Understanding the Mobile Consumer along the Customer Journey: A Behavioural Data Analysis based on Smartphone Sensing Technology

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Abstract

Digitalisation is shaping a new consumption era characterised by high connectivity, mobility and a broad range of easily accessible information on products, prices and alternatives. As a result, it becomes more difficult than ever to understand modern consumers along their complex and dynamic path to purchase. However, mobile data about consumers' behaviour captured on their phone has high potential for facing this challenge. Yet, there is no solution on how to use this data to follow the consumers on their mobile devices. This thesis proposes a first approach on how mobile data collected with smartphone sensing technology can be analysed to assess mobile consumer behaviour along their customer journey. Based on current practices in customer journey analytics, a mobile customer journey model is developed and three analysis concepts are created, which are implemented in an explorative analysis. The results show that mobile sensing data presents a great opportunity for analysing mobile behaviour in three main research areas: examining the touchpoint performance of a brand across mobile apps, describing different target groups by their smartphone usage behaviour and deriving real customer journeys on users' devices. Nonetheless, further exploration is necessary to unlock the full potential of mobile data in customer journey analytics.

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1 Introduction

The advancing digitalisation and its development of new technologies, platforms, digital services and devices is creating constant social, cultural, economic as well as political changes. Thus, the digital age has an immense impact on people's everyday life, especially on their way of consumption.[1] As a result, a new modern consumption era evolves. The modern consumers are broadly connected via social media and more mobile than ever with their smart devices. This empowers consumers to make sophisticated buying decisions based on a comprehensive amount of easily accessible online information, while having a broad range of options to choose from. Moreover, they compare prices, ask for opinions online and are willing to choose alternative products or services if they fit better in their lifestyle and meet their needs. Therefore, consumers are becoming more conscious and flexible in what they are purchasing.[2]

Meanwhile, this behaviour has become visible across all generations as the pandemic has forced people to quickly adapt to new digital and mobile ways of consumption.[3] In total, approximately 88.8% of the German population owned at least one smartphone in 2021.[4] Even among adults over 70, smartphone penetration was almost 70% one year ago.[5] Companies have recognised the importance of these changes and are focusing on their digital activities, particularly through mobile channels as the broad range of consumers can be reached here. The success of these actions can already be seen in the almost threefold increase in mobile advertising revenue that was generated from 2015-2021. Furthermore, the advertising revenue in mobile exceeded those of desktop advertisement for the first time in 2021.[6] This in turn emphasises the growing importance of the mobile world.

It can be seen that priorities, needs and wants are shifting fast in the mobile world. In order to serve these, it is crucial for a company to follow consumers along their customer journey and understand their behaviour.[7] Since the modern consumers are constantly online through their smartphones, they produce a notable amount of data about their

[1] Schweidel, Bart, Inman, Stephen, Libai, Andrews, Rosario, Chae, Chen, Kupor, Longoni and Thomaz (2022), p. 2; Peteva (2020), p. 32
[2] Peteva (2020), pp. 33-35
[3] Angus and Westbrook (2022), pp. 15-17
[4] Statista (2022a) as cited in VuMa (2021)
[5] Statista (2022b) as cited in VuMa (2021)
[6] PwC, Omdia, IAB UK and Interactive Advertising Bureau Europe (2021), pp. 109-110
[7] Angus and Westbrook (2022), p. 55

mobile and online behaviour such as movement, social media activities, online purchases or google searches. This behavioural data is immensely valuable for companies because it allows them to get a deep understanding about the mobile consumption behaviour of their customers.[8] Despite its potential for decoding the mobile path to purchase, it presents a number of challenges in collecting, processing, analysing and interpreting such data. The high degree of flexibility, interaction, information-seeking, and number of channels used during the shopping process makes the buying behaviour highly dynamic and complex. As a result, it becomes more difficult to follow the consumer on their customer journey. Consequently, new data collection approaches, analysis strategies and frameworks must be developed to gather the needed insights about the customers in this fast-changing environment efficiently.[9]

Therefore, this thesis investigates the extent to which mobile data collected with sensing technologies is useful to describe mobile consumer behaviour. The goal is to propose a first approach on how mobile data can be analysed to understand mobile consumers along their customer journey. For this purpose, an explorative analysis is conducted based on the following research question: What analyses can be performed using data generated with smartphone sensing technology to understand mobile consumer behaviour along the customer journey? The procedure is as follows: First, the current models, practices and challenges in customer journey analytics are reviewed. Thereafter, mobile sensing is introduced by a brief outline of the general approach, followed by the detailed description of the sensing technology used in this thesis. Chapter 4 presents a model for illustrating the mobile customer journey. On this basis, an analysis concept is developed, which is implemented in chapter 5. Subsequently, the limitations are listed and discussed. After a short summary of the key findings, the results are evaluated with respect to the research goal in the concluding section.

[8] Peteva (2020), p. 34
[9] Angus and Westbrook (2022), p. 55; Li, Abbasi, Cheema and Abraham (2020), p. 127; Peteva (2020) p. 36

2 State of Research in Customer Journey Analytics

This first chapter summarises how consumers are currently analysed along their path to purchase. For this, latest theoretical customer journey models for describing the modern consumer behaviour are reviewed. Subsequently, nowadays practices in customer journey analytics are outlined. Lastly, current challenges companies and researchers are facing within the research discipline are addressed.

2.1 Modern Customer Journey Models

Since consumption has become rapidly dynamic and complex, traditional customer journey models cannot be used anymore to explain today's consumer behaviour. Consequently, established models had to be modified to fit to the new sophisticated consuming era.[10] Over the last years, models have been adapted, frameworks have been developed as well as new models have been created by market research, consultancies, and academia. However, there is a consistent understanding of the customer journey concept. The customer journey describes the ongoing process before, during and after a purchase. It includes contact points, so called touchpoints, on which the customer interacts with a brand or a company active or passively.[11] For instance, seeing an advertisement for a new product on Instagram, searching for this product online and asking a question about it to the customer services are all seen as touchpoints of this customers' journey. Besides the used term of customer journey, it is also referred to as the consumer decision journey, the path to purchase or the user journey. Latter is most common among user experience experts.[12]

Even though there is consent in defining the customer journey, the developed models for describing the proceeding of modern customer journey vary in many aspects. Nonetheless, the most notable change that can be seen across almost all current models compared to traditional models is the circular form. The decision process during a journey is no longer considered as linear and static, since customers are dynamically changing their

[10] Peteva (2020), p. 32; Edelmann and Singer (2015), p. 90
[11] Nenninger and Seidel (2021), pp. 69-70; Keller (2019), p. 37
[12] e.g., Schweidel et al. (2022), p. 3; Pumpurs (2022), pp. 205-218; Li et al. (2020), p. 127; Bremer, Chow, Funk, Thorndike and Ritterband (2020), pp. 2; Micheaux and Bosio (2019), p. 131; McKinsey (2017); Lemon and Verhoef (2016), p. 77; Edelmann and Singer (2015), p. 90

opinions and preferences by considering previous experiences and using a vast amount of available information on prices, products and alternatives.[13]

Moreover, consumers walk through three main stages in their journey in most models. The prepurchase stage includes all touchpoints before a purchase. The next stage is defined as the purchase stage, which covers all interactions between a consumer and a company and its products or services during the initial buying process. The third recognisable stage, the so-called postpurchase stage encompasses all touchpoints and interactions with a company after the buying process is completed and the consumption is starting.[14]

One of the most mentioned and first circular frameworks for describing consumer behaviour along their customer journey was invented by McKinsey in 2009 and further developed in 2015.[15] The model shows the dynamic in which buying decisions nowadays are made. For instance, McKinsey proposes different starting points for customer journeys based on the customers experience and previous purchases. This circumstance, in combination with the circular flow of a customer journey makes it hardly possible to differentiate the prepurchase stage from the postpurchase stage.[16] Whereas some other models show a clearer delimitation between the main stages, all are admitting overlaps due to the dynamic and unpredictable behaviour of the modern consumers.[17] Because of this, current customer journey models from marketing and consultancies remain on a superficial level to capture all aspects of the modern customers and their journeys.[18]

Latest academic research shows more detailed models by focusing on certain external factors influencing the customer journey or by limiting the research to a specific product type, service or industry. For example, Schweidel et al. are proposing a new customer journey model by emphasising the part digital signals of consumers play throughout their journey for explaining their buying behaviour. The authors then suggest how

[13] Vollrath and Villegas (2021), p. 108; McKinsey (2017)
[14] Lemon and Verhoef (2016), p. 76
[15] See Figure 34 in the appendix.
[16] McKinsey (2017); Edelmann and Singer (2015), pp. 90-91
[17] e.g., Schweidel et al. (2022), pp. 3-4; Stocchi, Pourazad, Michaelidou, Tanusondjaja and Harrigan (2022), p. 206; Micheaux and Bosio (2019), p. 131; Lemon and Verhoef (2016), p. 77; Wizdo (2016); Edelmann and Singer (2015), p. 90; Court, Elzinga, Mulder and Vetvik (2009)
[18] e.g., Wizdo (2016); Edelmann and Singer (2015), pp. 90-91

companies can use these signals for acting on their customers' journeys.[19] Another research conducted by Stocchi et al. examines how mobile apps are influencing customer experience along the customer journey which again stresses the importance of the consumer mobilisation.[20]

In view of the fact that there is no existing model that takes into account the customer journey on mobile devices, this thesis bases its explorative analysis concept on a currently existing model. For this purpose, the customer journey model developed by Lemon and Verhoef in 2016 and adapted by Micheaux and Bosio in 2019 is chosen.[21] Both models can be seen in Figure 1.

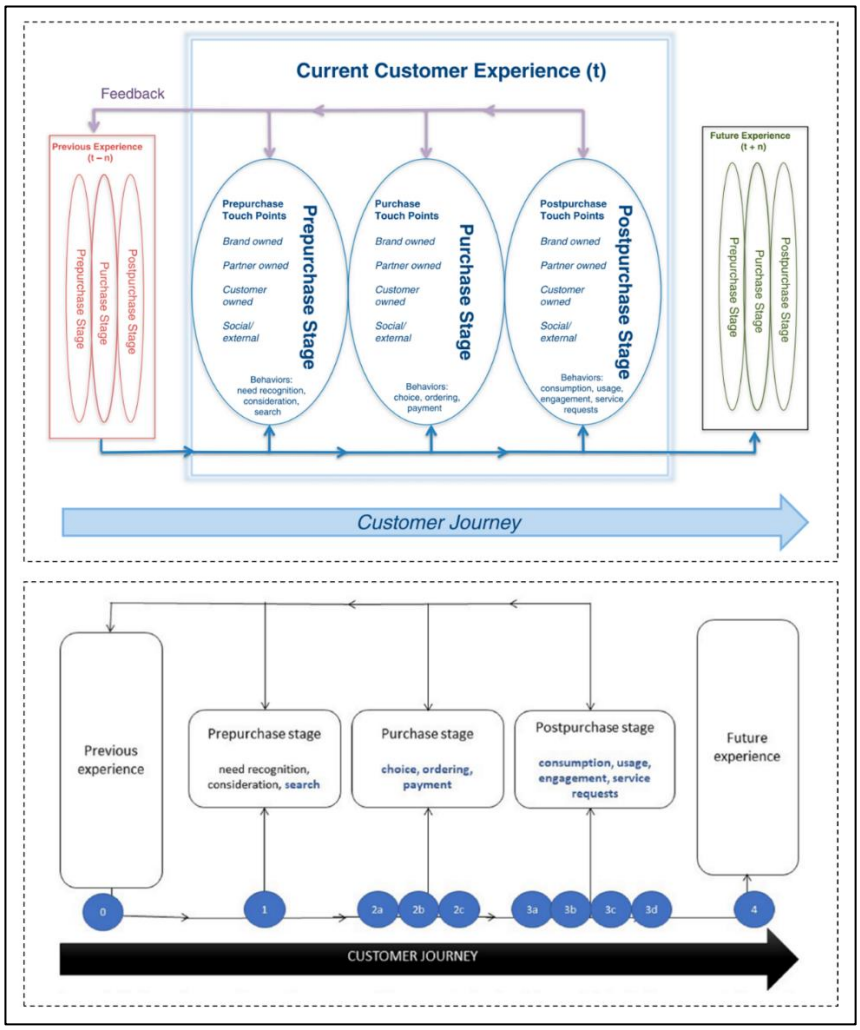

Figure 1: The Customer Journey Model by Lemon and Verhoef (above) and the adapted Customer Journey Model by Micheaux and Bosio (below)[22] (Verhoef and Lemon, 2016, p. 77; Micheaux and Bosio, 2019, p. 131)

[19] Schweidel et al. (2022), pp. 1-20
[20] Stocchi et al. (2022), pp. 195-225
[21] Lemon and Verhoef (2016), p. 77; Micheaux and Bosio (2019), p. 131
[22] The numbers in the model represent potential touchpoints in each stage of the customer journey.

Aligned to the previously described customer journey models, both frameworks are showing a circular progression throughout the prepurchase, purchase and postpurchase stage. Moreover, the complexity and dynamic are emphasized with arrows connecting all stages in a circular way. The main difference compared to more simplistic frameworks is that concrete touchpoints between a customer and a company are illustrated in each stage. Additionally, Lemon and Verhoef included previous and future experiences to highlight the potential influence of these touchpoints on the journey.[23] Because of the more detailed description of each stage, this model offers indications for integrating touchpoints captured on the smartphone in the modern customer journey as well as giving first ideas on how to describe customer behaviour. Therefore, it is suitable for developing an analysis concept. Nevertheless, it should be noted, that both frameworks are only serving as a rough orientation for the customer journey on the smartphone as it has not been applied to mobile data yet. Thus, the next chapter is focusing on how customer journey analytics is done in practice nowadays to get further implications for conceptualising the data analysis performed in this thesis.

2.2 Customer Journey Analytics in Practice

Firstly, it is described how market research, consultancies and marketing are translating the developed models into actionable insights by using customer journey mapping. As a second point, it is outlined what research is conducted in order to create such maps. Subsequently, currently used research methods are illustrated.

2.2.1 Customer Journey Mapping

The customer journey model functions as base for comprehending the customer behaviour.[24] In order to reduce the complexity of the journey while still getting a deep understanding of the consumer, literature as well as market research, consultancies and marketing are resorting to customer journey mapping. This tool provides a map, which documents the customer perspective in every stage of the customer journey. Furthermore, the tool connects relevant marketing channels with the experience, emotions, needs and wants of a customer at each touchpoint.[25] Ultimately, the moments that lead to a

[23] Lemon and Verhoef (2016), p. 77; Micheaux and Bosio (2019), p. 131
[24] For reference see chapter 2.1
[25] Vollrath and Villegas (2021), p. 3; Ott (2019), p. 90; Tiffert (2019), p. 23

purchase, so-called moments of truth are identifiable and strategies on how to address and influence the customer journey at these points are developed.[26]

Today, a broad range of maps and mapping tools for displaying customer journeys are used by market research, academia and marketing practitioners among various use cases.[27] Upon reviewing existing models, it becomes obvious that the structure of these maps differs based on the customer journey model that is used. In some mapping approaches, a linear structure remains predominant. As an example, Nenninger and Seidel describe all stages before and after the purchase in a linear manner, while they are identifying and combining all relevant touchpoints in each stage with the customer experience measured at each touchpoint.[28]

Market research institutes and consultancies are using more flexible frameworks based on models such as the customer journey model by Lemon and Verhoef.[29] For example, the Nielsen Group developed a framework which is structured in three parts, so-called zones, in which firstly the purchase scenario, goals and expectations from the customer perspective are defined. Hereafter, all phases along the customer journey as well as actions, thoughts and emotions are described. In contrast to the previous map, this framework leaves the number of stages open. In the last zone, opportunities as the moments of truth are identified and recommendations are derived.[30] Figure 2 shows the basic framework, which is accessible as an open source.

