Neuromarketing in E-Commerce: Mouse tracking as a tool to uncover the cognition of a decision process

DIPLOMA THESIS

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Abstract

This diploma thesis aims to identify and understand the cognitive processes of a consumer when making purchases online. Literature shows that the theory of two distinct processes, one which is fast and intuitive and one which is slow and deliberate, can be used to explain decision difficulty in an E-Commerce scenario. As a medium, computer mouse tracking was used which is a valuable tool to give insight into the human mind's mental processes. Its ability to record motoric movements on a real-time scale and its simplicity of application and execution makes it useful for consumer behavior research. With an increase in decision difficulty, it is expected that mouse movements show higher complexity and curvature measures. This thesis includes interesting findings for online marketers concerning sales strategies and product placement but also addresses researchers to use mouse tracking to further investigate consumer behavior by analyzing cognitive processes. The results of this study were obtained with an experiment which was executed by 157 participants at the University of Innsbruck in which test subjects faced an E-Commerce like choice task. The recorded mouse movements were analyzed descriptively and graphically and were put in context to consumer behavior research.

Keywords: Mousetracking, E-Commerce, Cognitive Processes, Consumer Behavior

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List of Abbreviations

EKB-Model – Engel, Kollat, and Blackwell Model

AUC – Area Under the Curve

MAD/MAD_time – Maximum Absolute Deviation/Maximum Absolute Deviation time

RT – Rection Time

CSV – Comma Separated Value

bc – Bimodality Coefficient

xpos – x-axis position

ypos – y-axis position

SD – Standrad Deviation

DPI – Dots Per Inch

TXT – text file

HTML – Hypertext Markup Language

CSS – Cascading Style Sheet

PCA – Principle Component Analysis

1. Introduction

When walking from A to B in a straight path, different external influences can alter that path. When walking towards B and your favorite fast-food restaurant (which is located close by) captures your attention, it might slightly manipulate your walking direction so that you do not walk straight anymore. Even though you decide against a fast-food restaurant visit, your final walking line might show a slight pull towards the restaurant on your way from A to B.

Now it is questionable how this example can be appropriate to describe online marketing analysis methods. When sitting in front of a computer with your hand on the mouse, movements with that mouse can be influenced by numerous factors. Compared to the previous example, these mouse paths might show an unconscious pull towards an unselected option that captured your attention. The question remains of how this information can be helpful for online marketing. This thesis tries to explain how the tracking and analyses of mouse paths can be beneficial for E-Commerce strategies.

The E-Commerce Sector is growing and makes up a large part of total retail sales. Internet users grew by 6% each year and reached 3.8 Billion users in 2018, which corresponds to half of the world population in that year (Meeker, 2019). In 2020 the total U.S E-Commerce sales make up 16% of the total retail sales and the trend suggests growth for the upcoming years (U.S Census Bureau, 2020). Online shopping has clear advantages over a brick and mortar store as it provides constant availability and minimizes location-based barriers. Furthermore, with mobile shopping, a stationary computer or laptop is not necessary. However, a disadvantage of online shopping is that the purchase procedure cannot be accompanied by sales staff and marketing measures like advertisement is the only influence in a purchase. Nevertheless, digital ad spending is on the rise and reached in 2018 - 93.18 Billion $ in the United States (Prabhala & Umamaheswara Rao, 2019).

As a consequence of the mentioned disadvantage that shopping procedures cannot be supervised, it is important to keep the consumer’s attention high. For an effective advertisement, the three key elements (brand, pictorial and text) need to be adjusted. They are based on competitive strategies to catch and hold consumers' attention (Pieters & Wedel, 2004). As attentional resources are limited and browsing through the web often is fast-paced and goal orientated, Davenport and Beck state that attention belongs to one of the scarcest resources of in today’s consumer business (Davenport & Beck, 2001). For a consumer to complete a buying decision, the referring product must go through high competition and focus must not deviate until the decision is made. The infinite amount of information the web offers can impose a threat to the consumer’s ability even to execute a decision.

It is found that “cognitive load is fundamentally harming an individual's ability to effectively make choices “(Deck & Jahedi, p.110, 2015). Therefore, marketers must develop effective marketing strategies to facilitate, enhance and understand decision making.

To understand how decisions online are being made is becoming a crucial part for creating ads and can also be of help when designing a website (Arroyo et al., 2006). With an updated EKB Model, which is subdivided into five stages of the decision process, Darley at al. tried to incorporate a model to explain how decisions are being made on the web (Darley et al., 2010). Research in online consumer behavior and the online decision process was mainly performed in psychology research but certainly is becoming relevant for marketers.

In order to improve a websites' efficiency and to understand how online decision-making can influence shopping behavior, A/B testing can be a helpful method. Thereby factors influential to the website's marketing performance are isolated and compared to each other (Dixon et al., 2011). This method is relatively easy to implement but lacks efficiency. Much time is needed to achieve significant statistical results, which might be irrelevant at receive due to the website's ongoing developments (Jevremovic et al., 2014).

Another common method to uncover customer behavior on a website is Eye tracking, which belongs to user experience research and is especially effective in measuring a website's performance. Methods like eye tracking allow to inspect the website from a customer’s point of view and its usability extends over the development to post-launch optimization of a website. Heatmaps that display eye fixations of a customer can help in the design of a website as they show points of interest and structures of eye movement (Djamasbi, 2014). As eye tracking can point out conscious and unconscious behavior, decision-making research has also been making use of this method (Fiedler & Glöckner, 2012). Besides its advantages, eye tracking can be a time-consuming and costly practice.

Comparable to eye tracking, mouse tracking is a new method to trace cursor movements and uncover decision making styles. Neurophysiological research shows that hand movements are an indicator of cognitive decision processes (Freeman, 2018). It is a widespread method in the field of psychology but certainly has the potential for marketing research as well. As it is proven that cursor movements represent a proxy of eye movements, mouse tracking has received enhanced attention lately (Huang et al., 2012). A trigger of the recently obtained popularity is its ease of use and the capability to record large scale data (Demšar & Çöltekin, 2014). According to Darley et al. in 2010, online consumer behavior and online decision-making research are still under-researched topics and existing literature finds itself still in its early development stage (Darley et al., 2010). Mouse tracking as a tool to uncover mental processes in real-time can advance research in that field by providing an insight into the underlying structures of a decision process.

With the internet as an unregulated platform, users are constantly exposed to advertisement-pressure and choices. Online recommendation agents are continuously suggesting products to consumers based on their preferences and web browsing behavior (Häubl & Trifts, 2000). As mentioned earlier, the amount of cognitive load can have a negative influence on the decision ability. Nagpal and Krishnamurthy found that a choice under attractive alternatives can even lead to a denial of the decision (Nagpal & Krishnamurthy, 2008).

To conclude, understanding the processes of the human mind has been a long-term research goal. The emergence of the Dual Process Theory contributed to an approximation of that understanding and is still an accepted theory to uncover mental processes (Frankish, 2010). Using this theory of duality to explain online decision behavior with the help of mouse tracking is the objective of this thesis. To understand the processes behind a decision can be beneficial for marketers in terms of product placement, advertisement placement, product recommendations or web design. It will also be investigated whether mouse tracking is an adequate method to detect and explain online decision behavior. The research question is as follows:

"How can the analyses of computer mouse movements uncover cognitive processes in purchase decision difficulty? "

For the success of this thesis, a quantitative approach was used. In a two-choice decision scenario, participants had to choose between difficult and easy decisions. Mouse movements were recorded with the help of the newly developed program "Webtrackr".

2. Theoretical Background

2.1 Consumer Decision Making

The following sections summarize the main concepts of decision-making and Mouse Tracking to get a better understanding, which role decision difficulty plays in E-Commerce. First, economic decision-making and decision difficulty are explained. Second, the foundations of the EKB Model and the Dual Process Theory are explained briefly.

2.1.1 Economic Decision Making & Decision Difficulty

In 1993 the Decision Field Theory from Busemeyer and Townsend was introduced. This theory provides a mathematical grounded explanation of decision behavior in an uncertain environment. It is based on three other theories of approach-avoidance conflict regarding motivational aspects, decision-making aspects and information-processing theory in context to response time. They concluded that seven parameters are necessary to conduct a decision. These parameters are evaluated in a time-consuming process. Factors like strength of preferences, the approach-avoidance nature of the individual, or trade-off effects are essential for forming a decision output (Busemeyer & Townsend, 1993).

Research in economic decision making developed from only looking at the decision results to investigating the decision process itself. Findings were that decision-making is a deeply cognitive process and emotions and affections play an important role in the decision outcome. Therefore, decision making receives an individual touch and cannot be generalized (Kühberger & Schulte-Mecklenbeck, 2017). Two major cornerstones which influence economic decision making are value and utility. Value is defined in a way that the value of goods decreases when its occurrence is plentiful. Otherwise, it increases when it is rare. Concerning product utility, Bernoulli in 1954 introduced the Principle of Decreasing Marginal Utility, which states that a good's use incrementally decreases the more frequent the goods are consumed (Bernoulli, 1954). Kühberger and Schulte-Mecklenbeck also raise attention to risk and uncertainty as influence factors in decision making. Risk in decision making applies when the possible negative outcomes are known and integrated into the decision-making process. Uncertainty can come in various ways. According to Kahneman and Tversky, it is necessary to distinguish between internal and external uncertainty. Internal uncertainty relates to someone's arguments and knowledge, whereas external uncertainty relates to frequencies and propensities (Kahneman & Tvensky, 1982). The interplay of value, utility, uncertainty and risk build the basis for economic decision making.

Furthermore, decision difficulty is directly dependent on four different factors. According to Bettman et al., decision difficulty increases when the number of alternatives or attributes increases, those attributes' value is not clear, there is uncertainty about alternatives, and when the alternatives' attributes resemble each other. Several other influence factors, determining how difficult decision-making unfolds, need to be mentioned. It is important how the consumer can obtain information from his environment. Accessibility to information can complicate or facilitate decisions. Also, personal experiences and social influence play into decision difficulty. The available time for the decision process and the importance of the decision outcome can have an impact as well. To better understand all influence factors, they can be categorized; there are those dependent on the consumers' cognition and those dependent on the decision-making environment (Bettman et al., 1991).

Computers and the internet largely influence the decision-making environment of today. Guadango and Ciadini point out that computer-mediated group influence has an impact on how decisions are being made. As communication possibilities on the internet keep growing, this platform serves as a mediator and pusher of social connectedness. Decision behavior alters according to the social environment that is heavily influenced by cyberspace (Guadango & Ciadini, 2005). The possibility to rate, review or recommend products can have a big impact on the potential buyers. E-Commerce companies are trying to capture on this social dependence in buying behavior and filter data for suppliers in order to increase selling effectiveness (Kim & Srivastava,2007). Häubl and Trifts in 2000 performed an experiment where they tested 15 to 20 participants in several sessions on their online decision behavior. Subjects had to choose between backpacking tents and compact stereo systems in different orders and for different brands. They manipulated the decision process by adding interactive decision aids like a comparison matrix and a recommendation agent. Results show that it was easier for the participants to decide with these tools and their decision quality increased (Häubl & Trifts, 2000). Nowadays, these interactive decision tools are well spread across the internet platform and can no longer be imagined without.

As cyberspace provides an unfiltered flow of information, the amount of choice alternatives increases, and individual processing capabilities reach their limits. Haynes in 2009 tested 69 students on their decision difficulty, task enjoyment, regret and satisfaction when confronted with a certain number of alternatives which have to be chosen in a time limit. He found that decision difficulty rises, and the other test factors decrease when choice alternatives increase and time pressure increases (Haynes, 2009). Comparably, Deck and Jahedi tested the effect of cognitive load on economic decision making. They concluded, according to previous experiments and their experiment, which represented a digit-memorization task while solving economic decision problems, that the amount of cognitive load harms the ability to make effective choices (Deck & Jahedi, 2015). Therefore, the cyberspace poses limitation to an effective choice making.

To better understand decision behavior under environmental influences, it is necessary to inspect the decision process itself and determine what defines decision difficulty. Liberman and Förster showed that decision difficulty is strongly connected to the attractiveness of alternatives. Difficult decisions are characterized by comparable attractiveness of the alternatives, whereas a broader spectrum of alternative attractiveness characterizes easy decisions. They conclude that decision difficulty is a moderator of buying probability, as the not chosen alternative still has very high value. Costumers might reconsider the previously not chosen alternative in a second store visit (Liberman & Förster, 2006). These results are in accordance with Jacoby and Craik in 1979. They showed in four different experiments that after a participant completed a difficult choice task, the ability to remember was better compared to an easy decision (Jacoby & Craik, 1979). This memory effect of decision difficulty supports the assumption that the not chosen alternative still has a high value. To investigate how decision difficulty unfolds in the context of online decisions, Schneider et al. tracked computer mouse movements in an experiment, testing ambivalence. They conducted three experiments and showed that mouse trajectories had more pull towards the non-chosen alternative when the decision objects were high in ambivalence (Schneider et al., 2015). This result also concludes on decision difficulty's motoric effect, which corresponds with the cognitive effect. Decision difficulty seems to be largely influenced by the attractiveness of alternatives. This effect is enhanced by a multitude of those alternatives due to the unlimited capacity of the internet.

2.1.2 EKB Model

John Dewey was an influential American Philosopher and Psychologist who was a developer of the philosophy of pragmatism and functional psychology. Furthermore, his work about the “Five-Stage Problem-Solving Process” influenced the creation of the Engel, Kollatt, and Blackwell (EKB) consumer decision-making model (Darley, Blankson, & Luethge, 2010). This Model (1968) is still the foundation of recent decision-making research and holds up to today's requirements (Ashman, Solomon, & Wolny, 2015). According to the EKB Model, the consumer goes through five stages of decision making which are 1) problem recognition, 2) information search, 3) evaluation of alternatives, 4) purchase and 5) post-purchase evaluation (Engel, Kollat, & Blackwell, 1968). As this model was developed 52 years ago, technological progress changed society and greatly influenced today’s decision-making process. With the rise of the Internet, these five stages must be interpreted in the means of a digital world and in 2015, Ashman et al. created an updated version of these five stages as problem recognition must be seen in a much broader context.

Due to the information overload of the internet, unrecognized wants or needs appear and social influence, as well as marketing communication, play a much bigger role. The second stage, “information search,” must be updated so that nowadays much more information is available about a certain product. There is a shift from textual to visual information, which results in graphical marketing and attention-seeking banners. Also, non-professional sources of marketing information gain in popularity through social media platforms. Alternative evaluation in the digital world takes place with different tools like price comparison websites, product ranking and live chat support (Breugelmans et al., 2012). Most importantly, peer recommendations can have a major influence on the analysis process to narrow down the number of alternatives. When making the purchase, location-based barriers have been eliminated and there is no need to pay in cash. With a mobile phone, it is possible to purchase from any location with an internet connection. The last stage, “post-purchase evaluation”, must be adapted so that consumers are given reassurance of their purchase decision. Buying’s are shared on social media and future purchases are based and recommended on the received confirmation (Ashman, Solomon, & Wolny, 2015). Due to technological progress, the decision-making process became more effective and complicated as information overload and social transparency must be considered and filtered.

In 2010 Darley et al. developed an adapted and updated EKB Model, which includes four external factors to the decision-making process but still includes the five core stages of the decision process. One of these four factors is individual characteristics like motives, lifestyle, personality and value. Another is social influences, which contains elements like culture, reference group and family. Furthermore, situational economic factors and online environment like web site quality, web site interface, web site satisfaction and web site experience play an influential role. This model also gives an insight into the consequences of the decision process as the outcome can have four different reactions. These are cognitive dissonance, consumption, dissatisfaction/satisfaction and disinvestment, as shown in Figure 1 (Darley, Blankson, & Luethge, 2010).

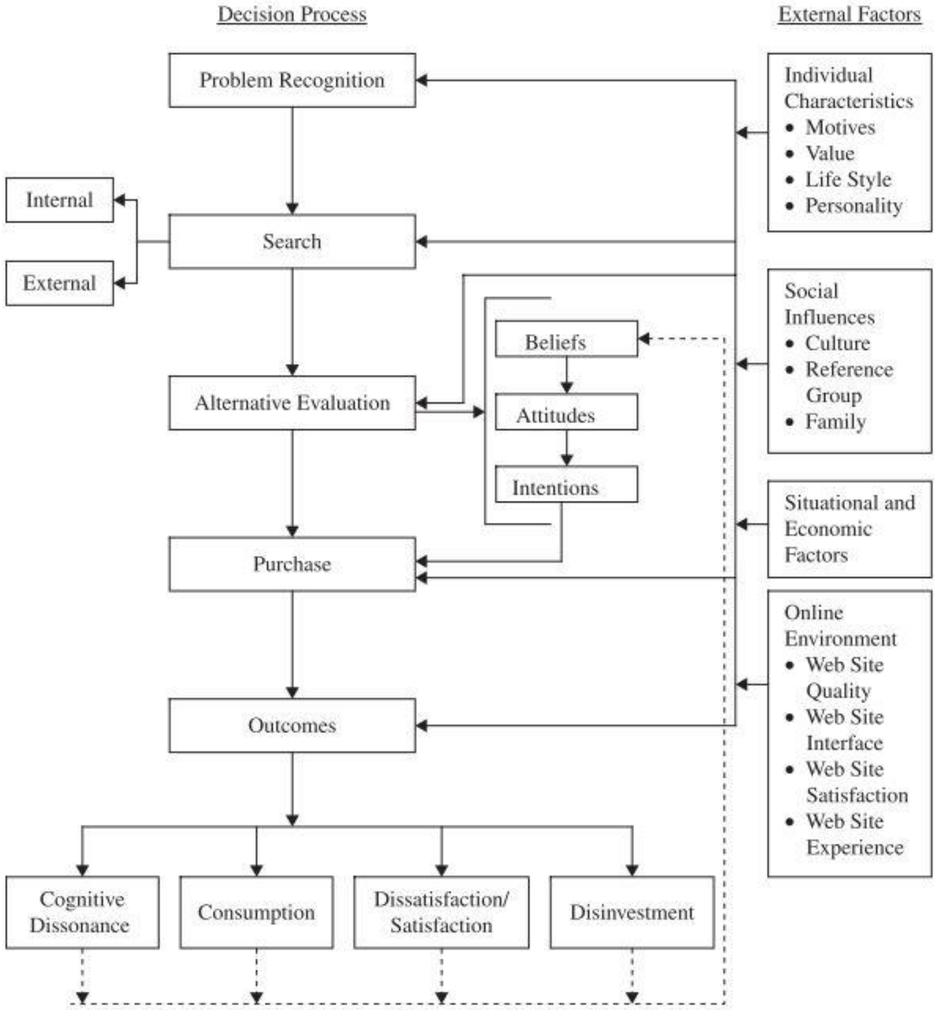


Figure 1 EKB-Model (cf. Darley, Blankson, & Luethge, 2010, p.96)

One criticism of the EKB Model is that it does not include the decision maker's motivational attributes. Therefore Tuan, Pham and Higgins (2005) developed the stylized EKB Model which includes emotional aspects. Consumer decision theory evolved out of the information processing theory and behavioral decision research (Longart, Wickens & Bakir, 2016). Kahneman and Frederick in 2012 contribute that in behavioral decision theory, the focus was on cognition and not on emotional aspects of the decision process. Consequently, it is reasonable to include the emotions of the decision-maker in the EKB Model. Figure 2 shows the stylized EKB Model which was used by Longart et al. in 2016 for research about the selection of restaurants for leisure meals.

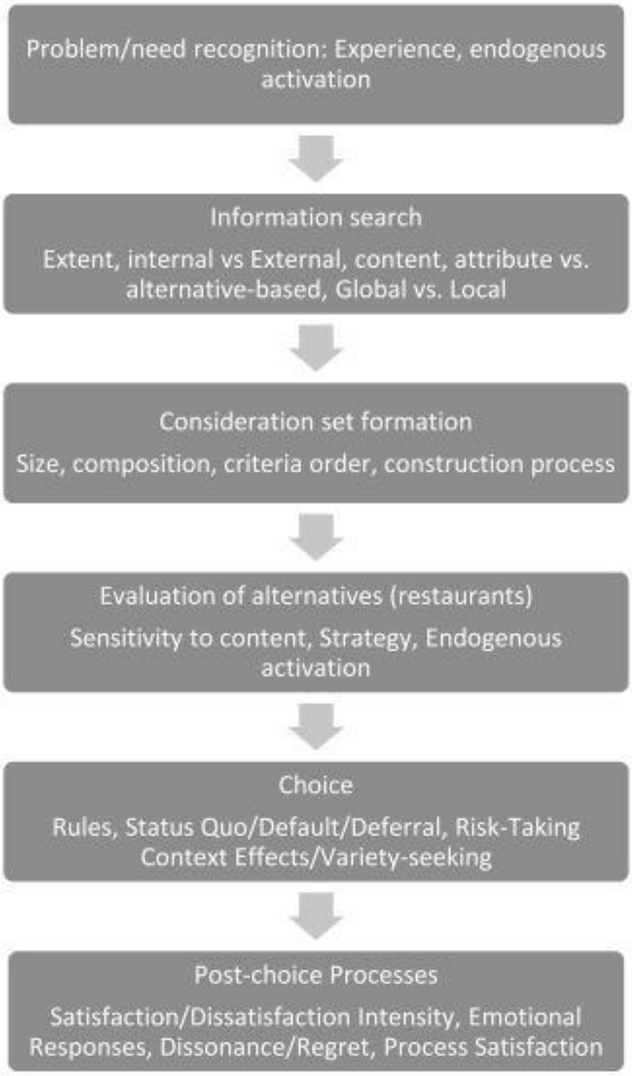


Figure 2 Stylized EKB Model (Longart, Wickens & Bakir, 2016, p. 177)

2.1.3 Dual Process Theory

The Dual Process Theory existed for the last 30 years and still plays an important role in today's psychological research. Nevertheless, theories about duality and division originate back to the 19th century with William James, who theorized about two kinds of thinking: associative and true reasoning. The most important pre-modern impact came from Freud, who held that the human mind comprises two systems: one conscious and the other unconscious (Frankish, 2010). The modern view of the dual process or dual-system theory is System 1 which is described as fast, associative and intuitive, and System 2 which is described as rule-based, analytical, and reflective (Melnikoff, Bargh

2018). Kahnemann and Frederick believe that System 1 quickly proposes answers for judgment and problems and that System 2 monitors the quality of those proposals and corrects them if necessary (Kahnemann, Frederick 2012). In 2015 even the world bank initiated an appeal that people should make more use of System 2 instead of System 1 (Melnikoff, Bargh 2018).

A modern perspective of the Dual Process Theory is described in Viswanathan and Jain's work in 2013. They argue that the younger generation's decision-making differs so that System 1 is the only active part and System 2 gets replaced by a social system. Because of digital media and the permanent social connectivity which comes with it, opinion-forming and reasoning are significantly different in what we used to know. As described earlier, digital media influences the EKB Model and also influences the Dual Process Theory. Viswanathan & Jain point out that with friends, family, and social media platforms being a proxy for System 2, corresponding marketing strategies can also arise (Viswanathan & Jain, 2013). The results from Viswanathan and Jain stand in accordance with the findings of Oaksford and Hall in 2016. They researched human reasoning behavior and tried to identify triggers for irrationality. Thereby, they relied on the Dual Process Theory and found that System 1 is rational, whereby System 2 is prone to errors. Nevertheless, System 2 is supported by social aspects like language, which serves as a correction tool (Oaksford & Hall, 2016). It shows that a digital shift alters the functionality of the Dual Process Theory.

