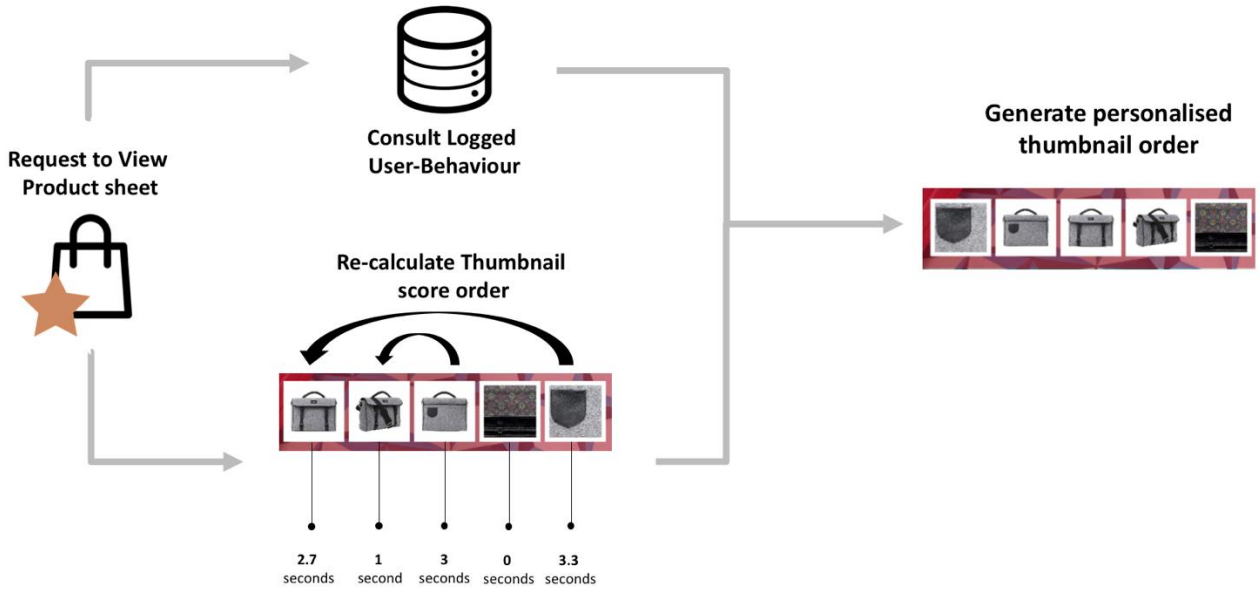


Figure 33. Smart order thumbnail system

The figure above displays the working process of a smart order thumbnail system. As soon as a user requests to view the product sheet of a product that may have attracted their attention to consult further information and purchase. The logged user-behaviour database is consulted to extract the overall time each thumbnail was seen. The time spent on each thumbnail from the overall user-behaviour is used as a scoring order to rearrange the thumbnails using a collaborative filtering algorithm. As a result, the consumer is exposed to thumbnails who have retained the most attention, with the objective of promoting purchase intentions.

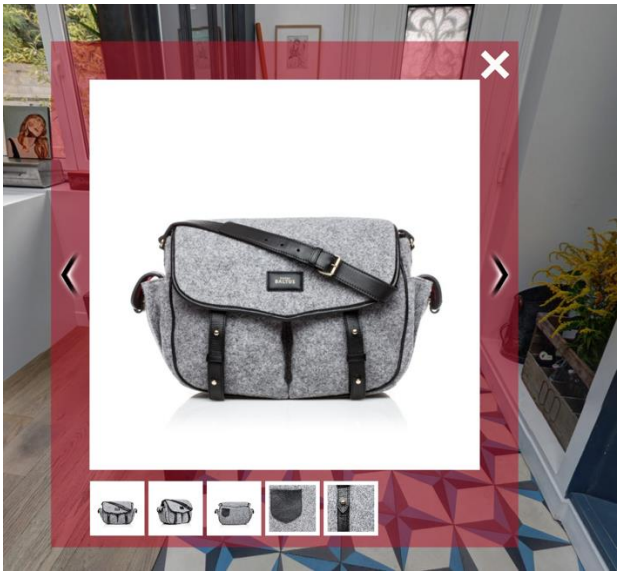


Figure 34. Product sheet zoom feature

Consumers who are often quality-oriented are driven to check the fabric and the material of the product prior to purchasing the product. In order to compensate for the consumer's inability to touch and diagnose the product's quality, a zoom feature was developed to bring out the small product attribute details. The zoom feature provides a better and realistic impression of what the product looks and feels like, which reduces the product return ratio [Krannert, Prabuddha De and Mohammad S. Rahman,2010]. The time spent on different product attributes helps identify what associated descriptors of the product attributes trigger the consumer's interest and effectively understand their preferences. It was important to also include alternative photos within the zoom feature to enable customers zoom into the different parts of the product and form a holistic impression of the product. The realism of the products was carefully chosen as to not create unrealistic expectations in to avoid product returns. As it can be displayed in the figure above, the alternative photos used in the zoom feature and the product staging, display the product only without any unusual attractive effects.

To access the immersive VR experience consumer may use a mobile device equipped with gyroscope. However, to favour smartphone mobility, today's devices have reduced screen size and weight for easier transportation. As a result, we identified the need to work on

responsiveness (the adaptability of the product sheet on different screens and virtual reality headsets to evaluate the importance of comfort in a consumer experience).

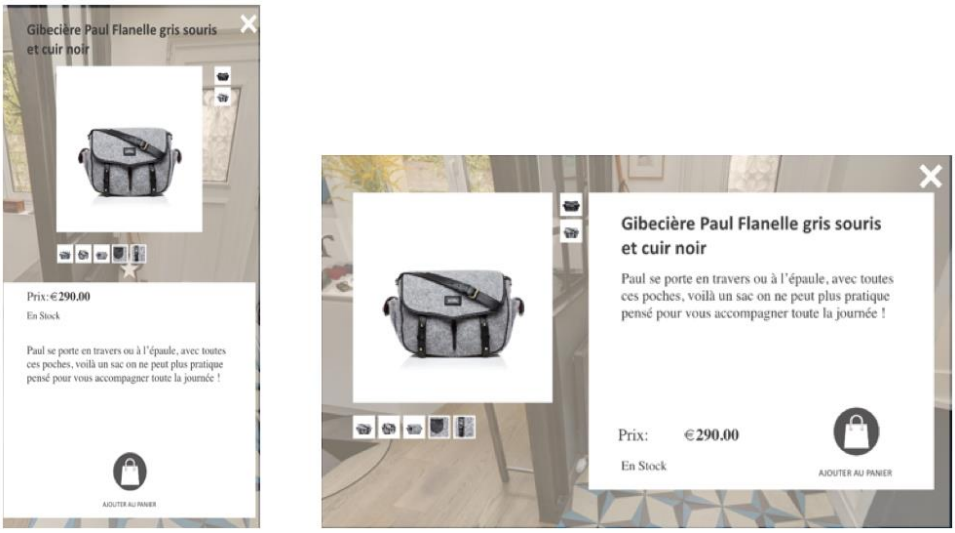


Figure 35. Product sheet in portrait mode (left) and landscape (right)

The portrait mode depicted in the figure above, is the product sheet design layout presented on mobile devices to fit in the smaller devices. This allows the user to keep an overview of all the key product details at a first glance. Inspired by the gestalt theory of law of connectedness to reduce the cognitive load, the contrast with white background regions was used to group similar information. For instance, in the landscape mode above the multimedia properties were grouped to the left, while descriptive texts that serve as motivators were positioned alongside the “add to basket” button to promote purchase intentions. A self-explanatory “add to basket” icon was used as a different colour to attract the attention of the consumers and indicate an interactive region within the product sheet system. The incorporation of a responsive product sheet system allows to easily change product attribute layouts and evaluate its’ impact on consumer behaviour.

III.IV Incorporating Affect

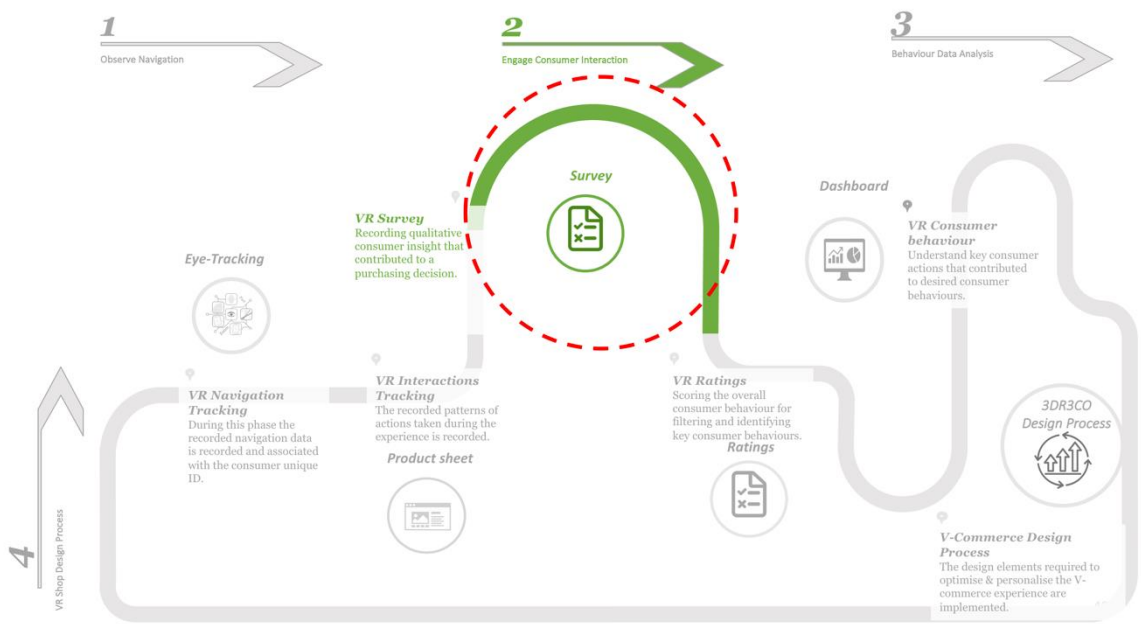


Figure 36. 3DR3CO methodology – engage consumer affective state

The carried literature review highlighted the critical value of emotions during the during a purchase-decisions making process. It was noticed that collecting navigation and interaction data was not enough into identifying, classifying and leveraging consumer psychographics and preferences to personalise the consumer experience. Therefore, throughout this section we will discuss the methodology and tools developed for a v-commerce that provides and uplifts the user-behaviour data with the subjective preferences of each consumer. The common convention noticed in the undertaken state of art required, the design of a consumer feedback protocol using a survey. Consequently, we developed a 3-step process that is administered on laboratory participants.

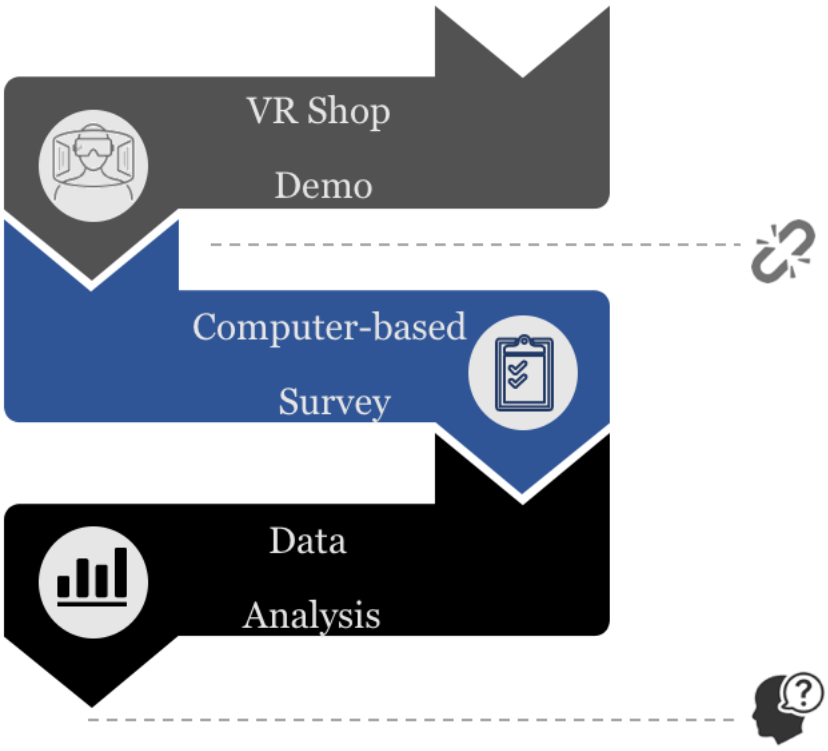


Figure 37. 3 Step Consumer Feedback Collection

The consumer feedback collection protocol displayed above consists in providing the participants with a simulated v-commerce scenario in which they are asked to browser a VR shop, purchase an item in the demo and fill up a computer-based questionnaire to evaluate the emotional state. As soon as the consumers quits the VR experience to move to the second step, there was a disconnection phenomenon. The computer-based survey is composed of Likert and semantic differential scales to quantify the emotional states. Finally, the recorded results displayed an incoherence, where most of the users quit the survey before completion due to confusion and fatigue. This, method of collecting qualitative consumer feedback has proven to be ineffective due to separation of experience and the evaluation mode. Consumers relied on their memory of the VR experience to answer the survey, which has proven to biased responses, due to survey fatigue, and frustration and hinders a v-commerce experience. The challenge was to identify a mode to observe in real-time the emotional state of consumers, without obstructing the v-commerce experience to overcome discontinuity issues.

Consequently, a VR survey was designed to be triggered during the v-commerce experience to allow for a consumer affective evaluation in immersion. This helps respondents remain in the same mindset as during their VR shopping experience and reduce the impact of media changes (immersive VR to a 2D computer-based layout) onto biasness. Moreover, the VR survey provides the respondents with the facility of no longer having to rely on their memory during the evaluation process, reducing survey fatigue. To help overcome survey-fatigue, the survey tool is equipped with a progress counter that reassures the respondents about the longevity of the procedure. The logged user-behaviour activity tracking allows to observe in real-time how participants respond to continually improve the survey feature.

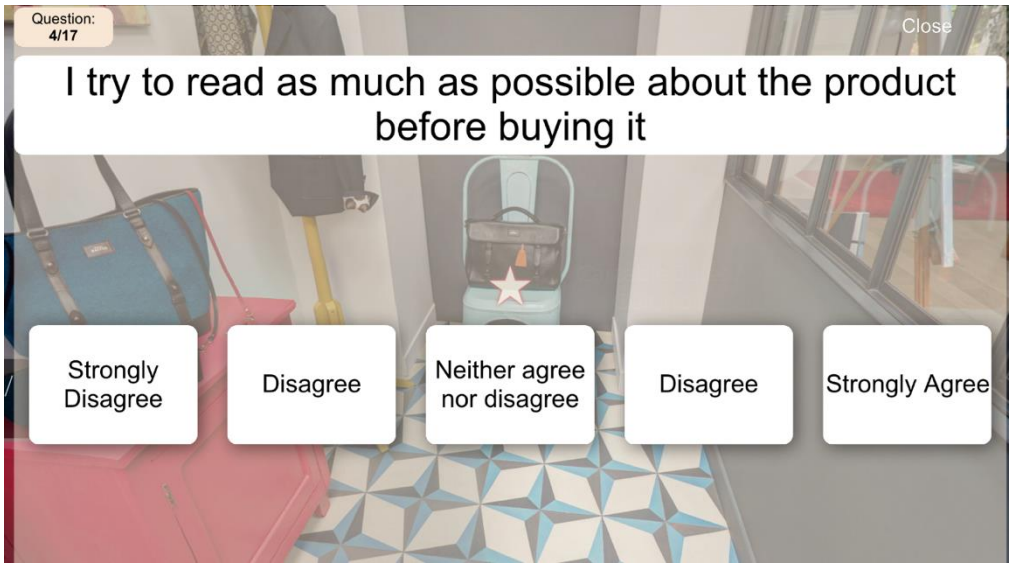


Figure 38. VR Survey feature

The VR survey corresponds to a platform that amasses qualitative feedback. The qualitative feedback data corresponds to the affective data that explain, justify and help classify the navigation and interaction data. Complimenting the navigation and interaction data with the consumer's emotions, psychographics and reactions to visual atmospherics insights in real-time helps uncover a clearer image of the consumer's perception. Overall this survey tool has been designed to have a configurable trigger and give e-merchants a channel to compliment user-behaviour data with by directly asking consumers questions at the right time (i.e.: when a desired behaviour, such as adding an item to the basket, takes place).

A difficulty encountered during this research was the reliability of the purchase intention evaluations in laboratory environments. Given the research scope of this study, which revolves around identifying consumer intentions, a discrepancy was noticed during the product evaluations. Through informal feedback during the alpha testing of the VR survey, it was noticed that the recorded product evaluations were based on products they wished to purchase and did not correspond to items they purchase in their day-to-day basis. The simulation of the consumer experience only allowed to record what the consumer wished to purchase and did not correspond to the real consumer purchase intention. To overcome this, a protocol was developed to bring VR survey tool to real online shopping platforms who use the DIAKSE v-commerce solutions, whose consumers truly have purchase intentions, when adding an item to the basket.

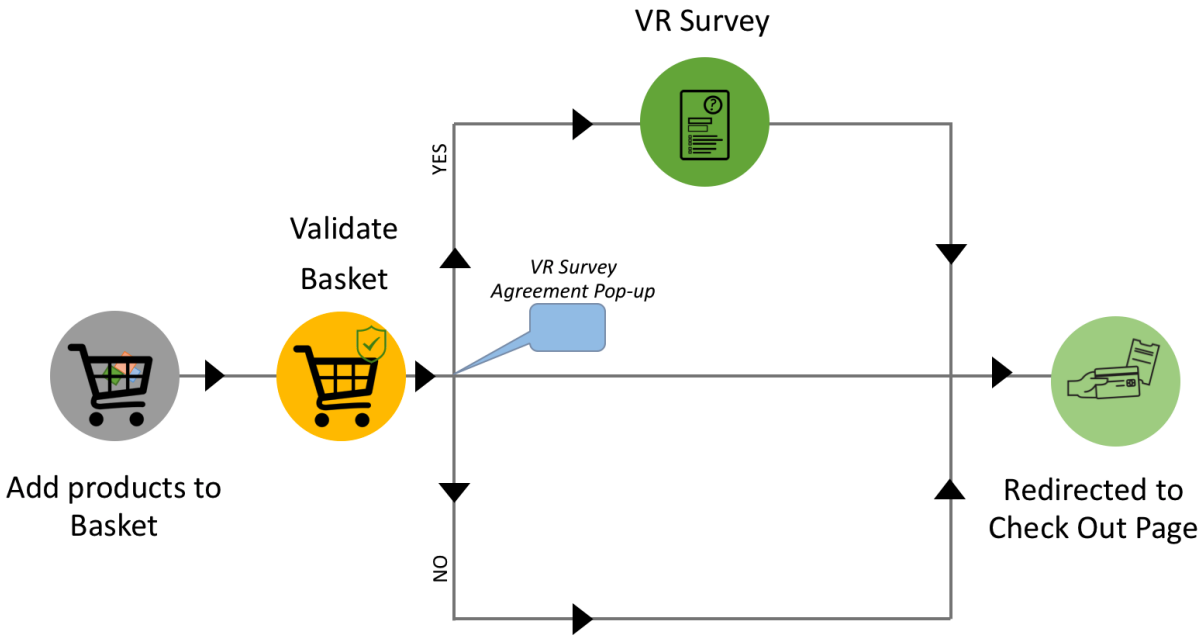


Figure 39. VR Survey protocol to evaluate true purchase intentions

The figure above displays a protocol that makes use of the VR survey tool to provide qualitative consumer evaluations based on true purchase intentions. As soon as the consumer proceeds to checkout after having added a product to their basket a pop-up is displayed requesting permission to participate in a survey. Upon the completion of their survey, or refusal to take part in the survey, they are redirected to the checkout page. The VR survey provides qualitative data to gain further insight into the psychographics that have contributed to a purchase decision and uncover the tryptic dynamics.

The VR survey allows to test for 3 modes of evaluations. The first mode (for simplicity reasons, let us call it **text mode**) corresponds to a text mode of questioning (illustrated earlier), which allows the consumer to respond to a text question in a multiple-choice. The answers are quantified using a 3/5/7 scale. The second (for simplicity reasons let us call it **hybrid mode**) refers to a text question with an image and Likert-like multiple choice of answers. This mode allows to display an image of an item to be evaluated and allow it to remain within the consumer's field of view during evaluation. Finally, the third mode (for simplicity reasons let us call it **image mode**) corresponds to a text question, with a set of images as multiple-choice answers. This mode allows for respondents to visualise complex answers prior to answering. All the answers are instants recorded and stored in the user-behaviour database.

Figure 40. Image Likert Scale mode (Left) & Image Selection mode (Right)

The VR survey platform provides qualitative psychographic data to aggregate the behaviour-based data (*navigation* and *interaction*) and better understand the v-commerce tryptic dynamics.

Figure 41. 5 step consumer modelling with the VR survey

The figure above describes the five main components of the VR survey to model the consumer's psychographics. The first component consists in using the *text mode* of questioning to profile the consumer using the OCEAN model, age groups, connection geo-location. Throughout this phase consumer's profile is as vector of openness, conscientiousness, extraversion, agreeableness and neuroticism (big five personality traits identified in the state of art). The consumer is directed towards the second of the component automatically. Throughout this phase, the purchased product is evaluated using the *hybrid mode* of questioning for semantic profiling and associate the product's attributes with a set of semantics. The selection of the semantic attributes is obtained through a CTA analysis [Bouchard, C., Omhover, J., Mougenot, C., & Aoussat, A., 2007] of the brand. A dimension reduction was then conducted to reduce the variables, which eventually reduces the complexity of the product analysis [Mantelet, F., 2006]. The third phase uses the *image mode* of questioning answers to allow the consumers to select an environment that best stages the purchased product. Upon choosing an environment the consumer is immersed in the chosen environment where the purchased product is staged. A second evaluation of the newly staged product is undertaken in the fourth phase with the same semantic variables using the *hybrid mode* of questioning to evaluate perception distortions associated to the selected

environment. Finally, the consumer is questioned on the nature of their VR staging environment choice using the *text mode* of questioning to evaluate why the staged environment was chosen to evaluate if the choice was for aesthetic or functional purposes.