[26] Plottek and Herold (2018), p. 160
[27] e.g., Sagina (2022); Ludwiczak (2021), pp. 22-35; Tueanrat, Papagiannidis and Alamanos (2021), p. 336; Mele, Russo-Spena, Tregua, and Amitrano (2021), pp. 420-433; Sünkel and Weber (2019), p. 144
[28] Nenninger and Seidel (2021), p. 75; An exemplary customer journey map from the authors is shown in Figure 34 in the appendix.
[29] e.g., Nielsen Group (2022); Haije (2021); Nenninger and Seidel (2021), p. 75; Tiffert (2019), p. 23; Middelberg (2019), p. 202; Kaplan (2016)
[30] Nielsen Group (2022)

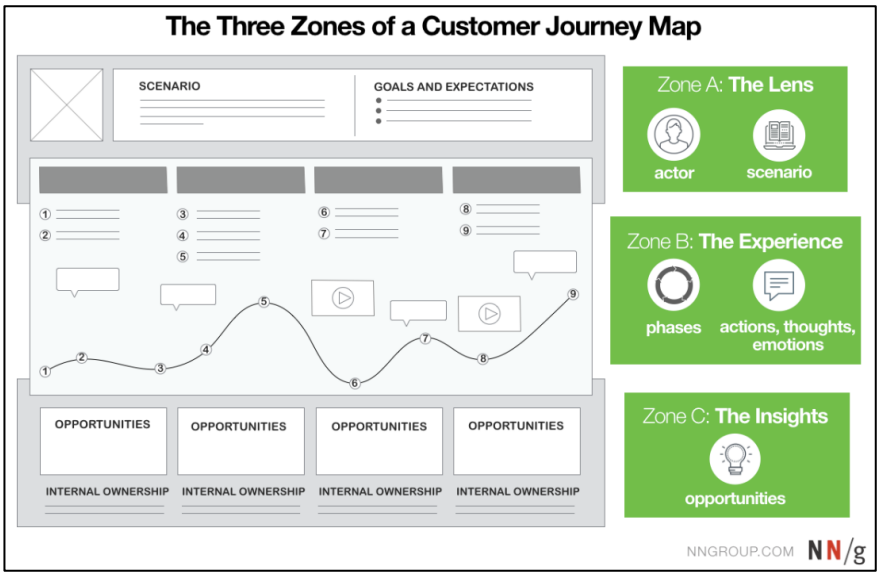

Figure 2: Exemplary Customer Journey template from Nielsen Group (Kaplan, 2016)

Moreover, maps appear different depending on the level of customer focus. Most customer journey maps are defining a persona, which represents a typical customer of a companies' target group. With this, typical customer journeys can be identified, which in turn allows a company to optimise their actions for their specific target groups.[31] This persona focus is also visible in the mapping of Nenninger and Seidel, in which two different customer journeys are displayed by connecting identified touchpoints across the stages.[32] Nielsen also provides an additional mapping template with a Persona focus.[33]

In order to get the relevant information to create and fill these customer journey maps, customer insights are needed.[34] For this, over time three main research areas have evolved in customer journey analytics, which are briefly described in the next chapter.[35]

2.2.2 Research Areas

Since the modern consumer shows complex buying behaviour, a broad range of research questions are coming up when studying the consumer along their decision journey. From these research questions three main research areas have been derived in customer journey analytics.[36] Figure 3 provides an overview of the three areas and first implications of what kind of research is being conducted in each.

[31] Nenninger and Seidel (2021), p. 69; Tiffert (2019), p. 22
[32] For reference see Figure 35 in the appendix.
[33] Nielsen Group (2022); The template can be seen in Figure 36 in the appendix.
[34] Nenninger and Seidel (2021), p. 73
[35] Ott (2019), p. 90
[36] Ott (2019), p. 90

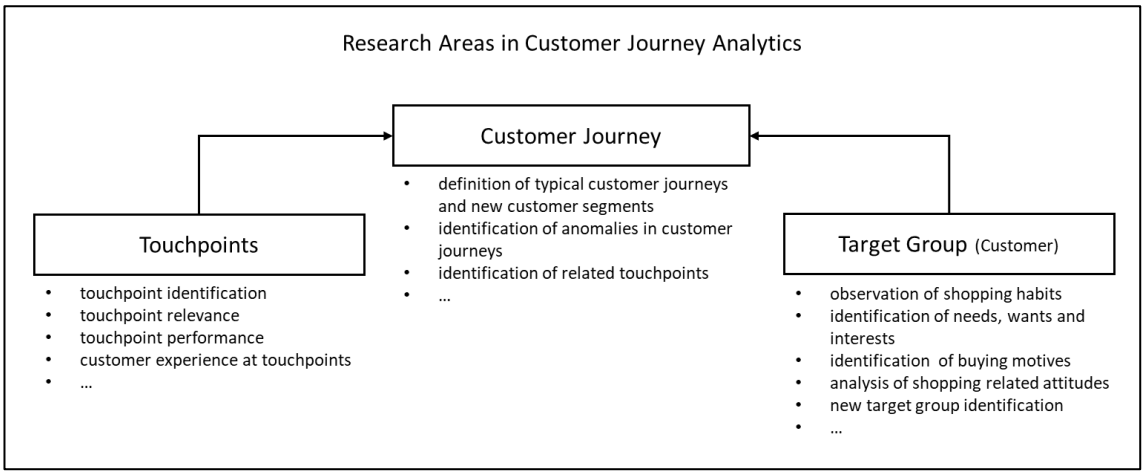

Figure 3: Research Areas in Customer Journey Analytics (own illustration)

In the research field *Touchpoints,* the focus is set on the contact points between a company and their (potential) customers. Researchers identify which touchpoints are the most relevant ones for making a buying decision and assess the companies' performance at each touchpoint by analysing different key performance indicators (short: KPIs) such as the number of relevant customers that were reached at this contact point. In combination with this, the customer experience, meaning the perception of the contact with the company, is evaluated. This detailed touchpoint analysis is done to optimize the company's performance at existing touchpoints and to simultaneously improve the customer experience.[37] Table 1 lists exemplary research questions.

Table 1: Research Questions in the research area Touchpoints (own illustration)

Research Questions
• Which touchpoints are perceived by customers? (Keller, 2018, p. 38) • Which channels are most effective in the customer journey? (Bonsai, 2022a) • Which company owned channels are used and how often are they used by (potential) customers? (Sünkel and Weber, 2019, p. 145) • What is perceived positive, what is perceived negative at each touchpoint? (Kantar, 2022, p. 16) • What are customer expectations at each touchpoint? (Sünkel and Weber, 2019, p. 146)

The second research area has its focal point on a company's target group and their shopping behaviour. For this, shopping habits and consumption related interests are observed as well as shopping motives, needs and wants which influence the decision-making process are explored. These insights help to describe target groups more precisely for developing personas and predicting future consumption behaviour on the path to

[37] Keller and Ott (2020), pp. 21-24; Kolle (2020), pp. 298-299; Ott (2019), p. 90

purchase.[38] The following Table provides research questions on which the target group analysis is based.

Table 2: Research Questions in the Research Area Target Group (own illustration)

Research Questions
• What are consumers buying besides the company products? (GfK, 2022a) • How are consumers buying? (GfK, 2022a) • What buying motives and needs are relevant for a purchase decision? (GfK, 2022a; Nielsen, 2022) • What are emotional needs during a purchase decision? (Bonsai, 2022a) • Which shopper attitudes are relevant along our customers' journeys? (Bonsai, 2022a)

In the third research area, the insights about the touchpoints and the target group are combined to analyse the customer journey. For instance, typical customer journey paths are displayed to identify the moments of truth along the path to purchase. Moreover, the most relevant touchpoints for the purchase decision and the ideal customer experience at these contact points are derived. Ultimately, these insights are used to develop customer journey maps and based on that marketing strategies for engaging effectively with the target group along their journey. Table 3 presents research questions that customer journey analytics addresses in this area of research.

Table 3: Research Questions in the Research Area Customer Journey (own illustration)

Research Questions
• What new types of customer segments can be identified by using specific touchpoints in the customer journey? (Lemon and Verhoef, 2016, p. 87) • Which typical customer groups can be identified by looking at individual customer journeys? (Keller, 2019, p. 38) • How can target groups be described beyond demographic information by analysing typical decision journeys? (Keller, 2019, p. 38) • Which touchpoints should be focused on in the identified target group? (GfK, 2022a) • How are touchpoints related to each other within these typical customer journeys? (Lemon and Verhoef, 2016, p. 87)

For answering the formulated research questions, a broad range of research methods and analytics tools are used. In order to get an overview on how analyses are conducted in customer journey analytics, current analysis methods and tools are outlined in the following section.

[38] Kolle (2020), pp. 319-323; Ott (2019), p. 90

2.2.3 Analytics Methods

Researchers in customer journey analytics are resorting to quantitative and qualitative market research methods as well as modern data collection technologies and internal data to answer all relevant research questions.[39] In the Table 4 a brief overview of classic market research methods and their application in customer journey analytics is given.[40]

It can be seen that with well-established market research methods valuable insights on touchpoints and customers as well as implications for the customer journey can be generated. To complement this research, customer journey analytics often resorts to data that is already available in the company such as sales figures, customer feedback from customer service interactions, social media interactions from own brand or company accounts, website analytics data or previous journey mapping results.[41]

Table 4: Market Research Methods in Customer Journey Analytics (own illustration)

Method	Application in the Context of Customer Journey Analytics
Questionnaire Surveys	• Brand tracking across marketing channels (brand awareness, consideration, purchase frequency, etc.) (Kantar, 2022, p. 15)
Observations at relevant Touchpoints	• Mystery shopping to evaluate the shopper experience and detect problems during the shopping process (Bonsai, 2022b) • Observations of real shopping behaviour by following the customer on a typical in-store shopping tour (Keller, 2019, p. 50) • Indirect observations through shopping diaries in which costumers collect all purchases, emotions and thoughts before, during and after the purchase (Wolny and Charoensuksai, 2014, p. 321)
(Online-) Communities and Focus Groups	• Customer feedback on specific aspects of the customer journey to identify problems and potential for optimisation (Keller, 2019, p. 38) • Detailed customer experiences at specific touchpoints with long-term observation (Dlugosch, 2019, p. 98)
In-depth Interviews	• Interview of relevant customers for analysing purchase motives, needs and wants as well as emotions regarding a brand (Kantar, 2022, p. 15; Quiring, 2022) • Ethnographic Interview to understand the triggers for certain behaviour at touchpoints (Kantar, 2022, p. 16)
Eye-Tracking	• Identification of purchase stimuli during the shopping process (online and offline) (Bonsai, 2022a)

In order to get a more complete picture of the modern consumer and the customer journeys new methods, tools and evolving technologies are used for tracing and

[39] Schweidel et al. (2022), p. 2; Vollrath and Villegas (2021), p. 4
[40] The given table makes no claims to completeness. Further information on used methods and fields of application within customer journey research can be found in the given references in the table.
[41] Kantar (2022), p. 15; GfK (2022b); Weber (2020), p. 68

processing digital and mobile behaviour and actions.[42] Table 5 lists technology-based research approaches used within customer journey analytics.

Table 5: Technology-based approaches in Customer Journey Analytics (own illustration)

Approach	Description
Realtime-Reporting	Real-time capturing of touchpoints and feedback of the experience at each recognised touchpoint that is reported by a consumer via a mobile device. (Puhlmann, 2013, p. 15)
Social Listening	Observation of brand-related content in social media (interests, comments, likes, opinions, etc.) as well as competitive interactions with a brand or company. (Talkwalker, 2022; Lemon and Verhoef, 2016, p. 87)
Predictive Analytics	Prediction of customer needs and wishes and prediction of typical customer journeys for specific products or services by using historical and current consumption data. (Keller, 2019, p. 45; Qualtrics, 2022)
Other emerging technologies	Algorithm based text analysis of customer feedback to analyse sentiments; photo and video analytics technology to capture shopping relevant brands or content in user generated content.[43](Lemon and Verhoef, 2016, p. 88)

The fact that both classic and modern analysis methods can be used for customer journey analysis suggests that a mixed-method approach is crucial to draw a complete picture of the modern consumers along their journeys.[44] Particularly since the smartphone has become an integral part of people's everyday life and therefore plays an important role in their consumption, methods for collecting data about the consumers mobile behaviour are getting more relevant.[45] However, such methods have not been in the focus of researchers yet, as can be seen at the current methods portfolio in customer journey analytics. For this reason, this thesis examines smartphone sensing as a new approach to study the mobile consumer in the context of the customer journey. The technological approach is presented in the following chapter.

3 Behavioural Data Collection with Mobile Sensing

Mobile devices such as smartphones, smart watches or fitness tracker enable the collection of objective real-time data.[46] Because of this, so-called mobile sensing technologies have already been used in research for the last ten years to study people's mobile behaviour.[47] The purpose of this chapter is therefore to explain how the mobile sensing

[42] Bonsai (2022a); Schweidel et al. (2022), p. 16; Hagiu and Wright (2020)
[43] The listed technologies are examples of other technologies that are used in customer journey analytics.
[44] Vollrath and Villegas (2021), pp. 4-5; Lemon and Verhoef (2016), p. 89
[45] For reference see Introduction.
[46] Phan, Modersitzki, Gloystein and Müller (2022), p. 2; Baumeister and Montag (2019), p. xiii; Harari, Müller, Aung and Rentfrow (2017), p. 2; Harari, Lane, Wang, Crosier, Campbell and Gosling (2016), p. 838
[47] e.g., Phan et al. (2022), pp. 1-49; Harari et al. (2017), p. 6; Andone, Błaszkiewicz, Eibes, Trendafilov, Montag and Markowetz (2016), pp. 624-629; Harari et al. (2016), p. 840; Yan, Yang and Tapia (2013), pp. 95-98

approach is applied to research. There follows a description of the mobile sensing technology and the sensing data used for the data analysis performed in this thesis.

3.1 The Mobile Sensing Approach in Research

In general, mobile sensing can be described as the process of collecting data by using sensors such as GPS, Bluetooth or the microphone built in mobile devices.[48] For this purpose, most sensing technologies are based on applications (short: apps) which are operating in the background without any interference directly noticeable for the device user.[49]

Depending on the targeted sensors different behavioural patterns can be observed. Harari et al. conducted a first review of past research papers to provide an overview on used sensors and analysed behaviours.[50] Since then, sensing technologies have emerged, and further studies have been published. While previous research has mainly used smartphones as tracking devices due to their wide distribution, researchers currently develop solutions for wearables such as smart watches or fitness tracker.[51] An updated overview of the sensors used in current research and what behaviours they capture is presented in Table 18 in the appendix. In addition, current references are given.