Another detection of the dual-process theory in decision making was made by Koop & Johnson in 2011. With a mouse tracking program, they researched online decision behavior in a risky decision-making task. Participants had to choose between economic gambles, which resulted in either gains or losses. The recorded mouse trajectory showed a straight path when the participants chose the safer gamble option compared to the risky gamble option. The participants at first tended to select the safer option but then switched towards the riskier option. To relate that to the Dual Process Theory, the safer gamble option corresponds to the first intuition (System 1) of the participants, whereas in some cases, participants changed their minds (System 2) and chose the riskier gamble option (Koop & Johnson, 2011).

Critics of the Dual Process Theory say that this model is too simple to describe the human mind's processes and alternative cognitive models should be considered. Furthermore, only a couple of those processes could clearly be attributed to either System 1 or System 2. Most of the cognitive processes are a mixture of System 1 and System 2 features (Melnikoff & Bargh, 2018). Melnikoff & Bargh even assume that research in cognitive science that relies only on the Dual Process Theory underestimates the human mind's dimension and would be counterproductive for this field of science. In addition to that, Dynamic Models like the Decision Field Theory state that there is only one cognitive process that is determinant for decision making (Busemeyer & Townsend, 1993). In

2018 Diederich and Trueblood described a Dynamic Dual Process Model of decision making, which implies that System 1 and System 2 are different, but they interact and cannot be separated. On the one hand, they show that greater affection could lead to quicker response times concerning decision making. On the other hand, the two systems can also come into conflict which results in longer response times (Diederich & Trueblood, 2018). Dhar and Gorlin came to a similar realization by researching the interplay of System 1 and System 2 in a decision task. They found that cognitive load, time pressure, or the number of alternatives are an inhibitor for the functionality of System 2. These influences reduce the ability to make deliberate choices and support evidence that System 1 has an important role in the decision outcome. They conclude that both systems are strongly connected, but the one which finally makes the decision is highly dependent on various influences (Dhar & Gorlin, 2013). Furthermore, Conrey et al. developed the Quad Model, which assumes four distinct cognitive processes. This model was tested on implicit task performance and the four processes can be separated into association activation, discriminability, overcoming bias and guessing. The decoding of the structure behind automatic associations can give insight into the decision-making process of the human mind (Conrey et al., 2005). Sherman et al. used this quad model to differentiate between automatic associations and behavioral impulses. They found that this model is a valuable tool to identify triggers of human behavior and that the human mind's controlled processes have a bigger influence as initially assumed (Sherman et al., 2008). As recognizable there are several alternative theories on how the human cognition behaves. For this thesis, the Dual Process Theory was chosen as it is most consistent with the experiment carried out.

2.1.4 Neuromarketing

The term neuromarketing is a connection of two different areas of research: marketing and neurosciences. With an in-depth brain analysis, neuromarketing aims to explain consumer behavior in order to increase marketing effectiveness scientifically. The advantage of imaging neuronal processes is that even hidden preferences that were unconscious to the consumer can be displayed according to the activated brain regions and analyzed retrospectively. Therefore, neuromarketing has the potential to outperform or improve conventional marketing methods. Neuromarketing research is in its early stage and has been active since the beginning of the 21st century. It has its origin in scientific areas like neuropsychology, neurophysiology, neuroethology or neuroanatomy (Morin, 2011). Measuring consumers' brain activity could show preferences or the effectiveness of marketing campaigns and predict buying and decision behavior. If there would be reliable information about the success of a newly developed product before it is introduced to the markets, resources and logistics could be managed more effectively. Figure 3 displays where neuromarketing during the product development phase could be implemented.

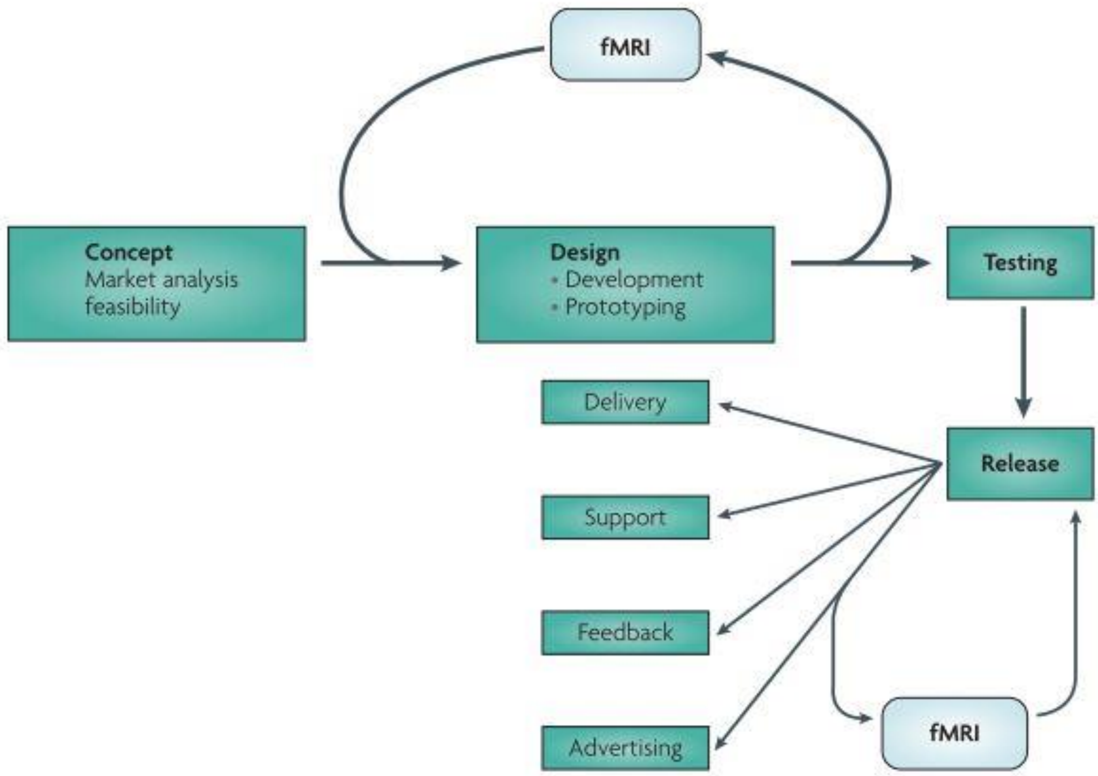


Figure 3. Product development cycle with neuromarketing (Arieli & Berns, 2010, p.286)

Neuromarketing methods could be active before product release and after product release (Arieli & Berns, 2010). Common methods for neuroimaging are scanners for functional magnetic resonance imaging (fMRI), which measure the blood-oxygen-level in certain brain regions; Electroencephalography (EEG), which measures changes of electrical fields in the brain region; Magnetoencephalography (MEG), which identifies magnetic fields caused by electrical fields of the brain or methods like Eye tracking and Mouse tracking which analyze unconscious motoric movements (Arieli & Berns, 2010; Morin, 2010). Rangel et al. in 2008 found that consumer decision making is dependent on a fixed sequence of five neurobiological processes which form the decision outcome (Rangel et al., 2008). An analysis of those processes on a neuronal level could help to predict consumer decision making. McClure and colleagues in 2004 performed an experiment where participants had to differentiate between the beverages Coca Cola and Pepsi. With the help of an fMRI scanner, they showed which parts of the brain were active when cultural influences were incorporated into the decision-making process. The results revealed that when participants were unaware of what beverage they consumed, they decided for Pepsi. When they were aware of the brand, they decided for Coca Cola (McClure et al., 2004). Because neuromarketing goes beyond the consciousness of consumers, several ethical concerns appear. As businesses will have a window in consumers' minds, the question arises to which extent the privacy of thoughts must be protected. Profit optimization is a major goal, so that companies might not always act in the consumers' best interest and exploitation could arise (Arieli & Berns, 2010). Neuromarketing is a novel method that could significantly change the future of marketing processes.

2.2 Mouse Tracking

Analyzing motor movements while using a computer mouse is a recently developed research tool to unveil cognitive processes (Freeman & Ambady, 2010). Mouse tracking is a time-sensitive tool that can display decision behavior in the millisecond range and question unconscious movements. In most cases, participants in a research experiment are confronted with a choice between two options. The mouse cursor's start point is located on the bottom of the screen, from where the participants must either select an option on the top left or the top right corner of the screen, as visible in Figure 4. This decision conflict does not only measure reaction time and output but also how the decision process unfolds over time. From the start point to the selected option, the mouse trajectory is recorded and displayed in their x- and y-coordinates (Freeman, 2018). The trajectories are then aggregated and overlayed to show decision procedures of all participants. Further analysis of the mouse paths will be discussed later within this topic.

2.2.1 Mouse tracking research

Spivey and Dale in 2006 showed that the motor movements made with a mouse could be connected to the mental state of the mouse user. They displayed graphically in a three-dimensional state space how cognition is connected to linguistic labels using mouse tracking and eye tracking (Spivey & Dale, 2006). Yamauchi and Xiao researched how computer mouse motions are related to affective states of the computer user. They argue that emotions, regulated by the dopamine system, influence sensorimotor subsystems that coordinate hand movements. Therefore, trajectory analysis can give feedback on mental states (Yamauchi & Xiao, 2017). Mouse tracking has not only been used in affective computing research but also in Human Computer Interaction (HCI) research. As it is not easy for computers to conclude on human emotions, there has been interest in creating an emotional-intelligent machine system that can detect humans' affective states (Picard, 1997). Zimmerman et al.

tried to influence participants' mood with film clips and then recorded mouse movements in an e-commerce setting. Their goal was to detect the induced moods with a mouse trajectory analysis. For HCI to be effective, the computer must adequately recognize the emotional state to respond correctly (Zimmermann et al., 2015). Mouse tracking is a promising tool to unveil the user's cognitive states as with the theory of embodied choice, motoric movements and mental activity are in constant interplay (Freeman, 2018). Most research done with the help of mouse tracking is done in the field of decision behavior. Szaszi et al. found that differences in decision making between high capacity and low capacity individuals consist in the fact that if an initial answer was incorrect, high capacity individuals would revise the choice more often. If it is correct, fewer changes were made compared to low-capacity individuals (Szaszi et al., 2019).

Furthermore, Maldonado et al. showed how changes during the decision-making process affect the mouse trajectory. In an experiment with 54 participants, they tested two different decision patterns: one where a decision change was unforced and a forced decision change. They found that mouse paths are a more reliable analysis than reaction time concerning decision behavior (Maldonado et al., 2019). Other research in decision making done with mouse tracking tries to uncover self-control patterns. Temporal discounting refers to the conflict of choosing a sooner reward versus a bigger but delayed reward. Mouse tracking showed that test subjects who chose the delayed reward were biased towards that option, whereas test subjects who chose the sooner reward were characterized by high uncertainty between the two options (Calluso et al., 2015). Following these results, Stillman et al. found that successful self-control manifests itself in a smooth rather than abrupt trajectory. They conducted a mouse-tracking experiment in which participants had to choose between healthy and unhealthy food options. When participants resisted the unhealthy food temptation, their mouse path runs smoothly towards the healthy food option. Therefore, they concluded on a dynamic rather than abrupt conflict resolution, which refers directly to whether a decision conflict follows the dynamic model or the dual-process model (Stillmann et al., 2017).

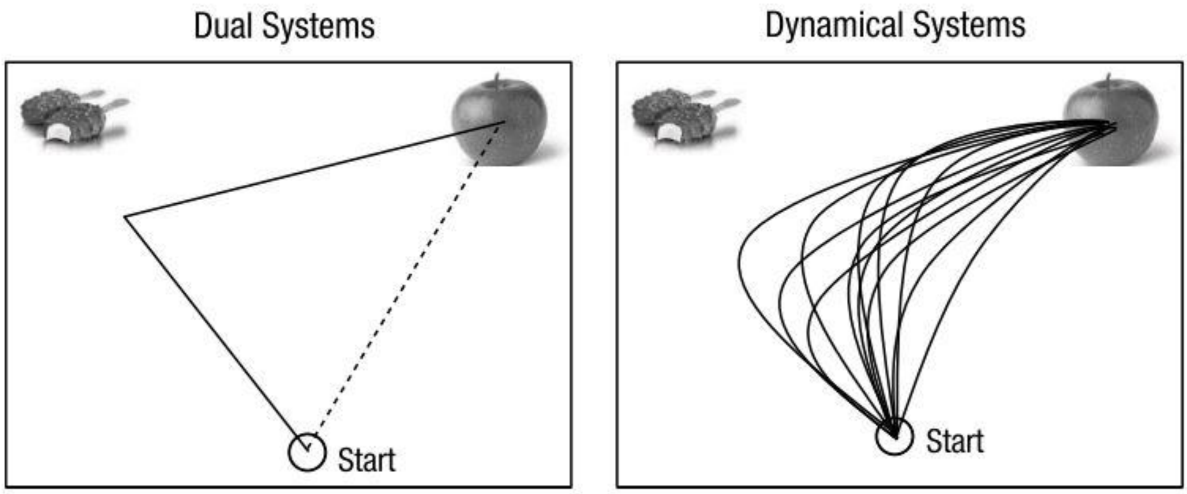


Figure 3 Trajectories displaying decision conflict resolved by dual system and dynamical system (Stillman et. al., 2017, p.1242)

An important topic for most marketers is the measurement of attention. Eyetracker is an established tool to capture eye movements that can help identify advertisement effectiveness (Chandon, 2002). Johnson et al. showed that mouse tracking is an equivalent tool to measure attention behavior. By telling the participants to follow their eye movements with a computer mouse, they combined eye-tracking and mouse-tracking, which resulted in a high correlation between those two paths (Johnson et al., 2012). Xiao and Yamauchi tested how top-down attention can influence unconscious semantic processing. Mouse tracking was used to carry out a semantic priming task where participants had to use a mouse to identify whether a number was smaller or larger than five. Results showed that the task's time course was altered through top down attention, but the essential hypothesis that top down attention facilitates semantic processing could not be confirmed fully (Xiao & Yamauchi, 2017).

Furthermore, tracking mouse movements has become popular in the field of social psychology. Yu et al. tested how mouse tracking could be implemented in the Implicit Association Test (IAT). The IAT is a procedure to measure someone’s unconscious, implicit bias towards objects and has been used in research areas like racial attitude, implicit self-esteem, and gender stereotypes. Tracking mouse movements during the course of an Implicit Association Test can uncover mental processes that could not be explained before (Yu et al., 2012). A relatable study by Freeman and Ambady investigated how human faces are associated with stereotypes. In a mouse-tracking experiment, they showed sex typical and sex atypical faces with corresponding gender stereotypes. The trajectories revealed an attraction towards the opposite gender stereotype when a sex atypical face was visible. Their results prove a parallel activation of stereotypes in social categorization (Freeman & Ambady, 2009). Further research used mouse tracking to facilitate web design and software interfaces. It is possible to see how users navigate the website by tracking mouse movements, which thereby enables corresponding design changes according to these movements (Diego-Mas et al., 2019). Therefore, the consumer usability of software and the design of graphical interfaces have been in the focus of mouse tracking research (Schoemann et al., 2019).

This study categorizes itself in the research area of decision making. It will be simulated and analyzed how decision behavior proceeds in an E-Commerce setting. For this purpose, a mouse tracking program was used. The following subitems will provide an overview of common mouse tracking programs.

2.2.2 MouseTracker

MouseTracker is a free of charge downloadable software that was developed by Freeman and Ambady in 2010. It was one of the first programs to trace mouse movements for scientific purposes and was validated several times in publications (Freeman & Ambady, 2010). MouseTracker is a three-part program that is separated into the Designer, Runner and Analyzer. The Designer is a program to construct experiments based on a .CSV file graphically. The program can alter the file's graphical parameters and response options, whereby features like a start button and the response options remain constant in every design option. The Runner is a data collection program that conducts the experiment and records the mouse movements. Every 13-16 millisecond the raw time, the y-coordinate and the x-coordinate in pixels is recorded. The program can record up to 60 to 75 x and y coordinates per second. When the experiment is finished, the Runner generates a Mouse Tracking data file, which can then be imported into the Analyzer program. There, graphical and other analysis methods of the recorded trajectories can then be conducted (Freeman & Ambady, 2010). Figure 4 shows a typical mouse-tracking experiment in a two-choice design. With a click on the start button, one or more pictures appear which simulate the decision-making scenario. The mouse has to be moved to the preferred option and with a click on the picture, the decision can be confirmed. The mouse movements are recorded and can be analyzed retrospectively.

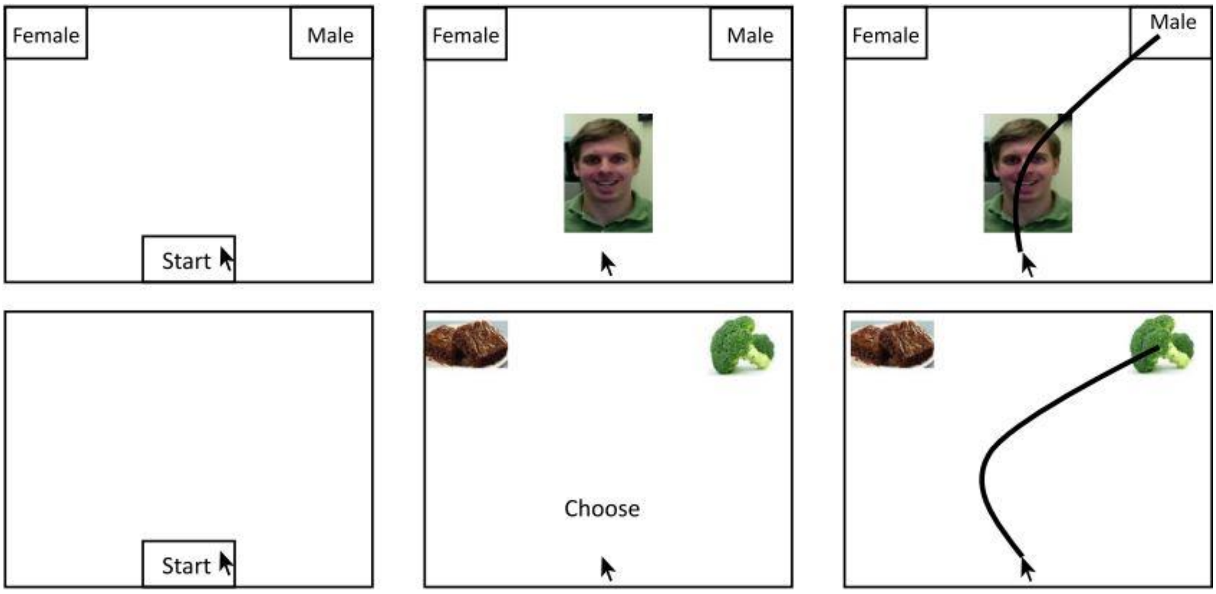


Figure 4 Example of mouse-tracking paradigm (Stillman et al., 2018, p.533)

At first, participants must click on the start button to set a comparable starting position for all runs (Kieslich & Henninger, 2017). They are then presented with a stimulus that can manifest itself in a picture, a letter string or sound. Also, multiple stimuli can be presented sequentially or simultaneously (Freeman & Ambady, 2010; Lopez, 2018). Like the portrait in Figure 4, a stimulus can be presented in the middle of the screen. The participant must then choose a response option in the upper left or upper right corner. The response options can also display pictures that must be clicked on. Both versions are considered as a binary choice scenario.

2.2.3 Mousetrap

Mousetrap is a plugin for the graphical experiment builder *OpenSesame*, which allows to create mouse-tracking experiments effortlessly due to a well-arranged interface and a simple design. The experiment data can then be analyzed with R, a programming language and environment for statistical computing and graphical analysis. In 2017 Kieslich and Henninger published Mousetrap and validated its functionality by replicating a mouse-tracking experiment that originated from Dale, Kehoe, and Spivey in 2007. Participants were confronted with an animal categorization task (Kieslich & Henninger, 2017). Mouse trajectories are then recorded with *OpenSesame Run,* which is responsible for data collection. The data analysis in R is supported by the *mousetrap* package, which provides functionalities for visualization, preprocessing of data and additional analysis tools (Kieslich et al., 2018). For a full overview and download of the R package, all necessary information is provided at http://pascalkieslich.github.io/mousetrap/.

2.2.4 Webtrackr

Webtrackr is a mouse tracking program developed by Patrick Neef (2020). It is compatible with the web browser Google Chrome or Firefox and is displayed on an index.html page. A mouse-tracking experiment's design with Webtrackr is comparable to the standard two choice model where participants have to select either the item in the top left or top right corner. All formatting is conducted with JavaScript, which allows to implement a mouse-tracking experiment in a questionnaire with several slides. Webtrackr has the advantage to function in a web browser and can consequently simulate computer mouse behavior in an Internet environment. Furthermore, it is possible to trace computer mouse movements in a location-independent scenario as participants could perform a tracking experiment from any compatible computer with a mouse. As Webtrackr was used for this thesis, more technical information relating to the program can be found in "4.2.2 Experiment Set Up" and on https://webtrackr.de/.

2.2.5 Eye Tracker

Eye tracking describes the recording of eye movements. The recorded data can give insight into information processing, preference, choice behavior and valuation (Van Loo et al., 2018). Corresponding tracking devices are either mounted on a helmet or on the table just below the computer screen. Both methods can have disadvantages, but the variant mounted to the table is most commonly used (Jacob & Karn, 2003). Six different muscles control eye movements and visual information is converted into electrochemical stimuli processed in the human brain. Mostly eye movements manifest themselves in fixations, which can last up to 0.4 seconds. With a rapid eye movement, the point of interest alters which is called a *saccade* (Goldberg & Wichansky, 2003). According to the "eye-mind-hypothesis", eye movements are considered to provide a window in the human mind. This process-tracing method has several application possibilities and was mostly used in economic and psychological research (Van Loo et al., 2018; Kim et al., 2012). As eye movements reflect the amount of momentary attention, eye tracking can close the gap from visual attention to consumer behavior. For marketers, this represents valuable information as it offers insight in consumer decision making behavior (Khachatryan & Rihn, 2014). Büttner et al. in 2014 conducted an experiment about consumer impulsiveness with the help of Eyetracker. They showed that impulsive buyers are more likely distracted by unrelated products than non-impulsive buyers. Thereby the attractiveness of unrelated products has no impact on the amount of distraction, which consequently is dependent on the amount of individual impulsiveness (Büttner et al., 2014). Bang and Wojdynski in 2016, researched how personalized advertisement affected consumers prone to cognitive load. They showed with eye tracking that personalized ads receive more attention from consumers influenced by cognitive load (Bang & Wojdynski, 2016). As well as mouse tracking, eye tracking is a method for neuromarketing research. When comparing both practices concerning their usability, eye tracking does not capture all eye movements and cannot be performed by participants with eye lenses and certain pupil colors (Khachatryan & Rihn, 2014). Mouse tracking, however, is easy to implement and uses only a computer mouse as a transmission medium (Freeman, 2018).

3. Trajectory analysis

For the mouse movements analysis from the Webtrackr, the program R was used. Several commands provide information about mouse tracking parameters. In the following, the most common analysis methods are introduced for Mouse Tracker, the Mousetrap plugin and Webtrackr.