III.V Quantifying the consumer's mindset in VR

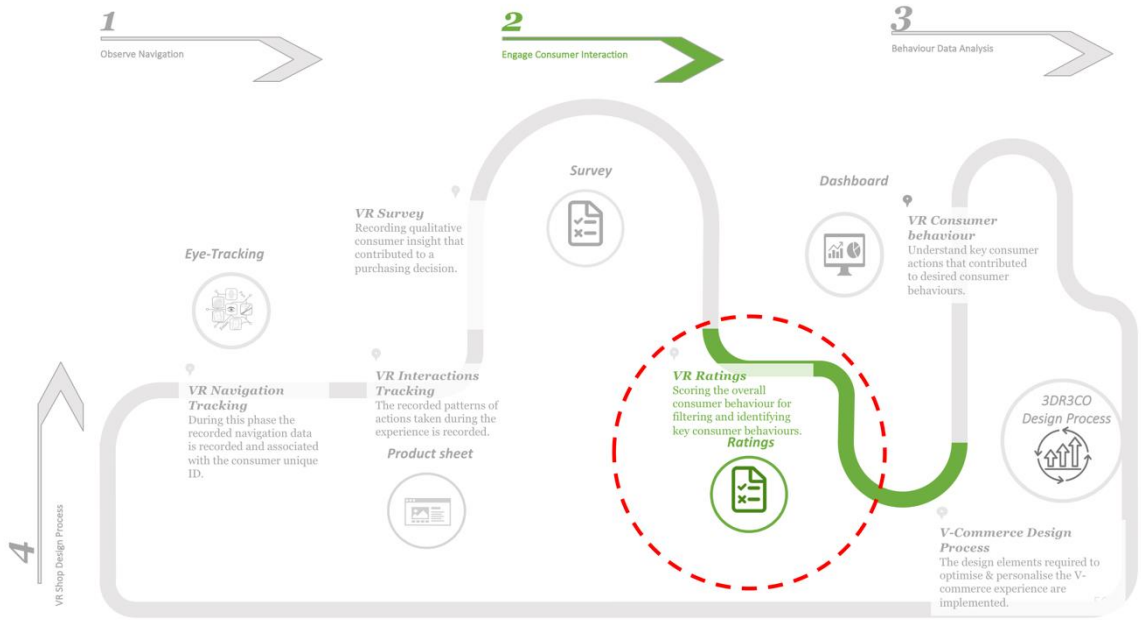


Figure 42. 3DR3CO methodology – evaluating overall v-commerce experience

An evaluation tool (we refer to as the *rating feature*) integrated within the v-commerce solution to rate the consumer experience was developed to quantify and rate the overall consumer experience. This tool is designed as a modular plugin, that is easily enabled or disabled for each virtual shop.

Figure 43. DIAKSE rating feature

The development of the rating feature provides with a platform that evaluates whether consumers are willing to rate the overall v-commerce experience. Furthermore, this solution provides a method to associate a given rating to a consumer's behaviour data and effectively quantify the consumer experience. Quantifying the consumer behaviour data helps identify purchasing behaviour patterns that have contributed to a hedonic experience, to improve the v-commerce experience. The association of the ratings is done by allocating the ratings with the same ID as the user-behaviour data. Currently, the ratings feature is deployed as a popup at the end of the consumer experience (before proceeding to the check-out page). As displayed by the figure above the ratings uses a 5-star scale method to evaluate the experience. The 5-star scale method of evaluation was chosen due to its' abundance on the most popular online solutions (i.e.: Facebook, Google, Amazon, Netflix, etc...). This has allowed it to become the conventional mode of rating services, experiences and products. Their ease of use highlighted their interest and minimised biased evaluations [McGlohon, M., Glance, N., & Reiter, Z., 2010].

Currently the ratings feature is employed to evaluate the overall consumer experience and is only associated with the virtual environment entity. This feature has the potential to be extended onto the product entity to incorporate the user-ratings towards a product and its' influence onto the consumer behaviour. The integration of the ratings features to the product entity allows to evaluate whether consumers are likely to evaluate products they buy or don't

buy and how the recorded ratings impact the consumer behaviour. Associating the ratings feature with a product allows to extract and quantify correlations between the tryptic characteristics, (consumer behaviour, product and virtual environment characteristics).

III.VI The Dashboard (Analytics Platform)

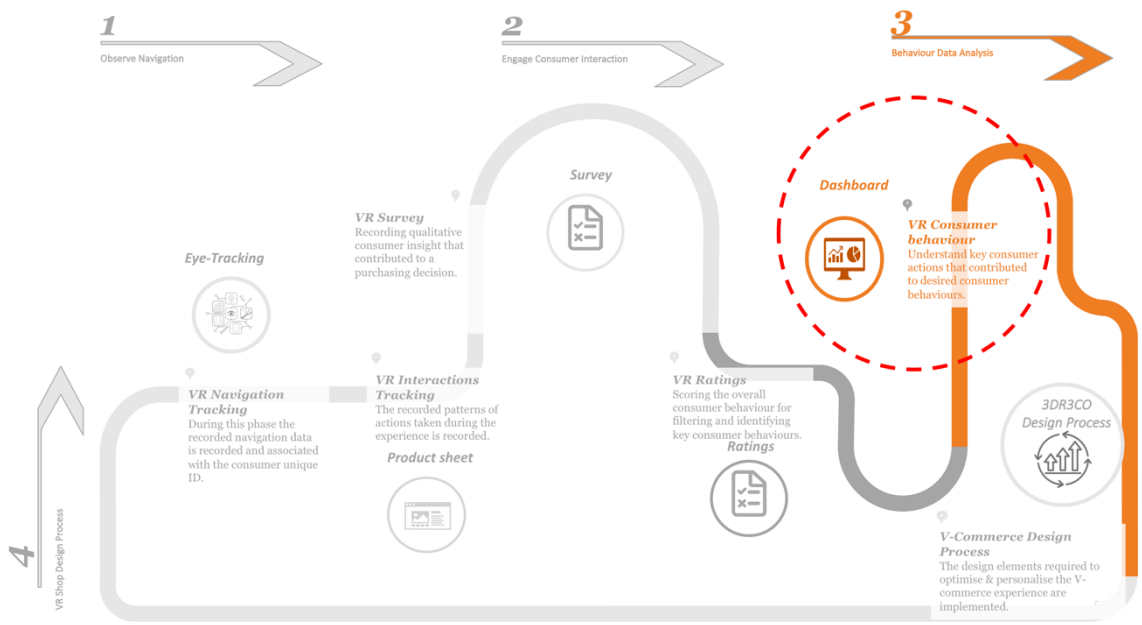


Figure 44. 3DR3CO methodology – behavioural data analysis

The navigation and interaction behavioural system assistants BSA's provide massive data that logs the context of the purchasing process of each consumer. This data is stored in a user-behaviour database, that is analysed to gain insight about the v-commerce and provide a general overview of consumer behaviour. In order to analyse and understand the content of the database, an analytics platform to interpret the consumer behaviour raw data into visually insightful graphics was developed. The raw data is depicted through a set of bar graphs, pie charts and radar charts. The analytics platform (let us name this tool the *dashboard* throughout this research work) represents a tool that e-merchants use to evaluate the current status of the v-commerce and study the consumer behaviour. The *dashboard* parses through user-behaviour data to parse raw data and generate visually insightful graphs. These insights are used as key performance indicators (KPIs) to help identify VR features that correspond to specific consumer preferences to continually optimise v-commerce and personalise the shopping experience to promote purchase intentions.

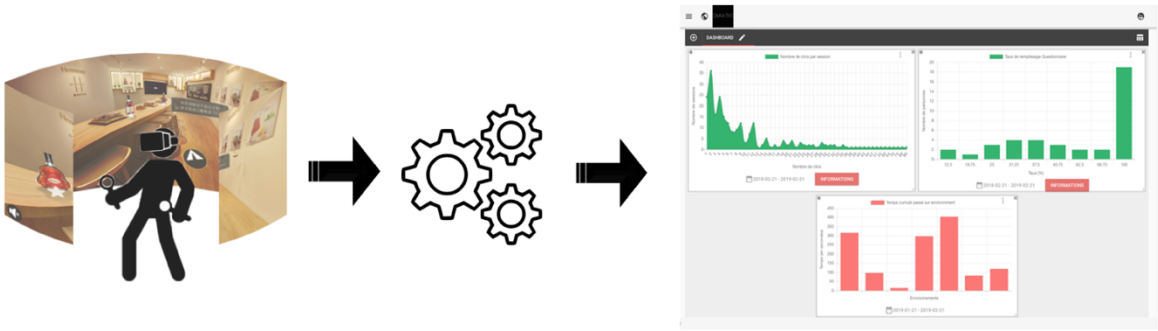


Figure 45. DIAKSE V-Commerce Dashboard

The *dashboard* allows to represent the v-commerce user-behaviour database into a platform that provides the e-merchants with data such as: average consumer activity in v-commerce, top-browsed products, top-purchased products, most successful virtual environment scenes, age-groups, consumer-profiling, product-profiling, etc… The *dashboard* provides low-level insight, such as: the average number of clicks, top virtual environment region coordinates, common first behaviours, etc… for A/B testing. A/B testing refers to a random controlled experiment with two variants to for a two-sample hypothesis testing. This is used to identify low-level insight to identify most opportune time to trigger specific actions (i.e.: discount posters, surveys, ratings pop-ups, etc…) to increase user-engagements. Prior to the deployment of the VR survey to a v-commerce, a study was undertaken on the existing low-level data using the dashboard to identify the most opportune moment to trigger a survey to augment the consumer's engagement. The *dashboard* takes advantage of the abundant recorded raw data to help build a better sense of the consumer audience and their behaviour to assess how VR shop changes impact their perception. Analysing the low-level data to identify factors that contribute the most to a purchasing behaviour, aggregated with the high-level data helps infer factors to replicate and modifications to optimise the v-commerce.

Overall, the *dashboard* aggregates the data collected throughout the aforementioned tools into a platform that helps understand the tryptic dynamics (the cognitive mindset of consumers and the coupling of the semantic product and virtual environment preferences). The *dashboard* allows to reconvert and export the complex user-behaviour database into an

exploitable format (CSV) for advanced statistical analysis. The objective of applying statistical analysis is to be able to analyse the exported raw VR consumer behaviour data and extract formalised descriptive models. This can be done by applying the statistical analysis in the literature review. An open-source statistical computational and graphics software called "R" was used to achieve and formalise the descriptive models. The descriptive models determine correlations in the tryptic v-commerce relationship (consumer, product and virtual staging environment). For instance, each session can be categorised as:

$$Session_i = \sum_{i=0}^{n} (C_i\, x_i + P_i\, y_i + E_i\, z_i)$$

The equation above describes how the survey aids into modelling a user's *session*$_i$ (consumer's perception) by considering their consumer profile attributes (*C)* product attributes (*P*) and staging environment attributes (*E*). The discrepancies in the product/environment coupling and the proximity of the tryptic factors are verified to study the impact of the staging environment onto the consumer perception. The analysis of the various consumer behaviour during the v-commerce experience allows to develop a descriptive model of the different consumer types. The descriptive model is constituted of the survey retrieved data (*Session*$_i$) and the recorded navigation and interaction data (IN_i) displayed through the analytic dashboard:

$$Descriptive\ Model = f(Session_i, IN_i)$$

This phase is undertaken at a server-level, where the user-behaviour database is parsed to aggregate the harvested consumer behaviour data. The dashboard synthesises the massive consumer behaviour logged data for a rapid overview of the consumer key performance indicators. Throughout this stage low-level and high-level calculations are undertaken to convert raw data into insightful graphics, tables, eye-tracking platforms and heatmaps.

III.VII 3DR3CO Design Process

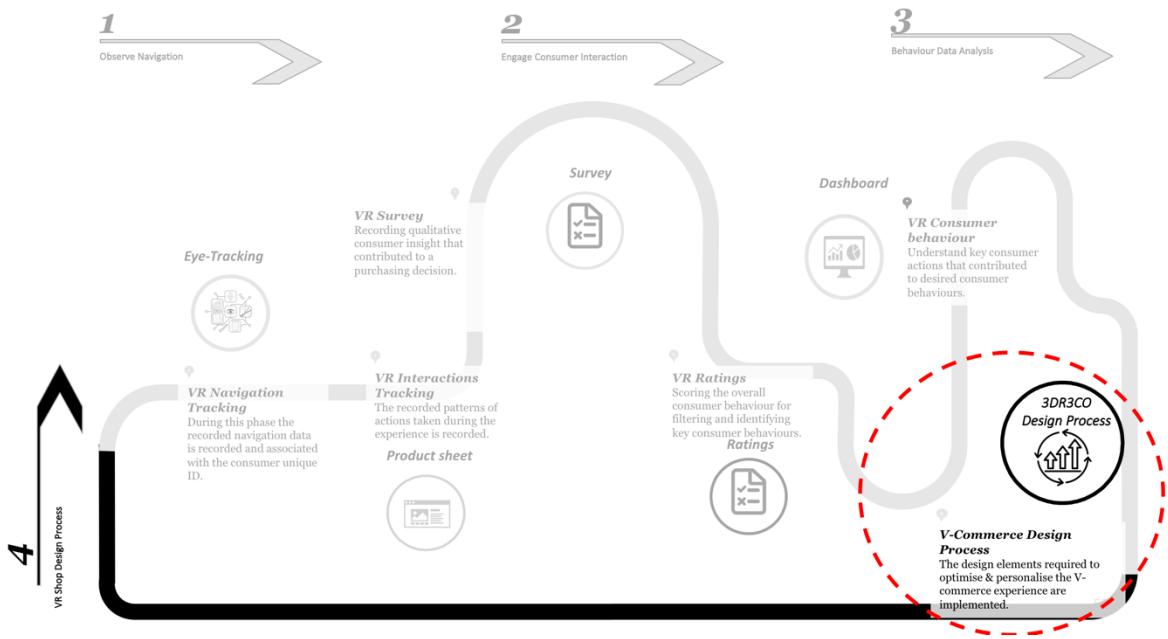


Figure 46. 3DR3CO methodology – VR shop design process

The ensemble of the v-commerce tools contributes to the development of constitute a 3DR3CO technology. The aim of the 3DR3CO technology is to determine real-time consumer preferences towards products and staging environments and help continually optimise the v-commerce experience. This process is undertaken on an administrative level (e-merchants, product owners, etc…) in which the dashboard data is leveraged to optimise and adapt the consumer experience based on the overall user-behaviour. The overall consumer behaviour data is studied to identify new VR shop design improvements on a tryptic level. The dashboard graphical data is exportable to an exploitable format (CSV) to allow for product owners to analyse the insights using any business intelligence tools. Throughout this stage the product owner undertakes a 4-phase analysis:

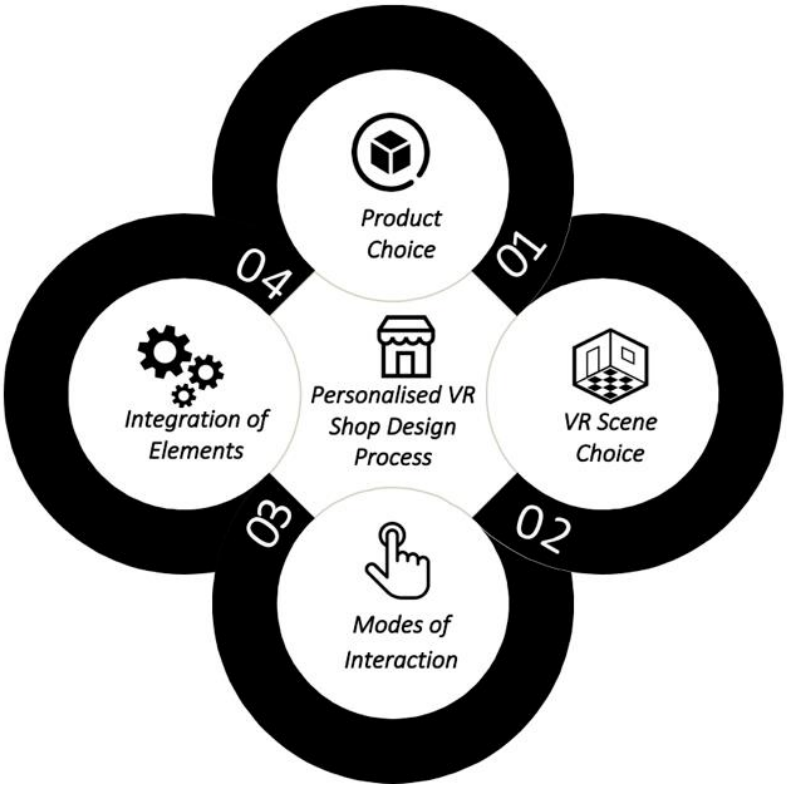


Figure 47. VR shop design process

The four-step process above infers from the consumer VR shopping behaviour new design elements for a personalised VR shopping experience to entice a desired behaviour (i.e.: purchase intentions). The first step involves the extraction of rules that define a new product ranking based on the (product attributes, product categories and price range). This helps uncover what type of products are being considered for a given consumer group. The second step refers to extracting the data that describe the current consumer behaviour on the VR staging environment to provide insight on the virtual environment. Insights, such as: the most viewed scenes, most engaging areas in each scene, the number of times spent in each scene, the number of scenes seen in total etc… can be extracted to describe the environment entity of the tryptic. The third step consists in investigating and extracting insight on the modes of consumer interaction with the VR shop. This includes studying what modes are being used to navigate throughout the shop, such as: the use of radar maps, different usage of BSAs (to study different modes of navigations). Other modes of interactions are also studied, such as: what product sheet features are clicked/viewed on during a purchasing decision process, how do users browse various types of VR shops when in a marketplace mode etc…). Finally, the fourth step consists in aggregating the sum of the design elements

uncovered to provide an optimised version of the VR shop that matches the consumer's overall behavioural preferences and promote purchasing. The optimisation of the design elements allows to personalise in real-time the consumer experience by tailoring key VR shop design elements to match preferences. Continually feeding the descriptive model database with consumer behaviour logged data in response to a VR shop's design elements allows to extract patterns and behaviour trends that provide insight on consumer preferences and develop predictive models (recommender systems). A revised version of the VR shop continually loops through the above framework to optimise the predictive model's efficiency.

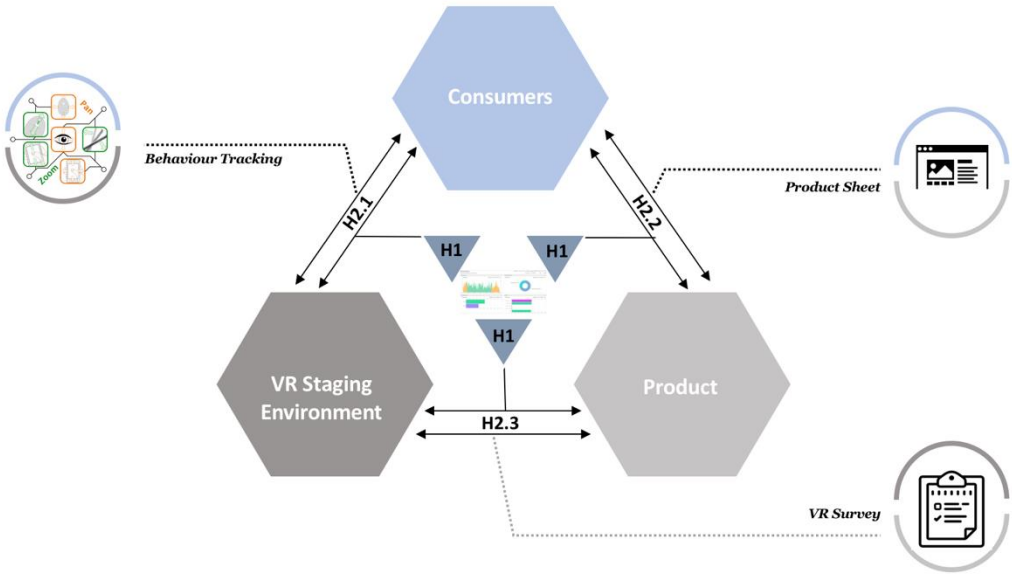


Figure 48. V-commerce tryptic analysis

III.VIII 3DR3CO V-commerce suite

The various v-commerce solutions intervene in the 4 phases of the 3DR3CO methodology. The ensemble of the solutions constitutes the 3DR3CO technology, whose objective is to determine a consumer's insight over the product and staging environment coupling.