Currently, four aspects of human behaviour can be examined with sensing technology: physical movements (e.g. daily movement patterns between home and work, vacation locations, use of public transportation), social interactions (e.g. calls, usage of social media apps, notifications), daily activities (e.g. household activities, sport) and consumption behaviour (e.g. shopping interests on social media, price comparisons, purchases in shopping apps such as Amazon).[52] Over the past decade, mostly psychologists have shown an interest in using these behavioural patterns to study human personality, mental health and mental illnesses or even sleeping behaviour.[53] As a result, sensing

[48] Harari, Vaid, Müller, Stachl, Marrero, Schoedel, Bühner and Gosling (2020), p. 650; Harari et al. (2017), p. 4
[49] Harari et al. (2017), p. 839
[50] Harari et al. (2016), p. 6
[51] e.g., Ciordas-Hertel, Rödling, Schneider, Di Mitri, Weidlich and Drachsler (2021), pp. 1-26; Wang, Xiong, J. Zhang, Yang, Boukhechba, Branes and D. Zhang (2021), pp. 1-22; Nepal, Wang, Sharma and Paudel (2021), pp. 28-33; Perez and Zeadally (2021), p. 1
[52] Harari et al. (2017), pp. 839-841; Harari et al. (2016), pp. 5-7
[53] e.g., Wen, Sobolev, Vitale, Kizer, Pollak, Muench and Estrin (2021), pp. 1-14; Byrne, Lind, Horn, Mills, Nelson, Branes, Slavich and Allen (2021), pp. 1-11; Suruliraj, Bessenyei, Bagnell, McGrath, Wozney, Orji and Meier (2021), pp. 1-6; Harari et al. (2020), pp. 649-669

technologies have been already established in psychology.[54] An example for studies is a research conducted by Harari et al in which a framework for analysing personality dynamics and their impact on real-life situations using mobile sensing data is proposed.[55]

Recently, researchers in the fields of psychology, social science, and health science are closely cooperating to conduct interdisciplinary studies in areas such as social interactions, mental health issues, or post-pandemic effects on people's daily lives.[56] For instance, Fulford and colleagues lately examines social interactions of people with schizophrenia by using passive smartphone sensing data. The researchers considered mobile sensing as the only suitable method here because self-reporting methods among people with schizophrenia cannot be used to obtain a realistic picture of their behaviour in certain social interactions due to their different perception of their surroundings.[57] Another study from Ciordas-Hertel et al. analyses the effects of social distancing on the learning behaviour of students during the pandemic. Since the data collection in this study is done with smart wearables, this research presents how fast mobile sensing methods are evolving in these research disciplines.[58]

However, consumers and their behaviour in the context of decision making, have not been in the focus of academic research yet. Nonetheless, especially companies and market researchers are showing growing interest in studying consumption behaviour since the customers have become increasingly dynamic and complex in their purchase decision making. For this reason, companies working with sensing data have published articles that discuss how to use such data to draw valuable insights about mobile consumption behaviour.[59] In addition, some market research institutes have integrated sensing technologies into their portfolio in order to provide comprehensive customer journey analytics.[60]

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[54] Harari et al. (2016), pp. 840-841
[55] Harari et al. (2021), pp. 763-790
[56] e.g., Wang, Xiong, Tang, Boukhechba, Flickinger and Barnes (2022), pp. 1-13; Fulford, Mote, Gonzalez, Abplanalp, Zhang, Luckenbaugh, Onnela, Busso and Gard (2021), pp. 613-620; Ciordas-Hertel et al. (2021), pp. 1-26; Byrne et al. (2021), pp. 1-11
[57] Fulford et al. (2021), pp. 613-620
[58] Ciordas-Hertel et al. (2021), pp. 1-26
[59] e.g., Hedewig-Mohr (2022); Gemius Global (2022); Kleindienst und Halscheid (2022); Halscheid (2022); Murmuras (2020); Kantar and RealityMine (2019)
[60] e.g., Innofact (2022); Bonsai (2021); Infas Quo (2022)

Furthermore, researchers are using classic questionnaire data to supplement mobile data to obtain a better understanding of participants' feelings, emotions, and motives. Some sensing apps offer the possibility to directly send so-called smart surveys to the participants phone after they performed certain actions which then trigger the questionnaire.[61] For instance, a questionnaire about perceived ad content is sent when a participant closes a social media app. It can be assumed that collecting answers right after the triggered action was performed, minimises memory biases. Because the survey data is available almost simultaneously with the passive sensing data, it is evaluated in real-time, and insights are derived immediately. Therefore, smart surveys shorten and accelerate the research process compared to external surveys.[62]

A preliminary summary shows that most research on sensing data and sensing technology is conducted by academia. As the topic becomes more relevant in the context of customer journey analytics, market research is starting to adopt mobile sensing methods. Nevertheless, mobile sensing research for commercial purposes is still in its infancy. Yet there is no solution which examines the entire customer journey by analysing mobile consumer behaviour with sensing data.

3.2 Murmuras Smartphone Sensing Technology

The following chapter provide an overview of the company and its technology development history. Subsequently, the function of the mobile sensing technology from Murmuras is described, followed an outline of the different datasets that are used in the upcoming data analysis.

3.2.1 Company and Sensing Market

In 2019 the Murmuras GmbH is founded by Ionut Andone, Konrad Błaszkiewicz, Qais Kasem and Prof. Dr. Alexander Markowetz as a spin-off from the University of Bonn where they initiated their research on big data in 2012. Due to the lack of data and the growing spread of mobile phones, the academic research team including all founders of today's company as well as psychologist Prof. Dr. Christian Montag started to develop an android app called Menthal to capture large scale behavioural data from smartphones.[63] This included phone and app usage data captured via app logs as well as

[61] Markowetz and Kasem (2021), p. 2; Harari et al. (2016), p. 839
[62] Markowetz and Kasem (2021), p. 2
[63] Murmuras (2022a)

location data tracked with the GPS sensor of the device. Besides this, information about the context the mobile phone is used in, demographics about the study participants and their moods are collected through questionnaires integrated in the app.[64]

As the technology attracted attention of various researchers in different disciplines, Murmuras founders decided to commercialise the smartphone sensing technology.[65] In order to provide the option for setting up individual research projects with own participant samples, the Murmuras app was developed based on Menthal.[66] Moreover, the company extended the sensing capabilities to capture in-app behaviour in social media apps and the Amazon shopping app as well as mobile browser behaviour.[67] Since then, a variety of academic and public projects using Murmuras' sensing approach have been realised.[68] For instance, the currently ongoing SanePhone project, funded by the Federal Ministry for Research and Education in Germany, uses smartphone sensing to develop an AI-based smartphone user interface to offer people a healthier digital lifestyle.[69]

Murmuras has been introducing its methodology in the market and media research industry over the past two years. Since the successful participation at the 2nd Startup Pitch on Marktforschung.de in April 2021, the company has set up several corporations with panel providers to build up its own smartphone sensing panel which continuously provides detailed and large-scale behavioural data.[70] In addition, data products for studying consumption relevant topics such as mobile advertising, in-app shopping behaviour or competitive app analysis are currently developed in collaboration with market and media research.[71]

Although no German company follows the same technological approach as Murmuras so far, the company faces competition on the European sensing technology market. In Figure 4, an overview of the main competitors and their provided sensing data is shown.

[64] Andone et al. (2016), p. 625
[65] Murmuras (2022a); Murmuras (2022c)
[66] Murmuras (2022b)
[67] Murmuras (2022c)
[68] e.g., BMDV (2022); FZI (2022); BMBF (2021)
[69] BMBF (2021)
[70] Marktforschung.de (2022)
[71] Innofact (2022); Infas Quo (2022); Hedewig-Mohr (2022)

	murmuras	RealityMine	wakoopa (Part of GfK)	GEMIUS
App Usage Tracking	✓	✓	✓	✓
Browser & Google	✓	✓	✓	✓
Mobility Tracking (i.e. GPS, Network)	✓	✗	✗	✗
Smart Surveys	✓	✓	✗	✗
In-App Ads Tracking (i.e. Facebook, Instagram, TikTok)	✓	✓	✗	✓
In-App Ads Success Measurement (i.e. Clicks on Ads)	✓	✓	✗	✓
In-App Consumer Behavior (i.e. Amazon Buying Journey, incl. Pricing)	✓	✓	✗	✓
In-App Media Consumption (i.e. Clips in YouTube, TikTok, Netflix)	✓	✓	✗	✓
Feedback/ Gamific. App for Participants (mean to reduce incentivization costs)	✓	✗	✗	✗
VPN for iOS (app usage, browser)	✗	✓	✓	✗

Figure 4: Market Overview of Sensing Technology Provider in Europe
(Q. Kasem, personal communication, September 20, 2022)

Considering the amount of different sensing data types and the methodology to capture this data, the company RealityMine can currently be seen as the biggest competitor of Murmuras. With the exception of mobility data, the company offers comparable sensing data like Murmuras, which is also captured via an application. Moreover, the cross-system solution with the ability to track devices across all operating systems presents a notable competitive advantage of RealityMine over Murmuras, since Murmuras' technology only focusses on android devices so far.[72] However, RealityMine is not able to collect in-app data on iPhones due to restrictions of the iOS. Further explanations on this issue are given in chapter 3.2.2, which discusses the data collection technology.

Wakoopa also bases its sensing technology on an app which runs on smartphones, tablets and computers. Besides app usage tracking via app logs, their key competence lies in capturing browser behaviour. In 2014 the company merged with Netquest, a panel provider specialised in digital panel services to extent their behavioural data collection capabilities.[73] As Netquest has become a part of GfK, all three companies are joining their competencies to expand the consumer experience research. However, with Wakoopas' technology there is no in-app tracking possible.[74]

The third relevant competitor on the sensing market is Gemius. In comparison to the other companies, Gemius uses a different sensing approach. For the study period participants receive modified devices that continuously capture sensing data in the

[72] RealityMine (2022a)
[73] Wakoopa (2022a,b); Netquest (2022)
[74] GfK (2016); Marktforschung.de (2016)

background. Additionally, Gemius combines mobile sensing data with site-centric data and survey data to get a deeper understanding of the targeted users.[75] However, this method is limited to the specific device and therefore cannot be applied to other operating systems. Moreover, mobility data and smart surveys are not integrated in Gemius' technology.

It can be summarised that the attention for mobile sensing data rises among market research, since not only Murmuras collaborates with different market research institutes across Germany, but also other sensing technology provider have partnerships within the commercial research industry.[76] However, the amount of data each provider can offer differs depending on the used technological approach.

3.2.2 Data Collection Technology

As with RealityMine and Wakoopa, Murmuras' mobile sensing technology is based on an app that manages the data collection. This chapter includes a description of the data processing with both the Menthal app and the later developed Murmuras app, since the analysis uses data collected with both apps. Firstly, the functionality of the Menthal app is explained. The process is visualised in Figure 5.

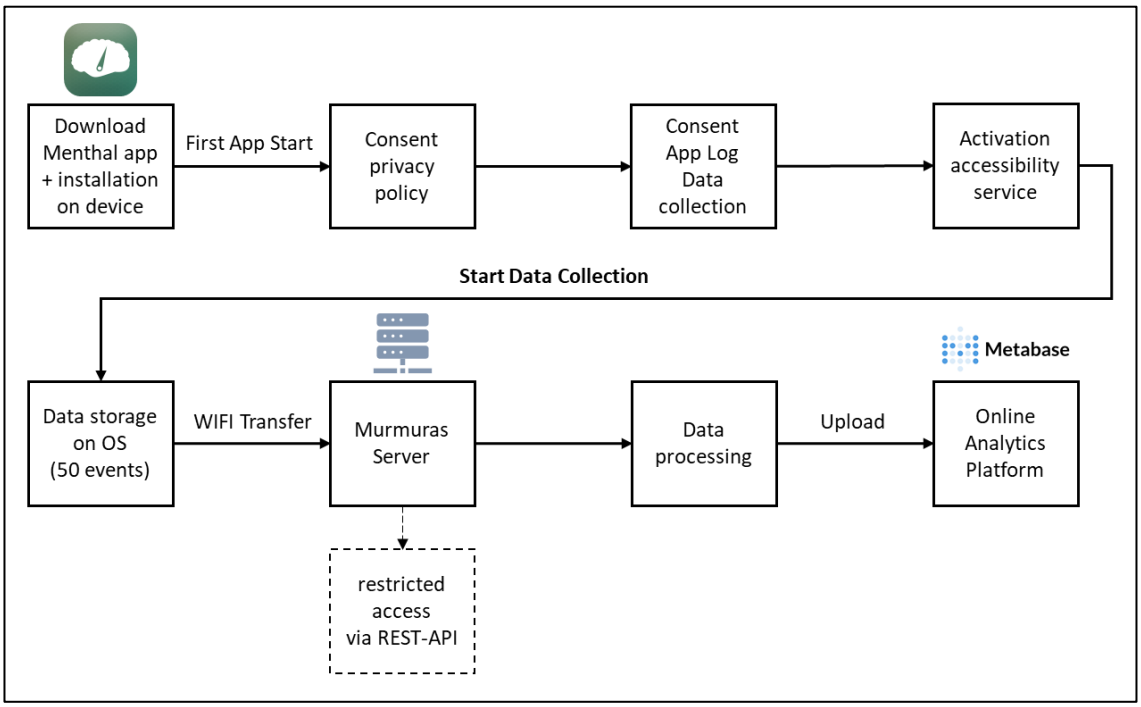


Figure 5: Data collection process within the Menthal app
(own illustration according to Andone et al., 2016, p. 627)

[75] Gemius Audience (2022)
[76] e.g., RealityMine (2022b); GfK (2016); Bonsai (2021)

The Menthal app is available in the Google Play Store and can be installed on every Android device. With the first app start the user is asked to give consent to the privacy policy[77] and the permission to collect, store and further process app log data about the app usage of the device owner. This is aligned to the local GDPR data privacy terms and happens on a voluntary basis, which means that users do not get monetary incentives for providing their behavioural sensing data.[78] Instead, the app provides feedback on their own phone and app usage time and offers personality analysis and a mood diary for the participating users. Based on this, a mental health score is calculated to assess how healthy the smartphone usage of the user is. Further, information on how the user is targeted by companies in social media is given.[79] In this context, it must be mentioned that the app is exclusively available for mobile phones with Android OS, because iOS (short for internetwork Operating System) used by iPhones is highly restrictive and does not permit to track what happens in other apps. As a result, no in-app data can be collected neither with the Menthal app, nor with the Murmuras app.[80]

The technical basis for capturing in-app data from the phone is the accessibility service. This service is normally used to support people with disabilities to navigate in their phone. For this, the function has the capability to capture what the user does on the smartphone (e.g. switching from one to another app). It is running in the background and has no significant effects on the battery life.[81] Thus, the accessibility service presents an efficient opportunity to collect smartphone sensing data. If the service is not activated, the users get asked for activation after consenting to the privacy policy and app log data collection. As soon as the accessibility service is activated, data is collected. This process stops if the users revoke their consent or uninstall the app. [82]

In order to protect the user's privacy, triggers are set on relevant actions while personal data is being hashed or removed. This is especially important when collecting in-app data, as it contains a broad range of personal information, e.g., account names, private

[77] The privacy policy for the Menthal app can be found on the following website: https://murmuras.com/privacy-menthal
[78] Andone et al. (2016), p. 625
[79] An overview of the Menthal interface and the provided information are given in Figure 37 in the appendix.
[80] Apple (2021a,b); Apps of third parties are required to be executed in so-called sandboxes. This inhibits to access data produced by other apps, system data and resources. The effect of this restriction on the data analysis and results is discussed in chapter 5.5
[81] Google Developers (2022a,b)
[82] Andone et al. (2016), p. 626

posted content, etc. The collected events are then saved by the OS of the phone. In order to maintain the correct sequence of events, the data bundle is kept in a queue and stored in a SQLCipher database.[83] SQLCipher is used to ensure a high level of data security as it provides an open-source extension for encrypting integrated app databases.[84] Once 50 events are captured, the encrypted data bundle is sent via WIFI to the Murmuras server that is located in Germany. The server can only be accessed locally via a REST-API.[85] REST APIs allow to directly access all datasets, as each data resource can be identified via a unique address.[86] Murmuras has direct access to the sensing data, whereas external researchers can only get limited access to aggregated data.[87]

For creating readable datasets, multiple data processing steps are performed. As these proceedings need to be done continuously as soon as new data is collected, the batch processing method is used. This enables an automatic data processing of all process steps.[88] Subsequently, the final datasets are uploaded to the online analytics platform Metabase where external researchers and Murmuras' analytics team are conducting most data analyses.[89]

The Murmuras app uses the same architecture as Menthal, which means that the data collection process is identical. However, the Murmuras app is mainly developed to run professional studies with recruited participants. For this, the company provides a study management platform for managing the recruitment process as well as controlling the field work.[90] Therefore, the onboarding process differs in comparison to Menthal. The detailed data collection process can be seen in Figure 6.