2.3.1 Curvature Analysis

In MouseTracker, all trajectories are rescaled to fit in a 2x1.5 space, which in most cases fits for the aspect ratio of a computer screen. In Figure 5 the start button is in the center bottom with the coordinates [0.00, 0.00]; from there, a trajectory can go to [-1.00, 1.5] or to [1.00, 1.5]. For the measurement of spatial attraction, the computation of the trajectories maximum deviation (MD) and the area under the curve (AUC) is useful.

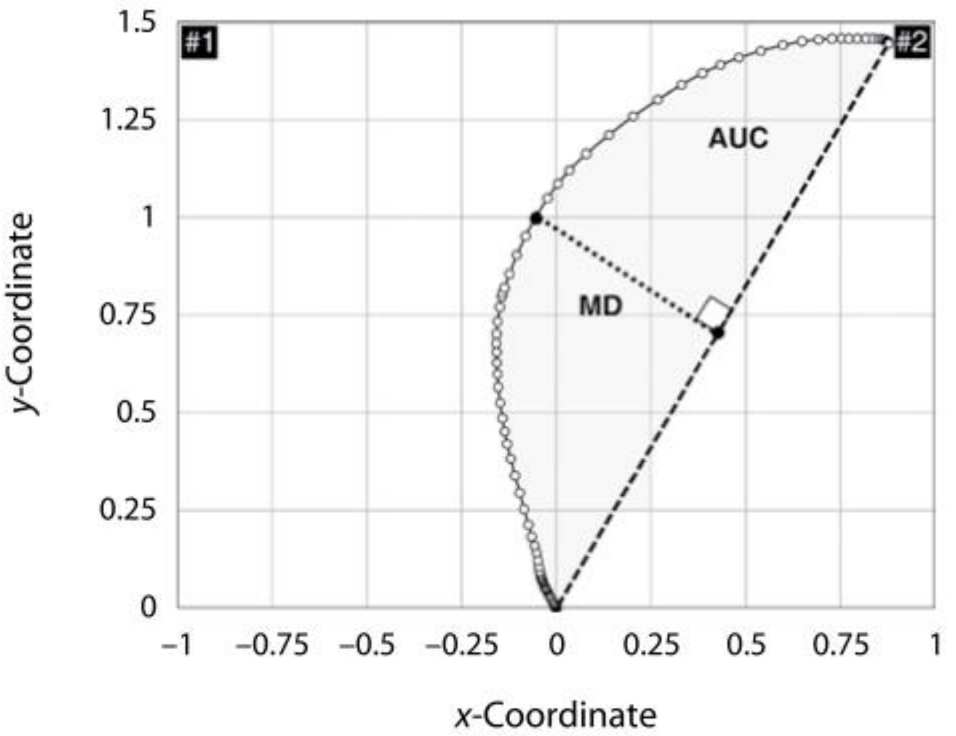


Figure 5 Mouse Tracker standard coordinate space with the spatial attraction measures MD and AUC (Freeman & Ambady, 2010, p.229)

The curvature of the trajectory is generated by the difference in activation between the response options so that a smaller difference leads to a stronger curvature of the trajectories (Spivey et al., 2010). To calculate the MD, an idealized response trajectory, a straight line from the start button to the response option serves as a reference. The MD displays the furthermost point from the actual trajectory to the reference trajectory. The higher the MD is, the bigger the attraction towards the other response option was. For the AUC, the geometric area from the reference trajectory to the actual trajectory is being computed. The expressiveness of AUC and MD is similar, whereas the AUC is a better indicator of the overall attraction and the MD a better indicator of the maximum attraction (Freeman & Ambady, 2010).

2.3.2 Temporal Analysis

Because each trajectory has a different length, to compare them, they must be time normalized. A trial that lasts longer than usual also has more x and y coordinates. Consequently, all trajectories are set to 101 time-steps. Each time step stands for an x and y coordinate (Freman & Ambady, 2010). A temporal analysis of the trajectory can reveal how and when cognitive processes influence the mouse movement (Hehman et al., 2015).

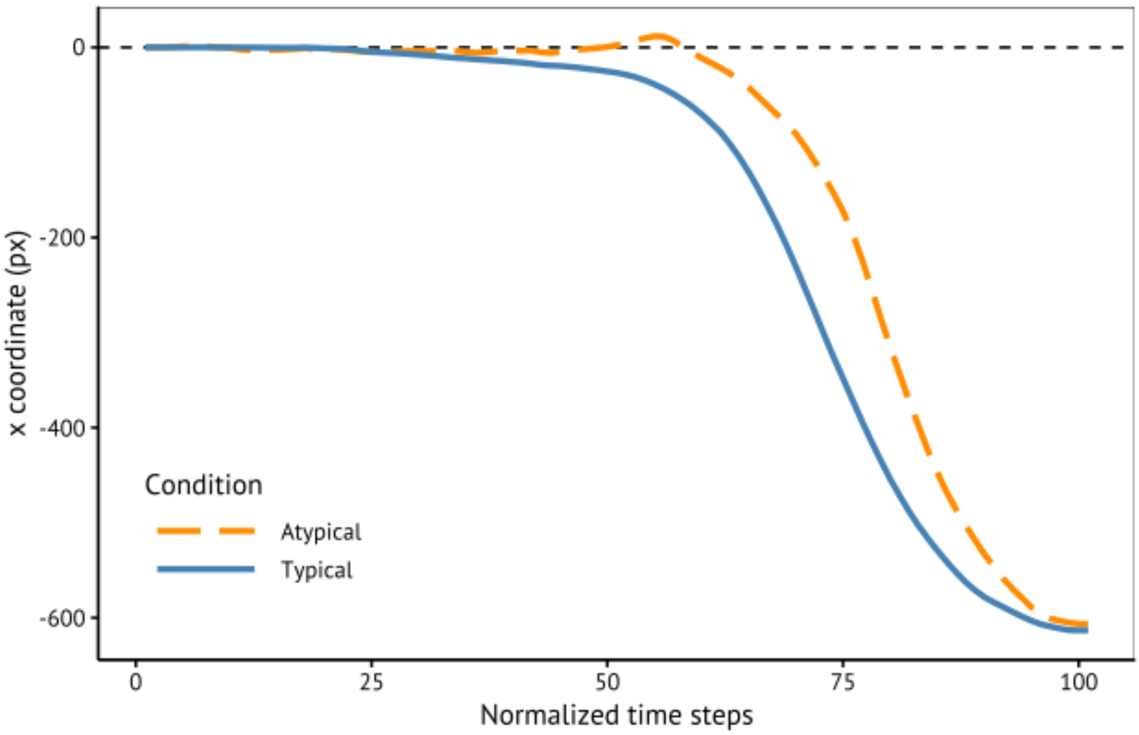


Figure 6 Time normalized trajectories with a difference in the average x-coordinates from time step 54 to 95 (Kieslich et al., 2019)

Further analysis methods are acceleration, velocity, and angle profiles. The velocity is calculated as the distance between coordinates at raw time points, and acceleration displays a change in velocity (Hehman et al., 2015). According to Hehman et al., research shows that strong competition between response options is characterized by an initial decreased velocity and an increased velocity once the decision was made. Figure 7 shows that velocity corresponds to how fast the cursor is moving and acceleration to how much the cursor speeds up. The angle profile measures how direct the movement towards the response option was between certain time steps, which can provide insight into how and when different factors influence the movement direction (Kieslich et al., 2019).

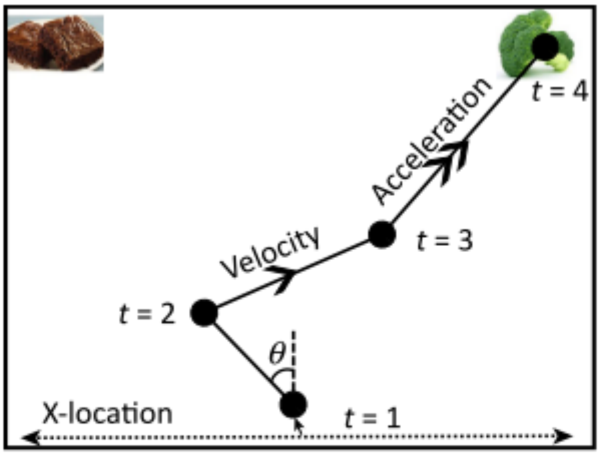


Figure 7 Angle profile, Velocity and Acceleration of mouse movement (Stillman et al., 2018, p.534)

Another measure for the temporal analysis is the cursor's proximity to the response option at a certain time point. Like that, the x-coordinate and the y-coordinate are included, and potential deviations can be measured. The Euclidean calculates the proximity with the formula:

$$\text{distance}((x, y), (a, b)) = \sqrt{(x-a)^2 + (y-b)^2}$$

Furthermore, response times (RT) and initial times (time from the start to when the mouse first was moved) can be included in the analysis.

2.3.3 Trajectory Complexity

The complexity of a trajectory can be determined in several ways. According to Hehman et al. in 2015, sample entropy is one of the most informative tools reflecting competition along the x-axis. It is computed by time normalizing the trajectories and then comparing the shifts along the x-axis for different window sizes (McKinstry, Dale & Spivey, 2008). Thereby the trajectory's unpredictability can be measured so that trajectories might resemble a certain section but differ considering the whole trajectory. Alternatively, it is possible to measure the total amount of x-flips (directional shifts along the x-axis) and y-flips (directional shifts along the y-axis) as an indicator of complexity. If the two response options are in the top left and top right corner of the screen, parameters along the x-axis are more significant than the y-axis. When there are multiple response options available, also parameters along the y-axis can become meaningful. X-reversals represent a shift along the x-axis crossing the vertical axis between the two response options. According to Koop and Johnson in 2013, x-flips represent a momentary shift in preferences, whereas x-reversals represent a definite shift in preferences. Another measure of complexity is whether the trajectory is smooth or abrupt in response to alternative competition. According to Freeman in 2014, an abrupt shifting trajectory can be classified as such when the maximum deviation exceeds 0.9. Also, the velocity and acceleration of mouse movements can be used to conclude on trajectory smoothness (Hehman et al., 2015).

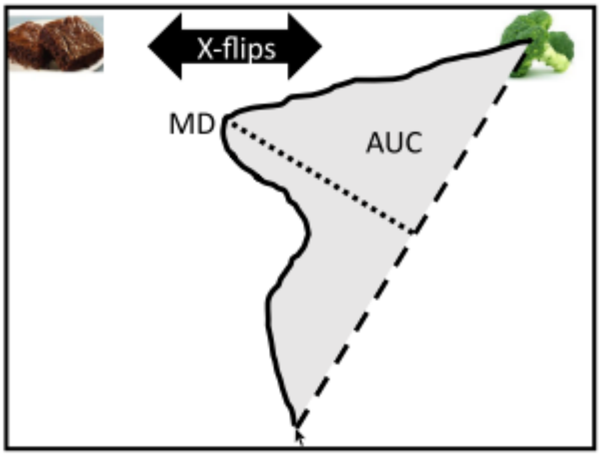


Figure 8 Graphical display of x-flips (Stillman et al., 2018)

2.3.4 Response Distribution

Figure 8 shows how the aggregated trajectories' slight attraction towards a response option can consist of very direct trajectories and trajectories, including an extreme shift, initially pointing towards the other response option. Therefore, the aggregated trajectory might be unable to conclude on cognitive processes. In order to distinguish between those two distribution types, the collected trajectories must be identified as either unimodal, which would resemble the upper panel of Figure 9 or bimodal, which would resemble the lower panel of Figure 9.

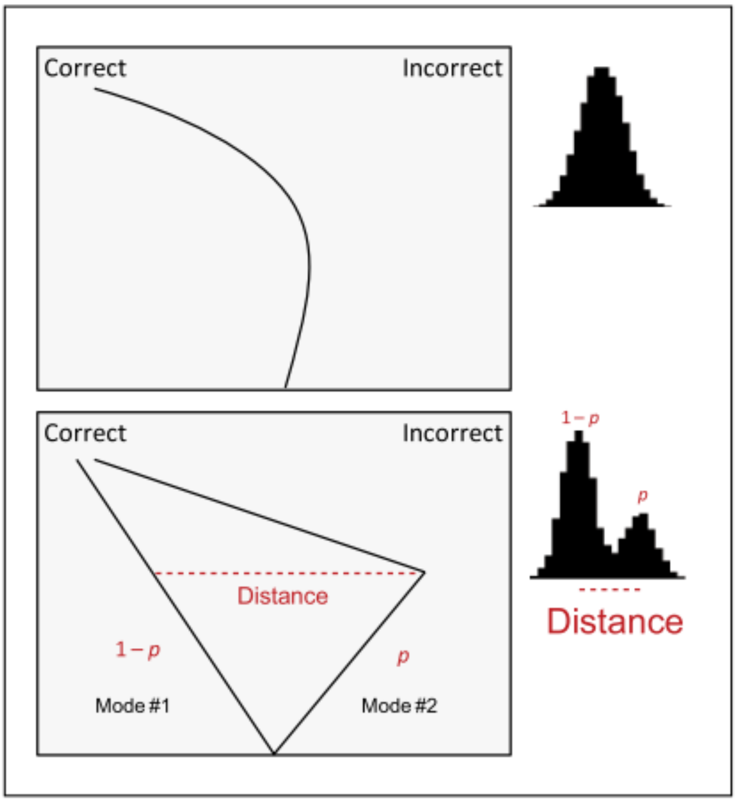


Figure 9 Illustration of unimodality and bimodality of trajectory distribution (Hehman et al., 2015, p.396)

Freeman and Dale in 2013 investigated three different bimodality measures: the bimodality coefficient (BC, SAS Institute, 1989), Hartigan's dip statistic (HDS, Hartigan & Hartigan, 1985), and the difference in Akaike's information criterion (AIC, Akaike, 1974). To calculate the BC the following formula can be used: whereas *s* is skewness, *k* is kurtosis and *n* the number of observations.

$$b = \frac{s^2 + 1}{k\,\frac{3(n-1)^2}{(n-2)(n-3)}}$$

The BC can range from 0 to 1. With a b > 0.555, the distribution of trajectories is considered to be bimodal, with a b < 0.555 the distribution is considered to be unimodal (Freeman & Ambady, 2010). For the HDS, the maximum difference of data distribution is compared to a uniform distribution to minimize this maximum (Freeman & Dale, 2013). The resulting values range from 0 to 1 and p-values less than 0.05 show a significant bimodality. The AIC measure can be implemented using one-component and two-component Gaussian mixture distribution models to see which of these minimized the AIC. When the one-component model minimizes AIC, the distribution is unimodal and when the two-component model minimizes AIC, the distribution is bimodal. Results from Freeman and Dale support that the HDS represents the most reliable measure of bimodality (Freeman & Dale, 2013). Measures of bimodality can be closely related to the theoretical dispute between Dual Process Models and Dynamic Models, which has already been mentioned above. Mouse movements, which include zero attraction and extreme attraction towards the unchosen option - displaying bimodality – would represent the Dual Process Model, and unimodal mouse movement with a strong, medium and weak attraction towards the unchosen response option would represent the Dynamic Model (Freeman & Ambady, 2010).

2.3.5 Principle Component Analysis

A Principle Component Analysis (PCA) is a tool to reduce vast amounts of data to certain components. Concerning mouse trajectory analysis, a PCA can identify and compare multiple components and measure their correlation. Hehman et al. in 2015 suggest that a PCA could help unveil how racial influence in face recognition can manipulate the first part of a trajectory compared to gender influence, which can manipulate the last part of a trajectory. To carry out a PCA, the x- and y-coordinates must be exported in a .CVS format and must then be analyzed in software for statistical computing like SPSS or R. In 2017, Kieslich et al. developed a mousetrap package for R in which certain commands can perform a PCA. Detailed information about the mousetrap package can be found in Kieslich et al. (2019a).

In the following, an overview of the commonly used mouse tracking measure is shown:

Type	Measure	Definition
Curvature	Maximum absolute deviation (MAD)	Signed maximum absolute deviation of observed trajectory from direct path
	MD Time	The point in time where MD is reached
	Maximum deviation above (MD_above)	Maximum deviation above direct path
	Maximum deviation below (MD_below)	Maximum deviation below direct path
	Average deviation (AD)	Average deviation of observed trajectory from direct path
	Average deviation (AD)	Average deviation of observed trajectory from direct path
	Area under curve (AUC)	Geometric area between observed trajectory and direct path
Complexity	x-flips	Number of directional changes along x-axis
	x-reversals	Number of crossings of y-axis
	sample entropy	Degree of unpredictability of movement along x-axis
Time	Response time (RT)	Time until response is given
	Initiation time	Time until first movement is initiated
	Idle time	Total time without movement across trial

Derivatives	Total distance	Euclidean distance travelled by trajectory $$\boldsymbol{distance}((\boldsymbol{x},\boldsymbol{y}),(\boldsymbol{a},\boldsymbol{b})) = \sqrt{(\boldsymbol{x}-\boldsymbol{a})^2+(\boldsymbol{y}-\boldsymbol{b})^2}$$
	Max velocity	Maximum movement velocity
	Max acceleration	Maximum movement acceleration
Bimodality	Bimodality coefficient	$$\boldsymbol{b} = \frac{\boldsymbol{g}_1^2+\boldsymbol{1}}{\boldsymbol{g}_2\frac{3(\boldsymbol{n}-1)^2}{(\boldsymbol{n}-2)(\boldsymbol{n}-3)}}$$ >0.555 = significantly bimodal
	Hartigan's dip statistic	< .05 = significantly bimodal, <.1 marginally bimodal >.1 unimodal

Table 1 Overview of commonly used mouse tracking measures (Hehman et. al., 2015; Kieslich et. al., 2018)

3. Hypotheses

X-flips are sudden directional changes along the x-axis in the course of a mouse trajectory (Freeman & Ambady, 2010). They do not display how preferences unfold during the decision process but resemble sings of uncertainty or intuitive instability (Koop & Johnson, 2013). Therefore, they represent the decision process's complexity and indicate strong response competition between two attractive choices.

As x-flips are relatively minor movements along the x-axis, bigger movements that cross the vertical axis in the middle between the response options are called x-reversals (Kieslich et al., 2019). Those x-reversals are expressive enough to indicate a change in preferences. Maldonado et al. in 2019, call these types of mouse movements a change of mind, as shown in Figure 10. In this figure, the red line (representing a mouse trajectory) tends towards the right response option but then switches to the left response option, crossing the vertical axis. However, the blue line is clear in preferences and follows a straight path to the left response option (Maldonado et al., 2019).

The theory that the human mind comprises two cognitive processes could explain a change of mind in difficult decisions, one automatic and one controlled (Sauer & Sauer, 2018). Looking at the red mouse trajectory in Figure 10, the first intuitive response option is targeted initially with the mouse. Still, a reevaluation of the alternatives due to strong response competition causes a switch to the other option resulting in an x- reversal. Inspecting this relation graphically, process one, which is represented by the part of the red line from the starting position to the right response option, precedes the second process, represented by the part of the red line from the right response option to the selected left response option (Kahneman & Frederick, 2012). When a reevaluation of alternatives occur, a transition from the intuitive process one to the deliberate process two of the human mind is assumed. This could be expressed graphically in a change of direction of the trajectory. Therefore, it is argued that difficult decisions, higher in response competition and alternative reevaluation, follow the sequence: first process-one then process-two. Easy decisions which are lower in response competition only include process one. These reevaluation procedures should express themselves in higher x-flips and x-reversals for difficult decisions and lower x-flips and x-reversals for easy decisions. As x-flips and x-reversals are computed along the x-axis, it is difficult to conclude the trajectory's curvature behavior (Maldonado et al., 2019). Nevertheless, they are expressive enough to indicate the existence of a competition between two different cognitive systems.

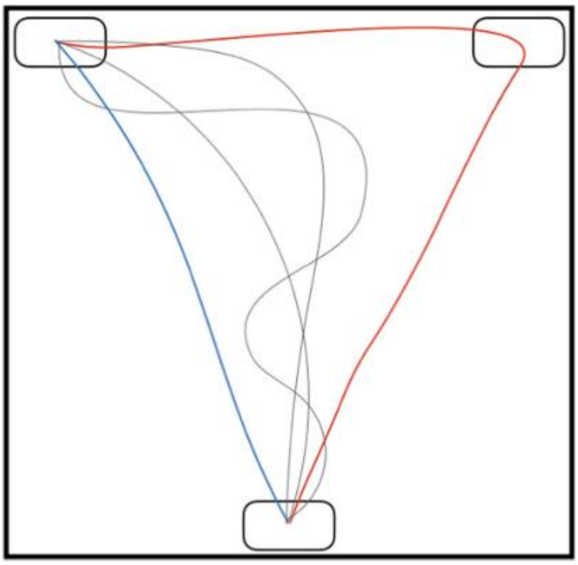


Figure 10 Trajectory (red line) representing a change of mind (Maldonado et al., 2019)

Kieslich et al. in 2019, mention that response competition might not always lead to horizontal directional changes but rather to the unpredictability of the trajectory (Kieslich et al., 2019). Several researchers who investigated trajectory complexity and trajectory unpredictability have used sample entropy as an equivalent measure. It is calculated in a spatial disorder analysis by comparing sequences of the trajectory (Hehman et al. 2015; Freeman and Ambady 2010). In 2008, Dale and colleagues researched in a mouse-tracking study the motoric pull towards the contradicting response options when confronted with yes or no questions, which vary in their truth-character. For middle-truth-valued questions, which should represent the highest competition between the response alternatives, they used sample entropy as a suitable measure. Even though their results indicated a dynamic decision process, sample entropy has been proven to be an adequate measure of response competition (Dale et al., 2008).

X-flips, x-reversals and sample entropy represent signs of uncertainty, change of mind and complexity. What they have in common is their cause - a response competition, expressing itself in unpredictable motoric movements. As difficult decisions are higher in response competition it is argued that:

H1: Difficult decisions in a purchase situation show a higher trajectory complexity compared to easy decisions so that there is an effect on a) x-flips b) x-reversals and c) sample entropy.

When directly inspecting the conflict between two response options the measures AUC and MAD are of relevance. They have been used in mouse tracking research to examine attraction to the non-selected response option. According to Freeman and Ambady in 2010, AUC is a better measure of overall attraction and MAD a better measure of maximum attraction (Freeman & Ambady, 2010). AUC is the differential area of a direct line from the starting position towards the selected response option and the actual trajectory. It, therefore, shows the total amount of response competition towards the unselected alternative. MAD represents the point on the trajectory closest to the non-selected alternative and therefore shows the maximum in response competition (Stillman et al., 2018). Figure 8 indicates how these two measures express graphically. Yamauchi and Xiao in 2018 used measures like AUC to advance affective computing. In a choice reaching task, they showed that trajectory behavior correlated to the participants' in advance assessed emotional state (Yamauchi & Xiao, 2018). Concluding that the measures MAD and AUC can be used to inspect the test subjects' emotional states, in this study, they are predicted to measure decision difficulty by showing the amount of response competition. As these curvature measures can conclude on the cognitive processes expressed in motoric mouse movements, they can be useful to indicate cognitive duality in the decision process (Koop & Johnson, 2011; Dale et al., 2008). Concluding back on Figure 10, decisions high in AUC and MAD would resemble the red trajectory. When assuming that in a difficult decision task (red line) the cognitive process, one would first lead the trajectory towards the unselected response option (right). Secondly, the cognitive process two would then lead the trajectory to the selected response option (left); AUC measures, in consequence, should be high. Also, MAD, which would represent the transition point of process one to process two, would be high in its value. It shows that these two measures represent an adequate tool to investigate duality in cognition.