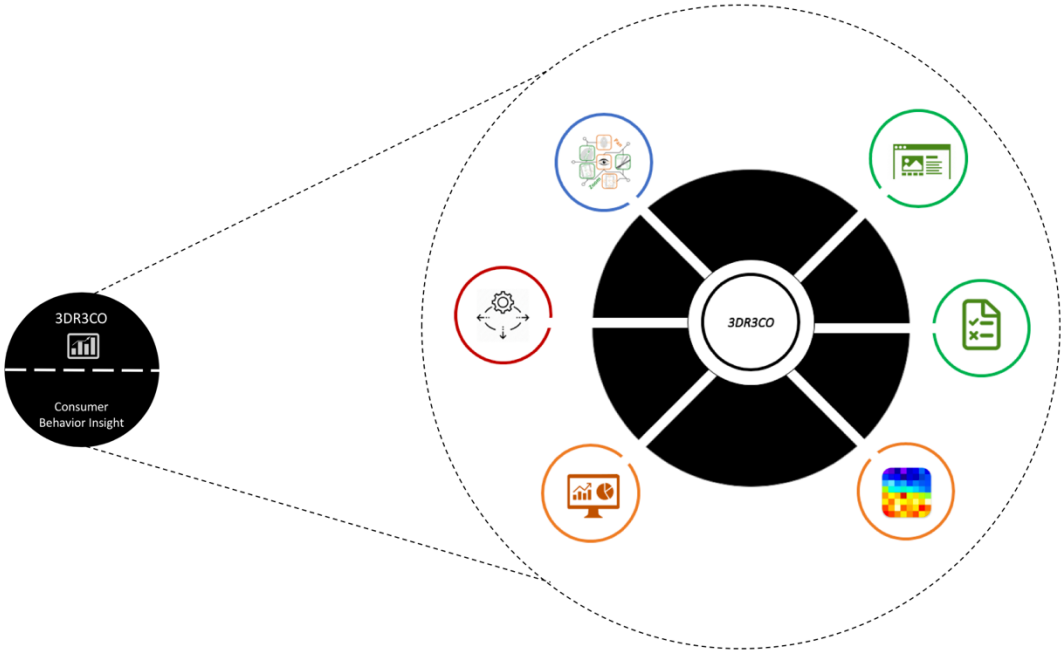


Figure 49. 3DR3CO suite of tools

The suite is used as a framework to design personalised and improved consumer experiences, by decoding the dynamics of the tryptic and leveraging v-commerce features to trigger desired behaviours. The insight retrieved from the 3DR3CO technology allows to take advantage of the virtual reality instrument to uplift the e-commerce experience with consumer behaviour insight and provide a personalised immersive shopping experience for each consumer.

III.VIIII VR Shop Case study – Plugin Mode

DIAKSE uses the plugin mode as a solution that is embedded onto an existing e-commerce site and allows consumers to dive into an immersive v-commerce solution that showcases the products in a virtual environment that stimulates purchase behaviour. Once the consumer is immersed in the v-commerce solution the 3DR3CO technology is implemented to record, analyse and personalise the consumer experience to promote purchase intentions. Throughout this case study we have conducted an analysis on a major e-tailor specialised in insurance, who wishes to showcase a variety of their products using the v-commerce solution. The experiment was conducted throughout a period of 1.5 years (December 2017- May 2019), which has provided us with 3,306 entries allowing for a good representation. A total number of 3,306 entries were recorded containing logs of navigation and interaction of the VR consumer behaviour. Amongst the total of visitors, 59 added a product to the basket and purchased it. This corresponds to a conversion rate of 1.79%. The aim of the VR shop provider is to immerse consumers within the brand identity and increase product purchasing. The 3DR3CO methodology was used to understand the consumer behaviour throughout the immersive experience and provide a personalised experience that promotes product purchasing. An A/B testing was conducted by displaying a VR shop and a conventional website layout to asses which platform drives the most purchases. It was noted that the VR shop has driven twice as much purchasing than the conventional website. The attributes of the 3DR3CO methodology, allowed us to understand further what factors contribute the most to purchasing intentions and eventually identify new design elements to promote purchasing.

The consumer navigation data was recorded, displaying the direction and length of the gazes as well as the number of VR clicks. It was recorded that the number of VR clicks ranged from 0-84 clicks. Amongst the total users, 294 have not undertaken any clicks and therefore have not been able to commence the VR shopping experience. This displayed that the guide commencement popup which explains the working modes of the experience, was not fully understood by 8.9% of the users indicating the first design element to be implemented and

validating H1. The sum of the navigation indicated that the median number of VR clicks was 4 clicks and a mean of 6.6 clicks the navigation data displayed that the majority of the consumer gazes was focused on interactive contents and the usage of interactive events attracted and retained attention. The average number of VR areas (scenes) a consumer was 4 scenes (first four scenes). This displays that the overall consumers visited 30.8% of the VR shop and recommends that the products to be staged in the first four scenes rather than a product per scene.

With the objective of identifying the consumer behaviour that has contributed to a product purchase act, a correlation analysis was undertaken on the sum of navigation and interaction data (products browsed, products purchased, and modes of navigation).

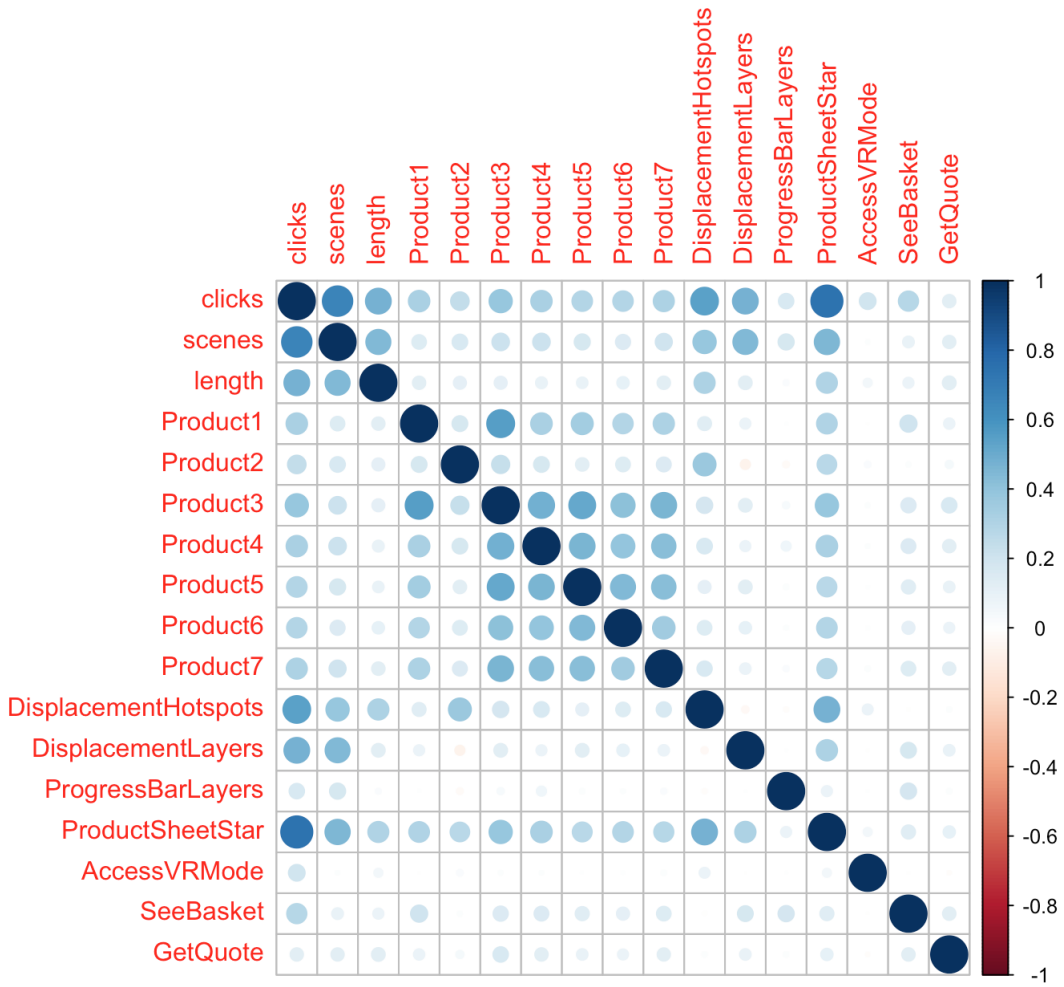


Figure 50. VR Shopping Behaviour Correlation Matrix

The "*GetQuote*" attribute refers to users that have requested a quote and validated their purchase. As a result, the objective of this study was to identify the various behaviour that has contributed to triggering such behaviour. It could be noticed from the graph above that the factor that correlates the closest to such behaviour is the scene (number of scenes visited), click (number of clicks undertook per user) and length(the time a user remains throughout the shopping experience) factor. As a result, it could be assumed that the users who have stayed longer during the VR shopping experience and viewed more scenes are more likely to add a product to the basket.

The highest correlation with the "Get Quote" button is the length attribute, with a correlation factor of 0.13 and p-value of 9.37e-14. The time span of a consumer's shopping experience correlates mostly with the number of clicks (0.47) and the scenes viewed (0.45) indicating that the longer a consumer is engaged by clicking more products and visiting more scenes the longer they tend to stay, which favours product purchasing. The correlation analysis displayed that the behaviour of browsing products had a correlation factor of 0.7 with the clicks, therefore it could be assumed that the increase of interactive contents (i.e.: product sheets) triggers more clicks and contributes to a prolonged engagement of consumers.

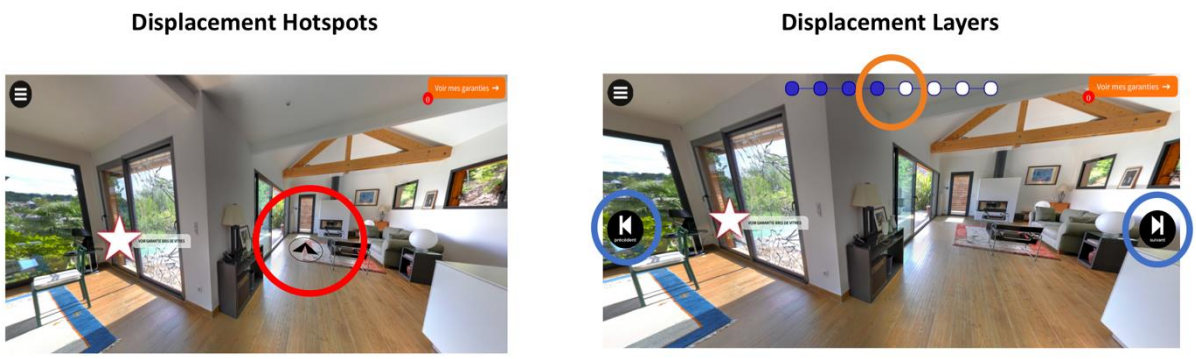


Figure 51. Modes of navigation within VR shop

The figure above displays 3 different modes of navigation: Displacement layers (encircled in blue), Displacement hotspots (encircled in red) and progress bar layers (encircled in orange). As it was defined earlier, layer buttons are anchored to the web-browser and are constantly in the consumer's field of view. Conversely, displacement hotspots are anchored in the virtual environment and only visible when the user is looking at its region. An A/B testing

was undertaken for a 2-month period where 1 month displays displacement hotspots and another month displaying progress bar layers and displacement layers. It was noted that the layer BSAs contributed the most to the exploratory behaviour of users, which correlated with a factor of 0.45 to the number of scenes viewed. Moreover, it was noted the number of scenes increased in the second month when implementing layer BSAs, which doubled the number of users who have seen more than 8 scenes.

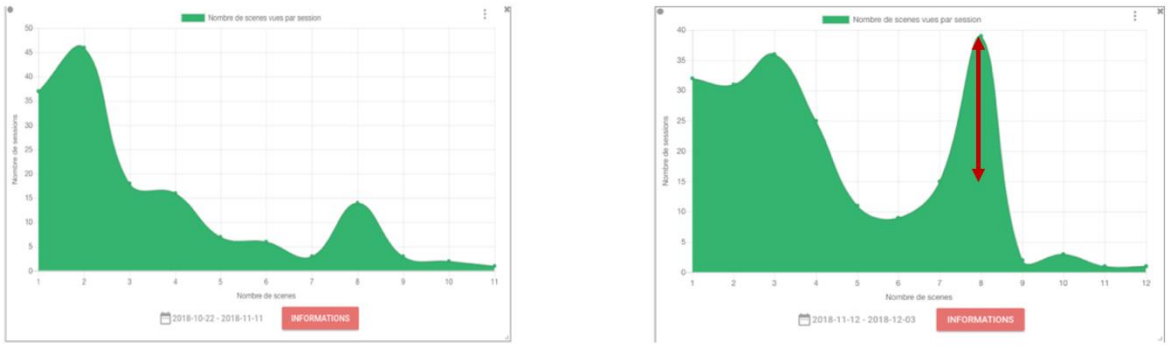


Figure 52. Number of Scenes viewed with displacement hotspots (left) and displacement layers (Right)

Finally, the progress bar layers were found to be slightly correlated with the “See Basket” call-to-action. This could be assumed that the visibility of buttons within the field of view of the user and the proximity to the “See Basket” call-to-action button increases the likelihood of triggering the desired behaviour. This provides us with new VR shop design elements that motivate the user to explore more scenes and effectively augmenting purchase intentions.

III.X VR Shop Case study – Marketplace Mode

The marketplace v-commerce mode provides consumers with the possibility of immersion into a virtual environment with various VR shops (art e-commerce sites, luxury leather goods, tourist sites etc…). Upon entering the VR market place the consumer is surrounded by buttons redirecting to each VR shop. Upon finishing the exploration of each VR shop the consumer can return back to the initial starting position (home). Let us think of this as a mall that hosts different brands.

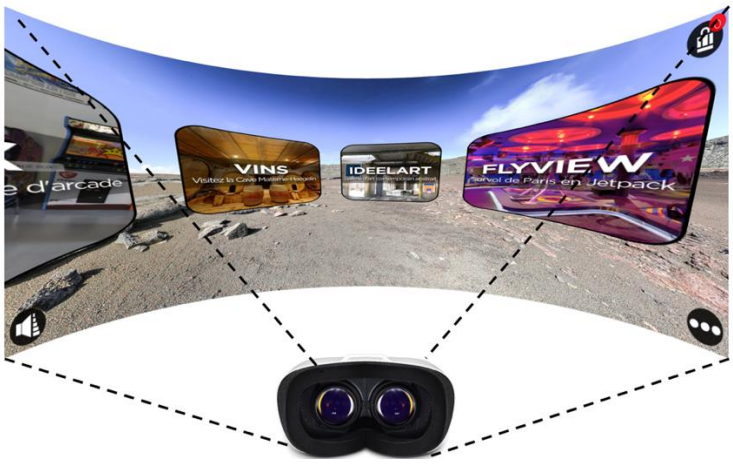


Figure 53. DIAKSE Marketplace

As it could be seen from the figure above each button, represents an entry point to each VR shop. Each button is distributed equally in a spherical coordinate encircling the consumer's field of view. The VR marketplace contains 8 VR shops. The consumer may enter a VR shop through gaze-for-click lasting 1 second. For a good representation we consider 885 random entries retrieved from a 1-year period (July 2018 – July 2019). The 3DR3CO framework was used to record, analyse and identify key tryptic elements that drive purchase intentions.

The behaviour tracking solution allowed to record the navigation and interaction of the consumer. Out of the considered 885 entries 89.9% corresponded to active users. The active

users were distinguished from inactive users by logs who display an experience lasting more than a defined time and contains a set of minimal clicks. An explicative welcome tutorial explains the working mode of the v-commerce solution at the beginning of the experience. Hence, the number of inactive visits, may correspond to the number of users who have either inadvertently entered the v-commerce solution or did not understand how the immersive experience works. Therefore, the consumer logged navigation data (H2.1) provided design element to consider for a personalised improved VR consumer behaviour. This highlights that the first design element to consider is the explanation of the working modes of a VR shopping experience to personalise the experience. As a result, throughout this paper we will consider only the 796 entries providing significant consumer behaviour data.

Projects	Products Purchased	Products Viewed	Total Scenes Viewed	Number of Users	Position
Tourist Attraction	1	24	171	60	Quad 2
Art Gallery	5	46	67	28	Quad 2
Home Decor	15	83	88	57	Quad 4
Beverages	9	69	251	84	Quad 1
Tourist Attraction 2	17	72	605	313	Quad 3
Gaming	60	150	181	254	Quad 1

Table 11. DIAKSE VR Marketplace Analytics (July 2018- July 2019)

The aim of the VR shop provider is to take advantage of VR to increase product purchasing. The table above displays a summary of the exported data by the dashboard concerning the overall logs of each of the valid 796 entries to be assessed. As it could be seen the VR shop who had the most user visits logins corresponds to *Tourist Attraction 2 with* a total of 313 users. Each VR shop is constituted of various scenes. The navigation data of a consumer in a VR shop allows to observe design elements for the VR shop (H1).

The consumer navigation data was recorded, displaying the number of scenes visited within each VR shop. The consumer behaviour was recorded by logging the data on the product sheet tool, providing qualitative consumer behaviour insight (i.e.: number of products purchased and type of products browsed). Amongst the VR shops available in the marketplace the “Gaming” VR shop had the most purchased and browsed products and stacked a conversion rate of 26.3%. The sum of the navigation indicated that the mean number of scenes visited for each project was 2 scenes. This displays that upon entering a VR shop from a VR marketplace the consumers are willing to explore 2 more scenes (validating the hypothesis 1 and hypothesis 2.1. The observed navigation data provides us with design element to extract consumer behaviour insight and optimise the VR shopping experience.

Each scene contains a set of products that a consumer may purchase. For simplification purposes we have represent each scene with a circular plane decomposed in 4 quadrants (Quadrant 1: Shops or Products positioned between 0-90°, Quadrant 2: Shops or Products positioned between 90-180°, etc...). This corresponds to the potential field of view of the consumer. As it was described earlier, the VR marketplace corresponds to a scene with a button pointing to VR shops equally distributed around its 4 quadrants. The objective of this study is to identify what characteristics in a VR marketplace contribute the most to purchase behaviours. Hence a correlation analysis was used to identify the interactions and navigation factors.

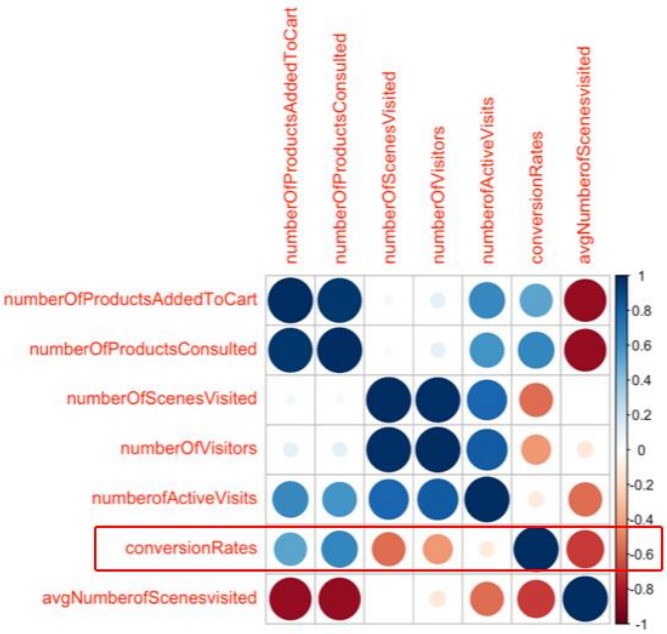


Figure 54. Correlation Analysis of VR marketplace insight data

The table above displays that the conversion rate is mostly correlated to the number of products purchased and the number of products browsed. Interestingly it also displayed a negative correlation to the average number of scenes visited, which indicates that consumers who have found a product of interest to purchase do not continue browsing in the VR shop. Due to the monotonic relationship between the ordinal factors of consumer behaviour and the uncertainty of a linear relationship, a spearman rank-order correlation was used. The analysis displayed that the conversion rate correlates positively to the products purchased (corr = 0.714 and p-value= 0.136). However, the conversion rate negatively correlated (corr = -0.657 and p-value = 0.175) with the average number of scenes visited. Hence, to increase conversion rates, consumers should be able to browse the products which display the need to increase traffic in each VR shop. The data retrieved throughout this experiment does not allow to distinguish returning users from new users and corresponds to a technical limitation to consider for a future study. As a result, a perspective analysis for the study, would involve investigating what scenes have been seen and what products have been purchased to deeper conclude on the relation between the number of scenes and the number of products purchased.

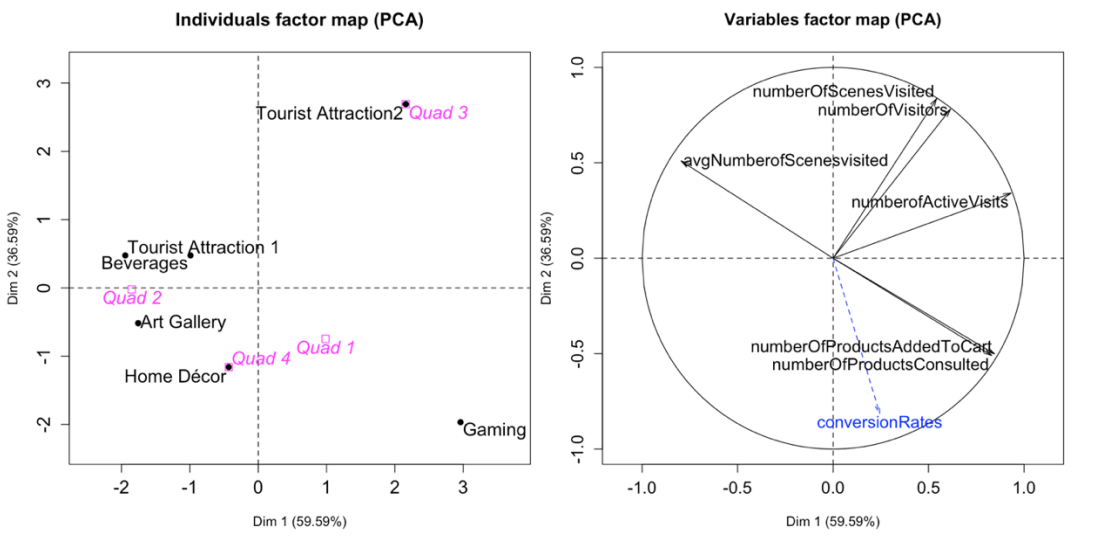


Figure 55. PCA analysis on VR marketplace consumer behaviour

The PCA analysis in the figure indicates the conversion rate variable is closely related to the VR shops located between the 1st quadrant (0-90°) and 4th quadrant (270-360°). It is to be noted that the consumer's starting view commences at 180° which is located between quadrant 2 &3 displaying buttons towards the Art Gallery and Tourist Attractions VR shops. The tourist attraction 1 VR had the highest number of visits, while the Art gallery had the fewest number of visits. However, the initial positioning of the of the VR buttons towards the VR shops had no impact on the conversion rates. The price ranges of the products sold in the two VR shops with the highest conversion rates varied from €8 - €2,500. The two most successful VR shops (Gaming consoles & Home Decor) sold solid objects as products. Therefore, it can be assumed that the VR experience bolstered the perception of physical products (home decors products and gaming consoles) more than abstract products (i.e.: tourist attraction tickets, art galleries, etc…). The exception of the leather goods VR shop not having a high conversion rate maybe to the tactual diagnosis need (need to touch the material and try the product) during the consumer decision making process.