[83] Andone et al. (2016), p. 626
[84] Zetetic (2022)
[85] Q. Kasem (personal communication, August 31, 2022)
[86] Kress (2021), p. 11
[87] Q. Kasem (personal communication, August 31, 2022)
[88] Q. Kasem (personal communication, August 31, 2022)
[89] Q. Kasem (personal communication, August 31, 2022)
[90] Murmuras (2022b,d)

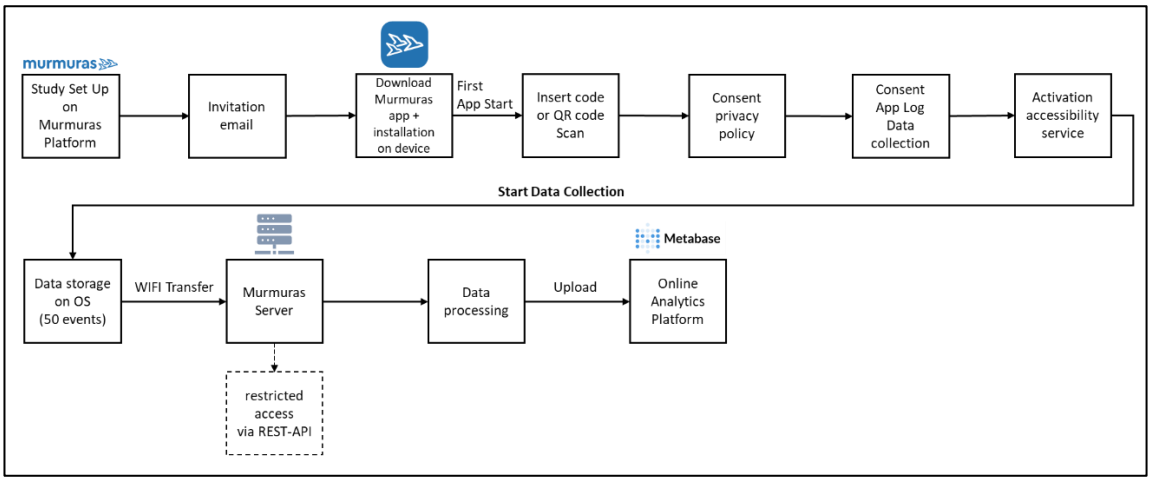


Figure 6: Data collection process within the Murmuras app
(own illustration according to Q. Kasem, personal communication, August 31, 2022)

In the first recruitment step, an individual QR-Code as well as a unique participant code are generated. Hereafter, the potential participants receive an invitation via email to download and install the Murmuras app.[91] For entering the study, either the QR-Code can be scanned with the app, or the code can be entered manually. The mobile sensing starts, identical to the Menthal app data collection, as soon as the participant consents to the privacy policy[92] and to the app log data collection and activates the accessibility service. The sensing process stops automatically with the ending of the study, or if the participants uninstall the app. The subsequent data processing procedure is identical to the process applied on Menthal data.[93]

Besides the sensing data, the Murmuras app includes the option of conducting smart surveys. The questions for the surveys are created in the study management platform. Following this, they are sent to the mobile phones of the participants after they have performed a triggered action on their devices. There are three main trigger types that the researcher can choose from. When setting a time trigger, the questions are being sent at a specific time, for example at eight am in the morning. The location trigger activates the survey when a participant is at a certain location, e.g., the grocery store. Furthermore, questionnaires are sent when an action is performed in an app.[94] For instance, the participant gets questions regarding the seen content after closing a social media app. In this case, the trigger is set to the event of closing the app.

[91] An exemplary invitation email can be seen in Figure 38 in the appendix.
[92] The privacy policy for the Murmuras app can be found on the following website: https://murmuras.com/privacy-murmuras
[93] Q. Kasem (personal communication, August 31, 2022)
[94] For reference the process for setting up a smart survey can be seen in Figure 39 in the appendix.

3.2.3 Sensing Datasets

With both data collection apps, Murmuras captures a broad range of data. This mainly includes app usage data as well as mobile browser data (e.g. google search terms, website visits, etc.) and specific in-app content.[95] Figure 7 provides an overview of all data points that are collected by Murmuras.

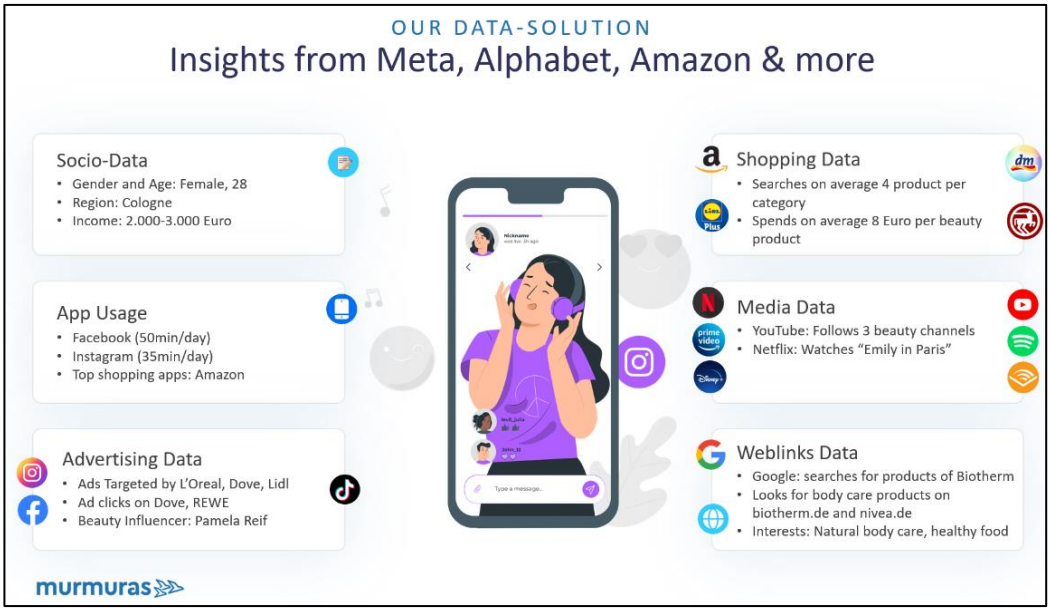


Figure 7: Overview – Sensing Data from Murmuras
(Q. Kasem, personal communication, September 20, 2022)

The data is collected from an ongoing smartphone sensing panel with a constant participant basis of approximately 700 participants that Murmuras manages in corporation with the Panel provider Trendresearch[96]. In addition to this sample, ca. 800 Menthal users are sending their smartphone data.[97] Murmuras provides access to data of both samples for the analysis in this thesis. However, since most of the shopping and media applications have been added recently to Murmuras' portfolio, no meaningful participant data and data processing for these apps exist yet.[98] For this reason, this thesis only focuses on processed datasets in which data of at least six months is accessible via Metabase. Detailed descriptions of the structure, content and limitations of the datasets are provided in the following paragraphs.

[95] Q. Kasem (personal communication, September 20, 2022)
[96] Trendresearch (2022)
[97] Kleindienst and Halscheid (2022); Q. Kasem (personal communication, December 9, 2022); As new participants are recruited constantly, and some participants leave the sample because the study ends or the app is uninstalled, only approximate numbers can be given.
[98] Q. Kasem (personal communication, August 17, 2022)

First, three datasets generated from app usage data are presented. The dataset *app sessions* shows the exact timestamp of every app start and every app ending that is captured on the smartphone of each participant. Table 6 displays how the dataset is formatted.

Table 6: Raw data excerpt from the app sessions dataset (own illustration)[99]

Participant Code	Study ID	Key	App Name	Start Time	End Time	Duration
FDvjT57Lmws	123	com.samsung.android.weather	Wetter	06.02.2022 10:51:22	06.02.2022 10:51:46	24
FDvjT57Lmws	123	com.whatsapp	WhatsApp	06.02.2022 11:02:27	01.09.2021 11:04:16	103
FDvjT57Lmws	123	com.instagram.android	Instagram	06.02.2022 12:39:48	02.09.2021 12:52:50	782
FDvjT57Lmws	123	com.samsung.android.email	E-Mail	06.02.2022 15:22:45	18.09.2021 15:24:51	126
FDvjT57Lmws	123	com.samsung.android.incallui	Telefon	06.02.2022 18:17:35	10.12.2021 19:32:41	1506

Initially, the *participant code* is given to allocate the app usage to a specific user. Moreover, the dataset contains the *study ID* which helps to point out which data is from which study. It is especially useful because app sessions data is collected in every study but is stored in a single set of data. Hence, the *study ID* can be used to filter for a specific study while still having the opportunity to do cross-study analysis on the entire dataset. The *key* describes the technical term for the app and the *app name* column gives the commonly known name of the app. The technical term is necessary for identifying the used apps during the data processing. The *start time* and *end time* shows the exact time when an app is opened and closed, while the amount of time a participant spends in an app is calculated in seconds in the column *duration*. Beyond that, there are no limitations associated with this dataset.

The dataset *daily apps aggregation* gives an aggregated view of the app sessions on a daily basis. With the column *aggregation type* it is possible to filter between app starts and the total daily app usage. Prior analysis showed that the latter view is particularly effective when calculating general app usage parameters such as the daily app usage time or the average phone usage per day.[100] Despite this column, the structure is identical to the app sessions dataset. As the table is based on detailed app sessions, there are no limitations. An excerpt of the dataset is illustrated in Table 7.

[99] The table shows real raw data from the app sessions dataset in Metabase. In order to secure the privacy of all study participants, the participant code and the study ID are fictional in the given excerpt. This proceeding is applied to all raw data excerpts in Table 7-10 and Table 13.

[100] This could be derived from own experience with the analysis of smartphone sensing data for previous studies.

Table 7: Raw data excerpt from the daily apps aggregation dataset (own illustration)

Participant Code	Time	Aggregation Type	Key	App Name	Value
FDvjT57Lmws	06.02.2022 00:00:00	APP_USAGE	com.samsung.android.weather	Wetter	24
FDvjT57Lmws	06.02.2022 00:00:00	APP_USAGE	com.whatsapp	WhatsApp	103
FDvjT57Lmws	06.02.2022 00:00:00	APP_USAGE	com.instagram.android	Instagram	782
FDvjT57Lmws	06.02.2022 00:00:00	APP_STARTS	com.samsung.android.email	E-Mail	4
FDvjT57Lmws	06.02.2022 00:00:00	APP_STARTS	com.samsung.android.incallui	Telefon	3

The third dataset considering app usage data is the *daily category aggregation* table. It is structured similarly to the *daily apps aggregation* table, however in this instance all apps are sorted by app categories such as productivity, communication, tools, etc. This allows an aggregated view on the data, as it can be chosen between *category usage* and *category starts*. Table 8 shows the structure of this dataset.

Table 8: Raw data excerpt from the daily category aggregation dataset (own illustration)

Participant Code	Time	Aggregation Type	Key	App Name	Value
FDvjT57Lmws	06.02.2022 00:00:00	CATEGORY_USAGE	tools	tools	238
FDvjT57Lmws	06.02.2022 00:00:00	CATEGORY_USAGE	communication	communication	1597
FDvjT57Lmws	06.02.2022 00:00:00	CATEGORY_USAGE	productivity	productivity	125
FDvjT57Lmws	06.02.2022 00:00:00	CATEGORY_STARTS	transportation	transportation	2
FDvjT57Lmws	06.02.2022 00:00:00	CATEGORY_STARTS	business	business	3

Besides app usage datasets, behavioural data from browser apps is collected and processed in the dataset *weblinks*. This table contains the complete links from all websites the study participants are visiting. An excerpt of the data is presented in Table 9. The used browser app can be seen in the column *app source*, the *website domain* gets extracted out of the weblink and the exact search terms are saved in the column *search*. Equivalent to the *app sessions* dataset the precise timestamp gets saved for every captured browser event.

Table 9: Raw data excerpt from the weblinks dataset (own illustration)

Participant Code	Time	Source App	Link	Website Domain	Search
FDvjT57Lmws	08.02.2022 16:33:20	Chrome	rtl.de/cms/coronavirus-liveticker-bericht	rtl.de	-
FDvjT57Lmws	08.02.2022 19:30:52	Chrome	https://outlook.live.com	outlook.live.com	-
GkfncUYDmdI	08.02.2022 20:20:45	Chrome	-	-	Schweden
GkfncUYDmdI	02.04.2022 12:02:12	Firefox	en.m.wikipedia.org/wiki/Swedish_royal_	en.m.wikipedia.org	-
GkfncUYDmdI	07.04.2021 16:22:36	Firefox	accuweather.com/de/de/barntrup/3268	accuweather.com	-

It is important to note that weblinks are exclusively collected from panel participants, because browser behaviour reveals extremely personal information. As Menthal app users provide their data on a voluntary basis, the company decided not to collect browser data.[101] However, regarding the data itself no further limitations are given.

[101] Q. Kasem (personal communication, September 14, 2022); Whether further privacy concerns can be stated in collecting detailed weblinks is discussed in chapter 5.5

Next, in-app data is described. This includes advertising data from social media apps and buying behaviour captured in shopping apps. Currently, marked advertisements[102] from Facebook, Instagram and TikTok are collected, while TikTok data is only available for the last three month. Therefore, this thesis focuses on ads data from Facebook and Instagram.

Several characteristics of the seen ads are captured in the dataset *daily ads*. An excerpt of this dataset is displayed in Table 10. First, the date on which the advertisement was seen as well as the name of the social media app are saved in the columns *date* and *source app*. Further, the advertising company is stored within the column *publisher* and the ad texts that a participant sees on his screen are shown in the column *content*. It is important to note that texts written in a picture or video ad are not captured. In addition, the dataset offers information about the *ad location* in Instagram. Ads located in the feed, story, or reel are measured.[103]

For evaluating the ad success, a number of KPIs are computed. These include the *ad impressions*, which indicate how many times a participant has been exposed to one advertisement. Moreover, user interactions with the ad are tracked (e.g. click on an ad, likes, shares or comments below an ad).[104] As the calculation of ad clicks is still in a testing stage, this KPI cannot be considered valid at this point. However, this presents a temporary limitation and will be resolved after testing and optimizing the process.[105]

Table 10: Raw data excerpt from the daily ads dataset (own illustration)

Participant Code	Day	Source App	Publisher	Content	Ad Location	Ad Impressions	Total Clicks	Likes	Shares	Comments
FDvjT57Lmws	14.04.2022 00:00:00	Facebook	ab-in-den-urlaub.de	TOP Last Minute Angebote	facebook	1	1	1	0	0
FDvjT57Lmws	14.04.2022 00:00:00	Facebook	Booking.com	Bleiben Sie flexibel mit kostenfreier Stornierung.	facebook	1	1	1	0	0
FDvjT57Lmws	14.04.2022 00:00:00	Facebook	Lidl Deutschland	Eine ganze Tafel Schoki in einem Happs?	facebook	2	2	2	0	0
FDvjT57Lmws	15.04.2022 00:00:00	Instagram	Outfittery	10 Jahre feiern mit 30 %	feed	1	0	0	0	0
FDvjT57Lmws	15.04.2022 00:00:00	Instagram	babbel_de	Erhalte lebenslangen Zugang zu allen Sprachen!	stories	2	0	0	0	0
FDvjT57Lmws	15.04.2022 00:00:00	Instagram	mini_deutschland	Welchen MINI möchtest du gewinnen?	reel	1	1	1	0	0

After an initial evaluation of the advertising dataset, the following limitations regarding the data processing can be identified. The column *publisher* does not always display the correct advertising company. Instead, it contains other information that the participants