When multiple trajectories are aggregated to one trajectory, they can either consist of very similar trajectories or very different trajectories, which results in the same mean trajectory. Figure 9 shows how two contrary trajectories result in an average trajectory when aggregated. Trajectories that resemble the aggregated trajectory originally could lose their expressiveness, as the data only consists of diverging trajectories. When these trajectories vary to a certain extent, the distribution of trajectories is considered bimodal. When trajectories are similar, the distribution is considered unimodal (Hehman et al. 2015). In social categorization, male faces with sex atypical features are sometimes only recognized under correction of the initial response. The reason for that is that female-like features in a male face could lead to an intuitively incorrect response. Only after a reanalysis, the correct answer is chosen. Since this correction behavior does not always occur, and the correct answer to the social categorization can also be made immediately, a bimodality in response distribution can be assumed (Freeman & Ambady, 2011). Investigating the modality of response distribution also helped indicate the motoric pull of diverse response alternatives on a cognitive level (Dale et al., 2008). In the theory of two cognitive processes, these processes can run uniformly on the one hand and inconsistently on the other. If the two processes are inconsistent, they come along with a correction of process one from process two (Frankish, 2010). Looking at Figure 9, the lower panel shows graphically how a trajectory unfolds when the two processes run uniform and in the upper panel when they run inconsistent, indicating bimodal distribution. Freeman & Dale in 2013 tried to assess cognitive dual-process phenomena by analyzing mouse trajectories with several bimodality measures. They found that dual processes tend to evoke bimodal features (Freeman & Dale, 2013). Therefore, it is argued that curvature measures like AUC and MAD can have a bimodal character and could give insight into how cognition behaves in a choice scenario.

With the two above mentioned curvature-measures, the trajectory can be analyzed for indices of a dual-process cognition. AUC and MAD are an indicator of response competition, and as described earlier and visible in Figure 9, they can show how dual processes can be graphically projected in a trajectory. Trajectories with a high AUC and MAD could show how dual cognition behaves in a difficult choice scenario. Furthermore, the bimodality of those measures could emphasize the presence of two cognitive processes in a choice scenario. Therefore, it is argued that:

H2: Regarding curvature measures, difficult decisions have a bigger impact on AUC and MAD than easy decisions. Also, the bimodality of those curvature measures should be higher for difficult decisions than for easy decisions.

With the presence of two distinct cognitive processes which operate on different time scales, the automatic and intuitive process, which is fast; and the controlled and reflective process, which is slow, it is hypothesized that trajectories classified as difficult should differ from trajectories classified as easy concerning their temporal behavior (Sauer & Sauer, 2018). If two processes are active and correction of process one to process two happens during decision making, the reaction time to click the response option should be longer than if just one process is active, or when the two processes act uniformly. Therefore, as difficult decisions need more cognitive effort and are more likely to show the counteracting of two cognitive processes, they should have a longer reaction time than easy decisions. When MAD is reached, the point in time should be later for difficult decisions than for easy decisions. As explained earlier, Kahneman and Frederick show that the dual-process theory has a fixed time sequence, which determines that process one can only be influenced by process two (Kahneman & Frederick, 2012). MAD could represent the point in the trajectory when the transition from process one to process two happens. A cognitive effort is needed in the case of a correction procedure from the intuitive system to the controlled system, which should entail temporal consequences. Difficult decisions that are more likely to hold this transition procedure should show that MAD is higher in value and that the time point when MAD is reached is later compared to easy decisions. It is argued that:

H3: Difficult decisions display a difference in temporal behavior to easy decisions so that for difficult decisions, MAD is met later in the trajectory progress and RT is longer compared to easy decisions.

4. Methodology

4.1 Pretest

The Pretest's objective was to find corresponding product pairs, which then could be tested in the Mouse Tracking Software. Additionally, it would be possible to predict and compare cursor behavior according to the results gained from the Pretest. A questionnaire on SoSci Survey with 18 pages was created. In total, 60 participants completed the test. The first questions where about sociodemographic nature. The average participant was 26.67 years old; 24 of them were female and 36 males. To see if the displayed products were affordable, we asked about the available monthly money. With an average of 1056.93 EUR, we can assume that all the showed products were in the potential buying range and would display realistic decision behavior. For the following 15 pages, the participants had to choose between two products displayed as a picture. After the product choice, three questions had to be answered with a seven-point Likert Scale. The first question asked about the difficulty of the decision, the second question asked how appealing the chosen product is and in the third how well they the chosen product was liked. The first question aimed at finding the decision difficulty, which will be tested again in the Mouse Tracking experiment. The second and third questions target at finding relevant product pairs that can be used in the main test and display realistic decision behavior. Like that, it was possible to extract corresponding product pairs for the mouse tracking experiment. The products used for the pretest had a regional origin as it was important that participants could identify with the products they see. Figure 11 shows a compilation of all products used for the pretest.

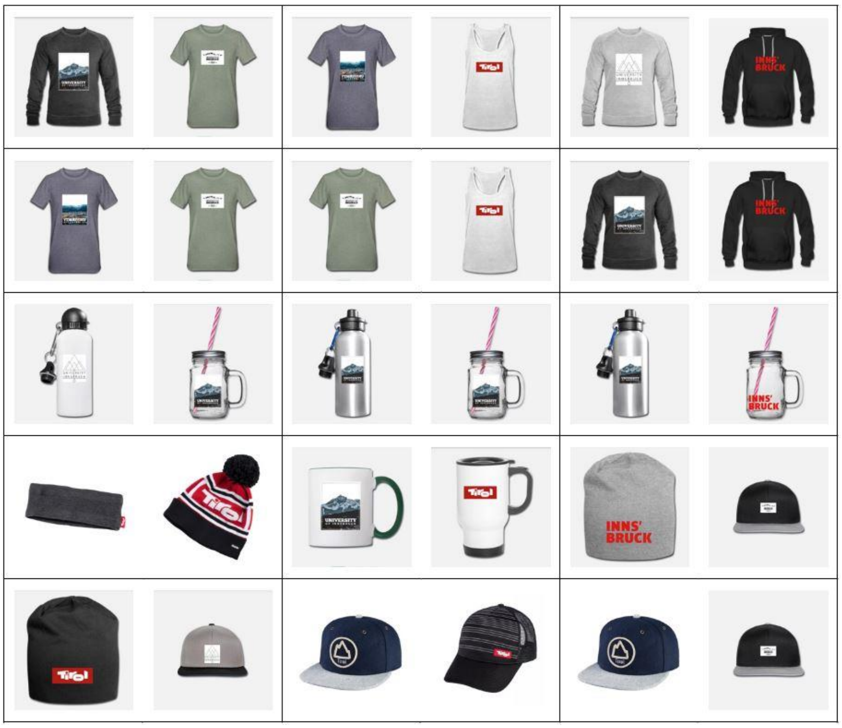


Figure 11 Compilation of products for the pretest

Figure 12 shows the mean values of the first question to each 15 product decisions. In this question, it was asked how difficult the decision between the two products was. It was rated on a one to seven Likert Scale, whereas one is very easy and seven very difficult. In the Pretest, the product pair decision number three was rated easiest on average with 1,92. Product pair decision number 12 of the test was rated hardest on average with 3,38.

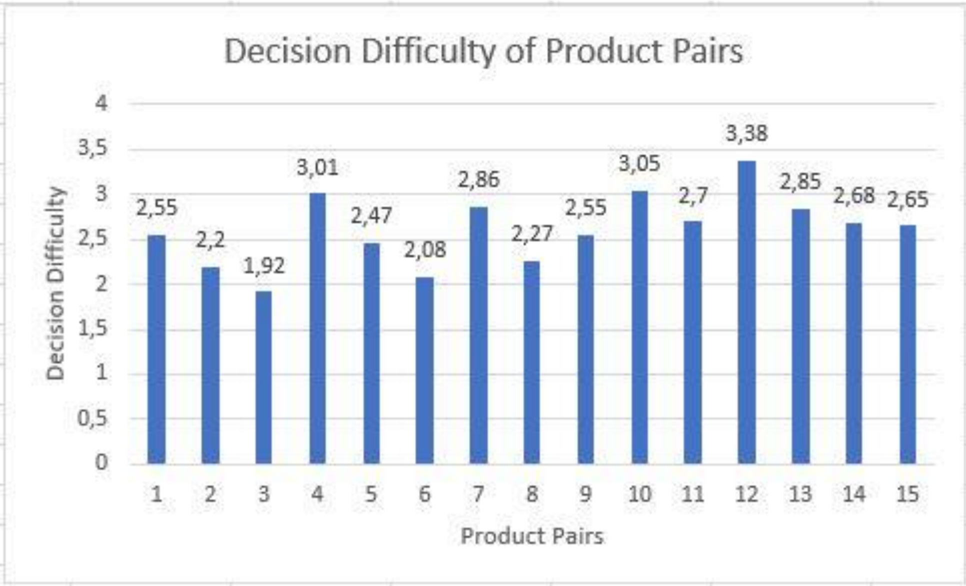


Figure 12 Bar Graph of Decision Difficulty

Figure 13 displays the mean value of the results of question two. In this question, it was asked how appealing the chosen product is to the participant. The question was rated on a one to seven Likert Scale, whereas one stands for not at all appealing and seven for very appealing. In the Pretest, the chosen product from product decision 14 on the test was rated most appealing with 5 on average. The chosen product from product decision 11 was rated least appealing, with 3,58 on average.

Figure 13 Bar Graph of Appeal of the Chosen Products

Figure 14 shows the mean values of question three. In this question, it was asked how well the participant likes the chosen product. The question was rated again on a one to seven Likert Scale.

Results show that the chosen product of the product decision number 14 was liked the most with 5,13 on average. The chosen product of the product decision number 11 was liked least with 3,53 on average.

Figure 14 Bar Graph of Likeability of the Chosen Products

As questions two and three of the pretest are similar in their intention, results show a strong correlation between both. Product decision number 11 shows that likeability and appeal have both the lowest value on the Likert Scale. Product decision number 14 has the highest value on the Likert Scale for likeability and appeal. Concerning decision difficulty, product decisions 3 and 12 represent the two extremes. Decision 3 displays the easiest decision and 12 the hardest decision. It shows that product decision 3 receives more likeability and appeal in the following two questions, whereas product decision number 12 receives less likeability and appeal in the following two questions. These results are in accordance with Liberman and Förster, who argue that the attractiveness of alternatives results from their decision difficulty. The pretest participants were unanimous about the alternative evaluation concerning attractiveness and appeal concerning the corresponding decision difficulty (Liberman & Förster, 2006).

As the average decision difficulty did not reach a value higher than 3.38 out of 7 and a t-test revealed differences in gender-preference, it was decided to revise the product pairs to achieve more significant results. The test spectrum of products was adjusted so that gender neutrality was given, and products were altered according to Bullens et al. (2012) so that decision-making difficulties could be delineated to easy, moderate and hard decisions. Figure 15 shows the new compilation of product pairs, which were used for the mouse tracking experiment.

Figure 15 Product Pairs for the mouse tracking experiment

4.2 Experiment

The experiment was conducted with two fellow students who researched for their master thesis in comparable scientific fields. Due to temporary access restrictions at the University of Innsbruck, the experiment took place at the University's canteen; more information can be found in 6.3 "Limitations" of this thesis. One hundred fifty-seven participants completed the mouse tracking test successfully.

4.2.1 Data Collection

The canteen at the University of Innsbruck (SoWi) was used to conduct the experiment and to gather participants for the experiment. After the successful completion of the test, a voucher for a café at the canteen was provided. In total, 157 participants completed the test, resulting in 1099 mouse trajectories due to seven tracking trails. The test persons ranged from age 17 to age 55, whereas 72 stated they were female (48%) and 78 males (52%). The monthly income amounted to 1092 Eur on average. In consideration of mouse usage and frequency of online purchases, most participants answered these questions in the Likert scale range from five to seven, which means that most respondents were familiar with mouse handling and online shopping. As these first questions set the foundation for the following part of the experiment, results were not used in the data evaluation.

4.2.2 Experiment Setup

The experiment was conducted on two tables with two comparable laptops. As the experiment area had many environmental influences, it was important to isolate the two tables as good as possible. Therefore, the participants were positioned in a way that visual distraction was kept to a minimum. After each trial, the setup was cleaned according to the hygiene regulations of the University of Innsbruck. To increase the expressiveness of mouse trajectories, two identical gaming mice with an infrared sensor were used. The DPI of the mice was set to a slow cursor movement to reduce unintentional flicks.

The mouse tracking experiment was conducted with the help of Webtrackr, a mouse tracking tool introduced by Patrick Neef (2020) to record motoric mouse movements and applicable with common Web Browsers – in this case, Google Chrome. Regarding the mouse tracking trial design, a standard two choice model was used where participants had to choose between a picture in the top left or the top right corner of the screen.

The experiment was created with JavaScript object notation (JSON); the mouse tracking trail's coding is provided in the Appendix. For the code construction, the text editor Notepad++ was used. Each page was written individually containing an items list and all the necessary variables like text boxes, pictures, Likert-Scales and mouse tracking trials. The Webtrackr distinguishes between general elements and tracking elements because a normal text input or Likert type scale is connected sequentially. Some text elements were adjusted with HTML formatting. There were always two pictures assigned to each tracking trail, whereby the position between left and right and the page sequence was randomized. The reason for randomization was to prevent learning effects. The experiment design features a cascading style sheet (CSS), where background color, images, or page size could be adjusted. In order to display the experiment, an index.html page was used. For the tracking experiment, it was important to show all the necessary objects on one page, so that participants did not have to scroll down to see all the information. Individual page formatting was performed on the test computers to guarantee the integrity of the mouse tracking experiment. The tracking frequency for the trail was set to 50 Hz, which defines the interval length between two data points when the mouse movement was recorded. All the in-detail information regarding the construction of our experiment can be found on https://webtrackr.de/.

4.2.3 Experiment Design & Test Procedure

In advance of the tracking experiment, participants had to complete a mouse tracking test run to get used to the mouse's feel and the simulated webshop environment. The experiment was split into a 13-slide questionnaire in a Google Chrome browser tab. The first questions were sociodemographic, asking about age, gender and monthly income. As this experiment intended to simulate an e-commerce environment, questions about computer mouse usage and online shopping frequency were also included. The third slide assessed the participant's mood, according to Allen and Janiszewski (1989). The fourth slide evaluated the decision-making style by implementing a four-item scale from Beißert et al. (2014), which is orientated towards the NFC scale from Cacioppo and Petty (1982). The fifth slide started with the first mouse tracking trail by facing the participants with a choice between two products. A screenshot is provided in Figure 16. Before the product choice started, participants had to click on a start button to align the cursor position to provide a continuous starting position. After the choice was made, five related questions had to be answered - the first two questions aimed at determining the psychological ownership, according to Bause et al. (2020).

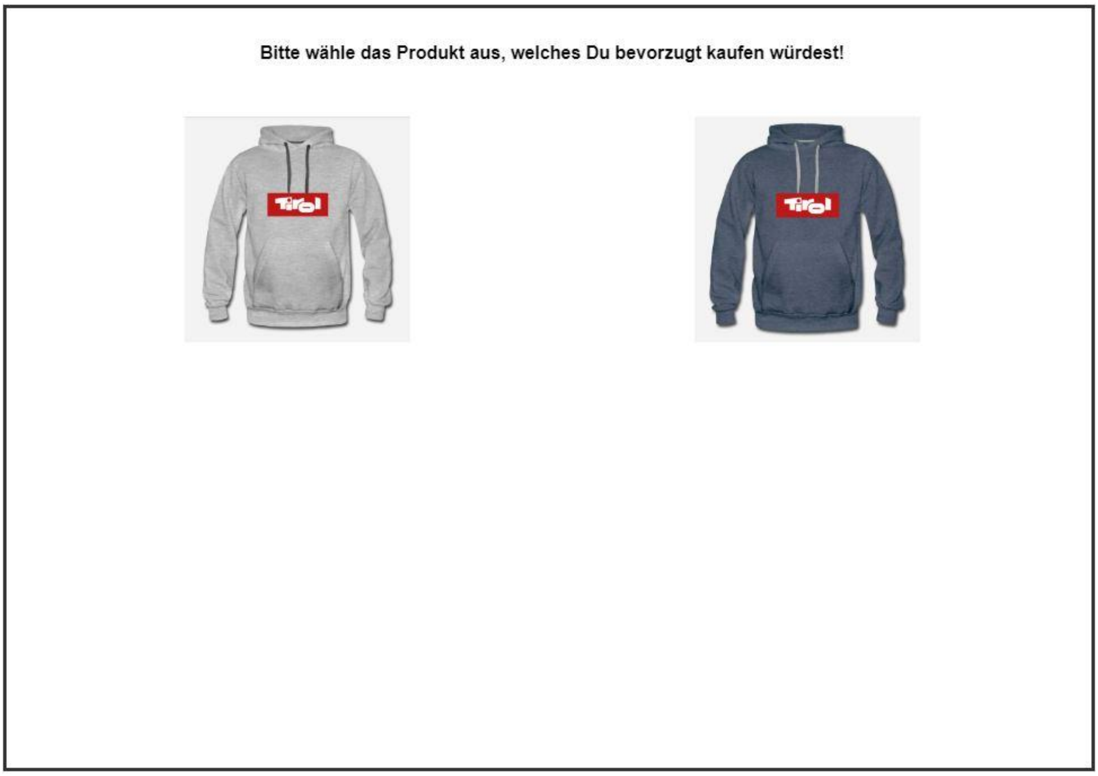


Figure 16 Example of a product choice in the experiment

In the following question, participants had to enter a price they would be willing to pay for the chosen product (Schmidt & Bijmolt, 2020). The last two questions tried to assess the perceived decision difficulty and the confidence of making that choice (Schneider et al., 2020; Langer et al., 2008). All questions, excluding question three, had to be answered on a seven-point Liker scale. This procedure was repeated for seven choice scenarios. The last content-related slide asked the participants which of the seven chosen products they would return if the choice had to be made. This task had the intention to estimate product returns in a webshop scenario.

5. Empirical Findings

This chapter will present the experiment findings and tests the hypothesis mentioned above in their meaningfulness to conclude on the research question. Data were analyzed with the programs SPSS and R.

5.1 Data Preparation

The “Webtrackr” files (.txt files) were read into R and converted into a .csv format so that analysis could also be conducted with SPSS. Nevertheless, most of the analysis was done with R's mousetrap package, which allows to visualize the data and compute several measures (Kieslich et al., 2020). As in the raw data, each trial was assigned to a separate file; it was necessary to merge all files into one. Another important step, necessary for visualization, was to remap all trajectories to one side. As it is recognizable in Figure 17, all trajectories were remapped to the right side and the same starting position. In a next step, mouse movement measures like the traveled distance, acceleration and velocity were calculated. Also, the mouse tracking standard measurements like the Reaction Time (RT), Area under the curve (AUC) or Maximum Deviation (MD) were computed in R.

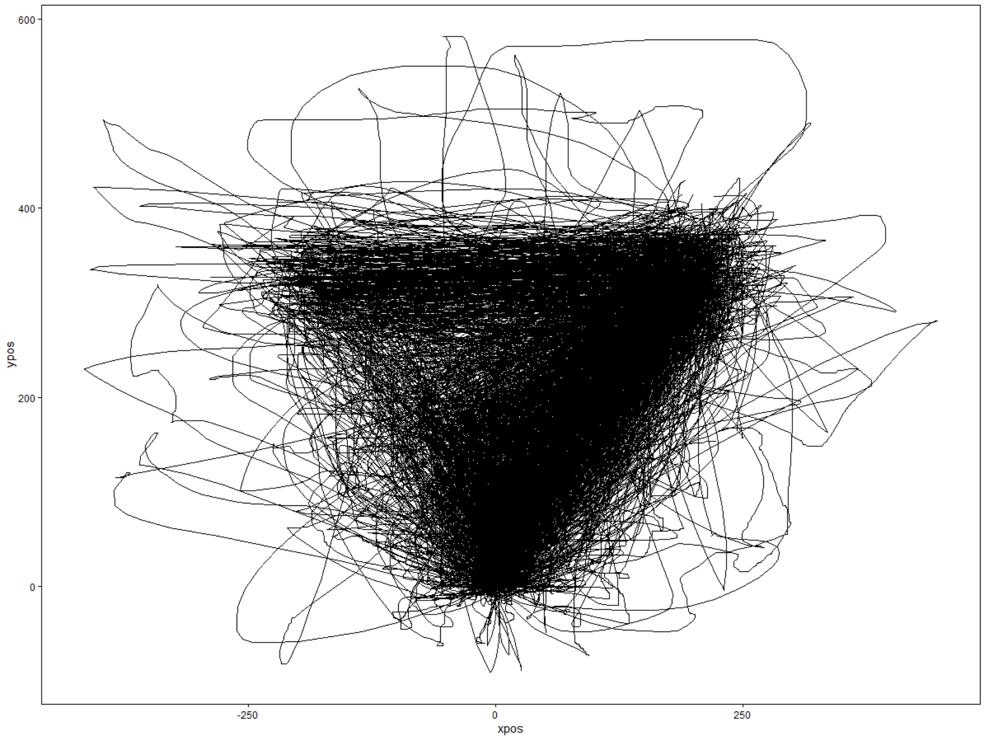


Figure 17 All recorded trajectories remapped to the right side

Concerning outlier behavior, all the mouse tracking measurements were checked in explorative data analysis in SPSS and outliers were excluded from the data set in R. Especially due to the external influences like people speaking and other noises in the experiment environment, the data set was filtered according to Maximum Absolute Deviation (MAD) < 854.019, Absolute Deviation (MD) < 475.114, Area Under the Curve (AUC) < 186621, x-flips < 17, Reaction Time (RT) < 21090 and the time until mouse initiation (initiation_time) <4510. All values above or the same as the mentioned values of the variables were identified as outliers and excluded from the data set. Notes on this resulted from boxplots computed in SPSS, showing the outliers located beyond the extremes. Nevertheless, changes to the data set were only made with care as it was a goal to keep the mouse movements as raw as possible. The data set was divided according to the self-assessed decision difficulty to find out differences between difficult and easy decisions. With the help of a seven-point Likert-scale, questioning the participants to their perceived decision difficulty, the data set was divided into easy decisions with values higher or equal to five and in difficult decisions with values lower or equal to two. This resulted in 170 difficult decisions and 621 easy decisions.

5.2 Results from R

Regarding hypothesis one of this thesis, corresponding statistical findings and graphics are presented in the following.

H1: Difficult decisions in a purchase situation show a higher trajectory complexity compared to easy decisions so that there is an effect on a) x-flips and b) x-reversals c) sample entropy.

As explained earlier, x-flips are small directional changes along the x-axis, and they are an indicator of trajectory complexity and unpredictability. Figure 18 shows the aggregated means of x-flips for difficult decisions and easy decisions in a boxplot. As already visible, there might be a difference in means between the two datasets. The computed mean of x-flips in R for the condition easy is 2,62 (SD= 1,98) and for the condition difficult is 3,3 (SD=2,54).