III.XI Summary

The conducted experiments allowed us to display the validation of the stated hypothesis.

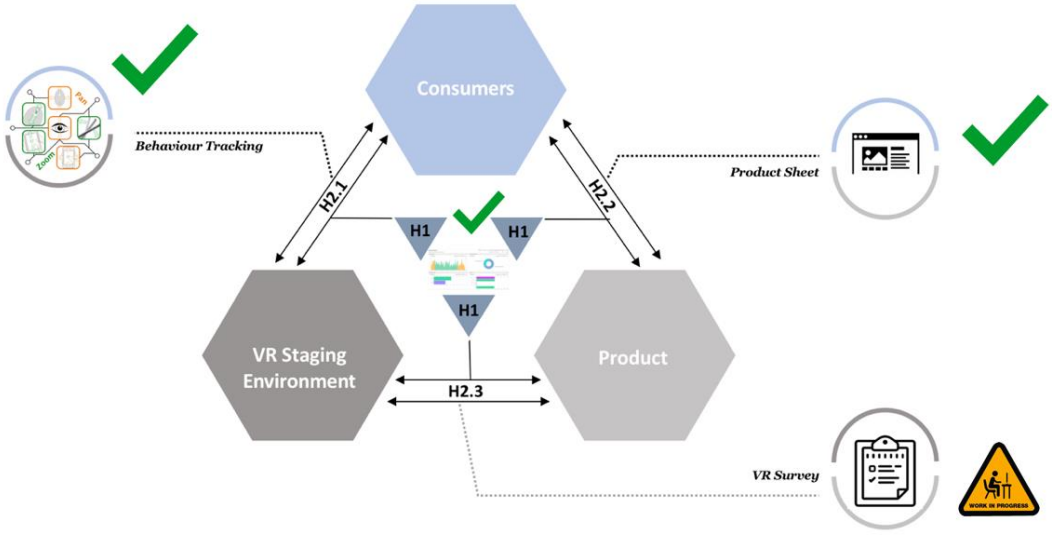


Figure 56. Hypotheses validation status

The purpose of both experiments is to establish a methodology that makes use of the developed suite of products to verify the validity of the hypotheses. The aim of the methodology – with our research question in mind – is to establish a process that clarifies **how to incorporate consumer behaviour analysis to optimise the V-commerce design process and promote purchase behaviour?**

The development of a behaviour tracking technology and a data storage protocol validates the first hypothesis. It was proven that the consumer navigation data can be observed and stored. The overall behaviour logged data is then accessible to extract general behaviour trends through the developed dashboard. The purpose of this methodology is to provide a platform that allows e-merchant owners and VR shop designers/developers to observe in real-time the general behaviour activity on the VR shop.

The hypothesis 2.1 refers to the analysis of the consumer navigation data to establish design elements and improve the consumer experience. The logged consumer behaviour navigation data is explored by extracting recommendations of the number of scenes explored, time spent, and modes of navigation between scenes (displayed in the e-merchant case study) to extract VR shop design elements. The development of various modes of navigation and assessing the general user behaviour allows to identify the most optimal mode of navigation.

The VR shop design elements serve as improvement criteria to be implemented to match the current general user-behaviour. The e-merchant experiment proves the validity of the hypothesis 2.1

The hypothesis 2.2 refers to the analysis of consumer interaction with a product sheet data to extract consumer preferences. The developed product sheet represents the gateway between a consumer and a product. The interactions with the product sheet (i.e.: main description texts reading time, most attractive thumbnails and most purchased products, price ranges of most purchased products) were logged into the consumer behaviour database. The extracted product design elements helped understand the general user-behaviour and extract design elements to match consumer preferences and promote purchasing. Product design elements such as such as the average time spent when browsing products were used as guidelines to re-adapt text description lengths. The purchased product's price was used as a guideline to identify optimal VR shop pricing strategies. The time spent on each product's images was used as design element to re-order the set of thumbnails. The purpose of this is to continually prioritise images that retain the most attention and promote an act of purchase. The interaction with the product through the product sheet tool help optimise and personalise the VR shopping experience to promote purchasing, which validates the hypothesis 2.2

The hypothesis 2.3 refers to the analysis of a consumer's perception and affect to identify design elements that personalise the VR shopping experience and promote purchase behaviour. The tools developed to extract such consumer feedback are the VR rating and VR survey, which allow to record in full immersion the consumer cognitive evaluations, to better understand the purchasing behaviour. The developed tools were subjected to a beta test, whose aim was to assess the acceptability of consumers during a VR shopping experience in a marketplace environment. The results of the beta test displayed the consumer's level of acceptability was too low for implementation. This meant very few users chose to evaluate the VR shopping experience using the VR rating solution or provide qualitative feedback with the VR survey. The validation of the hypothesis 2.3 could not be confirmed as the VR consumer experience's affect is not considered in the undertaken experiments. The experiments above indicated that a typical user on average undertakes 4-6 VR clicks during

a VR shopping experience. Therefore, the work currently done on the VR rating and VR survey solutions focus on identifying the optimal moment to launch such features, identifying new modes of extracting consumer cognitive feedback with less clicks or none (vocal). Another mode of extracting consumer cognitive feedback, currently being developed, includes the integration of a comment system to allow consumers to provide feedback or impressions of the item in virtual reality. This also serves as a potential motivational factor during the decision process to purchasing. The literature review and the research work undertaken, provides sustainable evidence that the incorporation of consumer's affect will provide valuable insight to better personalise the VR shopping experience.

Conclusively, the undertaken case studies allowed to observe and state the consumer behaviour in the two modes of diffusing a v-commerce experience (plugin and marketplace) varies greatly. It was noted that consumers that purchased items in a plugin mode had an exploratory behaviour within the store and browsed more scenes than the average user. It was also identified that consumers who purchased an item in a marketplace where consumers who had an initial exploratory behaviour and browsed around prior to accessing a VR shop that matches the preferences/needs. Once in a VR shop within the marketplace the consumers had few interactions and browsed less scenes than the plugin mode. The behavioural database allowed to understand how the increase of interactive contents (product sheets and behavioural system assistants) increases engagement with consumers and promotes retention. Finally, the case studies served as a test field to implement the developed 3DR3CO methodology and propose a response to the previously stated research question.

"Oppurtunity lies in the place where the complaints are."

– Jack Ma

Chapter IV

Conclusion & Perspectives

This chapter recapitulates the findings from the undertaken literature review. The research problem that arose from the industrial challenge of DIAKSE is re-stated. The objective of this research is to understand the dynamics of the tryptic phenomena of v-commerce systems. This scientific contribution of this research allowed to formalise a 3DR3CO methodology that tests the validity of the hypothesis. The scientific contribution of the developed 3DR3CO methodology overcomes the industrial challenges by bridging the typical laboratory analytic methodologies found in laboratories directly to consumers. This chapter illustrates the undertaken time plan and the scientific communications published throughout this research project. Finally, the perspectives of this research are discussed to describe how to overcome the challenges faced during this research project and further our work.

IV.I Conclusion

The undertaken research project is a collaboration between the Laboratoire de Conception de Produits et Innovation (LCPI) of Arts et Metiers and the start-up DIAKSE. This research project is based on and extends the work done at the LCPI for the past 10 years. The undertaken work helps understand how to consider user-behaviour in the design process of the VR staging environment to promote product purchase intentions (tryptic phenomena). The state of art in this thesis deciphers the psychological dynamics of the consumer decision process and highlights the motivational factors that trigger purchase intentions. The findings of the state of art defined the importance of observing consumer behaviour to identify preferences. Moreover, tailoring the VR shopping experience to each consumer's preferences is an essential driver to promoting purchase intentions. Based on the findings of the state of art, this project's research question and the question this thesis aims to answer to is: **How to incorporate consumer behaviour analysis to optimise the v-commerce design process and promote purchase behaviour.**

To understand consumer preferences, it is important to observe each consumer's behaviour, reactions and mode of navigation throughout the VR shopping experience. As a result, the first hypothesis stated: **the navigation data of a consumer in a virtual reality (VR) shop allows to observe design elements for the VR shop (H1).** This hypothesis was validated by the development of a real-time behaviour tracking tool, behaviour stocking database and a dashboard that displays the consumer VR navigation behaviour. To optimise the v-commerce design process and promote purchase behaviour, it is important to adapt the VR shop to each consumer's preferences. Therefore, the second hypothesis was formulated as: **the aggregated consumer navigation (H2.1), interaction (H2.2), and affect (H2.3) data improves the dynamics of the tryptic relationship to personalises the shopping experience and increases purchase intentions.** Each consumer's navigation data (*time spent in each scene, buttons used to navigate through scenes, what areas have been looked at the most, how many scenes visited, etc…*) was used to deduce the design rules to optimise the VR staging environment to match the consumer's preferences. The consumer's interaction data

(number of products browsed, number of products purchased, most successful price range, etc...) is used to determine the product's characteristics that correspond to each consumer's preferences. This hypothesis was validated by developing a dynamic VR product sheet that helped in real-time to determine product data and identify matches to consumer preferences with the objective of promoting purchase intentions. Finally, the consumer affect data (consumer's personality assessments, emotional analysis, VR experience evaluations, consumer's personal values, etc..) is used to assess the current's consumer psychological state during the VR shopping and segment consumer types. An internally run beta-test displays that consumers are not willing to provide sensitive personal information (partake in surveys nor rate the VR shopping experience) and therefore the H2.3 could not be verified. A perspective study in identifying modes of acquiring consumer affect data in an implicit and non-invasive mode and investigating incentives to promote consumer's willingness to provide affective data during a VR shopping experience is to be undertaken. A 4-step methodology was formalised based on the findings of the state of art and with the objective to verify the validity of the hypotheses. This methodology was transcribed into the development of various VR software tools that help incorporate consumer behaviour into the design process of a VR shop to promote purchase behaviour.

The incorporation of consumer behaviour in the design process of an optimised v-commerce has been proven with the proposed 3DR3CO framework. The 3DR3CO framework allows to extract design elements that serve as specifications for promoting purchase intentions and improving the VR shopping experience.

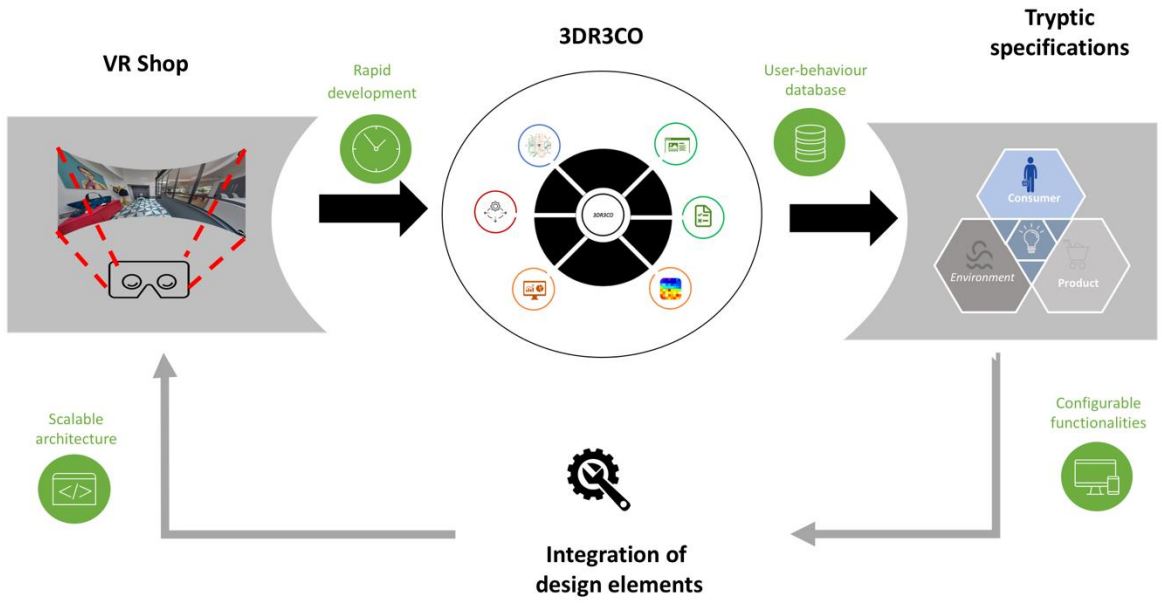


Figure 57. Optimisation process of a VR shop with 3DR3CO

The figure above summarises how the developed 3DR3CO framework helps uncover user-behaviour specifications that shed light on the tryptic dynamics of v-commerce. The user-behaviour specifications formalise design elements to consider for optimising the VR shopping experience and promote purchase behaviour. The contributions of the developed framework are:

<u>Rapid Develop Process:</u> This research project displayed the need to re-structure the system structure such that a faster development process could be achieved and produce various VR shops. The centralisation of common functionalities allowed to provide a common base amongst different VR shops and ensure a consistency in the v-commerce solutions. The re-structuring of the v-commerce solution allowed to cater for the development of the 3DR3CO

technology. The industrialisation of the operating process allowed to quickly prototype deploy VR shops to consumers in a record time of 48 hours.

Real-Time Consumer Insight: Given the nature of this research project, the developed 3DR3CO technology was deployed and implemented onto existing VR shops used by real consumers. This provided us with the opportunity to build a consumer behaviour descriptive model that provides real-time consumer insight of each VR shop. The undertook literature review provided insight of the data features required to understand consumer preferences, with regards to the product and the staging environments. The behavioural database allows to understand the overall behavioural trends and provide v-commerce analytics that are used to generate improvement specifications.

Configurable V-Commerce Features: This research work required the development of the 3DR3CO suite of solutions in a modular and configurable mode. This allowed to adapt each solution to each VR shop's brand. This allowed to rapidly adapt and test changes of the v-commerce and study the consumer's behaviour and responses. The configurability of the developed features allows to implement the best-practices extracted from the consumer insights and formalised the in the tryptic specifications. This allows to establish a data-driven design process of the VR shops that continually adapts to consumer behaviour and is iteratively optimised to promote purchase behaviour.

Scalable Architecture: The implementation of the new design elements to improve the v-commerce, required the development of a scalable architecture that allows for real-time changes to the v-commerce experience. This allows for the consumer to benefit in real-time the personalisation and interact with the v-commerce system to continually adapt the design elements to the preferences. Moreover, this v-commerce architecture allows VR shops with no prior consumer insight to benefit from existing best-practices that are derived from the descriptive consumer insight model.

This research work has contributed to a holistic understanding of the fundamental principles that shape a v-commerce system. This allowed us to understand the purchase decision-making process of a consumer and what elements influence the decision process. Moreover, this work highlights the importance of emotions and perception in behavioural design and the understanding consumer behaviour. Throughout this work we display the advantages of virtual reality and how it can provide a synergy between e-commerce and brick-and-mortar shops in providing emotionally engaging and personalised shopping experiences. The state of art has driven a user-centric approach into the design of a v-commerce solution.

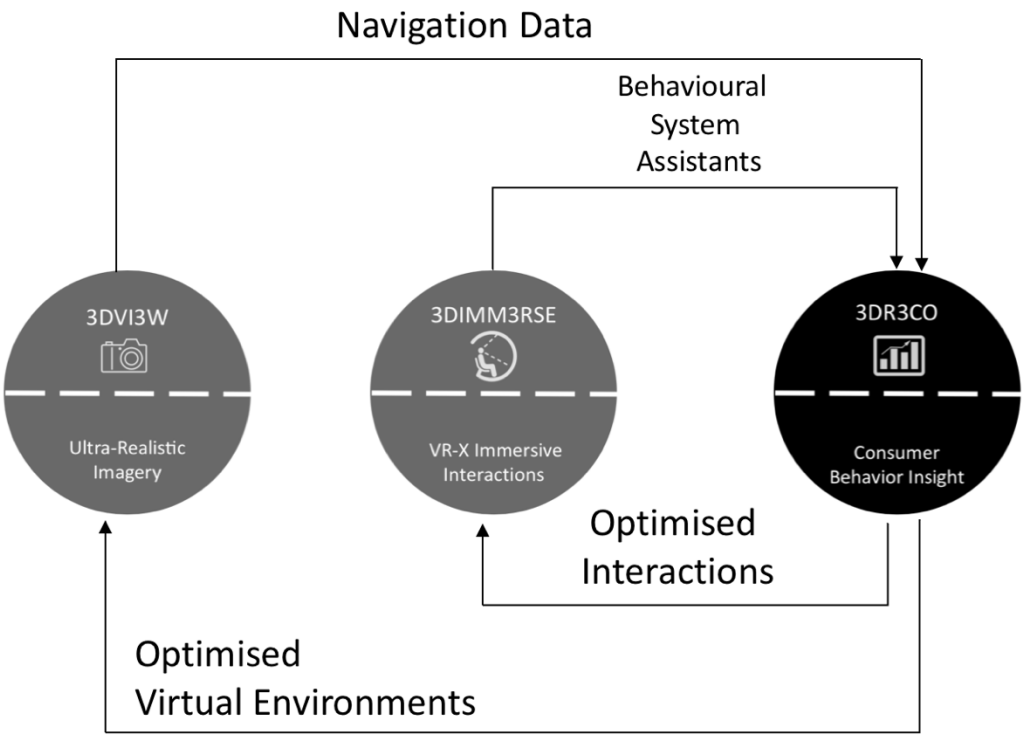


Figure 58. The DIAKSE v-commerce 3 core technologies

This study has contributed to the formalisation of a 3DR3CO technology that describes how to optimise a VR shop by incorporating consumer behaviour to promote purchase behaviour. The development of the 3DR3CO technology gave rise to an industrial contribution by developing a suite of VR tools that complement the already existing 3DVI3W and 3DIMM3RSE technologies that power v-commerce. The 3DR3CO technology provides insight on how to improve the immersive experience of the VR shopping experience by observing and studying the consumer's interaction during a VR shopping experience.

This 3DR3CO technology is currently deployed live and aids various v-commerce shops understand how to increase sales and better promote products through VR. The 3DR3CO suite of VR tools were developed in a scalable approach, which allows to centralise and better leverage consumer data to provide instantaneous consumer insight.

IV.II Perspectives

Integration of Human Affect in 3DR3CO

As it was stated earlier, a key driver into consumer behaviour is emotions. One of the challenges this research studies is to solve is the integration of human emotions and product perception in the design process of the VR shop. An attempt of acquiring consumer affect by deploying in a beta-test the VR survey and VR rating tools displayed consumer's resistance to providing explicitly providing personal information. Therefore, alternative methods of extracting consumer emotional states in real-time could provide substantial insight onto consumer preferences and purchase behaviour.

One of the possibilities currently explored is how to leverage "*Reactions"* in the product sheet to optimise the personalised VR shop design process. The reactions correspond to a button that lets consumers express their current emotional state, through the selection of 5 most common emotions experienced during VR shopping. Currently the data recorded by consumers is derived from the visual clicks and time spent on a section of the product sheet. Although this provides behavioural insight onto what attributes of the product are considered in the consumer decision process, the human behaviour is partially emotionally driven. To better define a consumer behaviour descriptive model that feeds the recommender system for predicting preferences, the consumer's real-time emotional states should be logged and leveraged.

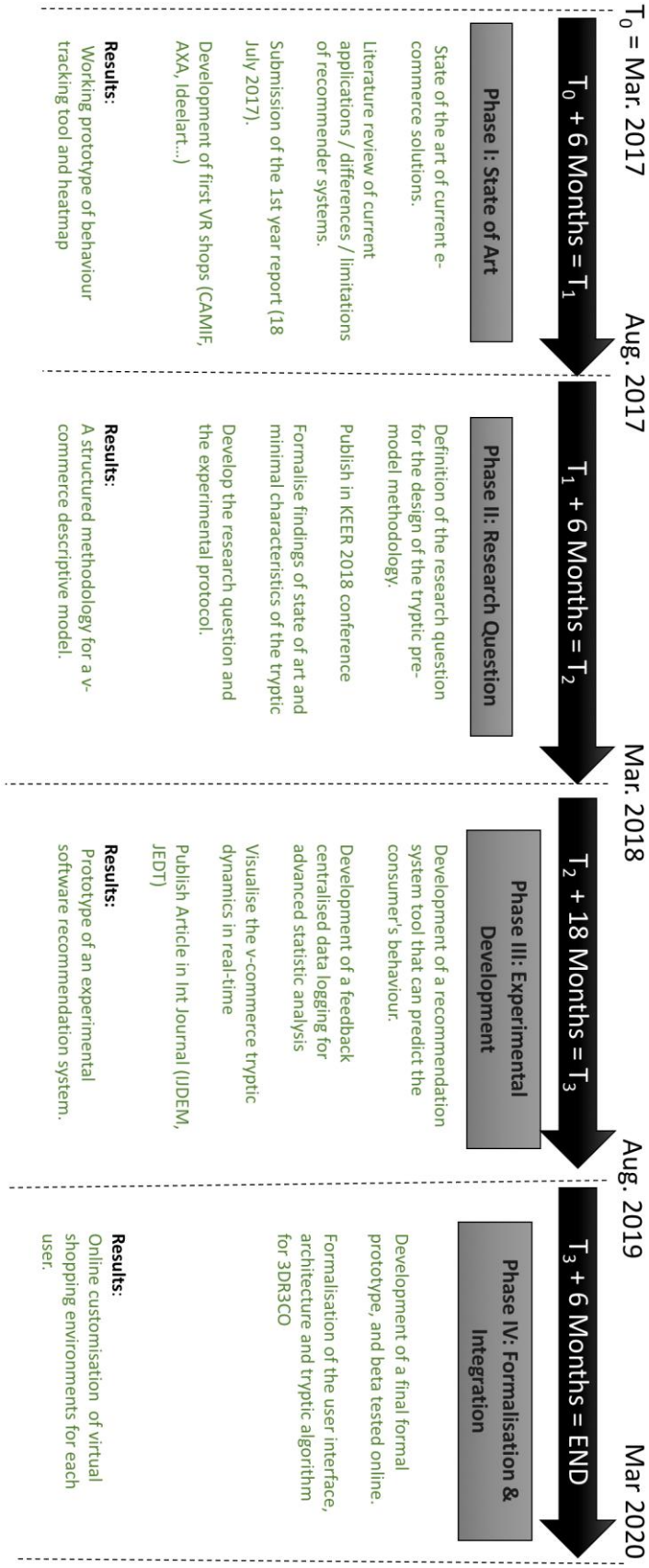
Another perspective study currently explores the integration voice assistive technology in the v-commerce experience. It was noted in this report's case study that consumers find the excess of clicks to undertake an action trivial and deterred the v-commerce experience. Hence, how can voice-assistant technology can be integrated to the v-commerce experience? The analysis of consumer voice interactions valuable insight onto the current emotional state of the consumer. Therefore, the perspective study focuses on the semantics words used, pitch, intonation, speech rate and loudness of the logged voice to extract consumer emotional state and the integration of such a model with the 3DR3CO technology.