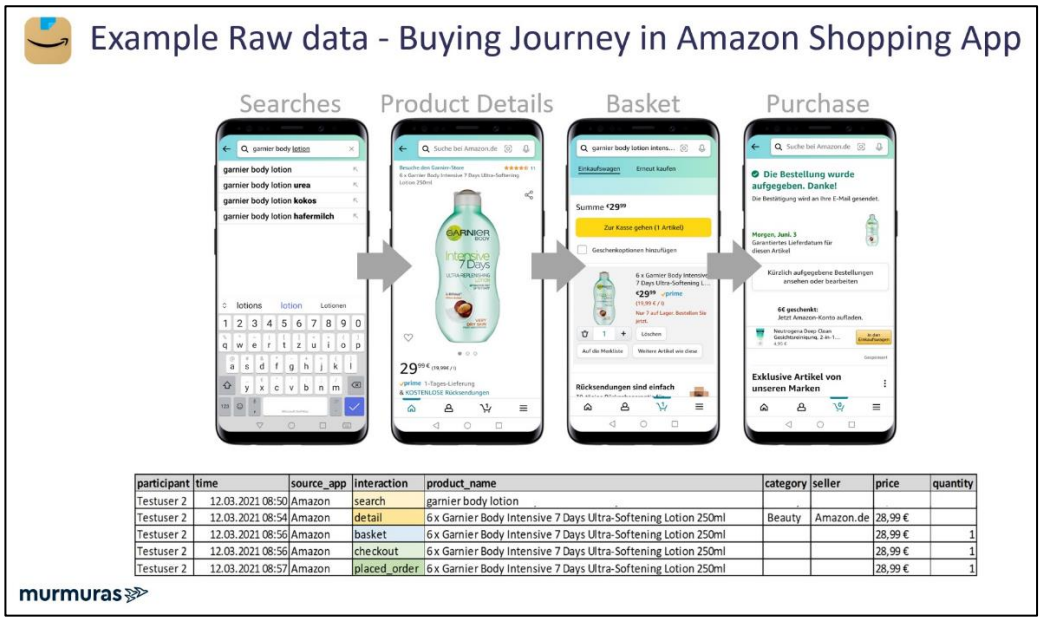
[102] According to the law against unfair competition (JURA, §5a Nr. 4) all advertising companies or private persons, who get paid for promotion, are obligated to mark the advertisement as such. The extract of the law can be found on the following webpage: https://www.gesetze-im-internet.de/uwg_2004/__5a.html
[103] The three ad placement options in Instagram can be seen in Figure 40 in the appendix.
[104] Figure 41 in the appendix illustrates which advertisement information are captured.
[105] K. Błaszkiewicz (personal communication, October 26, 2022)

have also seen on their phone screens.[106] Since the technical team from Murmuras is already working on improving data extraction for this column, it can be assumed that the problem will be solved in the near future.[107]

With regard to the column content, it is stated that approximately 11% of the ad content within the last six month is currently empty. This lack of data becomes especially obvious when looking at Instagram. About 22% of Instagram content is missing at this point. For Facebook only 0.66% of the ad texts are not available.[108] Consequently, the problem presents a limitation, particularly when analysing Instagram data. Therefore, it should be kept in mind that among Instagram ad data significant statements in both quantitative and qualitative analysis cannot be made yet.

Besides advertising data, in-app shopping data from the Amazon app is considered in the upcoming analysis. Here, the entire buying process is measured. With the column *interaction type* each event in the shopping app is classified. Thereby, it can be distinguished between five interaction types: *search, detail, basket, checkout* and *placed order*. The interaction type *search* describes the event when a user of the Amazon app uses the search bar to locate a product. The exact search terms are collected in the column *search term*. The event *detail* occurs when a user clicks on a product. In this case the product seller, the brand, the detailed product name, the price as well as the category the product belongs to are captured. The interaction type *basket* contains all products a participant puts in the basket. The checkout page gives an overview of the products a user is about to purchase. Logically, *placed order* includes all products after the final purchase. Figure 8 illustrates an exemplary buying journey of a user with both the app perspective and the data perspective.

[106] In Table 19 in the appendix errors within the column publisher for both Facebook and Instagram ad data are listed and described.
[107] K. Błaszkiewicz (personal communication, October 26, 2022)
[108] K. Błaszkiewicz (personal communication, September 4, 2022); These results are drawn from an internal analysis conducted by Murmuras' analytics team. For this analysis, a time frame of six month from 01.03.2022 to 31.08.2022 is chosen.



participant	time	source_app	interaction	product_name	category	seller	price	quantity
Testuser 2	12.03.2021 08:50	Amazon	search	garnier body lotion				
Testuser 2	12.03.2021 08:54	Amazon	detail	6 x Garnier Body Intensive 7 Days Ultra-Softening Lotion 250ml	Beauty	Amazon.de	28,99 €	
Testuser 2	12.03.2021 08:56	Amazon	basket	6 x Garnier Body Intensive 7 Days Ultra-Softening Lotion 250ml			28,99 €	1
Testuser 2	12.03.2021 08:56	Amazon	checkout	6 x Garnier Body Intensive 7 Days Ultra-Softening Lotion 250ml			28,99 €	1
Testuser 2	12.03.2021 08:57	Amazon	placed_order	6 x Garnier Body Intensive 7 Days Ultra-Softening Lotion 250ml			28,99 €	1

Figure 8: Exemplary Buying Journey in the Amazon Shopping App (Innofact and Murmuras, 2022)

The *Amazon shopping* dataset is particularly important for the analysis in this paper as it allows to identify actual customers along their customer journey. Therefore, it is even more relevant to mention existing limitations. Primarily, it could be observed that events with the exact same timestamp of one participant appear multiple times in the dataset. It could be concluded that without a cleaning procedure in the data processing step, further interaction analysis will cause wrong results. This issue should be considered in the upcoming analysis.

Secondly, it could be determined that the column *brand* contains irrelevant information. Table 11 illustrates the two most frequent issues in this column.

Table 11: Exemplary format problems in the brand column of the Amazon Shopping dataset (own illustration)

Brand	Error Description
Besuchen Sie den LEGO-Store	Too much information, should only contain "LEGO"
Marke: Google	"Marke:" is not necessarily needed

Similar format errors are detectable in the column *price*. Hence, data cleaning should be applied to both columns. This is presumably crucial for the price column since no calculations are possible in the current format. As there is no proceeding for standardising prices, a workaround for every occurring format issue is suggested in Table 12.

Table 12: Price column format issues and cleaning proceedings (own illustration) [109]

Example	Problem Description	Cleaning Processing
4,50 €	-	aimed format, no cleaning necessary
(0,01 € / stück)	quantity specification e.g., stück, Anzahl, ml, kg, etc.	quantity specification is not needed and could be deleted, since this is calculated in the column *quantity*
$10.01	wrong currency e.g., $, R$, etc.	prices could be transferred to euro with the valid exchange rate at the timestamp of the data collection
12,99 € - 17,99 €	price range (this only occurs in the interaction type *detail*)	calculating an average value would distort the analysis → recommendation: exclude entries with price range
0,69 € GRATIS Lieferung für Prime-Mitglieder	irrelevant information	delete all texts except price and euro sign
3,91 € (4,65 € inkl. USt)	two prices	keep price with USt because this is the price the user pays when purchasing the item

Lastly, the demographics dataset is described. It contains information about the exact age, gender and region of all study participants as can be seen in Table 13. This dataset is supplied by the panel provider and gets updated regularly when new participants enter the ongoing sensing panel. For Menthal users, demographics are not included as the information can be given voluntarily. In order to solve this problem Murmuras is currently working on a solution to predict age and gender based on the collected sensing data. For example, users who frequently open a period calendar app on their devices are more likely to be female.[110] As this approach is not implemented at the time of conducting the analysis in this thesis, demographic analyses are only performed for panel participants.

Table 13: Raw data excerpt from the demographics dataset (own illustration)

Participant Code	Age	Age Group	Gender	Region
FDvjT57Lmws	30	30-39	male	Bayern
GkfncUYDmdI	29	18-29	male	Niedersachsen
AsvdmTDmgLj	39	30-39	female	Hamburg
khlfewuiBTCkd	25	18-29	female	Sachsen

[109] It is recommended to create a new column in the dataset with the cleaned prices and maintain the uncleaned column, because some cleaned information may be of interest for a deeper analysis.
[110] K. Błaszkiewicz (personal communication, October 26, 2022)

3.2.4 Data Analytics Tool: Metabase

The described datasets are accessible on the online analytics platform Metabase. Since the platform is used to conduct the data analysis in this thesis, the tool and its functions are briefly outlined in this chapter.

Metabase is an open-source platform which offers easy and fast analytics options without the need of deep statistic knowledge and programming skills.[111] For an efficient data access, the platform can be connected to most of the common database systems such as PostgreSQL, SQLite, Microsoft SQL Server or Google Analytics.[112]

The platform itself is structured as follows: firstly, a personal workspace with folders can be created. All analyses can be arranged here, added to collections, altered further, or preserved.[113] Secondly, all basis datasets can be viewed and edited. Regarding this, it must be noted that Murmuras is able to control to what extent a client has access to the raw data.[114] In cases in which a client works with data owned by Murmuras, access is only given to aggregated data in order to protect participants privacy. Murmuras team members have access to all raw datasets and functions in Metabase. Hence, there are no restrictions when working with the data in this thesis.[115]

For data analyses, Metabase offers two main tools.[116] The notebook editor is a visual query builder based on basic SQL commands, which can be chosen from different command boxes.[117] Figure 9 shows an exemplary analysis performed within the editor. As a first step the basis data for the analysis must be selected. This can either be a dataset or previously performed analyses.[118] Moreover, two or more datasets can be joined to do cross-table analyses, as can be seen in the given Figure in the second step.[119] In this case, the *daily ads* dataset is merged with the *demographics* dataset by using a left join to analyse the advertisement distributed by gender.

[111] Metabase (2022a)
[112] Metabase (2022b)
[113] Metabase (2022c)
[114] Metabase (2022a)
[115] Q. Kasem (personal communication, August 31, 2022)
[116] Metabase (2022d)
[117] Metabase (2022e)
[118] Metabase (2022e)
[119] Metabase (2022f)

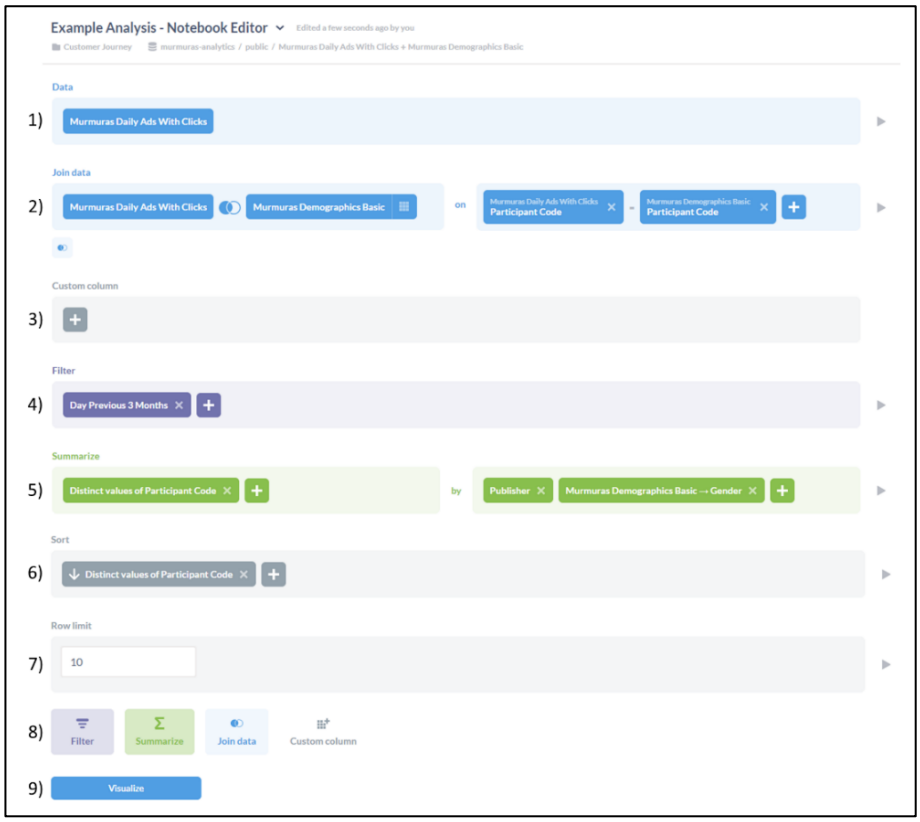


Figure 9: Exemplary data analysis in the Notebook Editor in Metabase (own illustration)[120]

Besides this, it is possible to add a custom column to the basis dataset which pre-calculates certain parameters before the actual analysis is conducted.[121] For example, in the app usage dataset the app usage is calculated in minutes by using a custom column with the formular: [Value] / 60 = app usage in minutes.

In the filter section different filter options can be applied to multiple columns. [122] The example in Figure 9 uses a filter on the time column in order to analyse only the last three months of the data in the table. After this, the actual analysis is conducted. In the summarize section a list of basic functions is given to choose from (e.g. count of rows, sum, average, minimum, etc.) as well as an option to write a custom expression in case the basic analysis functions are insufficient. The summarized results are then grouped. For this grouping, all columns of the basis dataset can be used.[123] For example, when grouping by publisher and gender as illustrated in the example, all publishers and gender attributes are displayed in the results.

[120] The analysis generates the absolute number of male and female participants that are reached on Facebook and Instagram from the top ten publisher.
[121] Metabase (2022e)
[122] Metabase (2022g)
[123] All basic functions and custom expressions are provided online by Metabase (2022h,i).

The findings can be sorted by the analysed parameters to make them more understandable. A row restriction can also be established for a better overview and increased analytical performance. Following that, the results may be further analysed by adding more filters, summarizing the prior result, merging data, or creating new custom columns. To keep track of the progress during the analysis process, every step can be executed for a limited amount of data by clicking on the arrows on the left side.[124]

With pressing the visualisation button, the analysis is executed, and the results are displayed in a table and automated chart. This chart can be edited, or a different visualisation option can be chosen. Metabase provides several basic charts (e.g. bar and row charts, pie charts, line charts or PIVOT tables) and offers customisation options for each chart such as colour adjustments, axis settings, etc.[125]

The second option for analysing data in Metabase is the native SQL query builder. This editor is used for more advanced analyses and requires SQL programming skills. It supports all SQL commands, which allows a customized and flexible data exploration. In order to simplify the analysis process, analysts are having access to a SQL template and snippets library.[126] Figure 10 presents the same analysis as above by using the native SQL editor. There are the same options available for visualisation as in the notebook editor.

Figure 10: Exemplary data analysis in the native SQL Editor in Metabase (own illustration)

Besides these analytics options, Metabase offers interactive dashboards for creating comprehensive overviews of the results. Here, filters can be added to the top of each dashboard, which are then connected to all displayed analyses. As a result, all analyses are calculated based on the set filters. For instance, when a time filter is applied to the dashboard, all connected analyses show results in the chosen time frame or on the

[124] Metabase (2022e)
[125] Metabase (2022j)
[126] Metabase (2022k)

filtered date. Thus, dashboard filters allow to flexibly adapted analyses and thus generate insights efficiently.[127]

4 Analysis Framework

In the following chapters the analysis framework is developed based on the information given in the previous sections. First, a model for illustrating the customer journey on mobile devices is constructed. On this basis, the analytics concept is created.

4.1 Mobile Customer Journey Model

This chapter presents a theoretical model of the customer journey on mobile devices. Since the process model by Lemon and Verhoef[128] is identified as useful in terms of deriving implications for a mobile journey, this model serves as the basis. Further presumptions are drawn from the current consumer behaviour and sensing data.[129] Figure 11 illustrates the developed mobile customer journey model.