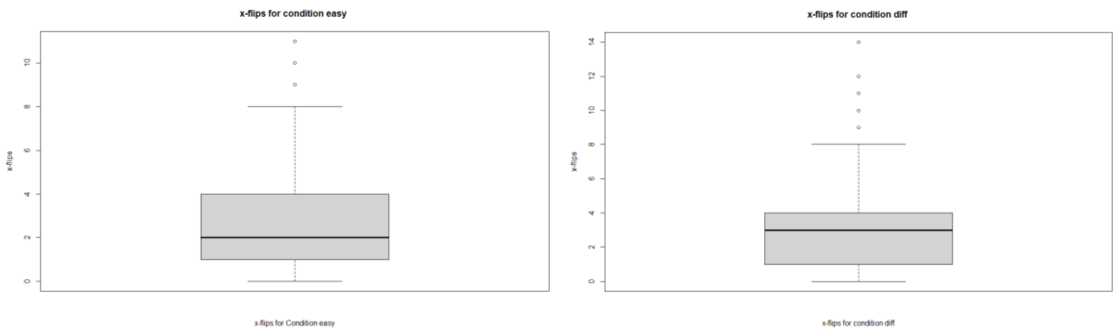


Figure 18 Boxplots for easy decisions (left) and difficult decisions (right) regarding x-flips

Looking at the variance of x-flips (3.92) in the condition easy, which is the square of the corresponding standard deviation, and the variance of the condition difficult (6.45), a difference is given. A Welch two-sample t-test could be conducted. The assumption that equality between the two means exists can be rejected as the Welch test states that p has a value of 0.001. The t-test also computed a t-value of 3.25 and degrees of freedom (df) of 240.78. Therefore, the means of x-flips for the condition easy and condition difficult are significantly different.

To test for a normal distribution of the data, a Shapiro Wilk test was conducted. For difficult decisions, the amount of x-flips is not normally distributed as the p-value of the Shapiro Wilk test was below the alpha of 0.05 (2.2e-16). For easy decisions, the number of x-flips also seems not normally distributed as the p-value is also below the 0.05 margin (2.508e-09). Figure 19 shows the corresponding histogram and a density plot for the x-flips in condition easy and difficult. It is already visible that the data in both cases has a great skew.

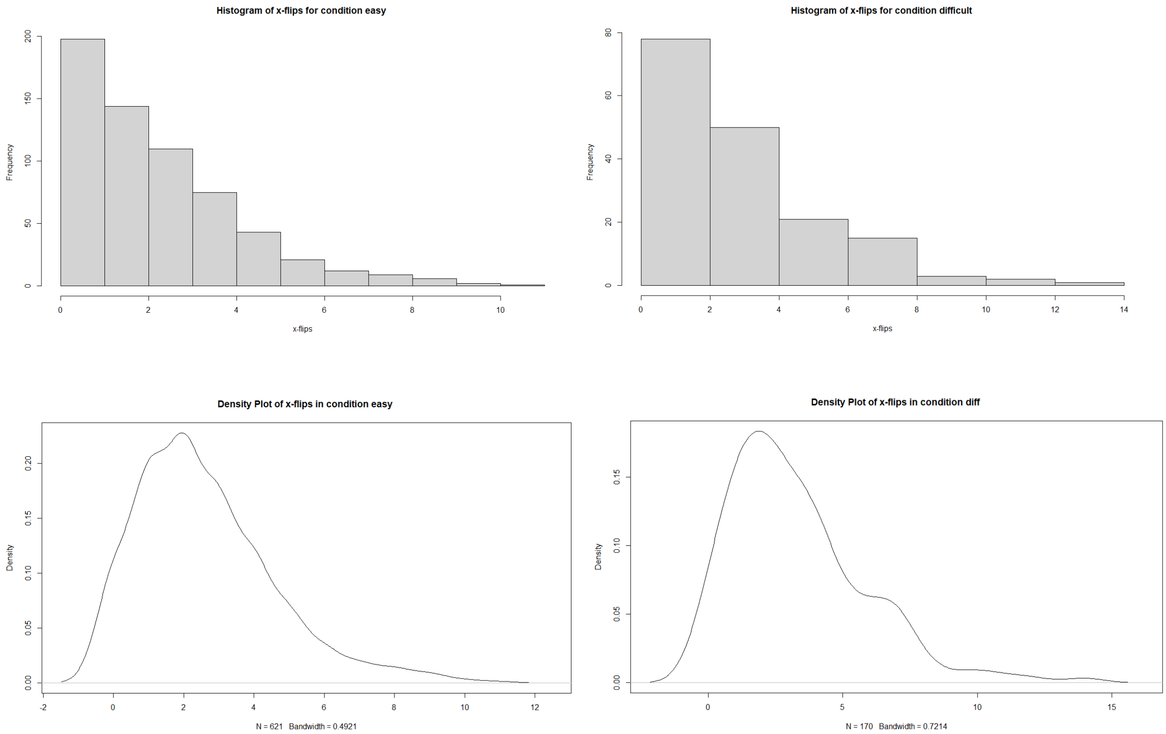


Figure 19 Histogram and Density Plot for x-flips in condition easy and difficult

According to Neuhäuser (2010), a Wilcoxon test can be conducted for a two-sample comparison for skewed data with unequal variances, which is the case here. For both conditions, p was smaller than the alpha of 0.05 with a p-value of 0.004 and a difference in means must be assumed. Also, the data's bimodality is not given as the bimodality coefficient is below the threshold of 0.55.

Regarding x-reversals, for both conditions, the aggregated mean for easy decisions was slightly lower with a value of 1.16 (SD=1.17) than for difficult decisions with a value of 1.48 (SD=1.48). The boxplot in Figure 20 shows that the means can have the potential to be similar. As the variances of both conditions for x-reversals differ, a two-sample Welch test was conducted. The corresponding p-value of 0.009 is smaller than the specified significance level of 95% and a difference in means must be assumed. As the skew for both conditions with 1.56 for the easy condition and 1.33 for the difficult condition, is even bigger than for the tested x-flips, a Wilcoxon test was conducted. The p-value with 0.025 states that the means still are different. The histogram in Figure 21 shows the skew of the data for x-reversals in condition easy and difficult. It points out that the data might not be normally distributed. The Shapiro Wilk test confirms this with a p-value smaller than 0.05 for both conditions. Nevertheless, bimodality was not the case as the bimodality coefficient was lower than the significance level of 0.55 with a value of 0.48 for the easy condition and 0.51 for the difficult condition.

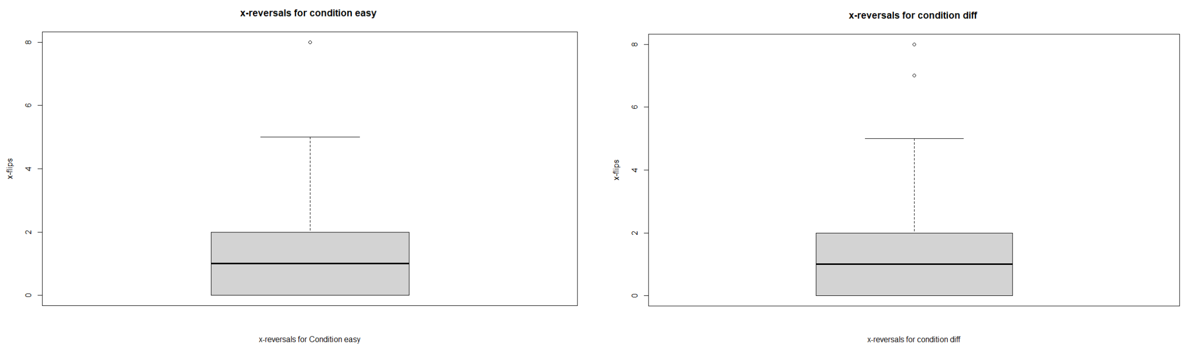


Figure 20 Boxplot for easy decisions (left) and difficult decisions (right) regarding x-reversals

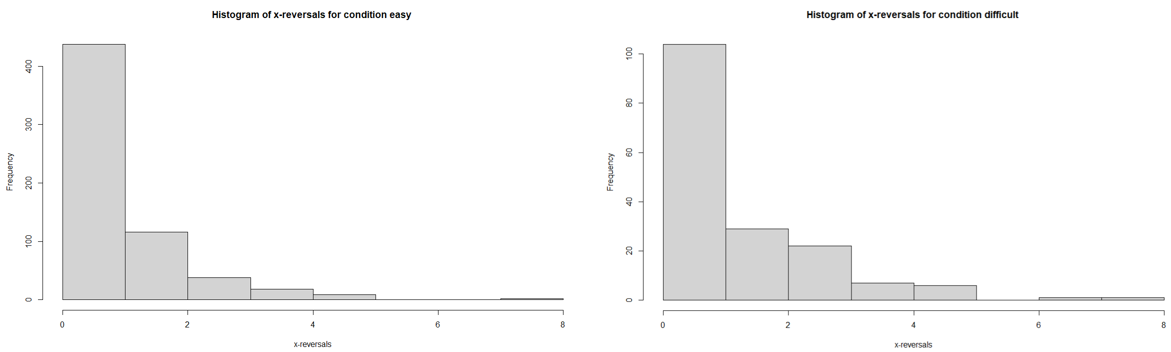


Figure 21 Histogram for x-reversals in condition easy and difficult

Sample entropy as a mouse tracking measure for trajectory complexity and unpredictability is a proper tool to check hypothesis one for correctness. The trajectories classified as easy, the sample entropy with a value of 0.132, is higher than for trajectories classified as difficult with a value of 0.124. When looking at the aggregated trajectories by condition easy and difficult remapped to the right side (Figure 22), it is visibly recognizable that the aggregated trajectories of the condition difficult have a more complex and unpredictable course, compared to the aggregated trajectories of the condition easy.

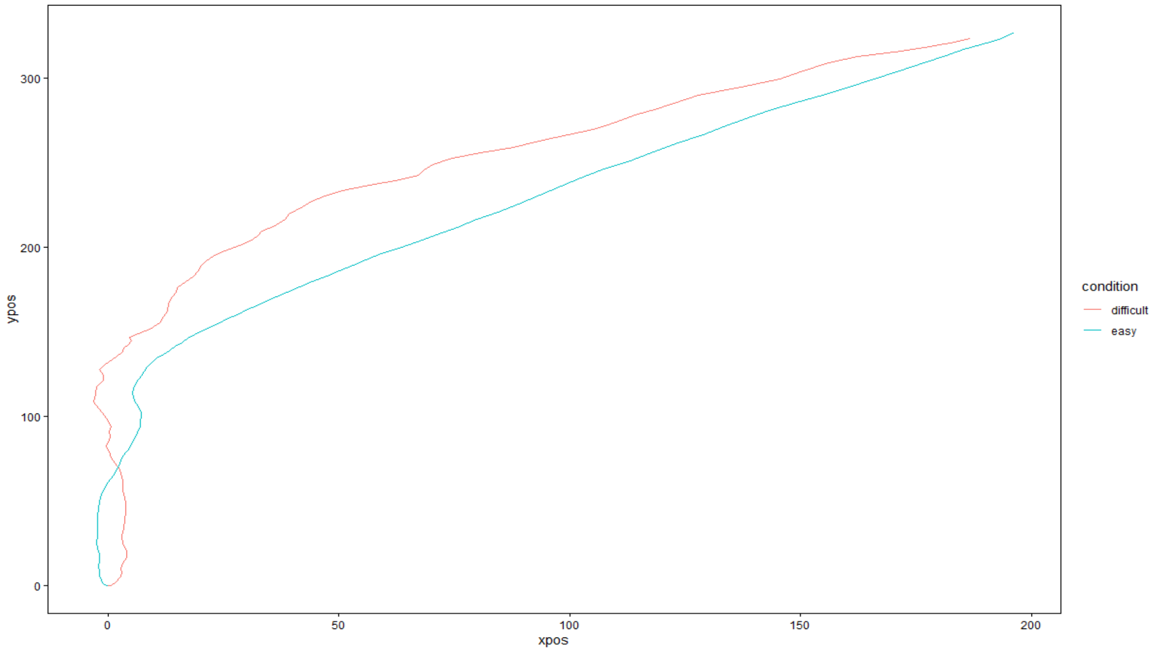


Figure 22 Aggregated trajectories by condition, remapped to the right side

A possible explanation for this controversy could be that, as visible in Figure 23, the density plot of x-reversals in the condition easy displays a multimodal behavior and might contribute to an increased sample entropy for trajectories classified as easy. Further relatable information can be found in the section "Limitations" of this thesis.

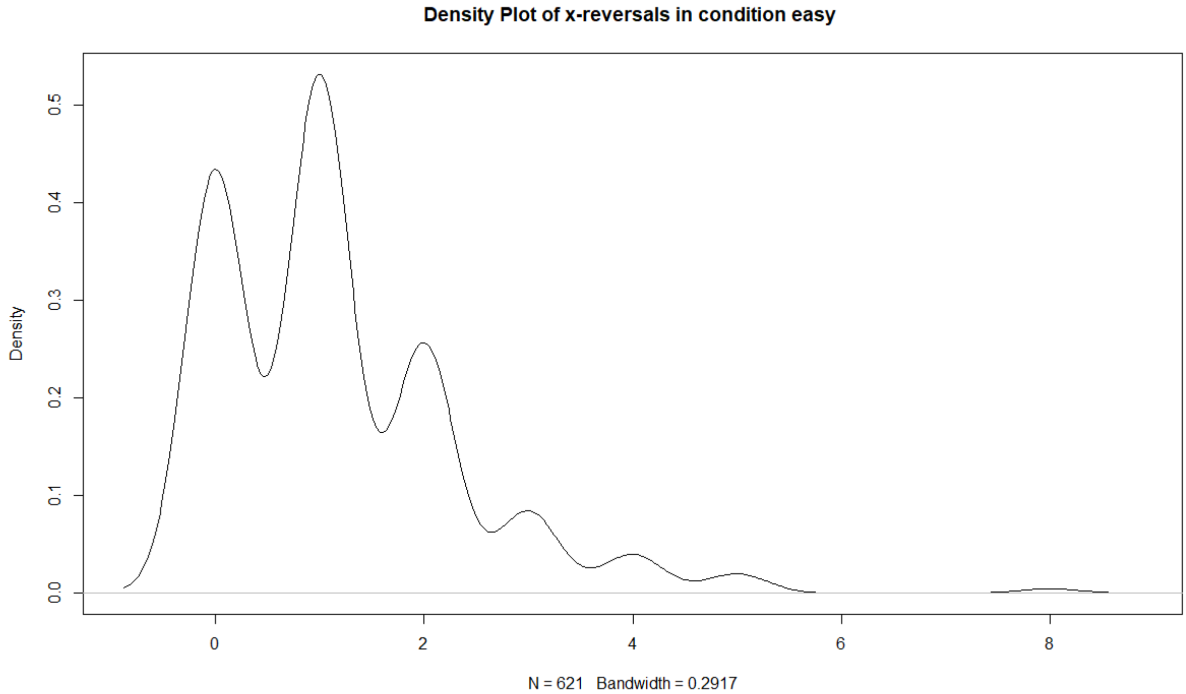


Figure 23 Density plot for x-reversals in condition easy

Measures	Condition Easy	Condition Difficult
x-flips	2,62	3,30
s-reversals	1.16	1.48
sample entropy	0.132	0.124

Table 2 Empirical Results for H1

Hypothesis two of this thesis was formulated in consideration of the mouse trajectory curvature and states that:

H2: Regarding curvature measures, difficult decisions have a bigger impact on AUC and MAD than easy decisions. Also, the bimodality of those curvature measures should be higher for difficult decisions than for easy decisions.

Regarding the aggregated means of AUC concerning the conditions, the trajectories classified as easy have a mean of 13340.31 (SD= 20514.47) and difficult have a mean of 18152.2 (SD= 21486.02). As the squares of the standard deviations differ, a two-sample Welch test was conducted. The corresponding p-value of 0.009 indicates a difference in means between the two groups. This is also visible in the boxplot of Figure 24.

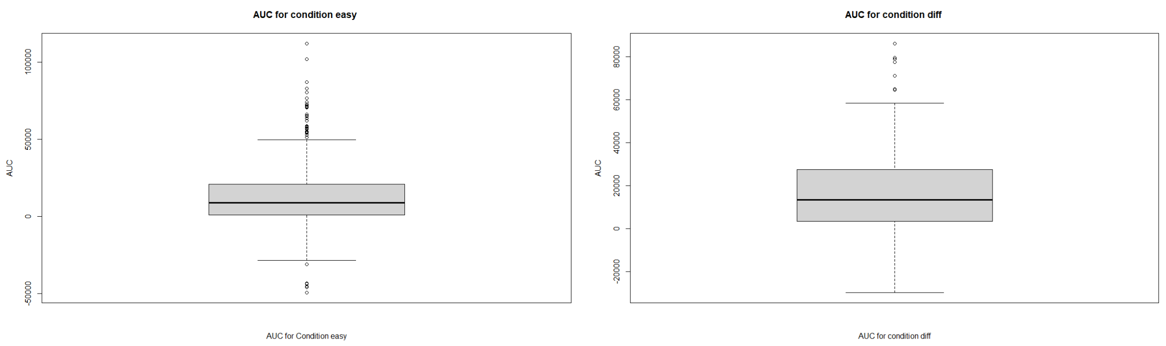


Figure 24. Boxplot for easy decisions (left) and difficult decisions (right) regarding AUC

The Shapiro Wilk test confirms both conditions with a p-value far below the significance level of 0.05. The data for each condition is not normally distributed and the alternative hypothesis must be assumed. A Kolmogorov-Smirnov test, however, confirms the null hypothesis of a normal distribution with a p-value of 0.073 bigger than the alpha of 0.05. As these two analytical tests for data distribution can have significance-issues with big data sets, a graphical analysis of the distribution is preferred. Figure 25 displays a histogram, a density plot and a quantile-quantile plot for the mouse tracking measure AUC by condition difficult and easy.

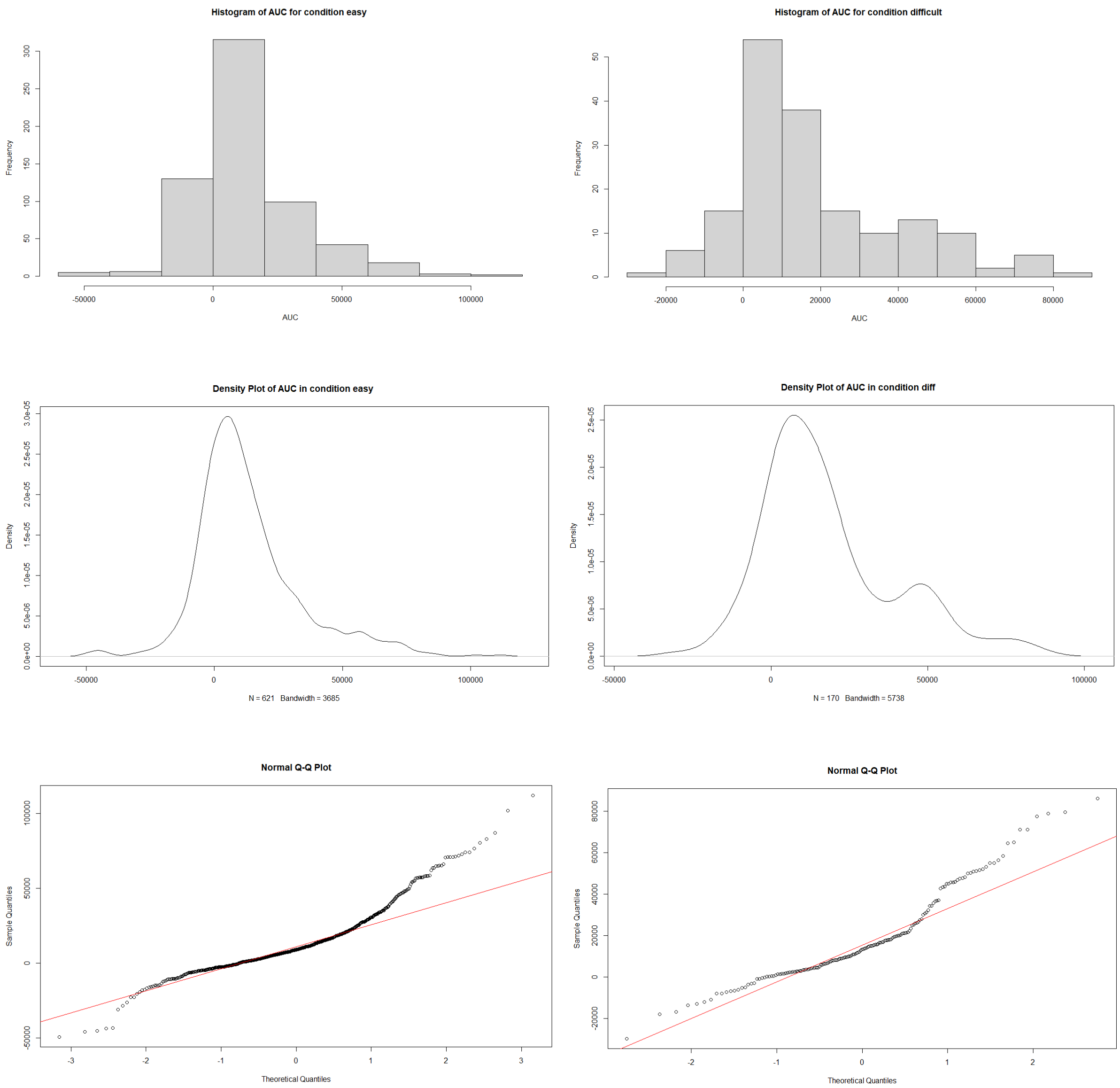


Figure 25 Histogram, Density plot and QQplot of AUC by condition easy (left) and difficult (right)

Regarding the graphics, a normal distribution of the data can be assumed. The histogram, density plot and Q-Q plot for the condition easy show no signs of a not normal distribution. Also, skew with a value of 1.11 in condition easy and 0.95 in condition difficult do not seem to represent a problem. The graphics for condition difficult could display bimodality sings; consequently, the bimodality coefficient (bc) and the Hartigan's dip statistic (HDS) for bimodality were computed. The bc shows a value of 0.52 and lies below the threshold of 0.55; the p-value of the HDS measure with 0.91 shows that the distribution has a unimodal character. Therefore, a Wilcoxon rank-sum test was neglected and a difference in means between AUC by condition is assumed.

The Maximum Absolute Deviation by condition states that for the condition easy, there is a mean of 94.9 (SD=127.35) and for the condition difficult, there is a mean of 135.67 (SD=142.99). As the conditions' variances differ with a value of 16218.02 for the condition easy and 20446.14 for the condition difficult, a Welch two-sample t-test (p= 0.0009) was conducted. The null hypothesis must be rejected, and the alternative hypothesis must be assumed. Looking at the two data sets' value distribution, a Shaprio-Wilk test and Kolmogorov-Smirnov test show a p-value below the significance level of 0.05. The data by condition, therefore, is not normally distributed. A histogram in Figure 26 for the MAD by trajectories classified as easy and the MAD by trajectories classified as difficult, supports that finding.