3DR3CO 2.0

This research has provided the fundamental bricks to develop the 3DR3CO technology, which helps DIAKSE personalise the v-commerce experience to each consumer in real-time based on their behaviour. The 3DR3CO framework is composed of a suite of VR solutions whose objective is to collectively collaborate to retrieve in real-time consumer preferences and personalise the VR shopping experience. However, the currently developed VR solutions require human intervention to infer design elements to personalise the VR shop experience. Hence a prospective study of this research work is to automate the 3DR3CO pipeline by integrating artificial intelligence. The development of an AI process depends on a structured consumer data pipeline. Due to the massive consumer data that is generated during a v-commerce experience, it is also essential to undertake a privacy study to ensure a transparent GDPR compliance.

The consumer products are staged in the VR shop only if they are clipped (background removed) and are associated with a description text and placed manually by the VR shop designer. Therefore, a prospective study of this research would focus on how computer vision techniques can be incorporated in the 3DR3CO methodology. How can computer vision be used for background removal of products, semantic object recognition to populate the product sheet and use a semantic segmentation on the VR shop to identify the most optimal position that promotes the product. The logged user-behaviour requires a human intervention for a statistical analysis to infer consumer insight about each consumer preferences. Therefore, a prospective study consists in identifying how can machine learning models be used to automatically infer consumer preferences based on consumer behaviour and automatically integrate the personalised design elements in the VR shopping experience.

IV.III Time plan



IV.IV Scientific Communications

Conferences

El Boudali A., Mantelet F., Aoussat A., Berthomier J., Leray F. (2018) A State of Art on Kansei-Engineered Virtual Shops: A Study on the Possibilities of V-Commerce. In: Lokman A., Yamanaka T., Lévy P., Chen K., Koyama S. (eds) Proceedings of the 7th International Conference on Kansei Engineering and Emotion Research 2018. KEER 2018. Advances in Intelligent Systems and Computing, vol 739. Springer, Singapore

International Journals

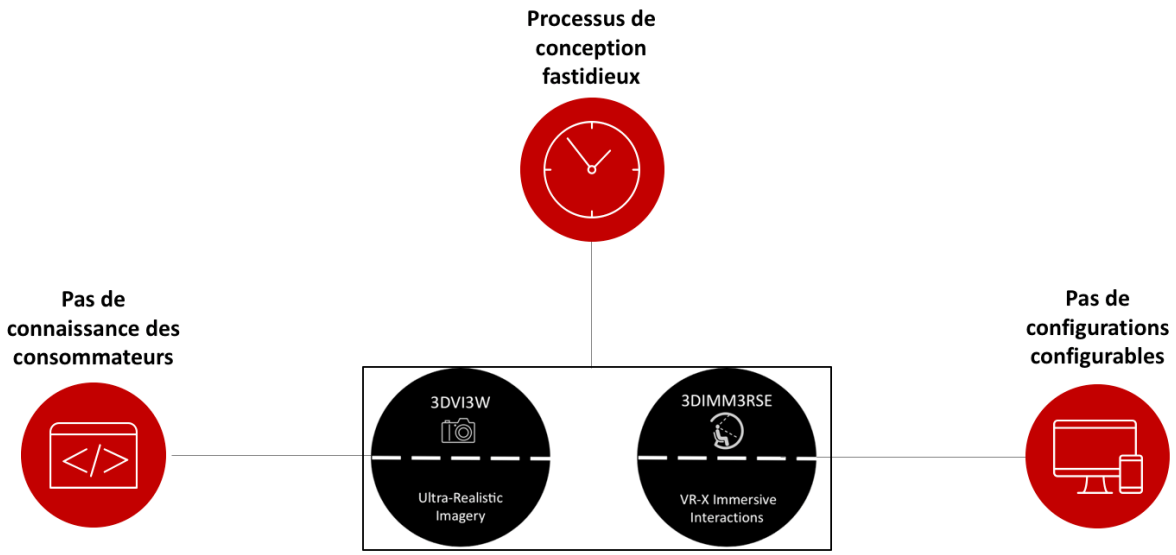
Elboudali, A., Aoussat, A., Mantelet, F. et al. A customised virtual reality shopping experience framework based on consumer behaviour: 3DR3CO. Int J Interact Des Manuf (2020). https://doi.org/10.1007/s12008-020-00645-0

Synthèse

Ce projet de recherche porte sur l'étude d'une nouvelle méthodologie d'aide à la conception d'environnements virtuels de vente, basée sur l'ingénierie émotionnelle appliquée à l'analyse de l'expérience des consommateurs. Cette nouvelle expérience d'achat immersive, donne la possibilité de fusionner les techniques de vente en magasin avec des solutions e-commerce pour créer des systèmes hybrides puissants qui favorisent le comportement d'achat. L'état de l'art du projet de recherche est centré sur le ressenti et le comportement des acheteurs dans des boutiques en réalité virtuelle. Ceci nous a permis de formaliser le contexte scientifique de nos travaux avec pour question scientifique : ***Comment peut-on intégrer l'analyse du comportement consommateur afin d'optimiser la création d'un environnement virtuel de vente ?*** *Cela nous a permis de développer la méthodologie 3DR3CO afin de quantifier le ressenti des consommateurs, valider les hypothèses et les tester sur des consommateurs en temps réel. Les apports de cette thèse ont permis de développer, déployer la technologie 3DR3CO et contribuer au développement d'un modèle descriptif comportemental. Ce modèle permet la personnalisation et l'amélioration de l'expérience consommateur et donne un avantage compétitif face aux solutions e-commerce déjà existantes.*

Contexte

DIAKSE est une entreprise française qui propose aux marques de luxe et aux e-commerçants une solution réaliste de e-commerce en 3D. Les visiteurs sont plongés dans un univers où ils évaluent, découvrent librement les produits et réalisent leurs achats depuis la terrasse d'un café ou confortablement depuis leurs canapés. DIAKSE est née d'un concept simple : tester les produits instantanément. DIAKSE a donc développée une technologie permettant la création de boutiques virtuelles sur mesure. Cette technologie permet de scruter finement et sans biais le comportement d'achat des consommateurs afin d'augmenter les ventes. Cette solution permet également à DIAKSE d'évaluer le comportement naturel des consommateurs et leurs parcours d'achat, dans le but de personnaliser leurs expériences et concrétiser leurs actes achat.



DIAKSE utilise deux technologies pour créer son expérience V-commerce. Le V-commerce utilise la WebVR (web réalité virtuelle) pour alimenter la technologie 3DIMMERSE. Une solution qui offre une fluidité et une qualité immersive de la réalité virtuelle sur un navigateur Web. De plus, DIAKSE se base sur une technologie d'utilisation d'images photographiques traitées à 360 ° par ordinateur pour fournir des rendus ultraréalistes. Avec le développement de sa technologie 3DVI3W, il est possible d'insérer toutes les images de produits dans un environnement à 360 °, offrant ainsi la possibilité d'alterner des arrière-

plans différents pour plusieurs produits. Cela confère à DIAKSE un avantage concurrentiel par rapport aux solutions WebVR existantes, en lui permettant d'adapter et de personnaliser de manière dynamique l'arrière-plan du produit en fonction des préférences du client. Le parcours d'un utilisateur est simple et ne nécessite pas le téléchargement d'applications spécifiques pour accéder à une expérience en réalité virtuelle (RV). En outre, DIAKSE fournit une solution multimodale Web, garantissant une expérience de réalité virtuelle pouvant être expérimentée via des ordinateurs, smartphones et casques de réalité virtuelle. Une fois connecté sur une plateforme de e-commerce, le consommateur a la possibilité de visualiser les produits vendus dans un environnement de RV en mettant en valeur les caractéristiques du produit. Une fois le consommateur convaincu, il a la possibilité d'ajouter directement le produit à son panier et d'être redirigé vers la plateforme e-commerce de la marque.

Les enjeux industriels décrits dans la figure ci-dessus nous montrent les éléments à investiguer afin de lui apporter un avantage compétitif. Avant d'entamer ce projet de recherche, nous avons constaté que la solution ne disposait pas d'outil permettant l'analyse de l'audience et la compréhension du ressenti des consommateurs. Le processus chronophage de développement d'une boutique v-commerce varie selon chaque marque et freine sa scalabilité. La volonté de l'entreprise de devenir leader dans le marché de v-commerce, reflète la nécessité de repenser l'architecture et développer de nouvelles solutions avec une perspective évolutive. Le processus de conception des environnements virtuels de mise en situation ainsi que l'emplacement des produits au sein de ces environnements sont actuellement définis par la direction artistique. De plus, cette solution offre la possibilité de personnaliser l'expérience d'achat en ligne pour chaque consommateur. Elle nous montre ainsi la nécessité de développer des fonctionnalités configurables, qui s'adaptent aux préférences des consommateurs afin d'améliorer leurs expériences et promouvoir l'achat.

L'objectif de ce projet de recherche est de développer une méthodologie d'aide à la conception d'environnements virtuels de vente basés sur l'ingénierie émotionnelle appliquée à l'analyse de l'expérience des consommateurs. Ce projet de recherche s'inscrit dans le développement de la technologie 3DR3CO de DIAKSE. Cette technologie vise à développer une méthode qui aide à identifier les préférences des consommateurs en temps

réel et en réalité virtuelle. Elle permet également de donner un aperçu sur les éléments de conception afin de promouvoir les achats pour différents profils de consommateurs et ainsi améliorer leurs expériences.

Ce projet de recherche est mené en partenariat avec l'École Nationale Supérieure d'Arts et Métiers ParisTech dans le cadre d'un contrat CIFRE avec le Laboratoire de conception et d'innovation de produits (LCPI). Sous la direction du Professeur Améziane Aoussat, le laboratoire LCPI mène des recherches en génie industriel sur les processus de conception de produits, ainsi que l'innovation et le design émotionnel. Cette collaboration a commencé en Mars 2016 dans le cadre d'un stage de master recherche en ICI-DI sous la direction de Dr. Carole Bouchard et Dr. Jean-François Omhover. Le stage avait pour objectif d'étudier et formaliser une méthodologie de caractérisation des 3 dimensions du V-commerce : expérience utilisateur, environnement immersif et produit. Ce modèle permet d'analyser le comportement d'un utilisateur plongé dans un environnement immersif, permettant la visualisation des produits qui sont présentés d'une manière favorisant l'achat. Le but de la recherche était de rassembler et créer des connaissances et un savoir-faire qui pourraient concevoir un environnement virtuel de vente en se basant sur les interactions de ces trois dimensions. En outre, la recherche a commencé avec le désir de clarifier la dynamique du triptyques V-commerce. Au cours des 6 mois de stages, nous avons conçu un prototype d'une boutique en réalité virtuelle que nous avons intégré dans le cadre d'une expérience en laboratoire. L'objectif de cette expérience était d'évaluer la perception d'un utilisateur par rapport à une mise en situation en réalité virtuelle. Nous avons observé une distorsion de perception de l'utilisateur lorsque l'environnement de mise en situation change. Ceci a motivé l'exploration des méthodes de modélisation des comportements des consommateurs dans le cadre d'une thèse.

Synthèse Etat de l'art

Ce projet de recherche porte sur l'étude d'une nouvelle méthodologie d'aide à la conception d'environnements virtuels de vente, basée sur l'ingénierie émotionnelle appliquée à l'analyse de l'expérience des consommateurs. Le marché du e-commerce, est en perpétuelle évolution, il est actuellement en train de redéfinir le comportement d'achat des

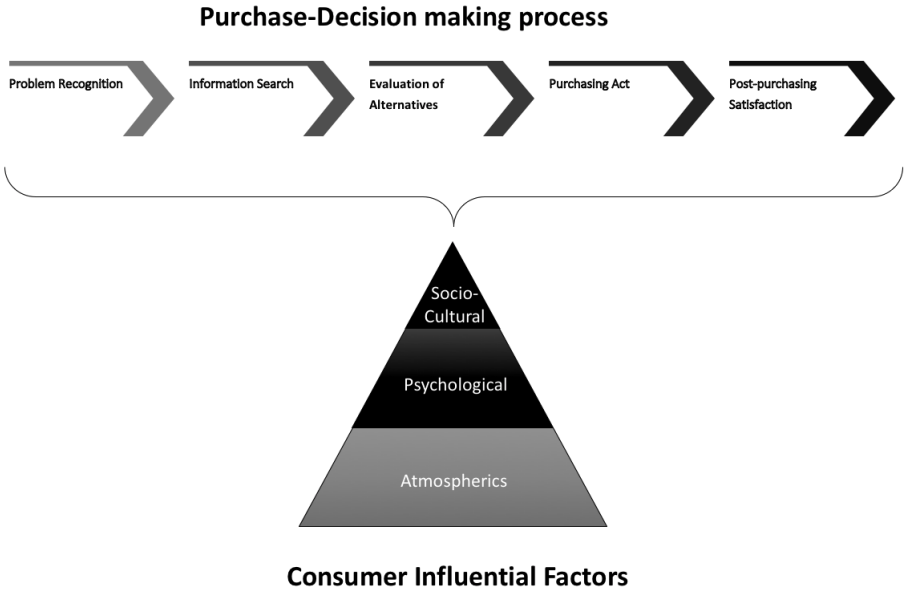
consommateurs. Les systèmes de recommandations et leurs intégrations avec des algorithmes d'apprentissage par machine et traitement de données, représentent aujourd'hui un atout principal pour le succès des sites e-commerce. De plus, grâce à la présence de l'informatique ubiquitaire dans les systèmes qui intègrent des données, les solutions e-commerce pourraient bénéficier des données précieuses des consommateurs afin de développer des solutions à fort impact et pouvant cibler au mieux leurs besoins [Dave Parro, 2015]. Des techniques tels que le SEO (Search Engine Optimisation) bénéficient d'une abondance dispersée de données à travers différents canaux pour rediriger les consommateurs vers des site de e-commerces qui sont conscients de leurs besoins. La croissance rapide des sites de e-commerce [Sunda, G. K., et du professeur V. Vaidhehi, 2017], a rendu indispensable l'utilisation des moteurs de recherche lors de l'expérience shopping en ligne. En conséquence, la compétition pour figurer parmi les premiers sites d'une page de résultats des moteurs de recherche (SERP) est devenue plus féroce. L'amélioration d'un tel processus est connue sous le nom d'optimisation des moteurs de recherche (SEO) [Beel Jöran, 2010].

Les sites de e-commerce recherchent également des techniques de reciblage publicitaire afin de rediriger les utilisateurs qui n'ont pas effectué un achat au sein de leurs boutiques vers de nouvelles propositions mieux adaptées à leurs besoins. Les solutions de reciblage publicitaire exploitent des plateformes à fort trafic telles que : Facebook, Instagram, Snapchat, etc. pour afficher des publicités ciblées. Pour donner un ordre de grandeur à cette solution, le réseau social Facebook a annoncé en 2016 un chiffre d'affaires de 8,8 milliards de dollars provenant de la publicité et du reciblage. La technologie de reciblage fournit un moyen de tracer les recherches effectuées par les visiteurs grâce à un cookie (code installé sur l'ordinateur, tablette ou mobile de l'utilisateur) permettant de stocker les données relatives à un produit, afin de les rediriger vers le site e-commerce. Ces stratégies ont contribué au développement de la méthode 3DR3CO dans laquelle nous avons conçu un outil de suivi de comportement d'utilisateur en réalité virtuelle.

Grace à l'adoption des réseaux sociaux dans le e-commerce, les normes socioculturelles peuvent être digitalisées afin de mieux comprendre les intérêts des consommateurs [Kim Y.A., Srivastava, J., 2007]. Cependant, les solutions existantes du e-commerce souffrent des

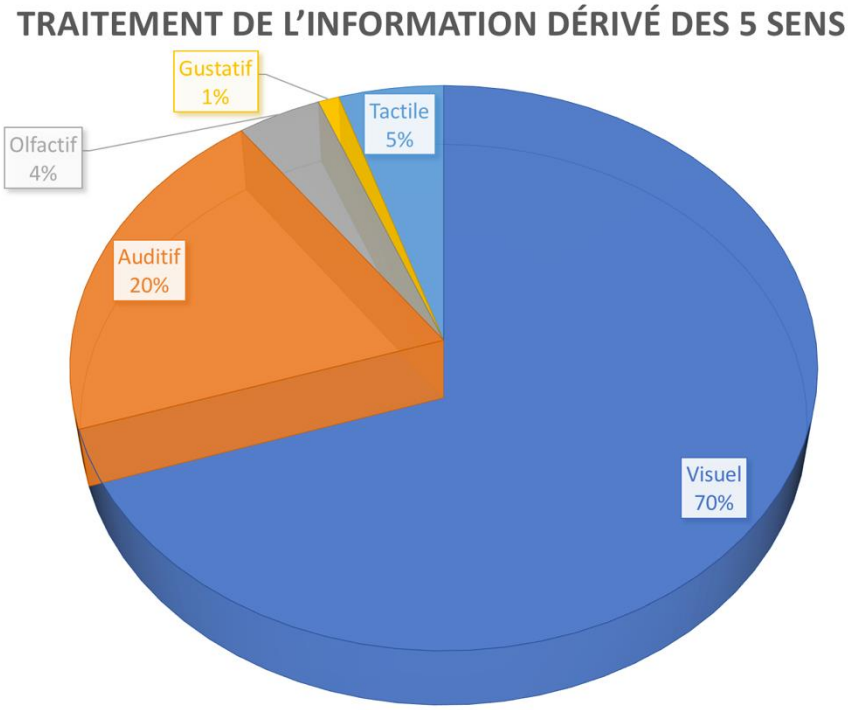
limitations des canaux web qui permettent leurs diffusions. De manière simple, dès qu'un consommateur entre dans un magasin, il est transporté dans un univers enchanteur représentatif de la marque grâce aux détails mis en exergue (luminosité, couleur, musique, etc.…). Cette même expérience ne peut être reproduite en accédant à la boutique en ligne du magasin, néanmoins, l'un des seuls moyens de véhiculer l'image de la marque consiste à l'utilisation des canaux multimédias. Par conséquent, les commerçants sont tenus d'adopter différentes stratégies aussi bien pour leurs boutiques en ligne que leurs magasins physiques afin de tirer profit des avantages procurés par chaque type de magasin.

Yoon (2002) a constaté que la commercialisation des produits au sein d'une boutique en ligne crée une dissociation entre le consommateur et la marque. Par conséquent, DIAKSE a développé une solution de commerce en réalité virtuelle (V-commerce) qui vise à recréer les atmosphères des magasins physiques au sein des sites de e-commerce. L'un des objectifs majeurs des sites de e-commerce est de déterminer quel produit doit être mis en avant pour chaque utilisateur, problématique transcrite dans les systèmes de recommandation actuels. L'intégration des systèmes de recommandation dans la solution DIAKSE rajoute un élément supplémentaire à la complexité de ces systèmes : celui de la conception de l'environnement ou du décor adéquat pour mettre en valeur les produits à commercialiser. La création d'un site virtuel de vente en ligne repose donc sur les dimensions clés suivantes : l'utilisateur, le produit et l'environnement virtuel de vente.



L'état de l'art du comportement des consommateurs nous a permis d'identifier que peu importe le type d'achat, les processus fondamentaux de décision d'achat se décomposent en cinq étapes : la reconnaissance du problème, la recherche d'informations, l'évaluation des alternatives, l'achat et l'évaluation post-achat. La décision d'achat comme toute autre décision humaine est fortement influencée par les émotions [Damasio A., 2005 ; Eser, Z., Isin, F. B., & Tolon, M. 2011 ; Michael R. Solomon, 2006 ; Shahrzad J. et al, 2013]. Cette influence est due à trois niveaux, situationnels, psychologiques et socio-culturels. L'influence situationnelle décrit les effets qui stimulent nos cinq sens pour déclencher les émotions favorisant le comportement d'achat [Naz, K. A. Y. A., and H. Epps., 2004 ; Babin, B. J., Hardesty, D. M., & Suter, T. A., 2003 ; Roslow et al. 2000 ; Baker et al. 1994 ; C. Areni and D. Kim 1993].

Nous avons identifié lors de notre étude bibliographique que l'émotion est définie comme une réaction mentale consciente. Cette émotion est un sentiment fort généralement orientée vers un objet spécifique, elle est également accompagnée de changements physiologiques et comportementaux du corps. Nous avons donc exploré l'influence des éléments atmosphériques sur chacun de nos cinq sens afin d'identifier les caractéristiques minimes qui contribuent à la volonté d'acheter. Outre la portée industrielle de ce projet de recherche il a été identifié que 70% du traitement de l'information est dérivé de la dimension visuelle [M. L. Heilig, 1992].