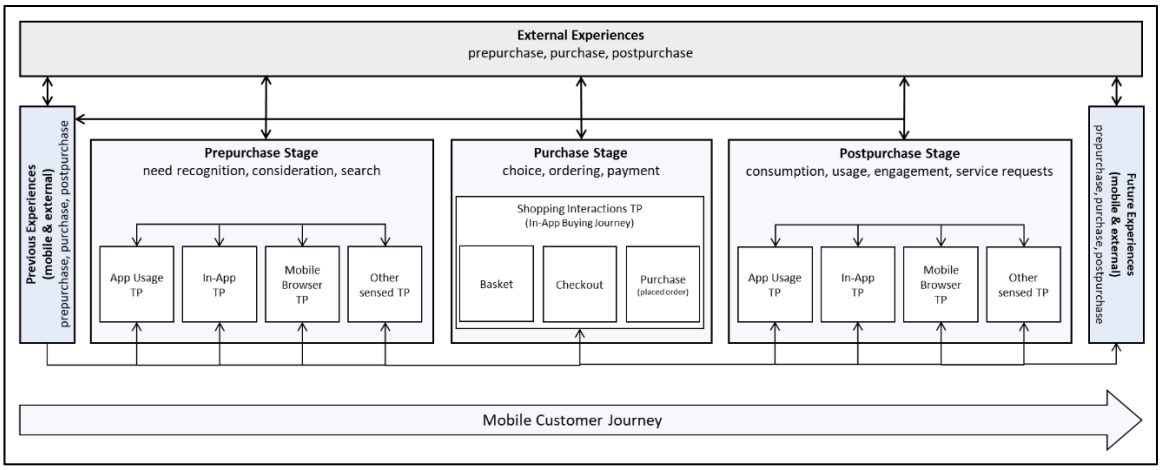


Figure 11: The Mobile Customer Journey Model (own illustration)

Align with recent literature on customer journeys, the here presented model consists of a prepurchase, purchase and postpurchase stage. These are iteratively connected by circular arrows, which emphasise the dynamic and high flexibility of modern consumers, which has been observed throughout the customer journey over the last years.[130]

Considering the sensing data, the potential touchpoints for this model can be specified. Prepurchase touchpoints can be divided into app usage touchpoints, app touchpoints

[127] Metabase (2022j)
[128] Lemon and Verhoef (2016), p. 77
[129] For reference see chapters 2.1 and chapter 3.2.3
[130] Angus and Westbrook (2022), p. 55; Li, Abbasi, Cheema and Abraham (2020), p. 127; Peteva (2020), pp. 35-36

within apps, and browser touchpoints. Moreover, touchpoints from other sensing data such as location or voice data can be derived. As with the three main stages, all touchpoint types are interconnected to illustrate the flexibility of consumers as they move between them. This is further stressed in the following example: one user sees an ad promoting a new Samsung smartwatch (in-app touchpoint). This person then clicks on the ad and opens the product in the mobile Browser app (Browser touchpoint). Hereafter, the user clicks on the Amazon Shopping app and searches for the smartwatch and compares different models (in-app touchpoint).

The purchase stage covers all actions regarding an in-app purchases. It is suggested that products in the basket can be interpreted as a closer consideration or buying intention. Checkout pages represent the ordering process, while the actual purchase can be seen by the payment and ordering confirmation. With regard to the given example, the purchase stage of the users' customer journey would include putting one smartwatch model in the basket. As a next step, the user may go to the checkout to give the bank and address details and is then directed to the order confirmation. However, this exemplary shopping process may not be seen in every app and for every customer since it can be assumed that apps vary in their purchase processes and customers have different purchase preferences. For instance, the Amazon app offers a buy now option to place an order with one click and the checkout information is automatically inserted.[131] For this reason, there is no purchase flow suggested in the model. It is recommended to derive the purchase process individually for every shopping app and target group to see differences in buying journeys.

The postpurchase stage contains the same touchpoint types as the prepurchase stage. This is due to the iterative dynamic of the mobile journey which results in an overlap between these two stages. Therefore, the same circular interconnections have been applied here. Nonetheless, touchpoints can be assigned to the postpurchase stage when after-purchase behaviour like product usage, engagement or service requests are recognisable. In reference to the mentioned example, the download of the smartwatch app (app usage touchpoint) and a google search for the smartwatch manual (Browser touchpoint) can be considered as postpurchase behaviour.

[131] Amazon (2022)

Besides the three main stages, experiences from previous and future customer journeys are included in the model. According to Lemon and Verhoef, past shopping experiences function as influential factors on the currently ongoing journey and further influence future experiences.[132] While the authors speak of general experiences, this model focuses on mobile experiences made while using a mobile device. In the example, this could be a previous in-app purchase related to the smartwatch. Moreover, external experiences are connected with the mobile customer journey as all mobile and external actions mutually influence each other. For instance, it might be possible that the user sees the smartwatch advertisement on TV. After seeing another ad on Instagram, the user may decide to go to a store to try out the product before making the final buying decision online. It must be noted that these external factors cannot be derived from sensing data. Thus, it can be stated that for describing the entire mobile customer journey, touchpoints outside the mobile phone must be considered in the analyses. This in turn emphasises the relevance of the mixed-method approach in customer journey analytics.

It can be concluded that the described mobile customer journey model focuses on mobile touchpoints influencing the customer journey in all three stages. Furthermore, it stresses the iterative connection between mobile and external past, present and future experiences. Therefore, it provides implications for the analysis concept and subsequently supports the mobile customer journey mapping process.

4.2 Analysis Conceptualisation

In the following chapters the preliminary considerations regarding the sensing data analysis are outlined. Hereafter, the analysis concept is presented in three sections.

4.2.1 Preliminary Considerations

For a better feasibility of the analysis, the next sections define a fixed time frame of observation and the target groups to be examined by conducting first analyses on the sensing datasets.

4.2.1.1 Definition of the Time Frame

When exploring the captured sensing data used in this thesis, a suitable time frame can be identified. In the first place, it must be noted that advertisement data is only collected

[132] Lemon and Verhoef (2016), pp. 74-75

from September 2021 onwards, since in-app sensing was implemented at that time.[133] Moreover, Murmuras started to continuously collect data with an ongoing participant pool in October 2021. Prior to that, only a few test studies had been conducted and the Menthal user base was relatively small. This can be seen in Figure 12, which shows the weekly number of participants over time.[134]

Figure 12: Participants over time (own analysis)

Since the beginning of October 2021, the participant base is constantly over 500 and rising, while it increased and decreased in the earlier months of 2021. Thus, the relevant time frame is set between the 1st of October 2021 and the 31st of August 2022, as this marks the end of the analysis phase for this thesis.

Due to the fact that in the defined period new participants are recruited randomly, it must be determined if the participant pool remains consistent in terms of demographics.[135] This is required to ensure the comparability of analyses results when considering the time perspective. In case the sample is not consistent, changes over time and anomalies in the results may be caused by different sample structure and therefore cannot be interpreted.[136] In this case the variables gender and age are used to review the sample stability.

Since Menthal users do not provide demographic information, the sample consistency can only be analysed from the official panel participants.[137] As a result, approximately

[133] Q. Kasem (personal communication, August 22, 2022)
[134] All analysis steps are documented in the analysis documentation file in the digital appendix. This was applied to all following analyses. Each analysis is named as the displayed Figure.
[135] Q. Kasem (personal communication, August 22, 2022)
[136] Kuß, Wildner and Kreis (2018), p. 171
[137] For reference see chapter 3.2.3

63% of the total sample cannot be assessed.[138] This results in a limitation, which must be considered in the upcoming analysis.

Figure 13 displays the gender distribution without any unknown entries during the chosen period. In general, the sample holds more men than women. The average weekly proportion difference in the group of women and men is approximately 0.1% and scatters on average by +/- 0.7%. Since the proportion for both gender attributes are scattering less than one percent per week on average, the deviations are acceptable. However, weekly differences outside this interval could be observed in weeks of high recruitment. That can be seen by the steep increase in the number of participants in December 2021, February and June 2022 in the prior Figure. These recruitment periods must be considered when analysing sensing data on a longitudinal level.

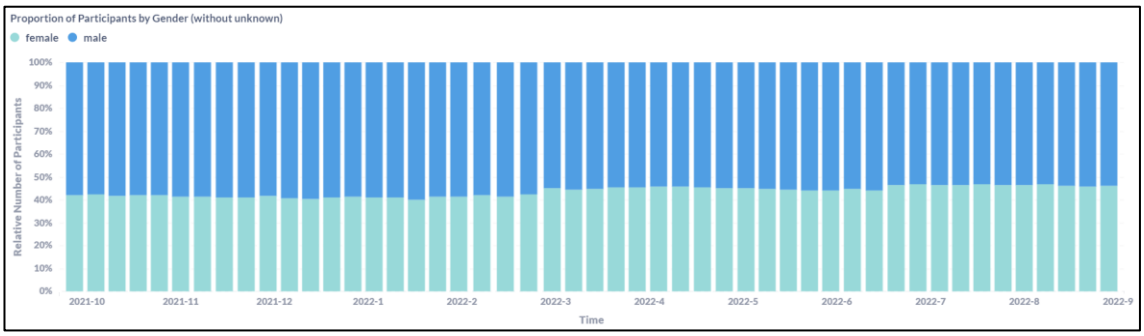


Figure 13: Proportion of Participants by Gender without unknown Gender information (own analysis)

In the next step, the identical analysis is performed to verify the stability among the variable age, which is classified in four age groups: 18 to 29, 30 to 39, 40 to 49 and over 50. As can be seen in Figure 14, young adults represent the smallest group, while elderly generations persistently dominate the sample.

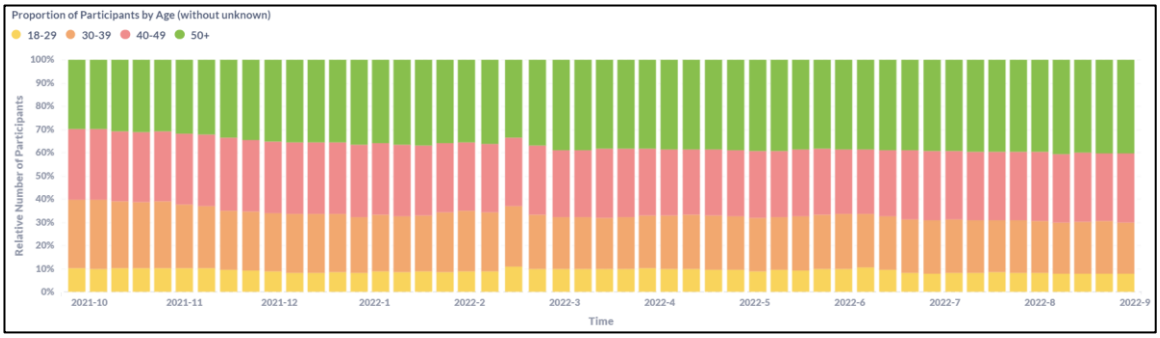


Figure 14: Proportion of Participants by Age Group without unknown Age information (own analysis)

[138] The exact results can be seen in File 1 in the digital appendix.

As more than two attributes are compared in this case, the mean, standard deviation and the interval is calculated for each age group and presented in Table 14.

Table 14: Weekly deviations by age group (own analysis)[139]

Age Group	18-29	30-39	40-49	50+
Mean	9.7%	23.8%	29.3%	37.1%
Deviation	+/-1.0%	+/-2.2%	+/-1.0%	+/-3.2%
Interval	[8.7%; 10.7%]	[21.6%; 26.0%]	[28.3%; 30.4%]	[33.9%; 40.4%]

Deviations higher than +/-1% are visible among the 30-39 years old participants and the participants over 50. This can be explained with the fact that mostly people in these age groups joined the sensing sample in the defined period, which is particularly observable in the weeks of high recruitment. Nonetheless, the deviations are tolerated because they are assignable to certain recruitment phases and therefore are traceable. As a result, sensing data can be analysed and interpreted within the identified time frame. If anomalies are detected, however, it is crucial to verify if sample structure differences are the cause, particularly during recruitment weeks.

4.2.1.2 Definition of Target Groups

Since customer journey analytics is centred around target groups that are relevant to a company, it is crucial to define these groups before conducting the data analysis.[140] Because the analyses in this thesis are not particularly performed for a specific company or brand, a company related target group definition is not useful. However, it is possible to provide target group definitions based on the developed mobile sensing model.

The first target group is classified based on the data collected from in-app purchases. Here, all participants who ordered a brand-related product are considered brand customers. For instance, an Amazon app user who buys shoes from the brand Nike via the app is classified as a Nike customer. Based on this information, the mobile customer journey can be tracked by looking at actions happening before and after the purchase. Moreover, smartphone usage habits and interests of this target group might be identifiable. This in turn could lead to a precise target group description, which then enables the company to efficiently influence their mobile customers on ongoing or future customer journeys. With regard to the sensing datasets used in this thesis, it must be said that exclusively customers who bought a product via the Amazon Shopping app can be

[139] The exact results can be seen in File 2 in the digital appendix.
[140] For reference see chapter 2.2.2

analysed. In the defined time frame ca. 47.4% of all Amazon app users in the sample have purchased at least one item and therefore are classified as customers.[141]

Furthermore, it is recommended to have a closer look at people who are having an ongoing mobile journey but are no customers yet. In the context of this thesis, this target group is defined as potential customers. Considering the model designed in chapter 4.1, potential customers are obtained from the touchpoints among all stages. For instance, a person who liked and clicked on a seen advertisement in Instagram may be at least interested in the advertised product, service or brand. Hence, all participants who have at least one brand touchpoint on their smartphone are classified as potential customers. An analysis of the mobile behaviours of this target group allows companies to follow and engage with their potential customers. Ultimately, this could lead to a purchase and positive postpurchase behaviour.

With regard to the following analysis, it can be stated that both customers and potential customers should be considered. Thus, it is proposed to integrate target group filtering in the analysis concept based on the different available touchpoints captured in each dataset.

4.2.2 Analysis Concept

The analysis concept serves as basis for the explorative data analysis. It is developed by considering implications from the state of research in customer journey analytics (chapter 2), the available data (chapter 3.2), the mobile customer journey model (chapter 4.1) as well as the preliminary considerations regarding time frame and target groups (chapter 4.2.1).

4.2.2.1 Touchpoint Performance Analytics Concept

The first concept is designed to capture the touchpoint performance of a company or brand, since one key element of customer journey analytics is touchpoints. The concept is designed as a dashboard to provide an efficient overview of the most relevant results. Considering the sensing datasets, this dashboard is structured in six main sections including app aggregation data, browser data and in-app data from social media and the Amazon Shopping app. The concept is presented in Figure 15.[142]

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[141] The exact result can be seen in the analysis documentation in the digital appendix.
See analysis “2.2. Relative Number of Customers in Amazon Shopping App”.
[142] See page 40.

On top of the conceptualised dashboard three filters are applied. The first filter is set on the defined time frame. However, this filter can be adapted in case the generated results should be further limited to a specific period, week or date. The second filter contains the company or brand name for which the touchpoint performance should be analysed. Additionally, the filter offers the opportunity to observe competitors' performance across touchpoints as any brand name can be inserted. Thus, a competitive benchmarking among all KPIs is possible. Moreover, a target group filter is implemented based on gender and age group.

In the first section, KPIs which give insights on the overall touchpoint performance are calculated. This includes the average number of brand touchpoints per user over the entire period and on a daily basis. Moreover, the relative number of users who are having at least one brand touchpoint is computed. These indicators should assess how present a company is on the participant’s phone. Since these analyses consider data from several datasets, it is proposed to create a new table including all in-app and browser data. It should incorporate the participant code, the exact timestamp, a column for identifying the brand for filtering and a touchpoint type column which categorises the touchpoints based on the datasets.

The second part analyses the *daily apps aggregation* dataset to generate insights on brand owned applications. It is calculated how long app users are spending in the apps on an average daily basis and how often they are using apps per day. These insights may be already known by the app owning companies. However, it is assumed that the app usage time and frequency of competitor applications in the chosen target group and period remain unknown. Therefore, these analyses are especially useful for competitor app observation.