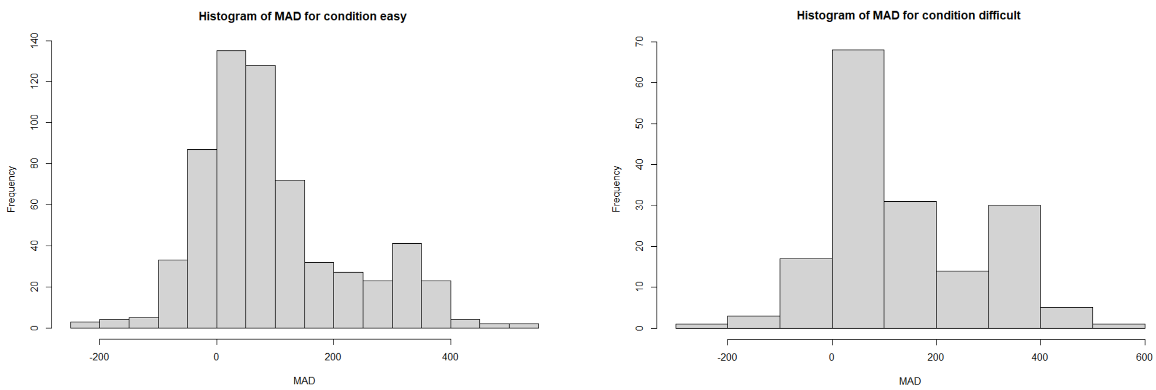


Figure 26 MAD for trajectories in condition easy (left) and difficult (right)

Signs of bimodality for the condition difficult, as visible in Figure x, led to a calculation of the bimodality coefficient with a value of 0.49 and a p-value of 0.025 considering the HDS statistic. According to Freeman and Dale in 2012, a test between several bimodality measures indicated that the HDS statistic is the most appropriate measure of bimodality (Freeman & Dale, 2013). Therefore, it is assumed, due to the p-value of 0.025 below the significance level of 0.05, that the distribution of MAD by trajectory for the condition difficult is bimodal. Displayed graphically in a density plot, this analytical result can be projected (Figure 27).

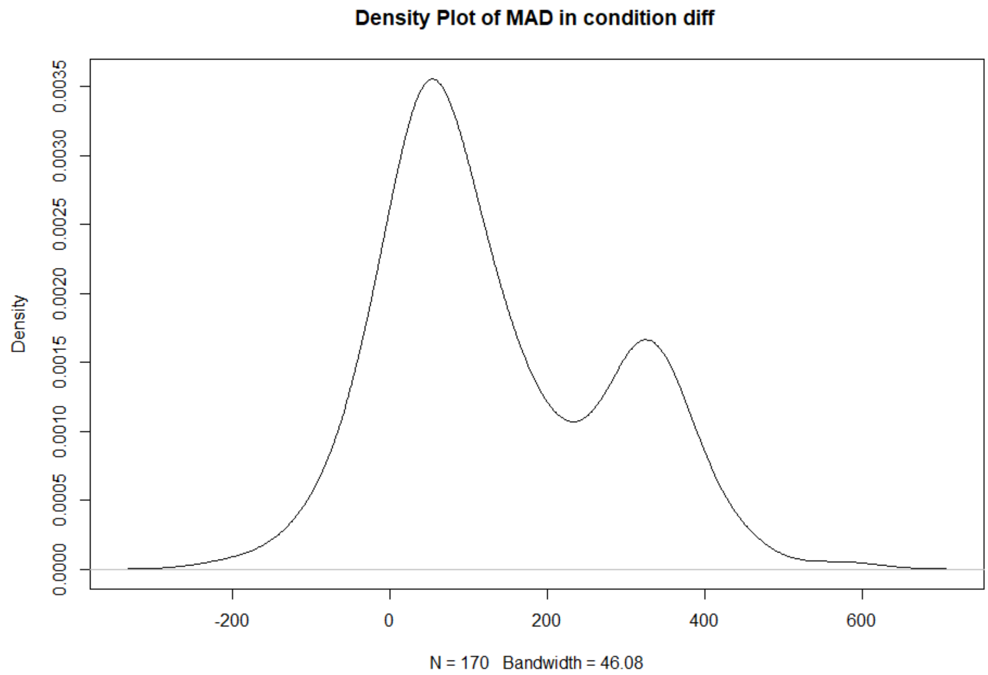


Figure 27 Density plot for MAD by trajectory classification difficult

As a normal distribution of the data sets is not given, a Wilcoxon rank-sum test was conducted to verify if a difference in means between MAD by condition easy and MAD by condition difficult exists. With a p-value of 0.001, the means between the two data sets by the condition are considered as different, although the data sets have a non-normal distribution.

For bimodality calculation, the bimodality coefficient (BC) and Hartigan's dip statistic (HDS) were used. According to Young-Jin Kang and Yoojeong Noh (2019) "both BC and HDS have characteristics that contradict each other" (Young-Jin Kang & Yoojeong Noh, 2019, p. 3). In 2012 Freeman and Dale investigated which bimodality measure is most fitting to display multimodality of a distribution. Their result was that the HDS is best suited to indicate bimodality (Freeman & Dale, 2013). Consequently, when statements between the measures BC and HDS differ, the HDS measure gets prioritized to indicate bimodality.

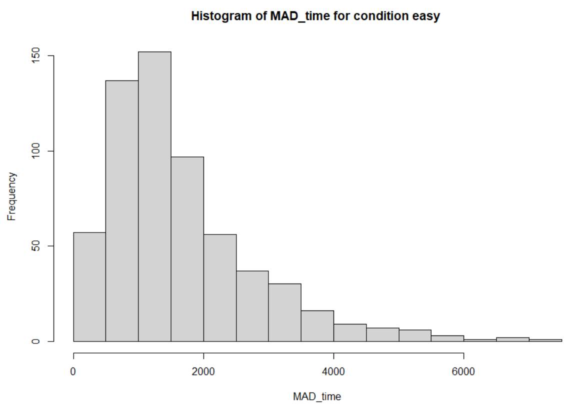
Regarding AUC, the BC has a value of 0.403 for easy decisions and a value of 0.518 for difficult decisions. HDS has a p-value of 0.987 for easy decisions and 0.911 for difficult decisions. The null hypothesis for the HDS states that the distribution is considered unimodal if the p-value is above the significance level of 0.05. Even though considered as unimodal, difficult decisions for AUC still have a higher tendency towards bimodality than easy decisions. Regarding MAD, the BC has a value of 0.491 for easy decisions and a value of 0.493 for difficult decisions. The HDS has a p-value of 0.046 for easy decisions and 0.025 for difficult decisions. Therefore, both easy and difficult decisions regarding the MAD are considered bimodal, whereas the p-value for the condition difficult shows a higher significance.

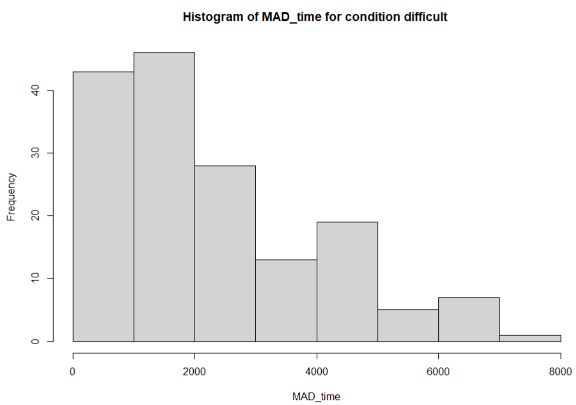
Measures	Condition Easy	Condition Difficult
AUC	13340.31	18152.20
MAD	94.90	135.67
bc of AUC	0.403	0.518
HDS of AUC (p-value)	0.987	0.911
bc of MAD	0.491	0.493
HDS of MAD (p-value)	0.046	0.025

Table 3 Empirical Results for H2

H3: Difficult decisions display a difference in temporal behavior to easy decisions so that for difficult decisions, MAD is met later in the trajectory progress and RT is longer compared to easy decisions.

Looking at the means for when the trajectory reaches its maximum absolute deviation from an imaginary direct line (MAD_time) concerning the decisions by condition, it shows that MAD_time for difficult decisions is met later in the trajectory with a value of 2325.154 (SD= 1731.98) than for easy decisions 1662.799 (SD= 1146.29). As both variances differ, a Welch two-sample t-test was conducted. The p-value of 7.258e-06 indicates a difference in means between both data sets. Figure 28 shows a Histogram and a Density plot of MAD_time by condition easy and difficult.





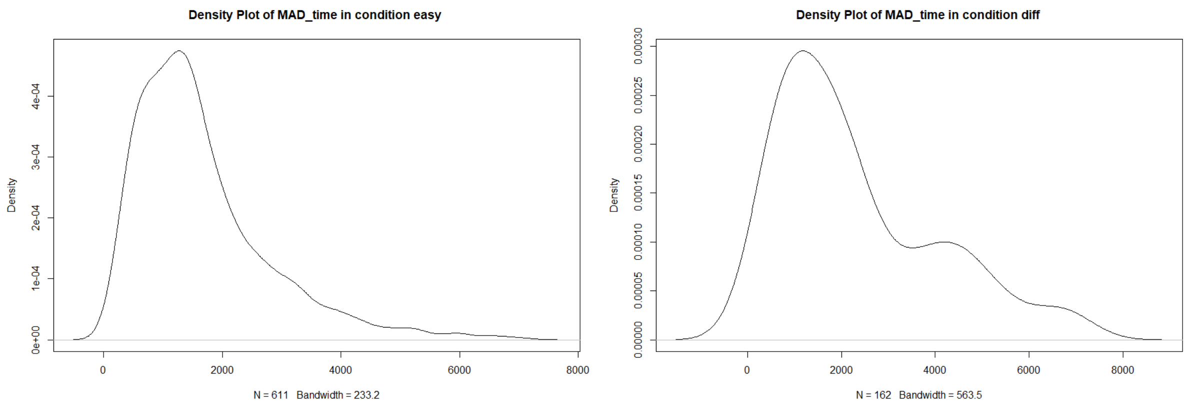


Figure 28 Histogram and Density plot of MAD_time by condition easy (left) and difficult (right)

It is visible that condition easy displays a skew in the data distribution. For the condition easy, 1.54 and for the condition difficult 0.98. The Shapiro Wilk test confirms that data is not normally distributed with a p-value (1.643e-09) below the significance level. The Wilcoxon rank-sum test confirms a difference in means with a p-value of 0.0001.

Concerning RT decisions classified as easy have a mean of 3097.81 (SD= 1576.95) and decisions classified as difficult have a mean of 4287.09 (SD= 2413.14). Variances differ and the p-value (1.221e-08) of the Welch t-test states a difference in means between both conditions. A Shapiro Wilk test for both conditions indicates that the data is not normally distributed (p-value easy: < 2.2e-16, p-value difficult: 6.972e-09). Figure 29 displays a histogram and a Q-Q plot for both conditions for the measure RT. Results from the Shapiro Wilk test can be projected. Nevertheless, a Wilcoxon rank-sum test confirms a difference in means with a p-value of 1.761e-09.

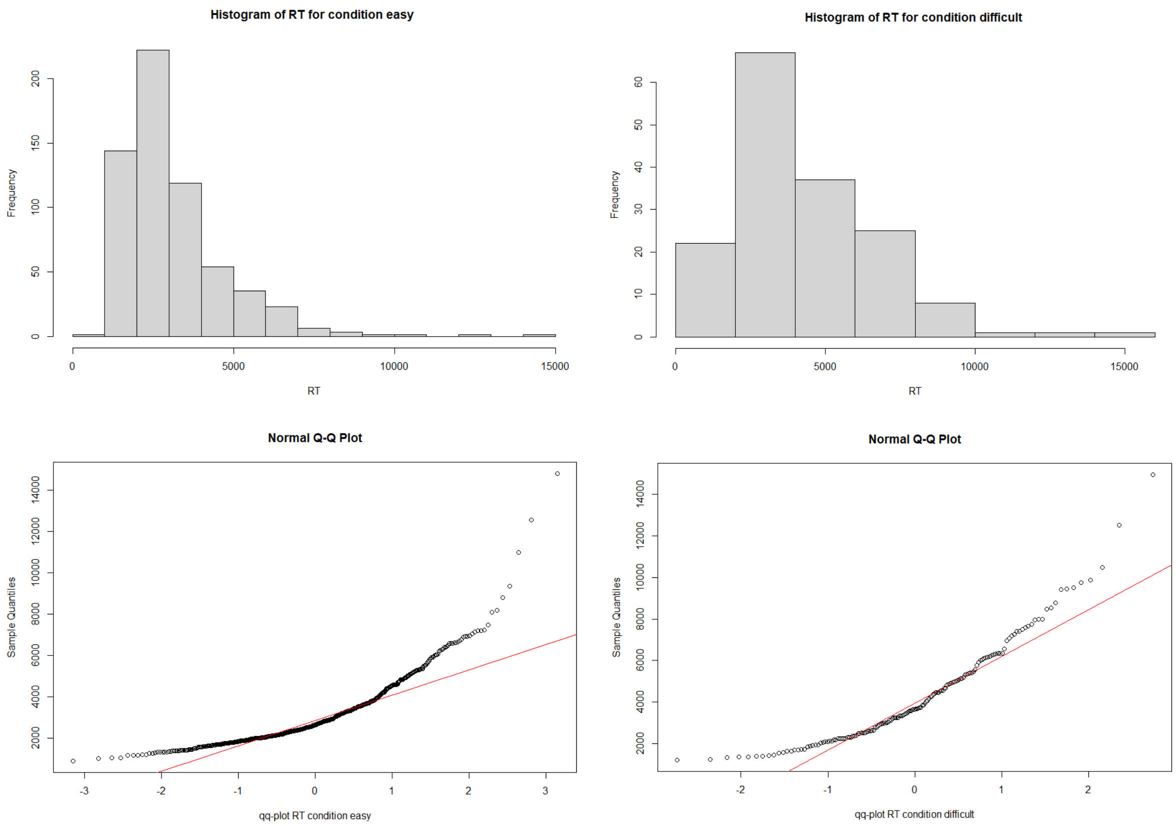


Figure 29 Histogram and QQ-plot for RT by the conditions easy (left) and difficult (right)

Measures	Condition Easy	Condition Difficult
MAD_time	1662.799	2325.154
RT	3097.81	4287.09

Table 4 Empirical Results from H3

In the following, an overview of the hypothesis and their correctness is presented:

Hypothesis	Supported
H1: Difficult decisions in a purchase situation show a higher trajectory complexity compared to easy decisions so that there is an effect on a) x-flips and b) x-reversals c) sample entropy.	
H1a: Difficult decisions in a purchase situation show a higher trajectory complexity compared to easy decisions so that there is an effect on a) x-flips.	✓
H1b: Difficult decisions in a purchase situation show a higher trajectory complexity compared to easy decisions so that there is an effect on b) x-reversals.	✓
H1c: Difficult decisions in a purchase situation show a higher trajectory complexity compared to easy decisions so that there is an effect on c) sample entropy.	✗
H2: Regarding curvature measures, difficult decisions have a bigger impact on AUC and MAD than easy decisions. Also, bimodality of those curvature measures should be higher for difficult decisions than for easy decisions.	
H2a: Regarding curvature measures, difficult decisions have a bigger impact on AUC compared to easy decisions.	✓
H2b: Regarding curvature measures, difficult decisions have a bigger impact on MAD compared to easy decisions.	✓

H2c: Also, bimodality of those curvature measures should be higher for difficult decisions than for easy decisions.	✓
H3: Difficult decisions display a difference in temporal behavior to easy decisions so that for difficult decisions, MAD is met later in the trajectory progress and RT is longer compared to easy decisions.	
H3a: Difficult decisions display a difference in temporal behavior to easy decisions so that for difficult decisions, MAD is met later in the trajectory.	✓
H3b: Difficult decisions display a difference in temporal behavior to easy decisions so that for difficult decisions, RT is longer compared to easy decisions.	✓

Table 5 Overview of the hypotheses

Overview of Aggregated Measures:

Measures	Condition Easy	Condition Difficult
x-flips	2,62	3,30
x-reversals	1.16	1.48
sample entropy	0.132	0.124
AUC	13340.31	18152.20
MAD	94.90	135.67
bc of AUC	0.403	0.518
HDS of AUC (p-value)	0.987	0.911
bc of MAD	0.491	0.493
HDS of MAD (p-value)	0.046	0.025
MAD_time	1662.799	2325.154
RT	3097.81	4287.09

Table 6 Overview of Aggregated Measures

6. Discussion

The following section processes the previously elaborated results and interprets its meaning concerning the discussed literature in a neuromarketing context. Correlations, common features and differences will be shown and structured by each of the hypotheses. As it is an essential part of this thesis to view these results from a business perspective, implications will arise and put in context to their applicability. This study was conducted under special circumstances; therefore, limitations and future research paragraphs will be appended.

6.1 General Discussion

Several studies showed that mouse tracking is a valuable tool to investigate decision difficulty (Szaszi et al., 2018; Maldonado et al., 2019). As the research about online consumer behavior and online decision-making is still in its development stage, this thesis tries to unfold the resolution of the decision-making process in the context of decision difficulty (Darley et al., 2010). Therefore, a mouse-tracking experiment was conducted where 157 participants were confronted with a choice task between two alternatives. The recorded mouse trajectories were analyzed according to their complexity, curvature and their temporal behavior. It was expected to see a difference in trajectory behavior between self-assessed decision difficulty of the alternatives. The results confirm the previous assumptions in almost all cases. Concluding on research about the theory of embodied cognition and the human mind's duality, the thesis tested bimodality of trajectory curvature (Markman & Brendl, 2005; Freeman & Dale, 2013). Results indicate no significant values, but a tendency that difficult decisions display higher bimodality in curvature measures was identified.

The hypotheses are arranged sequentially in a guideline so that the presence of dual thought processes can be emphasized and supported empirically. With the measurement of trajectory complexity, it was aimed to prove the mere existence of competition between two distinct processes. The analysis of trajectory curvature on bimodality had the goal to describe hand movements' motoric behavior in context to the duality of cognition. The third assumption tried to describe and explain the two processes' temporal sequence in a decision task. The intention behind all three hypotheses was to consider the resolution of the decision process from different perspectives in order to gain a comprehensive understanding.

Hypothesis one shows that trajectories classified as difficult have, on average, 0.7 x-flips more than trajectories classified as easy. Also, x-reversals for the difficult trajectory were 0.32 more in quantity than for the average easy trajectory. This result was not reflected in the sample entropy, a mouse tracking measurement for trajectory irregularity and unpredictability. To calculate sample entropy, the trajectory is time normalized to 101-time steps and compared in a spatial disorder analysis for different sequences of the trajectory (Hehman et al., 2015). In which sequence, trajectory complexity was the most could descriptively not be analyzed. Still, graphically, as visible in Figure 15, irregularities of the difficult aggregated trajectory accumulate in the beginning sequences of mouse movements. When comparing the two average trajectories visually, it is recognizable that the difficult mouse curve displays far more irregularities and unpredictable movements than the easy mouse curve. A possible explanation for the descriptive result was already given in "5.2 Results from R". Nevertheless, two out of three measurements indicated that difficult decisions provoke more complex mouse movements than easy decisions and the correctness of the hypothesis is assumed. X-flips and x-reversals orientate themselves exclusively according to movements along the x-axis. Still, as the used decision design supports the significance of measures along this axis, any concerns in this regard can be neglected. According to Koop and Johnson, x-flips represent a momentary shift in preferences and x-reversals a definite shift in preferences so that it can be concluded that in difficult decisions, this competition of preferences is more active than for easy decisions (Koop & Johnson, 2013). The motoric and temporal resolution of this preference competition will be discussed later on, but for now, the presence of such can be assumed. What has to be noted is that the fast, intuitive and emotional System 1 of thought is subject to a control function of the reflective and slow System 2 of thought. X-flips and x-reversals might represent this midflight correction, which can be seen in the mouse trajectory (Stillman et al., 2018). A more suitable analysis method to support this claim might be trajectory curvature measures, which are part of this thesis's second hypothesis.

Hypothesis two showed that curvature measurements for difficult decisions are consistently larger than for easy decisions. AUC in average is 4811.32 higher for difficult than for easy choices. Also, MAD for trajectories classified as difficult was on average, 40.77 bigger than trajectories in condition easy. Concluding on these results, curvature measurements show that difficult decisions evoke a higher response competition. AUC and MAD indicated that the non-selected alternative generated a pull whose dimensions depended on the choice scenario's alternative attractiveness. This finding is in accordance with Schneider et al. in 2015, who researched the ambivalence of choice alternatives. When looking at the aggregated trajectory in Figure 15, a noticeable presence of two distinct thought processes cannot be recognized. One such trajectory would have to have an extreme change of direction instead of an arc so that a dichotomy would be possible to see. For this thesis, the two processes of thought are not considered independent and as separate operations but rather as complementary and overlapping processes that interact dynamically with each other. Dhar and Gorlin made a comparable insight in 2013, who researched the interplay between intuitive and deliberate processes. Furthermore, Trueblood in 2006 introduced a two-part dynamical model of thought.

In order to determine a duality of cognition, the mouse tracking curvature measures were tested on bimodality with the bimodality coefficient and Hartigan's DIP statistic. For easy and difficult decisions regarding AUC, either BC or the HDS did not show significant results regarding bimodality. It must be noted that for difficult decisions, bimodality results were closer to significance than for easy decisions. Regarding MAD, the HDS measure confirms bimodality in both cases, whereas difficult decisions are higher in significance than easy decisions. Freeman and Ambady in 2010 stated that AUC is a better index of overall attraction towards the unselected response alternative, whereas MAD is a better index of the maximum attraction. The experiment shows that difficult decisions evoke a higher maximum absolute deviation in a challenging cognitive task. The point where the trajectory switches direction, which happens at the MAD, could represent the smooth transition from the intuitive system to the deliberate system. Freeman and Dale in 2013 investigated bimodality measurements as a foundation of the existence of dual cognitive processes. They came to the result that the HDS measure represents a more reliable explanation. MAD being bimodal in that aspect represents proof that two cognitive processes are active in a choice task. For difficult decisions, which need more cognitive effort, this recognition can be prioritized. To inspect how this process resolves temporally, hypothesis three was investigated.

The time point when MAD reached its maximum was met later for difficult decisions by 662.34 compared to easy decisions. When an alternative was selected, the reaction time was later by 1189.28 in a difficult choice task to an easy choice task. Dual-Process Theory research identified that the two cognitive processes follow a temporal sequence. The intuitive System 1 is active for the initial part of the decision process and the deliberate System 2 is active for the last part of the decision process (Kahneman & Frederick, 2012; Dhar & Gorlin, 2013; Stillman et al., 2018). As difficult decisions take longer in reaction time, it shows that two processes are active during the decision. That difficult decisions meet MAD later is proof of the ongoing competition of System 1 and System 2. Which System ultimately is responsible for the outcome of the decision can depend on various factors like the task's character, the time available for deliberation, the respondent's mood, intelligence, and statistical thinking (Kahneman & Frederick, 2012). As this study is limited to a trajectory analysis in a choice scenario, it is assumed that a later transition point, represented by MAD's time point, is a sign of activation of the deliberate cognitive process two in a difficult choice task.