Répartition des traitements d'informations dérivés des 5 sens [M. L. Heilig, 1992]

Par conséquent, les stimulations des sens visuels et auditifs jouent des rôles important (90%) dans le traitement de l'information qui permet de déclencher les émotions souhaitées. Étant donné le contexte industriel, nous avons focalisé notre recherche principalement sur les dimensions visuelle et auditive.

La revue de littérature menée par rapport à l'influence des divers éléments atmosphériques sur les 5 sens des consommateurs nous a permis d'identifier les caractéristiques minimales de chaque sens. Ceci contribue à l'identification des paramètres à modéliser dans le processus de conception d'un environnement virtuel de vente personnalisable. La dimension visuelle est caractérisée par la couleur (défini par la teinte, valeur et saturation) et la forme. Notre recherche bibliographique a souligné l'importance de la couleur et de ses associations aux émotions. Les états émotionnels sont les principaux moteurs de prise de décision

d’achat. En ce sens, le choix de la coloration pour les commerçants représente une stratégie clé essentielle pour émettre la perception de la marque et influencer le comportement du consommateur [Madden, T. J., Hewett, K., & Roth, M. S., 2000].

La dimension auditive (l’ouïe) est un mode d’influence généralement utilisé pour attirer, apaiser et retenir les consommateurs dans les magasins. Cette dimension prend la forme de musique afin de créer un lien entre l’expérience du consommateur et influencer la perception émotionnelle d’un produit. Cherng et Chien (2012) ; Arnould, E., Price, L. et Zinkhan, G., 2004 ont identifié que la musique est caractérisée par le tempo, le genre et la méthode de jeu (volume, transition et boucle) et sert de langage invisible qui stimule les émotions. Les stimulations émotionnelles entraînent des réactions comportementales menant à des comportements d’achat. Il a été constaté que la musique à faible tempo diminue l'excitation et contribue au ralentissement des consommateurs. Ceci, prolonge leurs expériences d'achat et les exposent à davantage de produit en promouvant le comportement d'achat grâce aux éléments atmosphériques du magasin. *C.Areni and D. Kim (1993)* ont identifié que l’utilisation de la musique classique procure une sensation de prestige dans une boutique, ce qui donnerait un attrait luxueux au produit. La musique classique influence la perception des prix, car celle-ci évoque que les produits sont de qualité justifiant ainsi les prix élevés. L'univers prestigieux créé par la dimension auditive promeut l’achat des produits couteux.

Le ressenti des consommateurs lorsqu’ils sont exposés aux éléments atmosphériques est dû aux facteurs psychologiques (perception, personnalité, valeurs, etc…) [Sheth 1975 ; Hanna Wozniak, 2013]. Les facteurs psychologiques déterminent la manière dont les consommateurs interprètent les stimulations atmosphériques et définissent le

comportement. Afin de modéliser la perception psychologique des consommateurs vis-à-vis des éléments atmosphériques des magasins, nous avons entrepris un état de l'art sur les dimensions de motivation, de personnalité, et de valeurs humaines. La motivation représente une force qui déclenche un comportement spécifique en fonction du contexte. Cette dimension est caractérisée par trois facteurs : direction, effort (ou intensité) et persistance [Arnold, J. Robertson, I.T & Cooper, C.L, 1995]. La direction fait référence à l'objectif visé par une personne dans un environnement spécifique (lieu de travail, shopping, etc.). L'effort correspond à la quantité d'énergie qu'un individu est prêt à investir pour atteindre son objectif. La persistance définit combien de temps on peut maintenir l'effort pour aller vers cette direction (objectif). Sheth (1975) a défini 5 potentielles raisons poussant le consommateur à acheter : la curiosité, les influences circonstancielles, les influences sociales, les facteurs esthétiques / émotionnelles, les attributs fonctionnels.

Nous nous sommes ensuite intéressés au domaine de la perception et à sa relation avec le comportement du consommateur, car cette dimension caractérise le processus de sélection, d'organisation et d'interprétation des sensations en un ensemble significatif [Hanna Wozniak, 2013]. La perception est constituée de 3 sous facteurs : exposition (quand un individu est en contact avec les atmosphériques), attention (l'affectation de la mémoire mentale aux éléments atmosphériques) et sensation (la réponse des récepteurs sensoriels humain et le transfert de l'information au cerveau). La perception des attributs des produits, tels que les couleurs, déclenchant des émotions chez les individus / consommateurs. L'utilisation des facteurs tels que la luminosité et les couleurs sont des modes souvent utilisés afin de capter rapidement l'attention des consommateurs. Les niveaux de luminosité et de saturation sont des facteurs déterminants, comparés aux niveaux de teinte, pour générer une attention induite par un stimulus [Camgöz, N., Yener, C., et Güvenç, D., 2003]. Le principe du contraste visuel de deux éléments (différence de couleur distincte entre l'arrière-plan et le premier plan) dirige l'attention visuelle du consommateur et contribue à la conception d'un environnement virtuel de vente impactant visuellement.

Les consommateurs peuvent être distingués en fonction de leurs valeurs psychologique [Milton Rokeach, 2010] et leurs personnalités. Bien que chaque individu soit unique, les consommateurs possèdent un ensemble spécifique de traits caractéristiques de préférence

par lesquels ils peuvent être identifiés et classés, appelés personnalités. Michael R. Solomon (2006) a déclaré que la personnalité est un élément clé dans l'identification des caractéristiques auxquelles les consommateurs sont les plus sensibles, afin de cibler un groupe approprié possédant les bons traits caractéristiques. Nous avons évalué l'adaptation des divers modèles de personnalités et valeurs psychologiques de tendance dans le cadre de notre projet industriel, tels que le test de Briggs-Myers [Gardner, William L; Martinko, Mark J., 2016], les 16 traits de Cattell [Cattell, H. E. P. & Mead, A. D., 2008], l'Ocean modèle [Costa, Paul & R. McCrae, Robert., 2012], les valeurs de Schwartz [Schwartz, Shalom H., 1992], et Kahle [Kahle, L. R., Kennedy, P., & Kahle, L. R., 1988] afin d'identifier une norme de segmentation des typologies des consommateurs. En identifiant les différents types de traits psychologiques pour modéliser une perception à un stimulus externe, les comportements généraux pourraient être identifiés et utilisés comme cadre de prédiction.

Les caractéristiques psychologiques qui façonnent la pensée cognitive des consommateurs ayant un impact sur leurs comportements sont définies par des influences socioculturelles. En conséquence, des préférences et des pensées cognitives similaires sont souvent remarquées chez les individus appartenant aux mêmes groupes socioculturels. Les éléments socioculturels sont composés des facteurs suivants : **croyances culturelles**, **classes sociales** et **générations**. Les croyances culturelles sont définies en tant que plans adaptatifs, dynamiques et structurés qui caractérisent un ensemble de croyances implicites, de normes de coutumes et de valeurs qui prescrivent un comportement socialement acceptable aux autres membres de la même culture [Du Plessis, P.J. & Rousseau, G. G., 2005 ; Arnould, E., Price, L. and Zinkhan, G., 2004]. Quant aux consommateurs de la même génération, ils représentent un groupe de personnes ayant la même tranche d'âge, partageant une vision du monde commune et éventuellement des préférences d'achat similaires [Williams, K.C. & Page, R.A., 2011]. Finalement, les facteurs de classes sociales font référence au regroupement de personnes ayant un comportement, des valeurs et un mode de pensée similaire en fonction de leurs statuts économique [Engel J.F. et al., 1995]. Ce facteur définit

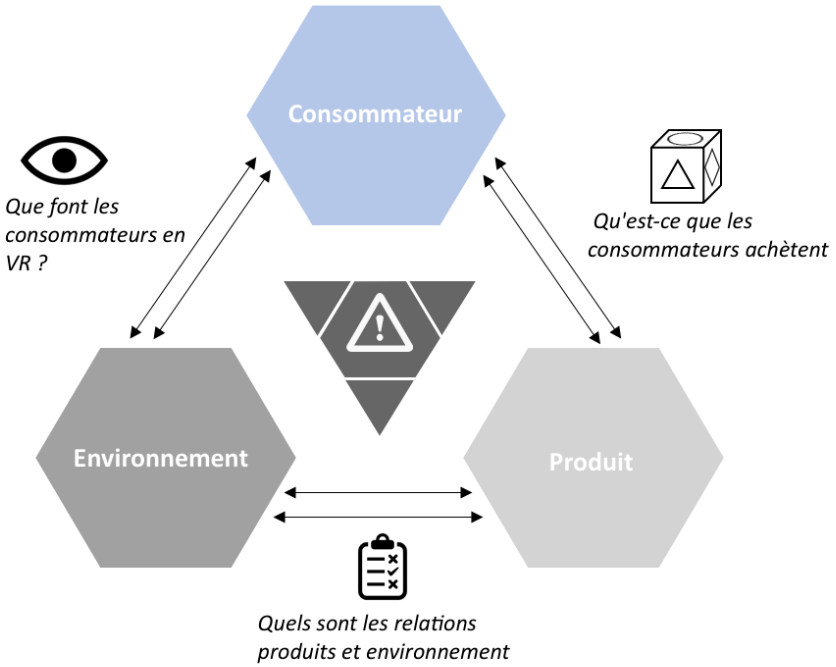
l'attention d'une personne vis-à-vis des facteurs économiques (à savoir : étiquette de prix, argumentaire commercial) au cours de l'expérience d'achat [Abraham, 2011]. Les influences socioculturelles contribuent à la classification des différents types de consommateurs. Cependant, les caractéristiques socioculturelles sont trop vastes pour identifier les préférences des consommateurs.

Le but de nos recherches est d'apprendre comment l'intérêt et les préférences de chaque consommateur peuvent être modélisés pour personnaliser l'expérience d'achat et promouvoir l'achat. C'est pour cela nous avons orienté nos recherches sur l'étude des systèmes de recommandation et l'identification du type d'approche qui serait le plus compatible avec un site de e-commerce en réalité virtuelle. Les systèmes de recommandation servent de systèmes de filtrage pour éviter une surcharge d'informations, en sélectionnant les informations pertinentes à afficher en fonction des préférences, des intérêts et du comportement de l'utilisateur. Ces systèmes identifient un ensemble de clients en ligne dont les articles achetés ou notés chevauchent les articles achetés ou notés de l'utilisateur et agrègent les articles provenant de clients similaires, éliminant ainsi les produits déjà achetés et proposant de nouveaux produits [Resnick, Paul, and Hal R. Varian, 1997]. Les systèmes de recommandation contribuent dans une large mesure à l'augmentation des revenus des solutions de e-commerces en l'absence de connaissances personnelles suffisantes sur les consommateurs ou les produits. Une étude ontologique des différents systèmes de recommandation nous explique que les systèmes de recommandation se décompose en trois types de modèles : filtrage collaboratif, similarité des contenus, et modèles hybride. Le modèle filtrage collaboratif construit des recommandations à l'utilisateur en se basant sur les évaluations et l'achat d'un groupe. Le modèle de similarité des contenus, comme son nom l'indique, prend en compte les attributs et les caractéristiques du produit. Ce système construit une modélisation de la classification spécifique à l'utilisateur à l'aide de la description de l'article et des attributs étiquetés avec les évaluations comme données d'apprentissage [Belkin, N. J. & Croft, W. B., 1992]. L'approche hybride permet le développement des systèmes de recommandation personnalisés, en combinant plusieurs modèles pour augmenter la performance et compenser les désavantages. L'étude sur les systèmes de recommandation souligne l'importance de la qualité des données pour produire des recommandations précises.

Notre recherche dans le domaine de la réalité virtuelle nous a démontré le potentiel de susciter des expériences émotionnellement puissantes et positives [Chirico, A. et al., 2018 ; Yaden, D. B. et al., 2017] ainsi que des qualités transcendantes en manipulant la réalité dimensionnelle. Les expériences de réalité virtuelle aident les individus à s'immerger dans des expériences semblables à la réalité et qui intensifient l'expérience émotionnelle de l'utilisateur [Vincent Rieuf, 2013]. La réalité virtuelle est définie dans la littérature actuelle comme la simulation électronique d'environnements remplis d'images de synthèses affichées sur des casques de réalité virtuelle. Ces simulations répondent aux mouvements humains, permettant ainsi à l'utilisateur final d'interagir dans des situations tridimensionnelles et réalistes [Fuchs, P. et al., 2011 ; M. Gigante, 1993 ; L. et E. von Schweber, 1995]. La réalité virtuelle est une expérience immersive et interactive dont les avancées actuelles et les degrés d'immersion sont mesurés par le niveau de présence (perception en profondeur), d'interactivité (modes d'interaction) et d'autonomie (qualité du contenu) [D. Zeltzer, 1992]. Cela aide les utilisateurs à contourner les interfaces utilisateur complexes non intuitives et génère des données de comportements naturels. En conséquence, diverses recherches sont entreprises pour évaluer l'influence de la réalité virtuelle sur le choix du consommateur [Burke, R. R, 1996], la télé-présence, la convivialité [Schnack, A. et autres, J.2019; Van Herpen, E. et al. .2016] et le comportement d'achat [Waterlander, W. E. et al., 2015].

Nous avons centré notre état de l'art sur l'identification des caractéristiques de la triptyque-produit, consommateur et environnement. Les recherches effectuées nous ont démontré l'importance de l'analyse des navigations, des interactions et des ressentis afin de mieux caractériser le dynamisme du triptyque. Elles sont caractérisées par une analyse sémantique, émotionnelle et comportementale des consommateurs [C. Bouchard, F. Mantelet et al, 2009 ; J. Kim, C. Bouchard et al., 2011]. Ainsi, un type d'utilisateur peut être déterminé et classifié.

Question de Recherche & Hypothèses



Problématique V-Commerce

La question de recherche que nous nous posons est la suivante :

« **Comment peut-on intégrer l'analyse du comportement consommateur afin d'optimiser la création d'un environnement virtuel de vente ?** »

Cela nous a mené à nous pencher sur les méthodologies et techniques de quantification de la perception en se basant sur l'ingénierie émotionnelle et Kansei [Mitsuo Nagamachi, 2004). Ces méthodes sont souvent utilisées dans le contexte de développement et conception de produit. Parmi eux figurent les travaux de Fabrice Mantelet qui ont permis de démontrer que

la perception d'un produit peut être quantifiée en utilisant une analyse sémantique et émotionnelle auprès des utilisateurs. Par la suite, C. Bouchard et al., 2009, a validé le fait que les perceptions d'un produit pour des utilisateurs de pays différents présentent des similarités et des différences. Cette même recherche a montré l'impact des valeurs sociologiques auxquelles les utilisateurs adhèrent dans leurs vies sur leurs réactions face à des produits spécifiques. Ces résultats ont permis d'offrir des pistes pour regrouper les utilisateurs en vue d'établir un modèle comportemental, puis de générer des règles de conception à partir de données issues de l'analyse sémantique. Plus tard, J. Kim a introduit des mesures physiologiques des émotions pour compléter les mesures sémantiques et émotionnelles réalisées par questionnaire [J. Kim, C. Bouchard et al., 2011]. Plus récemment, la thèse de Vincent Rieuf [V. Rieuf, 2013] a permis d'étudier l'influence de la réalité virtuelle sur la perception émotionnelle d'un produit, et de démontrer dans ce contexte une augmentation de l'intensité émotionnelle lors de la perception d'un produit en environnement virtuel.

Le principal défi auquel sont confrontés les sites de e-commerce et les boutiques physiques consiste à identifier le produit / service le plus susceptible d'être acheté par un consommateur. Les magasins entreprennent des études de marché afin d'évaluer et identifier le type de consommateur à cibler et ainsi décorer les magasins en conséquence. Des techniques tels que le merchandising déterminent la présentation de la marchandise dans son meilleur scénario, assurent une harmonisation des couleurs qui attirent et retiennent l'attention des consommateurs spécifiques et suscitent des émotions créant un environnement propice aux intentions d'achat [Taskiran, Z., 2009]. Le merchandising visuel est caractérisé par les vitrines [Pegler, M.M., 2006], les couleurs [Babin, B. J., Hardesty, D. M., & Suter, T. A., 2003], les éclairages [Lin, Y.-F., & Yoon, S.-Y., 2015], les signalisations [Alamanos, E., J. J. Brakus et C. Dennis, 2014] et les structures du design d'intérieur [Turley, L. W., & Milliman, R. E., 2000]. Ceci nous a montré l'importance de l'étude et la modélisation du regard des consommateurs afin de mieux comprendre leurs ressentis. Plusieurs entreprises s'intéressent à des techniques de 'eye-tracking' dans les études d'influence du packaging sur l'attention et l'intention d'achat.

La caméra de détection de mouvement oculaire, mesure des patterns des mouvements des personnes exposées à un ensemble de produits [Pieters, R., et Wedel, M., 2004], afin d'identifier les facteurs de stimulation qui influent sur les périodes saccades et les périodes de fixation. Les saccades font référence au mouvement de l'œil entre un point d'intérêt et un autre. Le processus des saccades fait référence à une recherche visuelle rapide (~ 20 à 40 millisecondes) dans laquelle une personne cherche à réduire les incertitudes de localisation [Van Der Lans, R & Pieters R, Wedel M., 2008]. Lors des périodes saccades, la vision est supprimée et aucune information visuelle n'est traitée. Inversement, les périodes de fixation se réfèrent à des durées plus longues (environ 50 à 600 millisecondes) et font référence à des points où l'œil repose sur un point d'intérêt et où les informations visuelles sont traitées de manière cognitive [Menon, R. et al., 2016]. Par conséquent, pendant les périodes de fixation, une attention plus longue est enregistrée et la perception du consommateur menant au choix de préférence est formée [Yang, L. (Cathy) et al, .2015]. Ces plages de données nous ont servi de lignes directrices lors de notre développement des solutions de V-Commerce centrées utilisateur. En conséquence, les gérants du magasin décorent les vitrines, harmonisent les couleurs, modifient l'éclairage, adaptent la signalisation utilisée dans le magasin et personnalisent l'aménagement de l'intérieur pour saisir et conserver les perceptions des consommateurs [Pegler, M.M., 2006]. En réglant et en personnalisant les éléments énoncés précédemment pour les adapter aux préférences du consommateur, il est possible de déclencher des intentions d'achat. Cependant, les solutions physiques ne sont pas en mesure de personnaliser tous les éléments énumérés précédemment en fonction des préférences de chaque consommateur.

Contrairement aux boutiques physiques, les solutions e-commerce sont capables d'adapter facilement le contenu de leurs magasins en ligne en fonction du profil du consommateur. Ceci est réalisé en étudiant les comportements des utilisateurs grâce aux outils d'analyse et d'agrégation avec les réseaux sociaux afin d'extraire les données personnelles. Ces données nourrissent les systèmes de recommandation pour améliorer la pertinence des résultats. Ces réseaux sociaux fournissent des données personnelles qui permettent aux marchands de e-commerce d'utiliser et identifier des segments socioculturels qui déterminent des stratégies marketing optimales qui correspondent aux préférences de la communauté et augmentent les ventes annuelles [Xing, B., & Lin, Z., 2005]. Les sites de e-commerces tirent parti de

l'avantage des données pour permettre aux systèmes de recommandation de personnaliser et de mieux cibler leurs produits [Belkin, N. J. & Croft, W. B., 1992 ; Lousame, F. P. et Sánchez, E., 2009]. Les systèmes de recommandation se servent des systèmes de filtrage pour éviter une surcharge d'informations, en sélectionnant et en prévoyant les informations pertinentes à afficher en fonction des préférences, des intérêts et du comportement de l'utilisateur [Isinkaye, F. O et al., 2015]. Cependant, une étude récente publiée dans un premier rapport de synthèse a révélé que les consommateurs dépensent davantage dans les magasins physiques qu'en ligne [Petro, Greg., 2019]. L'importance de l'expérience émotionnelle associée à la mise en avance des éléments 'atmosphériques' des magasins [Rick, S. I., B. Pereira et K. Burson, 2014] justifie une telle tendance et l'incapacité des boutiques en ligne à renforcer l'engagement émotionnel d'un consommateur.

Les travaux cités ci-dessus ne formalisent que le couplage produit-consommateur ou le couplage environnement-consommateur. Le verrou que nous cherchons à lever à travers cette recherche consiste à prendre en compte l'environnement de mise en situation des produits afin d'évaluer la perception d'un produit dans un environnement virtuel. Ceci nous a permis d'élaborer deux hypothèses :

H1 : *A travers la navigation du consommateur nous pourrions définir les paramètres des éléments de conception.*
H2 *: L'ensemble des données de comportement et de navigation, nous permettent d'optimiser la relation triptyque et personnaliser l'expérience.*

- *Les données de **navigation** du consommateur optimisent la relation triptyque et personnalisent l'expérience.*
- *Les données **d'interaction** du consommateur optimisent la relation triptyque et personnalisent l'expérience*
- *Les données de **ressenti** du consommateur optimise la relation triptyque et personnalisent l'expérience.*

Contributions et Apports

Afin de vérifier la validité de nos hypothèses nous avons développé une méthodologie 3DR3CO qui nous aide à mieux comprendre le dynamisme du triptyque. À la suite des avancées de notre état de l'art dans le domaine d'attention et eye-tracking, nous avons constaté que nous pouvons avoir une corrélation entre l'attention des consommateurs (mesurée avec des périodes de fixation) et les intentions d'achat. De ce fait, nous avons développé un tableau de bord qui nous permet de simuler le parcours du consommateur. Cet outil nous permet de revivre les interactions de chaque consommateur au sein d'une boutique virtuelle et d'analyser des périodes de longue fixation avant un achat. Nous avons optimisé notre outil afin qu'il puisse recréer les interactions du parcours utilisateur et pas seulement de rediffuser l'aspect spectateur du consommateur.