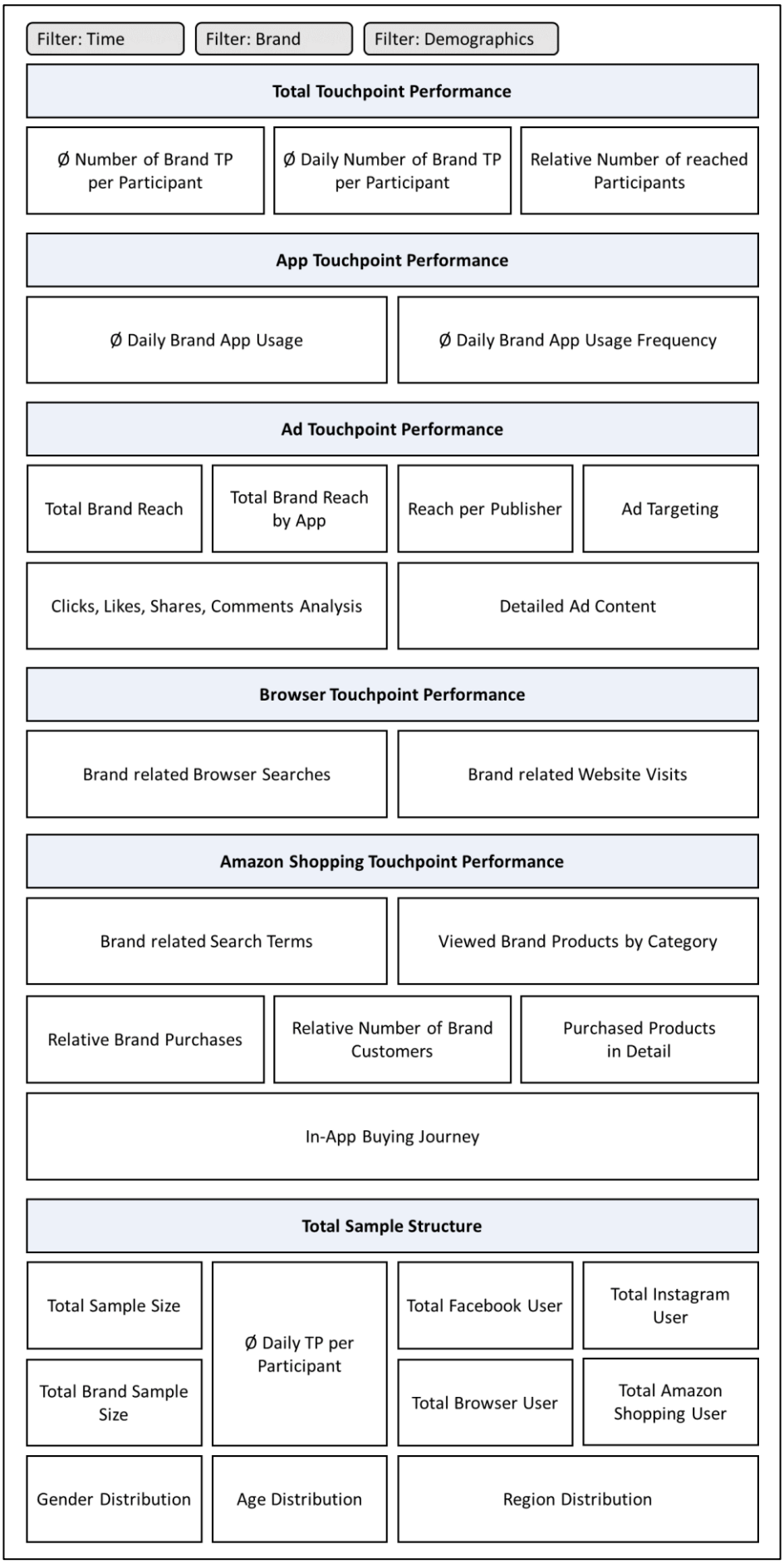


Figure 15: Touchpoint Performance Analytics Concept (own illustration)

Followed by this, the next dashboard section holds the advertisement performance based on the *daily ads* dataset. Since there has been previous research conducted on this dataset, more detailed implications for the concept can be drawn.[143] At first, the ad reach is displayed, which is a commonly used KPI in advertising research.[144] In this case, the indicator calculates how many people are reached by a company with advertisement in social media apps. As companies advertise on social media with multiple accounts, the reach is also generated for each advertising account.[145] Moreover, the results are differentiated by social media app for evaluating the ad performance separately for each platform. A third analysis should provide insights on how the (potential) customers of a company are targeted by other advertisers. The data analysis chapter examines what specific indicators could be used to conduct this analysis.

Besides the reach calculations, interactions such as clicks on ads, likes, shares and comments are used to measure the ad touchpoint performance. For this, the performance of each advertisement is evaluated by relying on the previous developed ad KPIs. This should assess what advertisements are most successful in terms of reach or interactions.

In the next section, brand or company related browser behaviour is analysed. Firstly, browser searches are extracted. Ideally, search terms including the brand or company name as well as search terms which are related to the company's industry, products or services should be displayed. In this way, it is possible to gain insights into what information users are seeking during their mobile customer journey. Thus, it gives implications on the information a company should provide to simplify the searching process. Furthermore, visits on company owned websites are analysed to track the mobile traffic in the filtered target group. Brand-related browser behaviour should also be assessed on websites that are not necessarily owned by the company, but where touchpoints are measured (e.g. retailer or online marketplaces).

The following part determines the in-app Amazon Shopping behaviour to generate insights on the shopping touchpoint performance. Considering the different interaction types in the dataset, insights concerning the prepurchase and purchase stage can be derived. Thus, the product searches related to a brand are analysed to see what the

[143] e.g., Murmuras, (2022e,f); Kleindienst and Halscheid, (2022); Halscheid (2021)
[144] Sutherland (2021), p. 22
[145] Table 20 in the appendix presents an example for multiple advertising accounts of the company Amazon.

chosen target group is specifically looking for in the app. Followed by that, viewed brand products are analysed by category. This is computed in relation to all products viewed in each category to get an idea of how many brand products are of interest in relation to all category products.

Subsequently, the focus is on brand purchases. For this, the relative number of ordered brand products and Amazon users who have bought at least one product of the filtered company are computed. On top of that, all purchased products are listed in detail by quantity and price. By including the exact timestamp, a company can see if their customers paid different prices for the same products. In addition, other relevant companies can be studied in order to gain a better understanding of the competition among the company's customers. Combining all actions captured in the Amazon app, the last analysis provides the in-app buying journey aggregated by time and Amazon app users. It is intended to show at what points in time brand products are actively searched for, viewed, or purchased.

For a better traceability of the generated insights, the last part of the concept contains information about the sample. First and foremost, the total number of participants in the chosen time frame as well as the sample size of participants who had at least one touchpoint with the filtered brand are computed. Additionally, the total numbers of Facebook, Instagram, Browser and Amazon Shopping app users are analysed. These absolute numbers provide information on the sample size and structure in terms of app usage in the filtered time frame and therefore helps to estimate the relative calculations in the upper sections. Besides this, the average daily events that are portraying potential touchpoints are computed. Lastly, demographic distribution among gender, age and region are given to provide general insights on the sample structure of the Murmuras study participants.

4.2.2.2 Target Group Analytics Concept

The second concept is designed to analyse mobile target groups for generating further information about (potential) customers. As explained in chapter 2.2.2, this also presents a research area in customer journey analytics. To be able to look at different target groups in the analysis, a filter based on different touchpoint types is integrated. These are derived from each dataset. For example, the touchpoint type *placed order* would generate results based on participants who have already bought a brand product. In

contrast, an ad touchpoint would include potential customers who have not made a mobile brand purchase. Besides this, a time and a brand filter are set similar to the touchpoint performance dashboard. By maintaining the structure of the first concept, this dashboard is subdivided into five main sections. The generated dashboard concept can be seen in Figure 16.[146]

The first section describes the chosen mobile target group by using demographic data. This provides basic information about how the filtered consumers are structured. It can be further used to identify new target group segments. For instance, a company finds out that the majority of potential customers within a mobile journey are young men between the age of 20 to 29, while the company mostly focused on mid-age men beforehand. For the analysis, the gender, age and regional distribution among study participants is calculated, as these demographics are available in the dataset. However, it is noted that the analysis is expandable by adding more sociodemographic variables such as income or household size.

The next section focuses on smartphone usage habits. The purpose of this analysis is to determine where the mobile target group is most likely to be reached. Consequently, the first step is to identify how intense and when (potential) customers are using their phones. Thus, the average phone usage is calculated on a daily basis and over time to observe changes in the phone usage intensity.

Hereafter, the focus is laid on app usage behaviour by analysing the most used apps within the target group. Therefore, the average app usage time and frequency as well as the relative number of app users are computed. The identical procedure is applied on the *daily category aggregation* dataset, as this could provide insights on general interests. As an example, a high category usage in media and press may indicate that the selected target group consumes current media and news primarily through their smartphones. This opens up several possibilities to address the target group.

[146] See page 44.

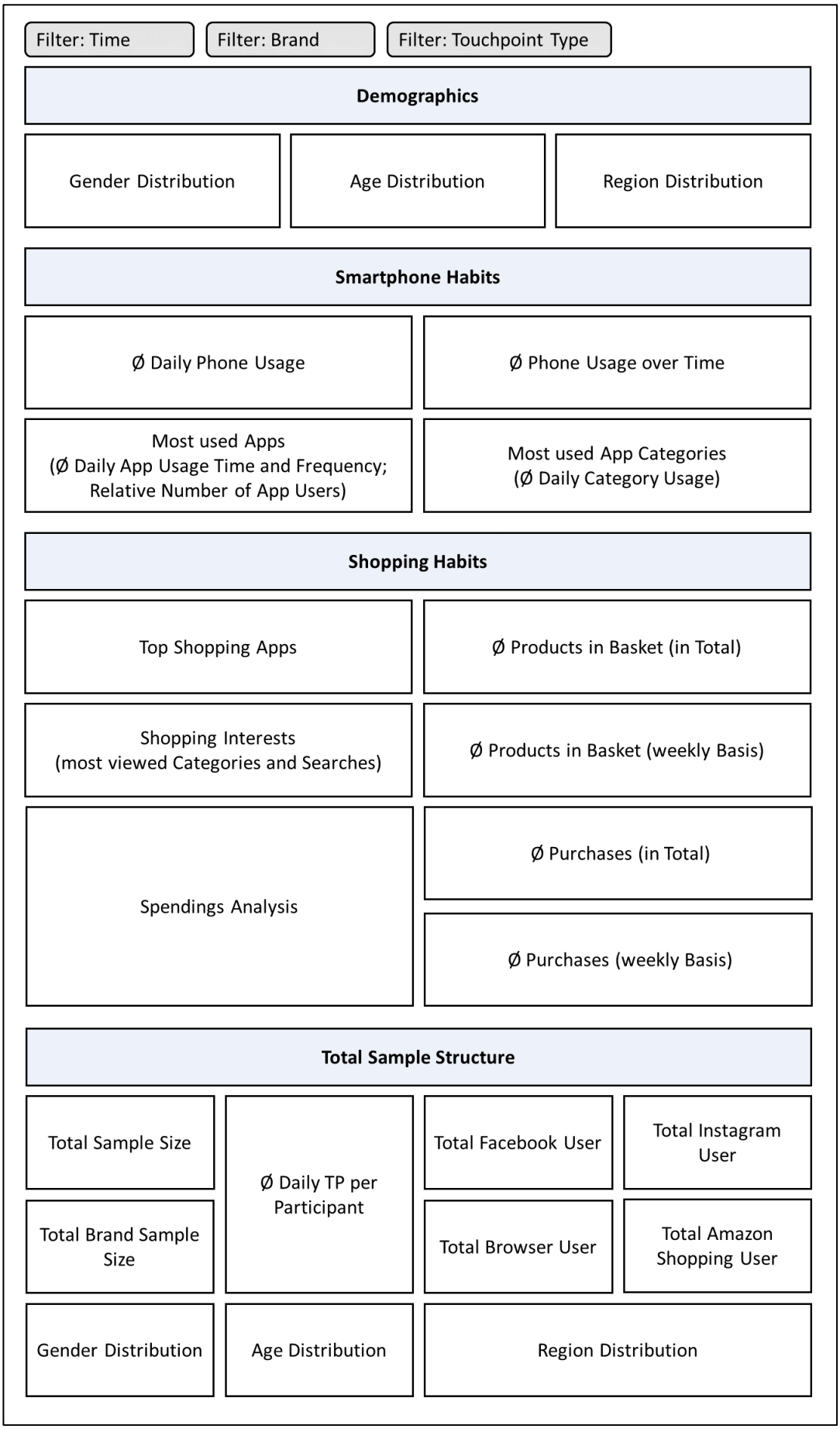


Figure 16: Target Group Analytics Concept (own illustration)

The last section of this dashboard analyses shopping habits drawn from shopping app usage and in-app shopping behaviour. It can be noted that once sensing data is available for more than just the Amazon app, these analyses could be extended to other shopping apps. With particular regard to shopping, one analysis computes the most frequent used shopping apps. In order to get a more detailed understanding of peoples mobile shopping behaviour and their shopping interests, most viewed shopping categories, most searched brands and products in the Amazon Shopping app are examined. Furthermore, a shopping basket analysis is carried out. For this, the average amount of products in the basket are computed over the entire time frame and on a weekly basis.

In relation to that, the purchasing power of the filtered target group is analysed by calculating the average mobile spendings on Amazon. Due to the format limitation of the price column, a cleaning procedure must be applied to the raw dataset before conducting the analysis.[147] Depending on the feasibility of this cleaning, further price-related analyses such as average spending over time or spending per product category could be performed. Regardless of the price column, the average number of purchases is calculated both in general and over time to assess how frequent the chosen target group is placing orders.

The last section is identical to the touchpoint performance dashboard and holds general information about the total sample. It is included in this concept so that the given insights are better understandable and comparable among different target groups.

4.2.2.3 Mobile Customer Journey Concept

The idea of the third concept is to illustrate mobile customer journeys. In combination with the insights generated by the touchpoint performance analytics dashboard and the target group analytics dashboard, these journeys aim to provide the basis to develop mobile customer journey maps. For this, the journeys are generated on an aggregated brand level as well as on an individual participant level. On one side, this allows to observe all touchpoints regarding a brand or company across multiple journeys and to detect rules as well as anomalies in the aggregated mobile journeys. On the other side, the individual perspective enables a company to understand consumer behaviour of real target group members along their personal customer journeys.

[147] A suggestion on how to clean the price column is given in chapter 3.2.3

Following the two previous concepts, all analyses are displayed on a dashboard with an integrated time and brand filter. In contrast to the other dashboards, this concept holds a third filter for calculating all results on an individual user level based on the personal participant code. Each code is assigned to a randomly generated user ID in order to protect the privacy of participants. The information about which code belongs to which user ID remains confidential. Figure 17 on the following page shows the mobile customer journey concept in four sections.

The first main part contains the mobile customer journey analysis. As a first step, the total number of brand touchpoints per touchpoint type is calculated. The results are then displayed over time on a daily basis to get a detailed view of the aggregated mobile journeys. However, this analysis can also be computed at a higher aggregation level, e.g., on a weekly, monthly or quarterly basis. When applying the brand filter to the described analysis, all brand touchpoints are displayed on a daily basis. In a long-term examination of the results, typical consumer behaviour among mobile customer journeys can be identified. For instance, a company could see that their potential customers who were reached at least twice with a social media campaign on Instagram mostly show a higher brand-related browser behaviour.

Subsequently, the average number of touchpoints per participant and day is computed. This should help to assess the total number of touchpoints, especially when comparing the aggregated brand journeys with relevant competitors. To ensure that the insights in the mobile journeys do not arise from changes in the sample size, the total number of participants is calculated and charted over time. This step may not be necessary in cases in which the sample remains constant over the whole data collection process.