6.2 Implications

This study intended to use mouse tracking to uncover the cognitive processes in a choice scenario. Mouse tracking is a relatively new method that was used for several fields of scientific research. It has not received yet acceptance and applicability in the business world, as Schoemann et al. in 2019 found that mouse tracking is very susceptible to errors, especially regarding environmental influences. As these external factors can usually only be controlled to a limited extent, one could question the significance of a mouse trajectory. Big E-Commerce companies could minimize these external influences by gathering massive amounts of data to create valuable information by averaging their findings. The experiment shows that two cognitive processes, one fast and intuitive and one slow and deliberate, can be active during the decision process. Increased activation of these two processes in a difficult decision task could be verified, whereas process two was responsible for the decision outcome in a difficult decision type. A conclusion for marketers in E-Commerce from these results is that they should manipulate decisions to be relatively easy when they aim for an intuitive and thoughtless decision outcome. When they aim for a decision outcome with a memory effect and a probability of a rebuy of the not chosen alternative, as Liberman and Förster state in 2006, they should manipulate decisions to be relatively difficult. Predicting buying decisions is a difficult task. With the unfolding and inspection of the cognitive processes, an approximation for these decisions can be made.

6.3 Limitations

This study's experiment was conducted during the times of a COVID 19 pandemic and, therefore, accessibility to University locations was limited and partly restricted. The only possible location to make the experiment feasible was the Universities canteen. In consequence, participants were prone to visual, acoustic and odorous influences. These influences could have represented a major manipulation of trajectory behavior as Schoenmann et al. in 2019 found that mouse tracking is very prone to external influences. In order to make the best possible use of the given situation, participants were spatially separated with partition walls and positioned in a way so that they faced a wall. For the experiment, two similar computers were used. It was ensured that the graphical settings were identical; nevertheless, a difference in screen size could still lead to varying perceptions by participants. Another limitation of this study was that outliers in the data set were treated relatively negligent to keep the average trajectory as raw as possible. One measure that could lead to a distorted perception of cognition in a decision-making process is the cursor's initiation time.

Participants could have determined the decision outcome before even moving the mouse. Different solutions to this problem have already been presented in mouse tracking research by setting reminders for participants when the mouse stands still or initiating the tracking experiment, not until the mouse is moved (Hehman et al., 2015; Kieslich et al., 2019). None of these approaches were used in the conducted experiment. During the evaluation process of the mouse-tracking data, it has been noted that a majority of the decisions were classified as easy. In total easy decisions were 3.6 times more frequent than difficult decisions. One possible explanation could be that the gathered pretest results had little influence in the creation the choice scenarios of the main test. Another explanation could be that people seek justification for their choices, which could lead to a compromise in a scenario with extreme selection possibilities (Simonson & Tversky, 1992). In application to the conducted experiment, participants might rather choose a low to medium value on a Likert Scale instead of going for extreme values like one or seven.

6.4 Further Research

Tracking mouse movements still is an under-researched scientific field. Recent literature deals with mouse tracking as a process-tracing tool but neglects the advantage of mouse tracking as a suitable medium for explaining online behavior. As Webtrackr is applicable in almost any Web Browser, new investigation possibilities open up. Tracking experiments with this software do not have to be conducted location-bound and it will be possible to simulate a perfect online scenario.

In the course of this thesis, the Dual Process Theory has been used to explain decision behavior. Nevertheless, signs of dynamic processing have been found, which asks for further research in a different experiment. It would also be interesting to see how a cognitive analysis unfolds in easy and difficult decisions as well as decisions classified with a medium difficulty. Due to limitations in the data processing, measures like velocity and acceleration of mouse movements could not be used but would be of interest for future research.

6.5 Conclusion

This thesis investigated the resolution of cognitive processes in a situation of purchase decision difficulty with mouse tracking. Findings show that easy purchase decisions follow System 1 and difficult purchase decisions follow System 2 of the Dual Process Theory. Nevertheless, both systems can be active during a decision task, especially when decisions are difficult and reaction time is longer. Computer mouse tracking proves to be a suitable tool to uncover mental processes by analyzing motoric hand movements, even though it is prone to environmental influences. An experiment was conducted where participants had to decide between two alternatives and confirm their decision by a mouse click on a computer screen. The results were analyzed by separating data according to self-assessed decision difficulty and investigated graphically and descriptively. With the mentioned findings, it was possible to extend research about decision difficulty in E-Commerce so that the analysis of human cognition could have the potential to unfold and predict mental decision processes.

References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, AC-19, 716–723. doi:10.1109/TAC.1974.1100705

Allen, C. T., & Janiszewski, C. A. (1989). Assessing the Role of Contingency Awareness in Attitudinal Conditioning with Implications for Advertising Research. *Journal of Marketing Research*, 26(1), 30. https://doi.org/10.2307/3172667

Arroyo, E., Selker, T., & Wei, W. (2006). Usability tool for analysis of web designs using mouse tracks, 484. https://doi.org/10.1145/1125451.1125557

Ashman, R., Solomon, M. R., & Wolny, J. (2015). An old model for a new age: Consumer decision making in participatory digital culture. *Journal of Customer Behaviour*, *14*(2), 127–146. https://doi.org/10.1362/147539215x14373846805743

Bang, H., & Wojdynski, B. W. (2016). Tracking users' visual attention and responses to personalized advertising based on task cognitive demand. *Computers in Human Behavior*, *55*, 867–876. https://doi.org/10.1016/j.chb.2015.10.025

Bause, I. M., Brich, I. R., Hesse, F. W., & Wesslein, A. (2020). Does touching information on a surface tablet affect how it is evaluated? 16(2), 127–146.

Beißert, H., Köhler, M., Rempel, M., & Beierlein, C. (2014). Eine deutschsprachige Kurzskala zur Messung des Konstrukts Need for Cognition [A German short-scale for measuring the construct need for cognition]. *GESIS- Working Papers Working Papers*, 32.

Bernoulli, D. ([1738] 1954). Exposition of a new theory on the measurement of risk. (Ed. & Trans.) *Econometrica*, 22(1), 23–36. DOI:10.2307/1909829

Bettman, J. R., Johnson, E. J., & Payne, J. W. (1991). Consumer Decision Making. In *Handbook of consumer behaviour* (pp. 50–84).

Breugelmans, E. Köhler, C.F., Dellaert, B.G.C., & de Ruyter, K. (2012). Promoting interactive decision aids on retail websites: a message framing perspective with new vs. traditional consumer actions. *Journal of Retailing*, 88(2), 226-235. doi: 10.1016/j.jretai.2011.10.003

Bullens, L., Forster, J., van Harreveld, F., & Liberman, N. (2012). Self-produced decisional conflict due to incorrect metacognitions. Cognitive Consistency: A Fundamental Principle in Social Cognition, 285–304

Bureau, U. S. C. (2015). *E-Stats 2013 : Measuring the Electronic Economy*. 1–5.

Busemeyer, J. R., & Townsend, J. T. (1993). Decision field theory: A dynamic-cognitive approach to decision making in an uncertain environment. *Psychological Review*, *100*(3), 432–459. https://doi.org/10.1037/0033-295X.100.3.432

Büttner, O. B., Florack, A., Leder, H., Paul, M. A., Serfas, B. G., & Schulz, A. M. (2014). Hard to Ignore: Impulsive Buyers Show an Attentional Bias in Shopping Situations. *Social Psychological and Personality Science*, *5*(3), 343–351. https://doi.org/10.1177/1948550613494024

Cacioppo, J. T., & Petty, R. E. (1982). The need for cognition. *Journal of Personality and Social Psychology*, 42(1), 116.

Calluso, C., Committeri, G., Pezzulo, G., Lepora, N., & Tosoni, A. (2015). Analysis of hand kinematics reveals inter-individual differences in intertemporal decision dynamics. *Experimental Brain Research*, *233*(12), 3597–3611. https://doi.org/10.1007/s00221-015-4427-1

Chandon, P. (2002). Do We Know What We Look at? An Eye-Tracking Study of Visual Attention and Memory for Brands at the Point of Purchase. *Journal of Consumer Research*, *60*, 1–41. https://doi.org/10.1300/J103v21n01_03

Conrey, F. R., Sherman, J. W., Gawronski, B., Hugenberg, K., & Groom, C. (2005). Separating multiple processes in implicit social cognition: The Quad model of implicit task performance. *Journal of Personality and Social Psychology*, 89, 469–487.

Dale, R., Kehoe, C., & Spivey, M. J. (2007). Graded motor responses in the time course of categorizing atypical exemplars. Memory & Cognition, 35(1), 15– 28, doi:10.3758/BF03195938.

Darley, W. K., Blankson, C., & Luethge, D. J. (2010). Toward an integrated framework for online consumer behavior and decision making process: A review. *Psychology and Marketing*, *27*(2), 94–116. https://doi.org/10.1002/mar.20322

Davenport, Thomas H. and John C. Beck (2001), The Attention Economy: Understanding the Currency of Business. Boston: *Harvard Business School Press*.

Deck, C., & Jahedi, S. (2015). The effect of cognitive load on economic decision making: A survey and new experiments. *European Economic Review*, *78*, 97–119. https://doi.org/10.1016/j.euroecorev.2015.05.004

Demsar, U., Cöltekin, A. (2014). *Quantifying the interactions between eye and mouse movements on spatial visual interfaces through trajectory visualisations*. https://doi.org/10.5167/uzh-105671

Dhar, R., & Gorlin, M. (2013). A dual-system framework to understand preference construction processes in choice. *Journal of Consumer Psychology*, *23*(4), 528–542. https://doi.org/10.1016/j.jcps.2013.02.002

Diederich, A., & Trueblood, J. S. (2018). A dynamic dual process model of risky decision making. *Psychological Review, 125*(2), 270–292. https://doi.org/10.1037/rev0000087

Diego-Mas, J. A., Garzon-Leal, D., Poveda-Bautista, R., & Alcaide-Marzal, J. (2019). User- interfaces layout optimization using eye-tracking, mouse movements and genetic algorithms., *78*, 197–209.

Dixon, E., Enos, E., Brodmerkle, S. (2011). *(12) United States Patent Primary Examiner Andrew Caldwell Assistant Examiner – Melvin H Pollack*. *2*(12).

Djamasbi, S. (2014). *T ransactions on H uman - C omputer I nteraction*. *6*(2), 37–54.

Engel, J. F., Kollat, D. T., & Blackwell, R. . (1968). *Consumer Behaviour*. New York: Rinehart & Winston.

Fiedler, S., & Glöckner, A. (2012). The dynamics of decision making in risky choice: An eye-tracking analysis. *Frontiers in Psychology*, *3*(OCT). https://doi.org/10.3389/fpsyg.2012.00335

Fiedler, S., & Glöckner, A. (2012). The dynamics of decision making in risky choice: An eye-tracking analysis. *Frontiers in Psychology*, *3*(OCT). https://doi.org/10.3389/fpsyg.2012.00335

Frankish, K. (2010). Dual-Process and Dual-System Theories of Reasoning. *Philosophy Compass*, *5*(10), 914–926. https://doi.org/10.1111/j.1747-9991.2010.00330.x

Freeman, J. B. (2018). Doing Psychological Science by Hand. *Current Directions in Psychological Science*, *27*(5), 315–323. https://doi.org/10.1177/0963721417746793

Freeman, J. B., & Ambady, N. (2009). Motions of the hand expose the partial and parallel activation of stereotypes: Research report. *Psychological Science*, *20*(10), 1183–1188. https://doi.org/10.1111/j.1467-9280.2009.02422.x

Freeman, J. B., & Ambady, N. (2010). MouseTracker: Software for studying real-time mental processing using a computer mouse-tracking method. *Behavior Research Methods*, *42*(1), 226–241. https://doi.org/10.3758/BRM.42.1.226

Freeman, J. B., & Dale, R. (2013). Assessing bimodality to detect the presence of a dual cognitive process. *Behavior Research Methods*, *45*(1), 83–97. https://doi.org/10.3758/s13428-012-0225-x

Goldberg, J. H., Wichansky, A. M., & Corporation, O. (2003). *Eye tracking in usability evaluation : A practitioner ' s guide*. *October*. In J. Hyönä, R. Radach, & H. Deubel (Eds.), The mind's eye. Cognitive and applied aspects of eye movement researcg (pp. 492–516). Amsterdam: Elsevier.

Guadagno, R. E., & Cialdini, R. B. (2005). Online Persuasion and Compliance: Social Influence on the Internet and Beyond. In *The Social Net: The Social Psychology of the Internet* (Issue APRIL 2009, pp. 91–113). https://doi.org/citeulike-article-id:1291763

Hartigan, J. A., & Hartigan, P. M. (1985). The dip test of unimodality. *The Annals of Statistics*, 13(1), 70–84

Häubl, G., & Trifts, V. (2000). Consumer decision making in online shopping environments: The effects of interactive decision aids. *Marketing Science*, *19*(1), 4–21. https://doi.org/10.1287/mksc.19.1.4.15178

Haynes, G. A. (n.d.). *Testing the Boundaries of the Choice Overload Phenomenon : The Effect of Number of Options and Time Pressure on Decision Difficulty and Satisfaction*. *26*(March 2009), 204–212. https://doi.org/10.1002/mar

Hehman, E., Stolier, R. M., & Freeman, J. B. (2015). Advanced mouse-tracking analytic techniques for enhancing psychological science. *Group Processes and Intergroup Relations*, *18*(3), 384–401. https://doi.org/10.1177/1368430214538325

Huang, Y. F., & Kuo, F. Y. (2012). How impulsivity affects consumer decision-making in e-commerce. *Electronic Commerce Research and Applications*, *11*(6), 582–590. https://doi.org/10.1016/j.elerap.2012.09.004

Jacob, R. J. K., & Karn, K. S. (2003). *Eye Tracking in Human – Computer Interaction and Usability Research : Ready to Deliver the Promises*. In J. Hyönä, R. Radach, & H. Deubel (Eds.), The mind's eye. Cognitive and applied aspects of eye movement researcg (pp. 573–605). Amsterdam: Elsevier.

Jacoby, L. L., Craik, F. I. M., & Begg, I. (1979). Effects of decision difficulty on recognition and recall. *Journal of Verbal Learning and Verbal Behavior*, *18*(5), 585–600. https://doi.org/10.1016/S0022-5371(79)90324-4

Jevremovi, A., Adamovi, S., & Veinovi, M. (2014). *Mousetracking Visitors to Evaluate Efficacy of Web Site Design*. *11*(2), 291–300. https://doi.org/10.2298/SJEE131223023J

Johnson, A., Mulder, B., Sijbinga, A., & Hulsebos, L. (2012). Action as a window to perception: Measuring attention with mouse movements. *Applied Cognitive Psychology*, *26*(5), 802–809. https://doi.org/10.1002/acp.2862

Kahneman, D., & Frederick, S. (2012). Representativeness Revisited: Attribute Substitution in Intuitive Judgment. In *Heuristics and Biases* (Issue January 2002). https://doi.org/10.1017/cbo9780511808098.004

Kahneman, D., & Tversky, A. (1982). The psychology of preferences. *Scientific American*, 246(1), 160–173. https://doi.org/10.1038/scientificamerican0182-160

Kang, Y., & Noh, Y. (2019). *Development of Hartigan ' s Dip Statistic with Bimodality Coefficient to Assess Multimodality of Distributions*. *2019*.

Khachatryan, H., & Rihn, A. L. (2014). Eye-Tracking Methodology and Applications in Consumer Research. *Electronic Data Information Source of UF/IFAS Extension*, 1–5.

Kieslich, P. J., & Henninger, F. (2017). Mousetrap: An integrated, open-source mouse-tracking package. *Behavior Research Methods*, *49*(5), 1652–1667. https://doi.org/10.3758/s13428-017-0900-z

Kieslich, P. J., Henninger, F., Wulff, D. U., Haslbeck, J. M. B., & Schulte-Mecklenbeck, M. (2019a). Mouse-tracking: A practical guide to implementation and analysis. *A Handbook of Process Tracing Methods.* , 111–130. https://github.com/pascalkieslich/mousetrap-os.

Kieslich, P. J., Henninger, F., Wulff, D., Haslbeck, J., & Schulte-Mecklenbeck, M. (2018). Mouse-tracking: A practical guide to implementation and analysis. In M. Schulte- Mecklenbeck, A. Kühberger, & J. G. Johnson (Eds*.), A Handbook of Process Tracing Methods.* New York. https://doi.org/10.31234/osf.io/zuvqa

Kieslich, P. J., Schoemann, M., Grage, T., Hepp, J., & Scherbaum, S. (2019b). Design factors in mouse-tracking: What makes a difference? *Behavior Research Methods*. https://doi.org/10.3758/s13428-019-01228-y

Kim, S. H., Dong, Z., Xian, H., Upatising, B., & Yi, J. S. (2012). Does an eye tracker tell the truth about visualizations?: Findings while investigating visualizations for decision making. *IEEE Transactions on Visualization and Computer Graphics*, *18*(12), 2421–2430. https://doi.org/10.1109/TVCG.2012.215

Kim, Y.A. and Srivastava, J. (2007) Impact of Social Influence in E-Commerce Decision Making. Proceedings of the 9th International Conference on *Electronic Commerce*, Minneapolis, 19-22 August 2007, 293-302. http://dx.doi.org/10.1145/1282100.1282157

Koop, G. J., & Johnson, J. G. (2011). Response dynamics: A new window on the decision process. *Judgment and Decision Making*, *6*(8), 750–758.

Koop, G. J., & Johnson, J. G. (2013). The response dynamics of preferential choice. *COGNITIVE PSYCHOLOGY*, *67*(4), 151–185. https://doi.org/10.1016/j.cogpsych.2013.09.001

Kühberger, A., & Schulte-Mecklenbeck, M. (2017). Theories of economic decision-making: Value, risk and affect. *Economic Psychology*, *June*, 19–34. https://doi.org/10.1002/9781118926352.ch2

Liberman, N., & Förster, J. (2006). Inferences from decision difficulty. *Journal of Experimental Social Psychology*, *42*(3), 290–301. https://doi.org/10.1016/j.jesp.2005.04.007

Longarta, P., Wickensb, E., & Bakirc, A. (2016). Consumer decision process in restaurant selection: An application of the stylized ekb model. *Market-Trziste*, *28*(2), 173–190. https://doi.org/10.22598/mt/2016.28.2.173

Lopez, R. B., Stillman, P. E., Heatherton, T. F., & Freeman, J. B. (2018). Minding One's Reach (To Eat): The Promise of Computer Mouse-Tracking to Study Self-Regulation of Eating. *Frontiers in Nutrition*, *5*(May), 1–6. https://doi.org/10.3389/fnut.2018.00043

Maldonado, M., Dunbar, E., & Chemla, E. (2019). Mouse tracking as a window into decision making. Behavior Research Methods, (2011). https://doi.org/10.3758/s13428-018- 01194-x

Markman, A. B., & Brendl, C. M. (2005). Constraining theories of embodied cognition. *Psychological Science*, *16*(1), 6–10. https://doi.org/10.1111/j.0956-7976.2005.00772.x

McKinstry, C., Dale, R., & Spivey, M. J. (2008). Action dynamics reveal parallel competition in decision making. *Psychological Science*, *19*(1), 22–24. https://doi.org/10.1111/j.1467-9280.2008.02041.x

Meeker, M., & Meeker, M. (n.d.). *Internet_Trends_2019_CH(1).pdf*.

Melnikoff, D. E., & Bargh, J. A. (2018). The Mythical Number Two. *Trends in Cognitive Sciences*, *22*(4), 280–293. https://doi.org/10.1016/j.tics.2018.02.001

Nagpal, A., & Krishnamurthy, P. (2008). Attribute conflict in consumer decision making: The role of task compatibility. *Journal of Consumer Research*, *34*(5), 696–705. https://doi.org/10.1086/521903

Neuhäuser, M. (2010). A nonparametric two-sample comparison for skewed data with unequal variances. *Journal of Clinical Epidemiology*, *63*(6), 691–693. https://doi.org/10.1016/j.jclinepi.2009.08.026

Oaksford, M., & Hall, S. (2016). On the Source of Human Irrationality. *Trends in Cognitive Sciences*, *20*(5), 336–344. https://doi.org/10.1016/j.tics.2016.03.002

Pascal J. Kieslich, Dirk U. Wulff, Felix Henninger, Jonas M. B. Haslbeck, Sarah Brockhaus (2020). *Package ' mousetrap .'*

Pieters, R., & Wedel, M. (2004). Attention Capture and Transfer in Advertising: Brand, Pictorial, and Text-Size Effects. *Journal of Marketing*, *68*(2), 36–50. https://doi.org/10.1509/jmkg.68.2.36.27794

R. W. Picard: *Affective Computing*, MIT Press, 1997

SAS Institute Inc. (1989). *User's guide*. Cary, NC: Statistical Analysis System Institute.

Sauer, H., & Sauer, H. (2018). Dual process theory. *Moral Thinking, Fast and Slow*, 5–19. https://doi.org/10.4324/9781315467498-2

Schmidt, J., & Bijmolt, T. H. A. (2020). Accurately measuring willingness to pay for consumer goods: a meta-analysis of the hypothetical bias. *Journal of the Academy of Marketing Science*, 48(3), 499–518. https://doi.org/10.1007/s11747-019-00666- 6

Schneider, I. K., van Harreveld, F., Rotteveel, M., Topolinski, S., van der Pligt, J., Schwarz, N., & Koole, S. L. (2015). The path of ambivalence: tracing the pull of opposing evaluations using mouse trajectories. *Frontiers in Psychology*, *6*(July), 1–12. https://doi.org/10.3389/fpsyg.2015.00996

Schoemann, M., Lüken, M., Grage, T., Kieslich, P. J., & Scherbaum, S. (2019). Validating mouse-tracking: How design factors influence action dynamics in intertemporal decision making. *Behavior Research Methods*. https://doi.org/10.3758/s13428-018-1179-4

Science, I. F., & Prabhala, K. (2019). *A Review of Phenomenal Raise of Advertisement Spending with Digital Marketing*. *July*.

Sherman, J. W., Gawronski, B., Gonsalkorale, K., Hugenberg, K., Allen, T. J., & Groom, C. J. (2008). The Self-Regulation of Automatic Associations and Behavioral Impulses. *Psychological Review*, *115*(2), 314–335. https://doi.org/10.1037/0033-295X.115.2.314

Spivey, M. J., & Dale, R. (2006). Continuous dynamics in real-time cognition. *Current Directions in Psychological Science*, *15*(5), 207–211. https://doi.org/10.1111/j.1467-8721.2006.00437.x

Spivey, M. J., Dale, R., Knoblich, G., & Grosjean, M. (2010). Do curved reaching movements emerge from competing perceptions? A reply to van der Wel et al. (2009). *Journal of Experimental Psychology: Human Perception and Performance*, 36(1), 251–254

Stillman, P. E., Medvedev, D., & Ferguson, M. J. (2017). Resisting Temptation: Tracking How Self-Control Conflicts Are Successfully Resolved in Real Time. *Psychological Science*, *28*(9), 1240–1258. https://doi.org/10.1177/0956797617705386

Stillman, P. E., Shen, X., & Ferguson, M. J. (2018). How Mouse-tracking Can Advance Social Cognitive Theory. *Trends in Cognitive Sciences*, *22*(6), 531–543. https://doi.org/10.1016/j.tics.2018.03.012

Szaszi, B., Palfi, B., Szollosi, A., Kieslich, P. J., & Aczel, B. (2019). Thinking dynamics and individual differences: Mouse-tracking analysis of the denominator neglect task. *Judgment and Decision Making*, *14*(2), 23–32.