Outil eye-tracking de boutique en réalité virtuelle

Ces plateformes, ne bénéficient que des données représentant les coordonnées sphériques dans un environnement virtuel et ce que peuvent voir les consommateurs. Ces données peuvent aider à reconstruire le parcours des consommateurs et donner un aperçu du comportement dans l'environnement virtuel. De plus, l'enregistrement des coordonnées dans un espace virtuel peut être utilisé pour construire une carte de chaleur. Ceci permet de présenter visuellement les points marquants et indiquer de nouveaux emplacements opportuns pour le placement des produits et ce afin de promouvoir l'achat. La complexité

du développement de cet outil fut l'étude de la granulométrie pour représenter le comportement des consommateurs. Afin d'être représentatif nous avons utilisé le regard des consommateurs comme indicateur. Ces regards, qui sont quantifiés via des coordonnées sphériques de représentation de la vue des consommateurs nous indiquent la fréquence et la longueur des temps de fixation dans un environnement. Ils permettent aussi d'examiner l'évolution du comportement des consommateurs.

Bien que la carte de chaleur affiche un aperçu sur le comportement du consommateur dans une boutique virtuelle, celle-ci ne montre pas explicitement les interactions de chaque consommateur lors d'une visite. C'est pour cela nous avons développé un tableau de bord qui recrée le parcours de chaque consommateur. Ceci est réalisé en recueillant les parcours des consommateurs et les enregistrements des coordonnées sphériques correspondant à ce que le consommateur a regardé chaque 500ms et visualiser son point de vue. Le développement des outils eye-tracking dans un contexte de boutique en réalité virtuelle nous a permis, de valider la première hypothèse en modélisant et quantifiant l'attention des consommateurs et de générer un aperçu sur les éléments de conception à base des données de navigation.
D'autant plus, nous avons enregistré les actions exécutées pour que la simulation puisse refléter chaque interaction dans la boutique. Les modes de navigation de la boutique virtuelle sont caractérisés par le couplage consommateurs et environnement (H2.2). Afin d'avoir un moyen de mesurer les ressentis des consommateurs en temps réel, nous avons développé un outil d'évaluation qui s'intègre aux les boutiques virtuelles afin que les consommateurs puissent noter leurs expériences en magasin. Dans le cadre de l'amélioration de l'expérience du consommateur, nous cherchons toujours à faciliter l'appréhension du consommateur afin d'influencer les comportements. Pour donner suite aux retours des utilisateurs nous avons conçu de façons progressives des interfaces explicatives de navigation et d'interactions pour les utilisateurs.

L'état de l'art mené nous a démontré l'importance des différents attributs des produits sur différents types de consommateurs. Nous nous sommes intéressés à des données d'interactions de consommateurs dans nos recherches, celles-ci sont représentées par la phase deux de notre Model V-Commerce. Nous avons essayé de mieux comprendre le

couplage produits-consommateurs et comment est-ce qu'un consommateur interagit avec le produit lors d'un processus d'achat. Le périmètre de la réalité virtuelle nous a orienté vers l'étude des influences visuelles. C'est pour cela que nous avons développé un outil des fiches produits en réalité virtuelle.

Outil Productsheet DIAKSE

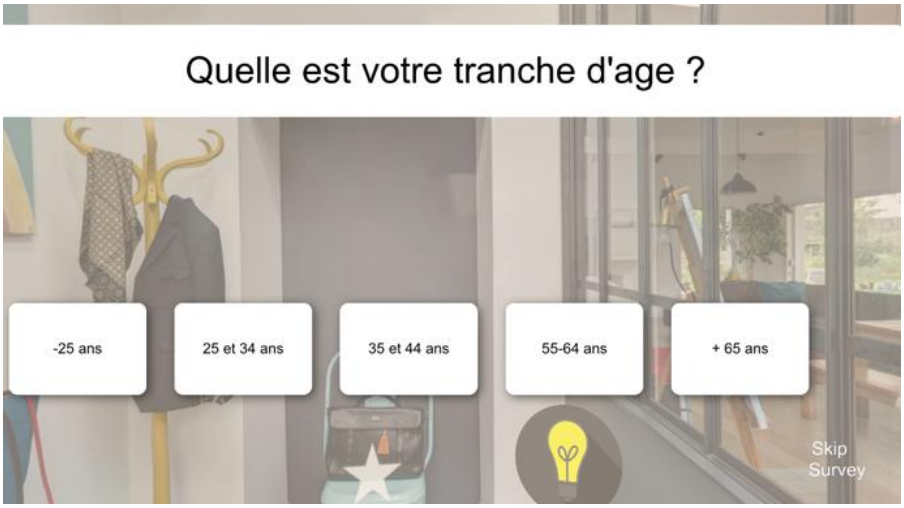
Cet outil construit une fiche produit de façon modulaire, ce qui facilite la modification et la personnalisation de celle-ci selon les préférences des e-commerçants. D'autant plus que le développement d'une fiche produit automatisée nous a permis d'avoir le contrôle sur le texte affiché. Nous avons pu automatiquement mettre à jour les prix des produits, identifier les stocks et personnaliser les textes descriptifs en temps réel. L'outil a contribué au développement de la fonctionnalité de gestion de la fiche produit sous différents langages.

Nous avons identifié le besoin d'avoir la possibilité de voir le produit sous différents angles. Cette exigence a souligné la nécessité d'afficher le même produit sous différents scénarios afin que les consommateurs puissent se projeter [J. N. Sheth, 1975]. Cependant, avoir plusieurs fiches produit pour le même produit n'était pas esthétiquement agréable. Nous avons donc optimisé une fiche produit automatisée pour exposer des vignettes du même produit sous différents angles [Krannert, Prabuddha De and Mohammad S. Rahman,2010]. Chaque consommateur est sensible à différents facteurs de produits. Ceci nous a inspiré à

intégrer un mode de zoom pour permettre d'évaluer la qualité des produits [Thu H. N and Ayda G., 2014 ; Lobasenko, V., 2017] et étudier l'influence des différents attributs de produits qui déclenchent un achat.

Le développement du système de vignettes permet de mettre en valeur les différents aspects des produits qui pourraient déclencher des intentions d'achat chez les consommateurs. Les vignettes permettent de focaliser l'attention du consommateur sur l'entièreté du produit, sur les matériaux/tissus ou bien mettre en avant son utilisation. Etant donné que notre programme de recherche est de détecter les facteurs de déclenchement de l'acte achat, cet outil nous permet de mettre en avant les différents attributs et détecter (grâce à une analyse fine des cliques et observations des consommateurs) le comportement du consommateur. Nous avons aussi identifié l'exigence des consommateurs vis-à-vis de leurs préférences de couleurs sur un produit. Nous avons ainsi développé la possibilité de voir les différents modèles de couleurs du produit. Cela permet de faire varier différentes caractéristiques des produits et étudier la variation des comportements face à ces données d'entrées. Notre étude bibliographique sur le design de comportement nous a indiqué que nous pouvons engendrer un comportement en augmentant les éléments déclencheurs et en simplifiant l'interaction. C'est pour cela que nous avons enregistré les différents modes de comportement qu'un utilisateur entreprend avec l'outil '*Productsheet*' afin de déterminer les éléments de conception qui favorisent un achat (H2.2).

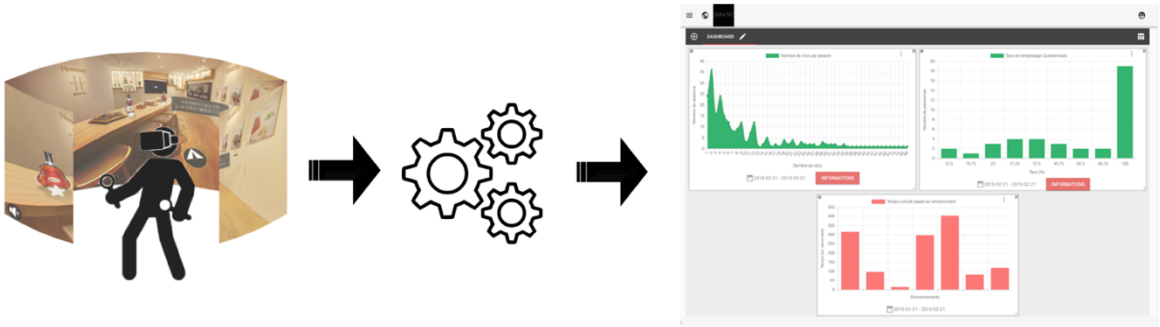
Nous nous sommes intéressés au couplage produit-environnement pour mieux comprendre l'influence des divers environnements de mise en situation sur la mise en valeur des produits. Nous avons utilisé comme format dans un premier temps, un questionnaire digital 2D ou les participants simulent un acte d'achat. Nous avons très vite remarqué une distorsion du ressenti quand le produit est évalué seul et qu'il est mis en situation. Cependant, l'évaluation des ressentis des utilisateurs lors d'une simulation n'est pas fiable car elle ne reflète pas nécessairement le ressenti actuel d'un consommateur lors d'un acte d'achat. C'est pourquoi nous avons développé un questionnaire qui permet et facilite la récolte de données des ressentis des utilisateurs lors de l'expérience d'achat en réalité virtuelle.



VR Survey DIAKSE

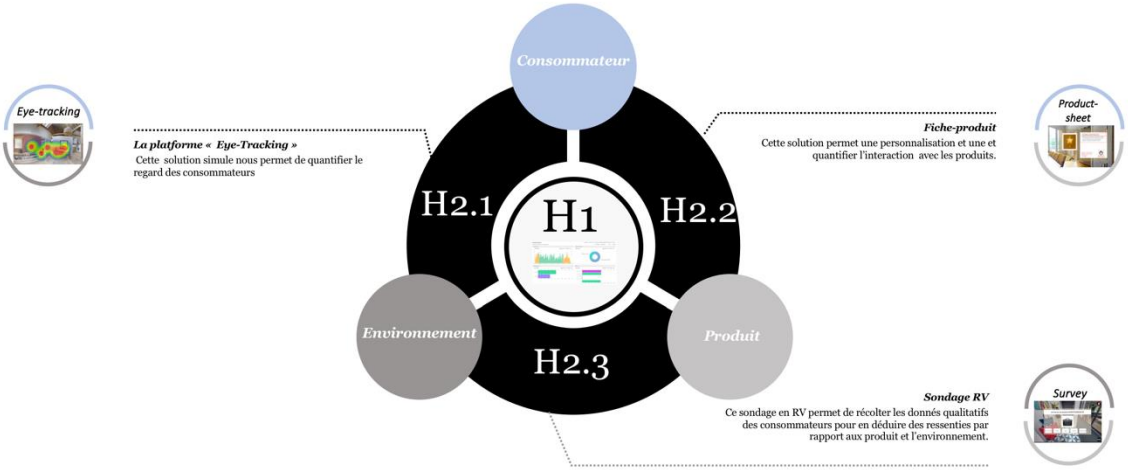
L'objectif du *'VR Survey'* est d'identifier quel environnement mettrait en valeur le produit. Plus précisément les caractéristiques sémantiques de l'environnement qui mettent en valeur les caractéristiques sémantiques du produit afin de promouvoir l'achat (H2.3). Afin de s'assurer que les ressentis évalués représentent ceux d'un consommateur avec une vrai intention d'achat, cet outil se déclenche dès qu'un consommateur valide un produit dans son panier. Nous nous sommes inspirés de notre état de l'art sur les valeurs sociologique de Rokeach [Rokeach, Milton., 2010] traits de personnalité [Cattell, H. E. P. & Mead, A. D., 2008 ; Gardner, William L ; Martinko, Mark J., 2016 ; Costa, Paul & R. McCrae, Robert., 2012] pour segmenter les typologies des consommateurs. Les travaux de Carole bouchard sur la méthode CTA [Bouchard, C., Omhover, J., Mougenot, C., & Aoussat, A., 2007] nous ont insufflé l'idée de récupérer les descripteurs sémantiques des produits et des environnements de mise en situation.

L'ensemble de ces données sont transférés dans un outil de recueil en phase 3 que nous avons développé.



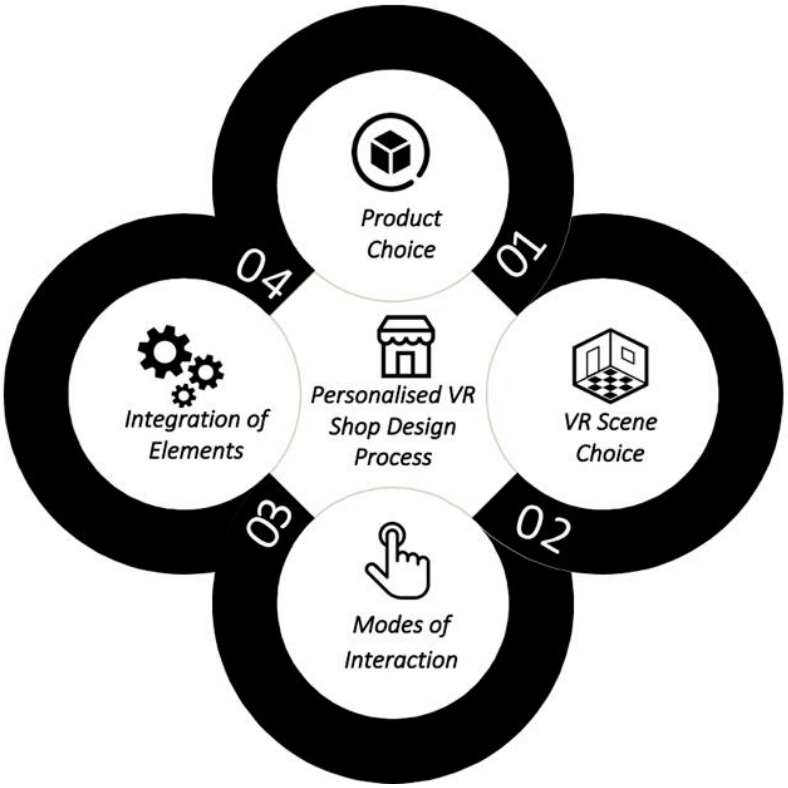
DIAKSE Dashboard

L'outil *dashboard* permet d'avoir une vision globale sur les différents comportements des utilisateurs afin d'en déduire des aperçus essentiels comportementaux et visuels. De plus, ce *dashboard* permet d'observer l'influence des changements dans nos visites virtuelles et leurs impacts sur l'acte d'achat (i.e. : l'ajout au panier). Grace à cet outil nous pouvons visualiser les données comportementales des consommateurs avec plus de précision. En outre nous pouvons extraire l'ensemble des données convertibles en un format tabulaire et exploitable (CSV). Ceci nous permet d'appliquer des tests statistiques de corrélation (i.e. : analyse multifactoriel, régression linéaire) afin de caractériser les profils des consommateurs en fonction de leurs préférences sémantiques des produits et environnements. Le dashboard permet d'évaluer en temps réel le parcours type des utilisateurs afin d'optimiser et améliorer leurs expériences. Ceci nous octroie la possibilité d'optimiser l'expérience émotionnelle d'un acte achat [Watson, L., & Spence, M. T.,2007] et voir l'influence du ressenti sur les divers comportements.



Positionnement des hypothèses par rapport à la technologie 3DR3CO

La figure ci-dessus décrit la suite des outils développés par rapport aux hypothèses mentionnées ci-dessus. L'outil dashboard permet une représentation visuelle rapide du comportement de navigation (lié au regard). Grâce à ces paramètres de comportement, nous pouvons mieux comprendre celui du consommateur dans les boutiques en réalité virtuelle. Nous pouvons voir dans la partie H2.1 de notre figure que les outils *eye-tracking* permettent de quantifier le couplage environnement de mise en situation et le consommateur. Ainsi les observations des comportements consommateurs dans un environnement de mise en situation (le temps passé, zones regardées, déplacements effectués, rating de l'expérience etc.) peuvent être synthétiques pour chaque utilisateur. De ce fait, des règles de conception par rapport aux navigations des consommateurs au sein des environnements de mise en situation peuvent être définis afin de favoriser les actions souhaitées. Le couplage produit-consommateur est défini par les interactions des utilisateurs avec le produit à travers l'outil *Productsheet* (la partie H2.2). Ceci nous présente les caractéristiques des produits les plus marquants et qui ont contribué à l'achat, tels que : l'image la plus persuasive, la grille de tarifs, la mise en place, etc…. Il nous permet également d'évaluer comment l'utilisateur perçoit le produit avant de l'acheter. Enfin, le couplage produit et environnement est défini par la perception du consommateur sur la mise en scène. L'utilisation de l'outil *VR Survey* en réalité virtuelle permet de récolter le ressenti d'un consommateur par rapport à l'impression du produit et sa cohérence avec l'environnement et d'obtenir des informations sémantiques qualitatives (évaluation de la mise en valeur, cohérence de l'expérience, définition du profil du consommateur, etc…).



Processus de conception d'environnement virtuel de vente personnalisable

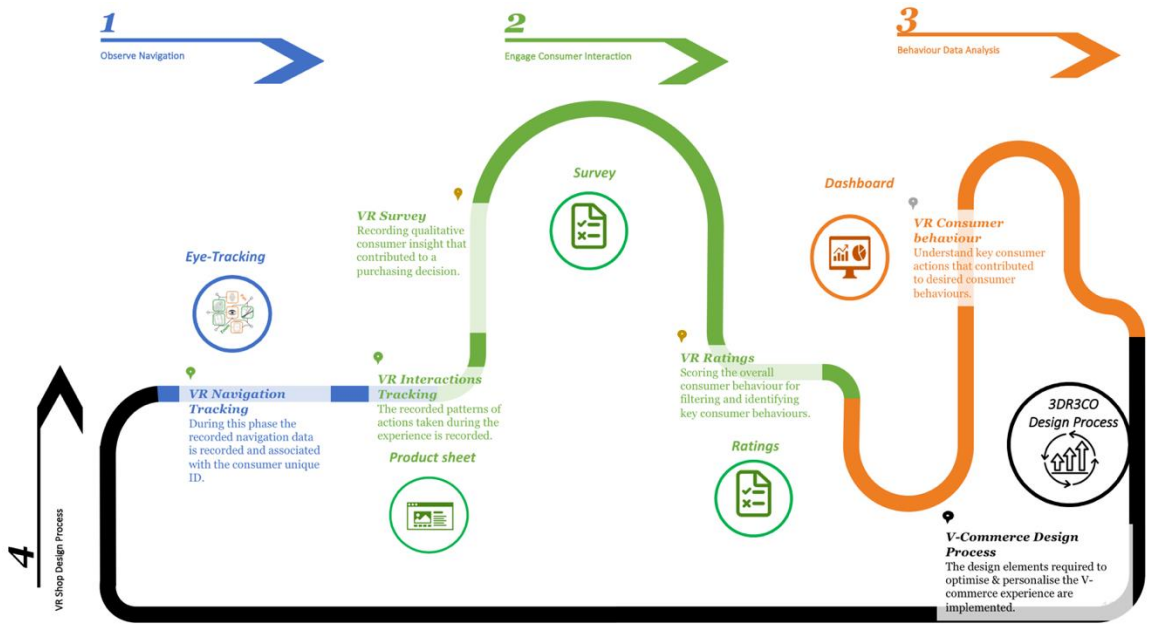
Le schéma ci-dessus décrit le processus de conception d'environnement virtuel de vente à base de règles de conceptions déduites du comportement du consommateur. La première étape consiste à identifier les paramètres de produit à mettre en avant. Par exemple, quels sont les produits qui étaient les plus consultés et/ou achetés. Les données récupérées nous fournissent un aperçu sur le type de produit (prix, utilité, mise en scène) qui a été le plus acheté, afin de mieux définir les paramètres de produit.

La deuxième étape consiste à personnaliser les environnements de mise en situation. Les données récupérées nous permettent de mieux comprendre le comportement des consommateurs au sein des environnements de nos boutiques en réalité virtuelle. Nous pouvons déterminer les zones les plus influentes pour un achat afin de mieux valoriser le produit et étudier le taux d'achèvement du parcours du consommateur (combien de scènes sont vues en moyenne par l'ensemble des consommateurs).

La troisième phase consiste à étudier la manière dont l'ensemble des consommateurs se comportent dans une boutique virtuelle, déterminant et facilitant les interactions pour

favoriser l'achat. Les données récupérées permettent d'analyser la manière dont les consommateurs naviguent au sein de la boutique virtuelle et les éléments consultés lors du processus d'achat. Nous analysons aussi la manière dont les utilisateurs naviguent dans une boutique virtuelle en utilisant des A/B test sur diverses méthodes de navigation (tels que : les boutons au sol, la barre de progrès ou les flèches sur l'écran de leurs appareils) afin d'évaluer la méthode la plus intuitive, la plus fiable et qui assure un parcours consommateur fructueux. Nous analysons les modes d'interactions avec les produits (la fiche-produit) pour optimiser la mise en valeur du produit en mettant en avant les images des produits les mieux appréciés. Les règles de conception qui en découlent, permettent une personnalisation de l'expérience selon l'ensemble des comportements des consommateurs.

La quatrième phase correspond à l'intégration des règles de conception dans l'expérience de boutique virtuelle. Ceci correspond à la personnalisation des éléments de conception pour chaque utilisateur de façon à ce que chaque boutique soit personnalisable selon le comportement du consommateur. En s'inspirant des divers modèles de système de recommandation, nous cherchons à identifier le meilleur algorithme que nous pouvons appliquer afin de promouvoir l'achat. Dans le cadre de l'amélioration des ajouts au panier nous nous sommes intéressés à l'intégration d'un système de recommandation dans le contenu des fiches produits. L'enjeu est d'identifier et de pouvoir personnaliser les paramètres de la fiche produit en incorporant l'analyse du comportement du consommateur.