Tuan-Pham, M., & Higgins, E. T. (2005) Promotion and prevention in consumer – the state of the art and theoretical propositions. In: S. Ratneshwar & D. G. Mick (eds.). *Inside Consumption – Consumer motives, goals and desires* (pp. 8-43), Abingdon, NY: Routledge.

Tversky, A., and Simonson, I. (1993). Context-dependent preferences. *Manage. Sci*. 39, 1179–1189.

Van Loo, E. J., Grebitus, C., Nayga, R. M., Verbeke, W., & Roosen, J. (2018). On the Measurement of Consumer Preferences and Food Choice Behavior: The Relation Between Visual Attention and Choices. *Applied Economic Perspectives and Policy*, *40*(4), 538–562. https://doi.org/10.1093/aepp/ppy022

Viswanathan, V., & Jain, V. (2013). A dual-system approach to understanding “generation Y” decision making. *Journal of Consumer Marketing*, *30*(6), 484–492. https://doi.org/10.1108/JCM-07-2013-0649

Xiao, K., & Yamauchi, T. (2017). The role of attention in subliminal semantic processing: A mouse tracking study. *PLoS ONE*, *12*(6), 1–17. https://doi.org/10.1371/journal.pone.0178740

Yu, Z., Wang, F., Wang, D., & Bastin, M. (2012). Beyond reaction times: Incorporating mouse-tracking measures into the implicit asociation test to examine its underlying proces. *Social Cognition*, *30*(3), 289–306. https://doi.org/10.1521/soco.2012.30.3.289

Zimmermann, P., Guttormsen, S., Danuser, B., & Gomez, P. (2003). Affective computing—a rationale for measuring mood with mouse and keyboard. *International Journal of Occupational Safety and Ergonomics*, *9*(4), 539–551. https://doi.org/10.1080/10803548.2003.11076589

Freeman, J. B., & Ambady, N. (2011). *A Dynamic Interactive Theory of Person Construal*. *118*(2), 247–279. https://doi.org/10.1037/a0022327

R-Script

```
library(mousetrack)
library(mousetrap)
library(ssMousetrack)
library(ggplot2)
library(readbulk)
library(dplyr)
library(foreign)

theme_set(theme_classic()+
      theme(
       axis.line = element_line(colour = "black"),
       axis.ticks = element_line(colour = "black"),
       axis.text = element_text(colour = "black"),
       panel.border = element_rect(colour = "black", fill=NA)
      ))
options(width=90)

mt_data_raw <- read_bulk(extension=".txt")
rawdata <- mt_import_wide(mt_data_raw)

rawdata$trajectories[,,2]<- rawdata$trajectories[,,2] - 1360/2
remapped<-mt_remap_symmetric(rawdata, use = "trajectories", save_as = "trajectories",
              dimensions = c("xpos", "ypos"), remap_xpos = "right",
              remap_ypos = "down")
remapped$trajectories[,,3]<- remapped$trajectories[,,3] + 600
remapped <- mt_align_start(remapped)
remapped <- mt_time_normalize(remapped)
remapped <- mt_measures(remapped)
remapped <- mt_derivatives(remapped)
```

```
mt_plot(remapped)

total<- merge(remapped[["data"]], remapped[["measures"]], by="mt_id")
total$rownumber <- 1:nrow(total)
total$usernumber <- ceiling(total$rownumber/7)
total$selecteditem <- total$options_left
total$selecteditem[total$selected== 1] <- total$options_right[total$selected== 1]
total$tracker.likert1<- total$tracker1.likert1
total$tracker.likert1[total$id=="tracker2"]<- total$tracker2.likert1[total$id=="tracker2"]
total$tracker.likert1[total$id=="tracker3"]<- total$tracker3.likert1[total$id=="tracker3"]
total$tracker.likert1[total$id=="tracker4"]<- total$tracker4.likert1[total$id=="tracker4"]
total$tracker.likert1[total$id=="tracker5"]<- total$tracker5.likert1[total$id=="tracker5"]
total$tracker.likert1[total$id=="tracker6"]<- total$tracker6.likert1[total$id=="tracker6"]
total$tracker.likert1[total$id=="tracker7"]<- total$tracker7.likert1[total$id=="tracker7"]
total$tracker.likert2<- total$tracker1.likert2
total$tracker.likert2[total$id=="tracker2"]<- total$tracker2.likert2[total$id=="tracker2"]
total$tracker.likert2[total$id=="tracker3"]<- total$tracker3.likert2[total$id=="tracker3"]
total$tracker.likert2[total$id=="tracker4"]<- total$tracker4.likert2[total$id=="tracker4"]
total$tracker.likert2[total$id=="tracker5"]<- total$tracker5.likert2[total$id=="tracker5"]
total$tracker.likert2[total$id=="tracker6"]<- total$tracker6.likert2[total$id=="tracker6"]
total$tracker.likert2[total$id=="tracker7"]<- total$tracker7.likert2[total$id=="tracker7"]
total$tracker.likert4<- total$tracker1.likert4
total$tracker.likert4[total$id=="tracker2"]<- total$tracker2.likert4[total$id=="tracker2"]
total$tracker.likert4[total$id=="tracker3"]<- total$tracker3.likert4[total$id=="tracker3"]
total$tracker.likert4[total$id=="tracker4"]<- total$tracker4.likert4[total$id=="tracker4"]
total$tracker.likert4[total$id=="tracker5"]<- total$tracker5.likert4[total$id=="tracker5"]
total$tracker.likert4[total$id=="tracker6"]<- total$tracker6.likert4[total$id=="tracker6"]
total$tracker.likert4[total$id=="tracker7"]<- total$tracker7.likert4[total$id=="tracker7"]
total$tracker.likert5<- total$tracker1.likert5
total$tracker.likert5[total$id=="tracker2"]<- total$tracker2.likert5[total$id=="tracker2"]
```

```
total$tracker.likert5[total$id=="tracker3"]<- total$tracker3.likert5[total$id=="tracker3"]

total$tracker.likert5[total$id=="tracker4"]<- total$tracker4.likert5[total$id=="tracker4"]

total$tracker.likert5[total$id=="tracker5"]<- total$tracker5.likert5[total$id=="tracker5"]

total$tracker.likert5[total$id=="tracker6"]<- total$tracker6.likert5[total$id=="tracker6"]

total$tracker.likert5[total$id=="tracker7"]<- total$tracker7.likert5[total$id=="tracker7"]

total$tracker.WTP<- total$tracker1.input1

total$tracker.WTP[total$id=="tracker2"]<- total$tracker2.input1[total$id=="tracker2"]

total$tracker.WTP[total$id=="tracker3"]<- total$tracker3.input1[total$id=="tracker3"]

total$tracker.WTP[total$id=="tracker4"]<- total$tracker4.input1[total$id=="tracker4"]

total$tracker.WTP[total$id=="tracker5"]<- total$tracker5.input1[total$id=="tracker5"]

total$tracker.WTP[total$id=="tracker6"]<- total$input8[total$id=="tracker6"]

total$tracker.WTP[total$id=="tracker7"]<- total$input9[total$id=="tracker7"]

total$dropitem<-0

total$dropitem[total$item.consideration==total$selecteditem] <- 1


total <- total[,!grepl("quantity$",names(total))]

total <- total[,!grepl("*tracker1",names(total))]

total <- total[,!grepl("^tracker2",names(total))]

total <- total[,!grepl("^tracker3",names(total))]

total <- total[,!grepl("^tracker4",names(total))]

total <- total[,!grepl("^tracker5",names(total))]

total <- total[,!grepl("^tracker6",names(total))]

total <- total[,!grepl("^tracker7",names(total))]

total <- total[,!grepl("^input8",names(total))]

total <- total[,!grepl("^input9",names(total))]


#Scale developement


write.csv2(total,"total.csv", row.names = FALSE)

#### add trajectories

#mt_data_raw$rownumber <- 1:nrow(total)
```

```
#total<- merge(total, mt_data_raw, by="rownumber")
#write.csv2(total,"all.csv", row.names = FALSE)
#rm(total)

#Devide Data in easy and difficult decisions
remapped$data$condition <- "condition"
remapped$data$condition[total$tracker.likert4 >= 5] <- "easy"
remapped$data$condition[total$tracker.likert4 <= 2] <- "difficult"
remapped2 <- mt_subset(remapped, condition == "easy" | condition == "difficult")

remapped_easy <- mt_subset(remapped, condition == "easy")
remapped_diff <- mt_subset(remapped, condition == "difficult")

#Filter the mousetrap objects for outlier identified in SPSS
remapped_easy<-mt_subset(remapped_easy, RT<21090, check="measures")
remapped_easy<-mt_subset(remapped_easy, AUC<186621, check="measures")
remapped_easy<-mt_subset(remapped_easy, xpos_flips<17, check="measures")
remapped_easy<-mt_subset(remapped_easy, initiation_time<4510, check="measures")
remapped_easy<-mt_subset(remapped_easy, MAD<854.019, check="measures")
remapped_easy<-mt_subset(remapped_easy, MAD_time<7200, check="measures")
remapped_easy<-mt_subset(remapped_easy, AD<475.114, check="measures")

remapped_diff<-mt_subset(remapped_diff, RT<21090, check="measures")
remapped_diff<-mt_subset(remapped_diff, AUC<186621, check="measures")
remapped_diff<-mt_subset(remapped_diff, xpos_flips<17, check="measures")
remapped_diff<-mt_subset(remapped_diff, initiation_time<4510, check="measures")
remapped_diff<-mt_subset(remapped_diff, MAD<854.019, check="measures")
remapped_diff<-mt_subset(remapped_diff, MAD_time<7200, check="measures")
remapped_diff<-mt_subset(remapped_diff, AD<475.114, check="measures")

remapped2<-mt_subset(remapped2, RT<21090, check="measures")
```

```
remapped2<-mt_subset(remapped2, AUC<186621, check="measures")

remapped2<-mt_subset(remapped2, xpos_flips<17, check="measures")

remapped2<-mt_subset(remapped2, initiation_time<4510, check="measures")

remapped2<-mt_subset(remapped2, MAD<854.019, check="measures")

remapped2<-mt_subset(remapped2, MAD_time<7200, check="measures")

remapped2<-mt_subset(remapped2, AD<475.114, check="measures")


#Calculate sample entropy for easy and difficult decisions

remapped_easy_sampleentropy<-mt_sample_entropy(remapped_easy, use = "tn_trajectories",
save_as = "measures", dimension = "xpos", m = 3, r = NULL, verbose = FALSE)

remapped_diff_sampleentropy<-mt_sample_entropy(remapped_diff, use = "tn_trajectories",
save_as = "measures", dimension = "xpos", m = 3, r = NULL, verbose = FALSE)


mean(remapped_easy_sampleentropy$measures$sample_entropy)

mean(remapped_diff_sampleentropy$measures$sample_entropy)


#Mean of measures

mean(remapped_easy$measure$RT)

mean(remapped_diff$measures$RT)


#Boxplot for measures

boxplot(remapped_easy$measures$MAD_time, main="MAD_time for condition easy ",
ylab="MAD_time", xlab="MAD_time for Condition easy")


boxplot(remapped_diff$measures$MAD_time, main="MAD_time for condition diff ",
ylab="MAD_time", xlab="MAD_time for condition diff")


boxplot.stats(remapped_diff$measures$xpos_reversals)


boxplot.stats(remapped_diff$measures$xpos_reversals)


#Histogram and Density plot for measures
```

```
hist(remapped_easy$measures$RT , main="Histogram of RT for condition easy ", xlab="RT")

hist(remapped_diff$measures$RT , main="Histogram of RT for condition difficult ", xlab="RT")

#density plot by condition for all measures
density_measures_easy <- density(remapped_easy$measures$MAD_time)
plot (density_measures_easy, main="Density Plot of MAD_time in condition easy ")

density_measures_diff <- density(remapped_diff$measures$MAD_time)
plot (density_measures_diff, main="Density Plot of MAD_time in condition diff ")

#qqplot by condition for all measures
qqnorm(remapped_easy$measures$RT, xlab="qq-plot RT condition easy")
qqline(remapped_easy$measures$RT, col="red")
qqnorm(remapped_diff$measures$RT, xlab="qq-plot RT condition difficult")
qqline(remapped_diff$measures$RT, col="red")

#check bimodlaity (bc,dip-test) for all measures by condition
mt_check_bimodality(remapped_easy,use = "measures",methods = c("BC", "HDS"),B = 2000)
mt_check_bimodality(remapped_diff,use = "measures",methods = c("BC", "HDS"),B = 2000)

#shapiro wilk test for normal distribution
shapiro.test(remapped_easy$measures$RT)
shapiro.test(remapped_diff$measures$RT)

#kolgomorov test for normal distribution
ks.test(remapped_easy$measures$MAD_time,remapped_diff$measures$MAD, c="two.sided")

#welch t-test for the means
```

```
describe(remapped_easy$measures$RT)

describe(remapped_diff$measures$RT)

agg_welch <- mt_aggregate_per_subject(remapped2,use_variables="RT",
use2_variables="condition",subject_id="mt_id")

t.test(RT~condition, data=agg_welch, paired=FALSE)



#wilcox test for means if distribution is not normal

agg_wilcox <- mt_aggregate_per_subject(remapped2,use_variables="RT",
use2_variables="condition",subject_id="mt_id")

wilcox.test(RT~condition, data=agg_wilcox, paired=FALSE)



#median test by measure (same as wilcoxon test?)

agg_median <- mt_aggregate_per_subject(remapped2,use_variables="MAD",
use2_variables="condition",subject_id="mt_id")

mood.medtest(MAD~condition, data=agg_median, paired=FALSE)



#aggregated trajectories by condition

mt_plot_aggregate(remapped2, use="tn_trajectories", x="xpos", y="ypos", color="condition")


#aggregated trajectories by condition, time analysis by steps

mt_plot_aggregate(remapped2, use="tn_trajectories", x="xpos", y="steps", color="condition",
subject_id="mt_id", points=TRUE) + scale_color_manual(values=c("darkorange","steelblue"))
```

Java – Script for Experiment

```
var jsonfile = {
  "mandatory": {
   "TrialID": '002',
  },
 "blocks": [
  {
   "options": {
     "random": false,
   },
   "pages": [
    {
     "items": [
      {
       "type": "infotext",
       "id": "infotext1",
       "text": "<b>Hallo! Vielen Dank für Deine Teilnahme. Damit Du dich auf unser Experiment einstellen kannst, benötigen wir einen Testlauf. Im Folgenden wird Dir immer ein Produktpaar gezeigt. Wähle mit der Maus bitte das Produkt aus, welches Dir besser gefällt!</b>"
      },
      {
       "type": "next",
       "id": "next1",
       "text": "weiter"
      }
     ]
    },
    {
     "items": [
      {
       "type": "tracker",
       "type_tracker": "image",
       "id": "tracker1",
       "title": "Bitte wähle das Produkt aus, welches Du bevorzugt kaufen würdest!",
       "desc": "Bildertracker",
       "random": true,
       "items": [
        {
         "name": "13-A",
```

"content": "./lib/bilder_experiment/13-A.jpg",
},
{
"name": "13-B",
"content": "./lib/bilder_experiment/13-B.jpg"
}
]
},
{
"type": "likert",
"id": "tracker1-likert1",
"ref": "tracker",
"question": "Magst Du das Produkt?",
"caption_left": "gar nicht",
"caption_right": "sehr gern",
"number_selectors": "7"
}
]
},
{
"items": [
{
"type": "tracker",
"type_tracker": "image",
"id": "tracker2",
"title": "Bitte wähle das Produkt aus, welches Du bevorzugt kaufen würdest!",
"desc": "Bildtracker",
"random": true,
"items": [
{
"name": "0-A",
"content": "./lib/bilder_experiment/0-A.jpg",
},
{
"name": "0-B",
"content": "./lib/bilder_experiment/0-B.jpg"
}
]

```
          },
          {
            "type": "likert",
            "id": "tracker2-likert1",
            "ref": "tracker",
            "question": "Magst Du das Produkt?",
            "caption_left": "gar nicht",
            "caption_right": "sehr gern",
            "number_selectors": "7"
          }
        ]
      },
                              {
        "items": [
                                              {
            "type": "infotext",
            "id": "infotext2",
            "text": "<a href=file:///C:/Users/Heimrich/Desktop/MousetrackerV0.15/index.html><b> <br> </br> Vielen Dank! Klicke hier, um zum Experiment zu gelangen.</b></a>"
          }
                                ]
      }
    ],
  }
 ]
};

var jsonfile = {
   "mandatory": {
    "TrialID": '001',
    "FilenamePrefix": 'dynamic'
   },
  "blocks": [
   {
    "options": {
       "random": false,
    },
    "pages": [
     {
```

```
"items": [
 {
  "type": "infotext",
  "id": "infotext1",
  "text": "<b>Vielen Dank, dass Du dir Zeit für unser Experiment nimmst. Du bekommst im Folgenden immer ein Produktpaar gezeigt aus dem Du das Produkt auswählen sollst, welches Du besser findest. <br>Bitte beachte, dass Deine Eingabe nach einmaligem Anklicken nicht mehr abgeändert werden kann.</br> (Beantworte danach bitte die angezeigten Fragen zu Deiner Auswahl).</b>"
 },
 {
  "type": "next",
  "id": "next1",
  "text": "weiter"
 }
]
},
{
"items": [
 {
  "type": "infotext",
  "id": "infotext2",
  "text": "<b>Bevor die Umfrage startet, beantworte uns bitte noch ein paar Fragen. Selbstverständlich sind alle Angaben anonym und werden ausschließlich im wissenschaftlichen Kontext ausgewertet.</b>"
 },
 {
  "type": "textinput",
  "id": "input1",
  "text": "<b>Wie alt bist Du?</b>"
 },
 {
  "type": "likert",
  "id": "likert1",
  "question": "<b>Geschlecht</b>",
  "caption_left": "weiblich",
  "caption_right": "männlich",
  "number_selectors": "2"
 },
 {
  "type": "textinput",
  "id": "input2",
  "text": "<b>Wie viel Geld hast Du monatlich zur Verfügung? (in Euro)</b> (inkl. Miete und Fixkosten)"
```

```
},
{
"type": "likert",
"id": "likert2",
"question": "<b>Wie oft nutzt Du eine Computermaus?</b>",
"caption_left": "nie",
"caption_right": "immer",
"number_selectors": "7"
},
{
"type": "likert",
"id": "likert3",
"question": "<b>Wie oft kaufst Du online ein?</b>",
"caption_left": "sehr selten",
"caption_right": "sehr oft",
"number_selectors": "7"
},
{
"type": "next",
"id": "next2",
"text": "weiter"
}
]
},
{
"items": [
{
"type": "infotext",
"id": "infotext3",
"text": "<b>Wähle bitte auf dieser Seite Deine aktuelle Stimmungslage.</b> "
},
{
"type": "likert",
"id": "likert4",
"question": "<b>Wie fühlst Du dich gerade?</b> <br> </br>",
"caption_left": "    traurig    ",
"caption_right": "    fröhlich    ",
"number_selectors": "7"
```

```
},
{
"type": "likert",
"id": "likert5",
"question": "",
"caption_left": "  schlecht    ",
"caption_right": "   gut            ",
"number_selectors": "7"
},
{
"type": "likert",
"id": "likert6",
"question": "",
"caption_left": "    negativ    ",
"caption_right": "    positiv      ",
"number_selectors": "7"
},
{
"type": "likert",
"id": "likert7",
"question": "",
"caption_left": "  unwohl    ",
"caption_right": "    wohl      ",
"number_selectors": "7"
},
{
"type": "next",
"id": "next3",
"text": "weiter"
}
]
},
{
"items": [
{
"type": "infotext",
"id": "infotext4",
"text": "<b>Die folgenden Aussagen können mehr oder weniger auf Dich zutreffen. <br>Bitte gib bei jeder Aussage an,</br> inwieweit diese im Allgemeinen auf Dich persönlich zutrifft</b>."
```

```
},
{
"type": "likert",
"id": "likert8",
"question": "<b>Es genügt mir einfach die Antwort zu kennen, <br> ohne die Gründe für die Antwort eines Problems zu verstehen</b>. <br> </br>  ",
"caption_left": "trifft überhaupt nicht zu",
"caption_right": "trifft voll und ganz zu",
"number_selectors": "7"
},
{
"type": "likert",
"id": "likert9",
"question": "<b>Ich habe es gern, wenn mein Leben voller kniffliger Aufgaben ist,<br>die ich lösen muss</b>. <br> </br>",
"caption_left": "trifft überhaupt nicht zu",
"caption_right": "trifft voll und ganz zu",
"number_selectors": "7"
},
{
"type": "likert",
"id": "likert10",
"question": "<b>Ich würde komplizierte Probleme einfachen Problemen vorziehen</b>. <br> </br>",
"caption_left": "trifft überhaupt nicht zu",
"caption_right": "trifft voll und ganz zu",
"number_selectors": "7"
},
{
"type": "likert",
"id": "likert11",
"question": "<b>In erster Linie denke ich, weil ich muss</b>. <br> </br>",
"caption_left": "trifft überhaupt nicht zu",
"caption_right": "trifft voll und ganz zu",
"number_selectors": "7"
},
{
"type": "next",
"id": "next4",
"text": "weiter"
}
```

```
      ]
    }
  ],
},
{
  "options": {
    "random": true,
  },
  "pages": [
    {
      "items": [
        {
          "type": "tracker",
          "type_tracker": "image",
          "id": "tracker1",
          "title": "Bitte wähle das Produkt aus, welches Du bevorzugt kaufen würdest!",
          "desc": "Bildertracker",
          "random": true,
          "items": [
            {
              "name": "1-A",
              "content": "./lib/bilder_experiment/1-A.jpg",
            },
            {
              "name": "1-B",
              "content": "./lib/bilder_experiment/1-B.jpg"
            }
          ]
        },
                                        {
          "type": "likert",
          "id": "tracker1-likert1",
          "ref": "tracker1",
          "question": "<b>Ich fühle ein persönliches Besitzempfinden für dieses Produkt.</b>",
          "caption_left": "trifft überhaupt nicht zu",
          "caption_right": "trifft voll und ganz zu",
          "number_selectors": "7"
        },
```

```
      {
    "type": "likert",
    "id": "tracker1-likert2",
    "ref": "tracker1",
    "question": "<b>Es fühlt sich so an, als ob das Produkt jetzt mir gehört.</b>",
    "caption_left": "trifft überhaupt nicht zu",
    "caption_right": "trifft voll und ganz zu",
    "number_selectors": "7"
   },
      {
    "type": "textinput",
       "ref": "tracker1",
    "id": "tracker1-input1",
    "text": "<b>Wie viel wärst Du bereit für dieses Produkt zu bezahlen? (in Euro)</b>"
   },
   {
    "type": "likert",
    "id": "tracker1-likert4",
    "ref": "tracker1",
    "question": "<b>Wie schwer war die Entscheidung für Dich?</b>",
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Affidavit

I hereby declare that this Diploma thesis has been written only by the undersigned and without any assistance from third parties. I confirm that no sources have been used in the preparation of this thesis other than those indicated in the thesis itself.

This Diploma thesis has heretofore not been submitted or published elsewhere, neither in its present form, nor in a similar version.

Innsbruck, 13.10.2020,

Place, Date, Signature