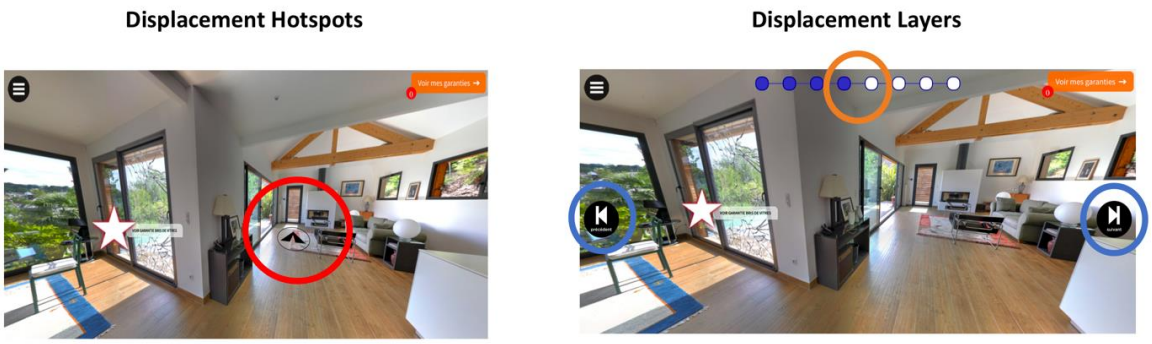


Méthodologie 3DR3CO

Le schéma ci-dessus démontre l'ordre chronologique des outils de la solution 3DR3CO. Nous pouvons voir que le cycle d'un consommateur se décompose en quatre phases. La première phase consiste à récolter les données d'interaction et de navigation du consommateur pendant l'expérience d'achat en boutique en réalité virtuelle. Ceci nous permet de récolter des données de navigation tels que le regard des consommateurs et les diverses interactions avec le produit. Lorsqu'un utilisateur ajoute un produit au panier, le comportement utilisateur souhaité dans ce cas de figure, les outils décrits en phase 2 sont déclenchés. L'outil d'évaluation (*VR Survey*) nous permet de mieux comprendre le processus cognitif qui a mené à l'achat. Finalement, un outil d'évaluation de l'expérience globale (*Ratings*) est déclenché pour noter l'expérience utilisateur en boutique virtuelle. L'ensemble des données (navigation, interaction, ressenti) sont hébergées au niveau du tableau de bord (*Dashboard)* en phase 3 qui permettent une agrégation de l'ensemble des données et une visualisation perspicace. Le tableau de bord permet d'exporter les données relatives aux comportements des consommateurs sous un format qui s'intègre facilement aux logiciels statistiques open-source. Ceci permet de modéliser les données afin d'établir un modèle descriptif du comportement du consommateur. En modélisant le comportement du consommateur, nous extrayons les règles de conception sous format de recommandations prédictives afin de promouvoir l'achat.

Pour vérifier les hypothèses, nous avons pris pour étude de cas 2 modes de diffusion du v-commerce chez DIAKSE : mode **plugin** et mode **marketplace**. La technologie 3DR3CO développée dans le cadre de ce projet a été déployée auprès des sites de e-commerce opérationnels dans le but d'améliorer l'expérience client. DIAKSE utilise le mode plugin comme solution embarquée sur un site de e-commerce existant et permet aux consommateurs de plonger dans des univers immersifs. Cet environnement virtuel met en valeur les produits afin de stimuler le comportement d'achat. Concernant le mode plugin, cette expérience nous a permis de récupérer des données sur une période d'un an et demi (décembre 2017-mai 2019), et d'analyser 3 306 connexions contenant des données de consommateurs. Grace à la technologie 3DR3CO nous avons pu obtenir des données de navigation / d'interaction et les stocker dans une base de données comportementale. L'ensemble de ces données sont analysées pour en déduire les comportements qui incitent à l'achat.

Grace à ces données nous avons pu identifier une corrélation entre le nombre de scènes visitées et l'acte d'achat. Ceci nous a poussé à investiguer davantage pour définir les critères qui influencent les consommateurs à visiter le plus de scènes durant l'expérience v-commerce.



Différents modes de navigation

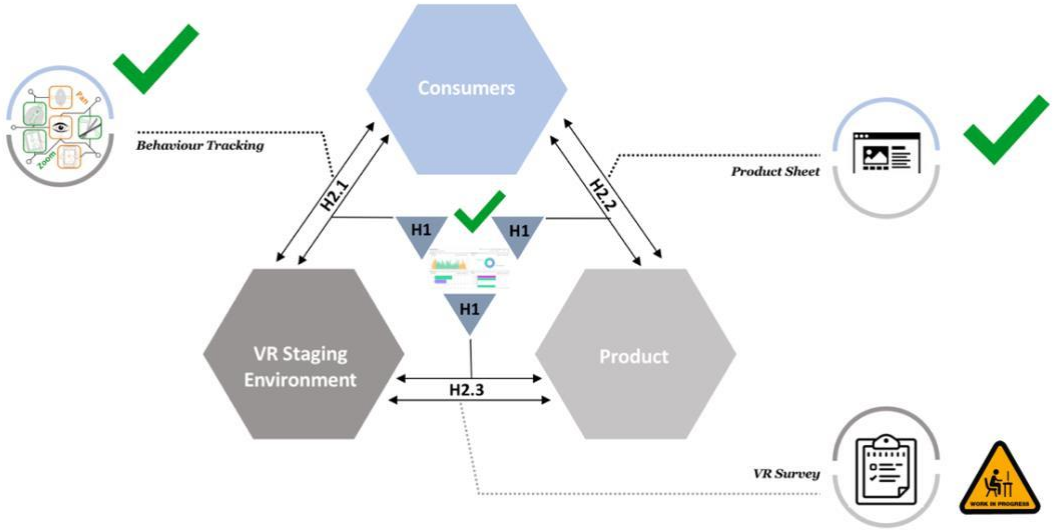
Il a été noté qu'en utilisant un mode de navigation de type « *Displacement Layers* », le nombre d'utilisateurs ayant visité a doublé (de 4 à 8 scènes sur 11).

Pour notre deuxième cas d'étude nous avons investigué le mode « Marketplace » qui offre aux consommateurs la possibilité de s'immerger dans un environnement virtuel avec différentes boutiques immersives (jeux vidéo, art, maroquinerie de luxe, billetterie, etc.…).

V-commerce : mode marketplace

Comme nous pouvons le constater sur la figure au-dessus, chaque bouton représente un point d'entrée à une boutique immersive labélisée selon une catégorie. Dans le cadre de notre étude, nous considérons 885 connexions aléatoires récupérées sur une période d'un an (juillet 2018 - juillet 2019). L'objectif est d'identifier les comportements de navigation et d'interaction qui incitent à l'acte d'achat. Grâce aux données comportementales enregistrées, nous avons pu constater que les personnes ayant acheté un produit ont consulté le plus de fiche-produit et exploré moins de scènes.

D'autant plus, nous avons observé que le positionnement des points d'entrées de boutique en RV n'influence pas le comportement d'achat, car les boutiques ayant connu le plus de succès n'étaient pas celles qui se trouvaient à la position de départ de l'expérience. Grâce à cette technologie nous avons pu en temps réel analyser le comportement des utilisateurs afin d'en définir de nouveaux éléments de conception et ainsi reconcevoir les préférences de chaque consommateur.



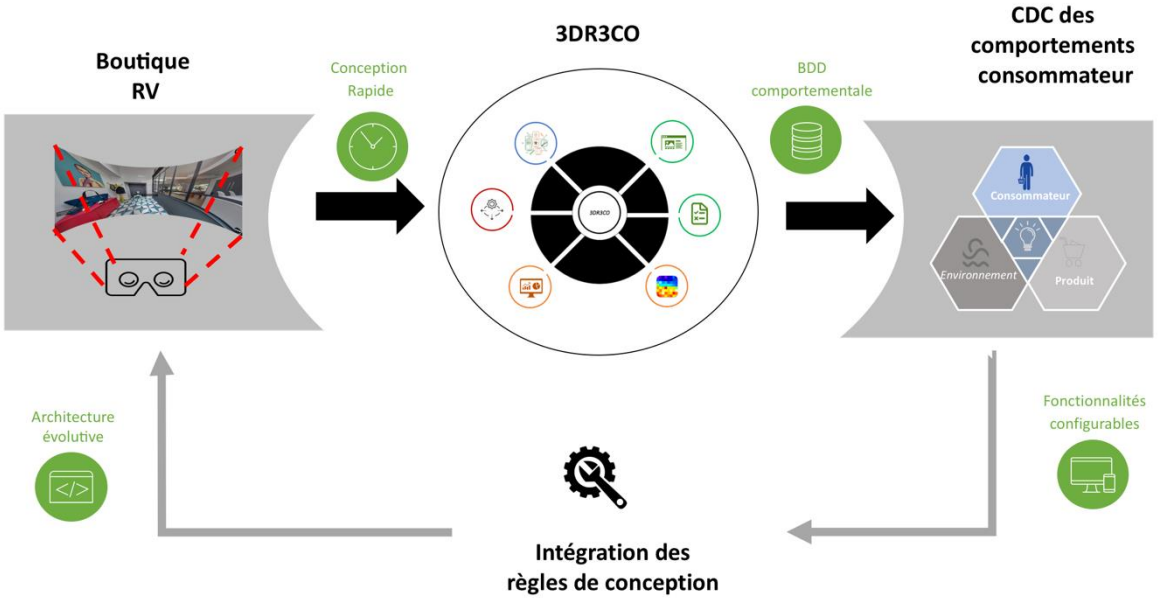
La technologie 3DR3CO développée dans le cadre de ce projet de recherche nous a permis de tester et valider l'ensemble de nos hypothèses. Les outils développés pour récupérer les données affectives sont la « VR Survey » et « VR Ratings ». Ces outils nous ont permis d'enregistrer en immersion totale les évaluations cognitives des consommateurs, pour mieux cerner leurs comportements d'achat. Les outils développés ont été soumis à un bêta test, dont le but était d'évaluer l'acceptabilité des consommateurs lors d'une expérience d'achat en RV dans un environnement virtuel de vente. Les résultats du bêta test ont démontré que le niveau d'acceptabilité du consommateur était trop faible pour être déployé auprès des clients réels. La validation de l'hypothèse 2.3 n'a donc pas pu être confirmée. Plus encore, les expériences ci-dessus ont indiqué qu'un utilisateur typique effectue en moyenne 4 à 6 clics pendant une expérience d'achat en RV. Par conséquent, les travaux en cours reposent sur l'identification du moment optimal de déclenchement des « VR Ratings » et « VR Survey ». Par ailleurs, nous nous intéressons aussi à l'identification de nouveaux modes d'extraction du ressenti du consommateur avec le moins de clics possibles.

Conclusion & Perspectives

Le travail mené dans le cadre de ce projet de recherche porte une ouverture scientifique sur divers sujets. Le verrou que nous cherchons à lever au travers de cette thèse, consiste à identifier comment incorporer l'analyse du comportement du consommateur afin d'optimiser la création d'un environnement virtuel de vente. En raison de la complexité de ce sujet nous avons détaillé un état de l'art centré sur la prise en compte des consommateurs. Cet état de l'art, sans doute non-exhaustif se porte sur les relations entre le comportement du consommateur et les diverses techniques utilisées par les magasins en ligne et physiques. Grâce à cette étude nous avons souligné des règles de conception qui nous ont servi de guide pour le développement de divers outils permettant d'étudier en temps réel le comportement du consommateur. Dans le cadre de cette thèse, nous avons formalisé une méthodologie qui utilise un ensemble d'outil de e-commerces en réalité virtuelle qui permettent de récolter et d'analyser le comportement des consommateurs. Ainsi, le comportement du consommateur est modélisé afin identifier des éléments de conception pour personnaliser et optimiser des environnements virtuels de vente et promouvoir l'achat.

Cette recherche a créé des moyens d'évaluer le ressenti et le comportement du consommateur en récoltant avec une fréquence déterminée le regard du consommateur. Ceci permet d'enregistrer les coordonnées sphériques d'un point au sein d'un environnement virtuel. Cette technique nous a permis de développer des outils tels que la carte des chaleurs et le eye-tracking. Cependant, cette technique n'est pas facilement compréhensible et nécessite une interprétation des coordonnées sphériques lors des analyses des comportements des consommateurs. Nous souhaitons intégrer des modèles de traitement d'image pour développer des techniques de reconnaissance d'objets et pour traduire sémantiquement les divers segments d'un environnement virtuel. La complexité scientifique consiste à développer une méthodologie d'aide à la description sémantique des objets en utilisant la reconnaissance d'image. Grâce aux avancées de l'intelligence artificielle dans la reconnaissance d'image, cette technique pourra optimiser l'analyse

comportementale dans les boutiques virtuelles afin de mieux comprendre le consommateur et promouvoir l'achat.



Processus d'amélioration d'une boutique en RV grâce à 3DR3CO

Le travail mené lors de cette thèse nous permet de développer, tester et formaliser la technologie 3DR3CO et l'incorporer dans un processus d'amélioration et personnalisation de la boutique en réalité virtuelle. La technologie 3DR3CO permet d'établir un cahier des charges basé sur le comportement des consommateurs. Ce cahier des charges vise à définir comment l'ensemble des utilisateurs entreprennent l'expérience d'achat dans la boutique en réalité virtuelle. Des informations telles que le nombre de scènes visitées, types de produits consultés/achetés, mode de navigation et ressenti global y figurent. Les éléments du cahier des charges sont reconvertis en règles de conception pour améliorer l'expérience et promouvoir l'achat.

Une des perspectives que nous souhaitons explorer à la suite des recherches menées lors de cette thèse est l'évaluation des ressentis des utilisateurs lors d'une expérience d'achat en réalité virtuelle grâce aux l'outils de DIAKSE la « VR Survey » et « VR Ratings ». Nous avons identifié lors de cette recherche l'importance des ressentis et des émotions lors d'une expérience d'achat. Nous souhaitons donc créer un processus qui est émotionnellement

intelligent (prend en compte le ressenti des consommateur) lors de l'expérience d'achat en réalité virtuelle. La difficulté de ce travail est de formaliser une méthodologie d'évaluation de ressenti cognitif des consommateurs. Nous souhaiterons investiguer sur comment cette méthodologie pourrait se retranscrire dans un processus de conception d'une base de données descriptive des consommateurs en réalité virtuelle.

La réalité virtuelle aujourd'hui est encore une technologie nouvelle confrontée à plusieurs limitations techniques. Néanmoins, les avancées scientifiques citées dans cette thèse, démontrent le potentiel de cette solution pour renforcer l'expérience émotionnelle. Dans une perspective d'amélioration et de renforcement de l'expérience des utilisateurs, ce projet de recherche nous conduit à explorer de nouveaux modes d'interaction pour améliorer l'expérience des consommateurs en réalité virtuelle. La complexité d'une telle perspective, consiste à formaliser une méthodologie d'identification du mode d'interaction dans le V-commerce. Comme nous l'avons montré dans ce projet de recherche, la fiche produit est un outil indispensable dans l'expérience d'achat, qui reprend les conventions existantes dans les boutiques en e-commerce. Nous souhaitons identifier les fonctionnalités, au sein des boutiques en réalité virtuelle, qui doivent être mises en avant afin d'améliorer l'immersion et l'expérience utilisateur. Grâce à cela nous pouvons développer des solutions tel que : l'intégration des avis des consommateurs, des interactions vocales, des retours haptiques / achats collaboratifs en réalité virtuelle et étudier leurs influences sur les comportements d'achat.

ANNEX

E-commerce Types

E-commerce types	Definition
Business-to-Consumer (B2C)	The most familiar form e-commerce corresponding to the conventional retail transaction between a business and the end-consumer.
Business-to-Business (B2B)	Refers to a transaction between companies, where the seller buys a product with the intention of reselling it. This corresponds to the manufacturing/wholesaler relationship in conventional commerce.
Consumer-to-Consumer (C2C)	Corresponds to online transactions of goods or services amongst consumers through the use of an online platform known as a marketplace (i.e. Amazon).
Consumer-to-Business (C2B)	Corresponds to a reverse conventional commerce, where end-consumers sell products (photography, music, etc..) or services to companies.
Business-to-Administration (B2A)	Refers to online transaction solutions that are offered by business to public administrations, which have given rise to the paradigm of e-government.
Consumer-to-Administration (C2A)	Encompasses transactions between consumers and administratio usually in the form of digitalizing conventional government servic (education, health, taxes, etc.)

Table 12. List of e-commerce types

Rokeach Values

Instrumental Values	Terminal Values
True Friendship	Cheerfulness
Mature Love	Ambition
Self-Respect	Love
Happiness	Cleanliness
Inner Harmony	Self-Control
Equality	Capability
Freedom	Courage
Pleasure	Politeness
Social Recognition	Honesty
Wisdom	Imagination
Salvation	Independence
Family Security	Intellect
National Security	Broad-Mindedness
A Sense of Accomplishment	Logic
A World of Beauty	Obedience
A World at Peace	Helpfulness
A Comfortable Life	Responsibility
An Exciting Life	Forgiveness

Table 13. Rokeach list of values

Schwartz Values

Schwartz Values	Definition
Benevolence	An altruistic concern for the well-being close friends leading to pro-social behaviours.
Universalism	An appreciation of the well-being *all* people and natural beings.
Security	The search for safety and confrontation avoidance. This value motivates people to seek harmony and good social relationships to attain a sense of belonging.
Tradition	The respect for custom behaviour that is based on traditions and religious beliefs.
Conformity	The self-discipline and restriction of behaviour and impulses that misaligned with social norms.
Power	The search for higher social superiority and dominance.
Achievement	The pursuit for success and esteem, and competence of the surrounding standards.
Hedonism	The search for gratification and joy of life.
Stimulation	The search for excitement and new excitement.
Self-Direction	The search for independence and autonomy and freedom of one's own judgement.

Table 14. Swhartz Values and definitions

Marketing Mix Factor

Marketing Mix factor	Definition
Product	Consists in understanding all the attributes (design, quality, brand, technology, value, etc…) that form the product/service.
Price	Refers to the different approaches (pricing strategies, pricing discounts, etc…) taken in order to price the product/service.
Promotion	Refers to the methods (public relations, media channels, message frequency, etc…) of communication to convey the product's information and persuade consumers.
Place	Refers to the various types of channels to market and improve the convenience to buy by considering factors such as: geographical distribution, market location, logistics.
People	Refers to the human factor (company personnel, consumer interactions) that participate in the delivery, selling of the product an interacting with customers
Process	Refers to the procedures, direct and indirect activities (technological, manufacturing processes, etc…) that add value to the product/service. The process is a service that enables the delivery of customer's proposition.
Physical Evidence	Refers to abstract cues that influence a consumer's purchase intention designed into services (souvenirs, invoices, delivery design, etc…).

Table 15. Marketing Mix definition

Data-mining techniques

Data mining techniques	Definition
Classifications	This involves the grouping and collection of items using distinguishable attributes. Often this requires this refers to the mathematical modelling that describes discernible item classes. This technique is used to identify to which pre-defined categories a new observation belongs to, given a training set of instances and their categories.
Clustering	This refers to the aggregation of various items based on its' attributes. Unlike classification, clustering gives a classification output without the use of predefined training sets.
Semi-supervised Classification	This technique is a mix of the aforementioned techniques in which both labelled and unlabelled observations are used to perform classifications. Nevertheless, the level of classification accuracy relies on an increased number of observations.
Association Analysis	This refers to the learning of patterns within a dataset amongst interdependent variables. This technique is used in order to deduce association rules and improve recommendation systems, customer relationship management systems and personalisation filters. One of the most known analogies is the oddly strong relationship between the purchasing of beers and diapers [Tan, P.-N & Steinbach, Michael & Kumar, Vipin., 2005].
Regression Analysis	This technique is used in prediction analysis and to know what category a variable fall in given a set of datasets. Unlike classification this technique is used as a form of modelling to predict the likelihood of continuous variables, whilst classification is used to determine the likelihood of discrete variables. Regression analysis is capable of making predictions based on relationships amongst variables in a dataset.
Outlier Detection	This method involves the detection of anomalies by identifying patterns that are significantly different (outliers) to the rest of the dataset.

Table 16. Most popular data-mining techniques

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Alaa Elboudali

Formalisation of a novel design methodology of virtual shopping environments using emotional engineering and consumer experience.

Résumé

Ce projet porte sur l'étude d'une nouvelle méthodologie d'aide à la conception d'environnements virtuels de vente, basée sur le comportement des consommateurs en réalité virtuelle. Le marché du e-commerce, est en perpétuelle évolution qui redéfinie le comportement d'achat des consommateurs. Dans le cadre d'une convention CIFRE, DIAKSE une entreprise spécialisée dans la création de magasin en réalité virtuelle pour les sites de e-commerce cherche à développer une nouvelle solution intelligente d'analyse comportementale. L'état de l'art nous a permis de nous intéresser à comment peut-on intégrer l'analyse du comportement du consommateur afin optimiser la création d'un environnement virtuel de vente ? Cette problématique nous a permis de nous intéresser aux méthodologies de quantifications de la perception en se basant sur l'ingénierie émotionnelle. Ces méthodes sont souvent utilisées dans le cadre de développement et conception de produit. Le verrou que nous cherchons à lever à travers cette recherche consiste à prendre en compte l'environnement de mise en situation des produits afin d'évaluer la perception d'un produit dans un environnement virtuel.

Mots clés : V-Commerce,Design d'experiences utilisateurs,Systèmes de recommandation

Résumé en anglais

This project involves the study of a new methodology to assist in the design of virtual sales environments, based on consumer behaviour in virtual reality. The e-commerce market is constantly evolving, redefining consumer purchasing behaviour. As part of a CIFRE agreement, DIAKSE, a company specialising in the creation of virtual reality shops for e-commerce sites, is seeking to develop a new intelligent behavioural analysis solution. The state of the art has enabled us to focus on how we can integrate the analysis of consumer behaviour in order to optimise the creation of a virtual sales environment. This issue has allowed us to focus on methodologies for quantifying perception based on emotional engineering. These methods are often used in the framework of product development and design. The obstacle that we are trying to overcome through this research consists in considering the environment in which the products are put into situation in order to evaluate the perception of a product in a virtual environment.

Keywords: V-Commerce,UX Design,Recommender systems