When adding the user filter, all daily touchpoints between the chosen company the filtered participant are shown. The categorisation of the contact points enables the derivation of the individual mobile customer journey among all three stages of the mobile customer journey model. For instance, it may be seen that an Amazon user bought a product of the brand Adidas in the shopping app on the 21st of May 2022. Brand touchpoints captured before this event can be assigned to the prepurchase stage, while contact points after the purchase are more likely to show postpurchase interactions.

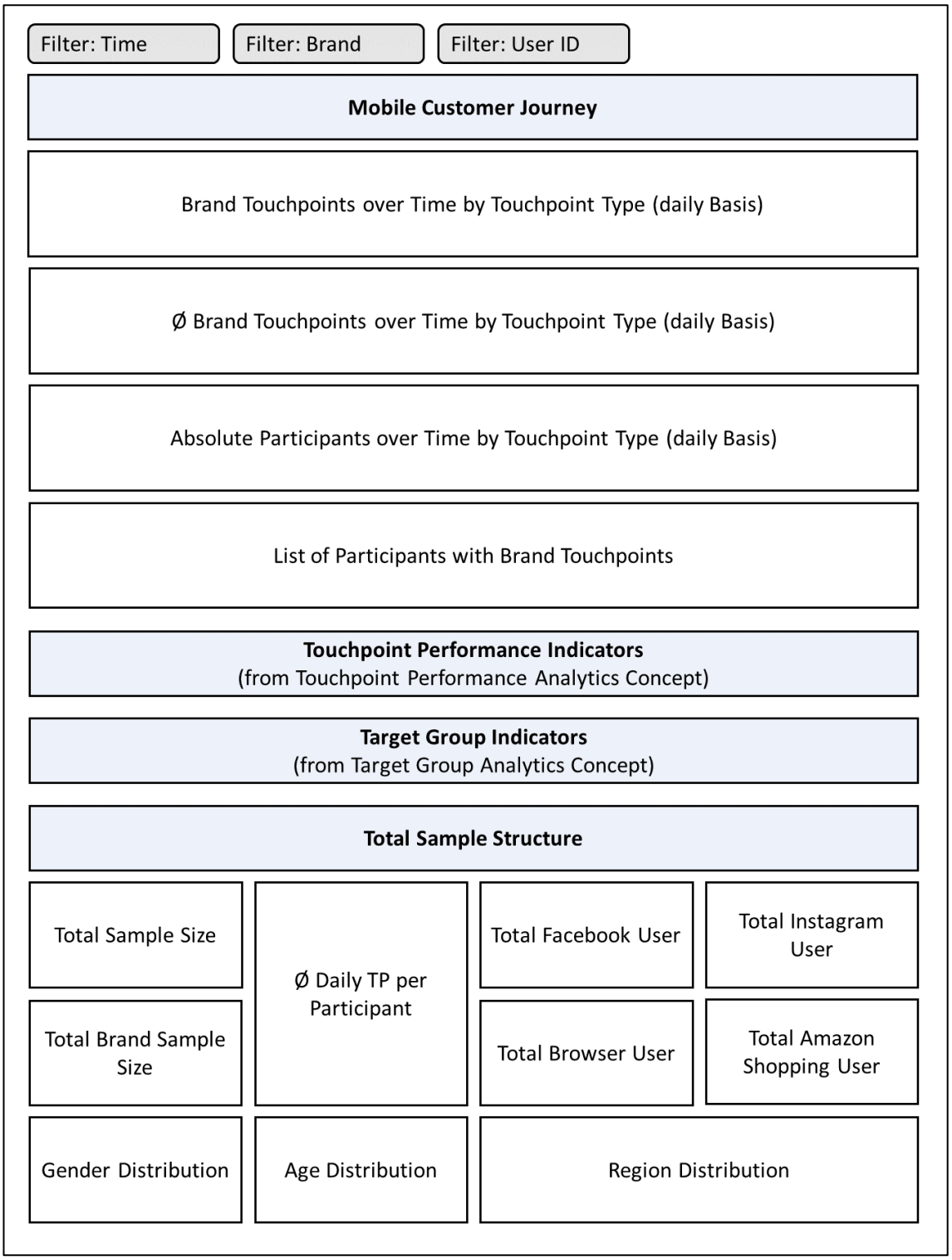


Figure 17: Mobile Customer Journey Analytics Concept (own illustration)

In order to apply the user filter, a list containing user IDs and the total number of brand touchpoints is created. Moreover, demographic information such as age and gender are included. This overview intends to provide insights on which study participants are of interest for the detailed mobile customer journey analysis. For example, a user who has several brand touchpoints in the Amazon shopping app in the touchpoint type *placed*

order can be identified as a customer. Thus, the entire mobile customer journey can be derived when analysing this user.

Aside from the mobile customer journey section, the dashboard includes two parts containing analyses from the touchpoint performance analytics concept and the target group analytics concept. This should give additional information about a specific user when the user filter is applied. It could be examined, which ads the customer has seen as this might imply why this person started a mobile customer journey or decided to buy a product. Which particular analyses are helpful when focusing on the participant perspective is evaluated during the explorative data analysis.

The last section of this concept contains the overall sample structure, similar to the previous two dashboards to make the results more comprehensive.

5 Analysis

This chapter describes the implementation of the developed analysis concepts. First, the analysis procedure is illustrated. Hereafter, the results are presented. Subsequently, limitations are examined.

5.1 Analysis Procedure

The sensing data analysis is mainly performed on the data platform Metabase as all relevant datasets are easily accessible here. Initially, a workspace is created which includes folders for organising the generated analyses and dashboards. In the following step, the basis dashboards are generated, to which the analyses are added.

Before beginning the analysis based on the first concept, a table is created combining in-app data from Facebook, Instagram, Amazon and Browser apps. As skills in the pre-data processing are required to do this, the new dataset is created with support from Murmuras analytics team. Subsequently, the table *study touchpoints* is uploaded to Metabase. Table 15 shows an excerpt of the dataset.

Table 15: Raw data excerpt from the study touchpoint dataset (own illustration)

User ID	Participant Code	Study ID	Time	Source App	Brand	Touchpoint Type
155426	FDvjT57Lmws	123	08.02.2022 16:33:20	Facebook	adidas	ad
155426	FDvjT57Lmws	123	08.02.2022 19:30:52	Facebook	Lidl Deutschland	ad
155426	FDvjT57Lmws	123	08.02.2022 20:20:45	Chrome	lidl.de	weblink
155426	FDvjT57Lmws	123	09.02.2022 12:02:12	Amazon Shopping	Original Kaiser Classic	shopping_detail
155426	FDvjT57Lmws	123	09.02.2021 16:22:36	Amazon Shopping	KitchenCraft Antihaftb	shopping_placed_order

Within the dataset, randomised *user IDs* are already considered for the analysis of individual mobile customer journeys. Besides that, the *participant code*, the *study ID*, a precises timestamp, and a source app column are included. The next column *brand* is the basis for the brand filter and is filled by selecting different columns from the considered datasets. For all captured social media ads, the publisher is used as brand, because it already includes the company or brand name. The shopping interactions dataset provides a brand column. However, as most brands are missing and the column is not cleaned, it is not suitable as filter basis. For this reason, the *product name* column is used instead. Following the same principle for the browser data, the *weblink* and the *search* columns are used as filter variables. Hereafter, the touchpoint types are computed based on the initial dataset. An overview of the touchpoint types can be seen in Table 16.

Table 16: Overview of all touchpoint types (own illustration)

Touchpoint Type	Dataset	Description
ad	Daily Ads	A touchpoint is marked as ad, when it is captured in social media apps (here: Facebook and Instagram).
weblink	Browser Data	A touchpoint is marked as weblink, when users are visiting a website via their mobile browser app.
search	Browser Data	A touchpoint is marked as search, when users are inserting a search term in the search bar in their mobile browser app.
shopping_search	Amazon Shopping Data	A touchpoint is marked as shopping_search, when users are inserting a search term in the search bar in the Amazon Shopping app.
shopping_detail	Amazon Shopping Data	A touchpoint is marked as shopping_detail, when users are clicking on a product in the Amazon Shopping app to see product details.
shopping_basket	Amazon Shopping Data	A touchpoint is marked as shopping_basket, when users put a product in the basket in the Amazon Shopping app.
shopping_checkout	Amazon Shopping Data	A touchpoint is marked as shopping_checkout, when users get to the checkout site during the purchase process in the Amazon Shopping app.
shopping_placed_order	Amazon Shopping Data	A touchpoint is marked as shopping_placed_order, when users completed the purchase process for a product in the Amazon Shopping app.

Regarding the shopping touchpoint types, it should be added that these may need to be adapted when in-app data from further shopping apps is added. This is necessary as the shopping process could differ compared to the Amazon Shopping app. As an example,

the Lidl Plus app contains a coupon section, which cannot be found in Amazon. As this section can be considered as relevant along the customer journey, it should be categorised as touchpoint type. [148] Thus, it is suggested to either extend the shopping touchpoint types or merge all shopping touchpoints to one type.

After completing the previous steps, the first analyses of the touchpoint performance analytics concept are performed and added to the basis dashboard.[149] As a next step, the dashboard filters are integrated and tested with these analyses. The time filter is based on the *time* or *date* column and is set to the defined time frame from the 1st of October 2021 to the 31st of August of 2022. All time-related filter options are selected in the settings since this filter has been designed to be used flexible. The options are presented in Figure 18.

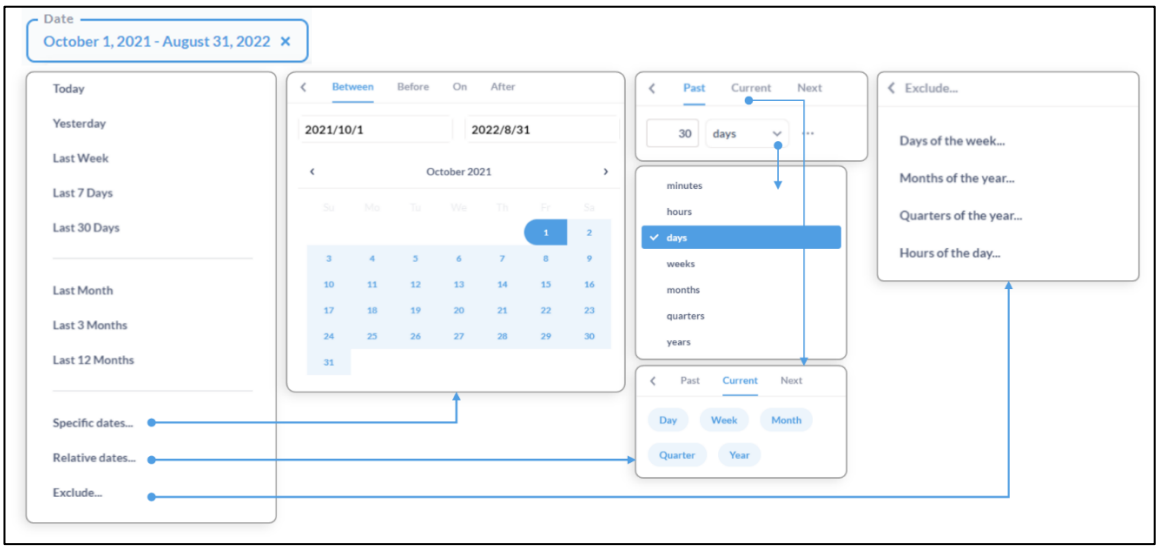


Figure 18: Time filter options (own illustration)

The brand filter is based on a text search. In order to apply the filter, the brand or company name must be entered into the filter field. The filter is working case insensitive, which means that both brand names written in lower and upper cases are considered in the analysis. As soon as a brand is inserted, results for that brand are generated. In addition, a second brand filter is connected to the ad touchpoint performance section. As advertising insights should be generated based on the company owned advertisement accounts, the filter offers the option to select all relevant publisher out of a list. This allows a more precise advertising analysis.

[148] Lidl (2022)
[149] All analyses procedures are precisely documented and can be found in the digital appendix.

In the next step, the demographics filters for gender and age are added. While testing both filters, multiple timeouts were produced because the query took longer than 60 seconds.[150] The query is automatically stopped after 60 seconds to ensure a fast insight generation. As a result, no insights are produced. Workarounds for extending the query time have been proposed.[151] However, the approach is not useful for this analysis as results should be generated fast and flexible by applying filter options. For this reason, the cause of the timeout is examined. It is assumed that the error is caused by joining the basic datasets with the *demographics* dataset, since it appears when the demographics filter is applied. To solve the issue, this filter is not integrated into the touchpoint performance analytics dashboard as it is not particularly required to perform the analysis. It should be considered to include basic demographic information such as age, gender and region in the raw datasets to avoid the join process in future analyses.

After integrating all filters into the dashboards, the constructed analyses are implemented. During the creation process of the mobile customer journey dashboard, it was determined that most of the insights generated in the first two dashboards are also valuable for an individual user analysis. Hence, the mobile customer journey concept is incorporated into both dashboards instead of adding all analyses to a third dashboard. Individual and aggregated brand journeys can be analysed in the touchpoint performance dashboard, while detailed user information is available in the target group dashboard. For this, the user filter is added to both dashboards. The filter is based on the participant code, because the randomised *user ID* has not been integrated to all datasets yet. Thus, all displayed participant codes are hashed in the upcoming results to secure the users privacy. For future analysis and publication purposes it is recommended to integrate the *user ID* column into all basic datasets.

5.2 Touchpoint Performance Analytics Dashboard

This chapter presents analyses that are performed on the touchpoint performance analytics dashboard. In each case, an exemplary brand is used to illustrate the results of the analysis. Thus, the brand has to meet two requirements. First, the company should be popular, as it is expected that more touchpoints will be visible in the sensing data. Additionally, brand purchases should be captured in the Amazon Shopping app. This allows

[150] Error documentation can be seen in the analysis documentation in the digital appendix. See analysis "3.1.1. Participants with Brand TP".
[151] Github Metabase (2020)

to generate insights for displaying the entire mobile customer journey. Both requirements are met by the brand Adidas. Globally and in Germany, Adidas is ranked among the top five most valuable fashion brands.[152] In total, 14 brand purchases could be captured.[153] The brand is therefore inserted in the brand filter and in the ad-related brand filter, 15 advertising accounts are selected. Several Adidas publishers are not chosen, either because they are not real accounts (e.g. FC Bayern München with Adidas Fußball) or because they are international accounts with ads from other countries (e.g. adidasbrasil, adidasthailand). Subsequently, the time filter is set to the pre-defined time frame. The user filter is not applied yet as the individual touchpoint performance is analysed later. The filter settings can be seen in Figure 19.

Figure 19: Filter settings on the Touchpoint Performance Analytics Dashboard – Example Adidas (own analysis)

Formerly, it must be noted that all presented brand insights are exclusively applicable to the sample and cannot be generalised due to the missing representativeness of the sample. The following subchapters are describing the results of each dashboard section.

5.2.1 Total Touchpoint Performance

The first dashboard part includes the total touchpoint performance parameters developed in the theoretical concept as well as the analysis for displaying the mobile customer journey. The results are shown in Figure 20.

Initially, the share of participants with brand touchpoints and the average brand touchpoints per user are calculated. No performance-related issues are identified during the analysis. With regard to the example brand, it can be seen that one fifth of all study participants have 33 touchpoints with Adidas on their smartphone on average. Furthermore, it can be said that every participant with brand touchpoints has one contact point with Adidas every three days on average. Taking into account that a typical smartphone user has approximately 59 touchpoints per day, the Adidas touchpoints can be

[152] Brand Finance (2022), p. 11; Statista (2021) as cited in IFDAQ (2021)
[153] The analysis can be seen in the analysis documentation in the digital appendix. See analysis “3.6.12. purchased Products”.

considered small.[154] Thus, Adidas could still improve their reach and contact frequency among smartphone users in this sample.

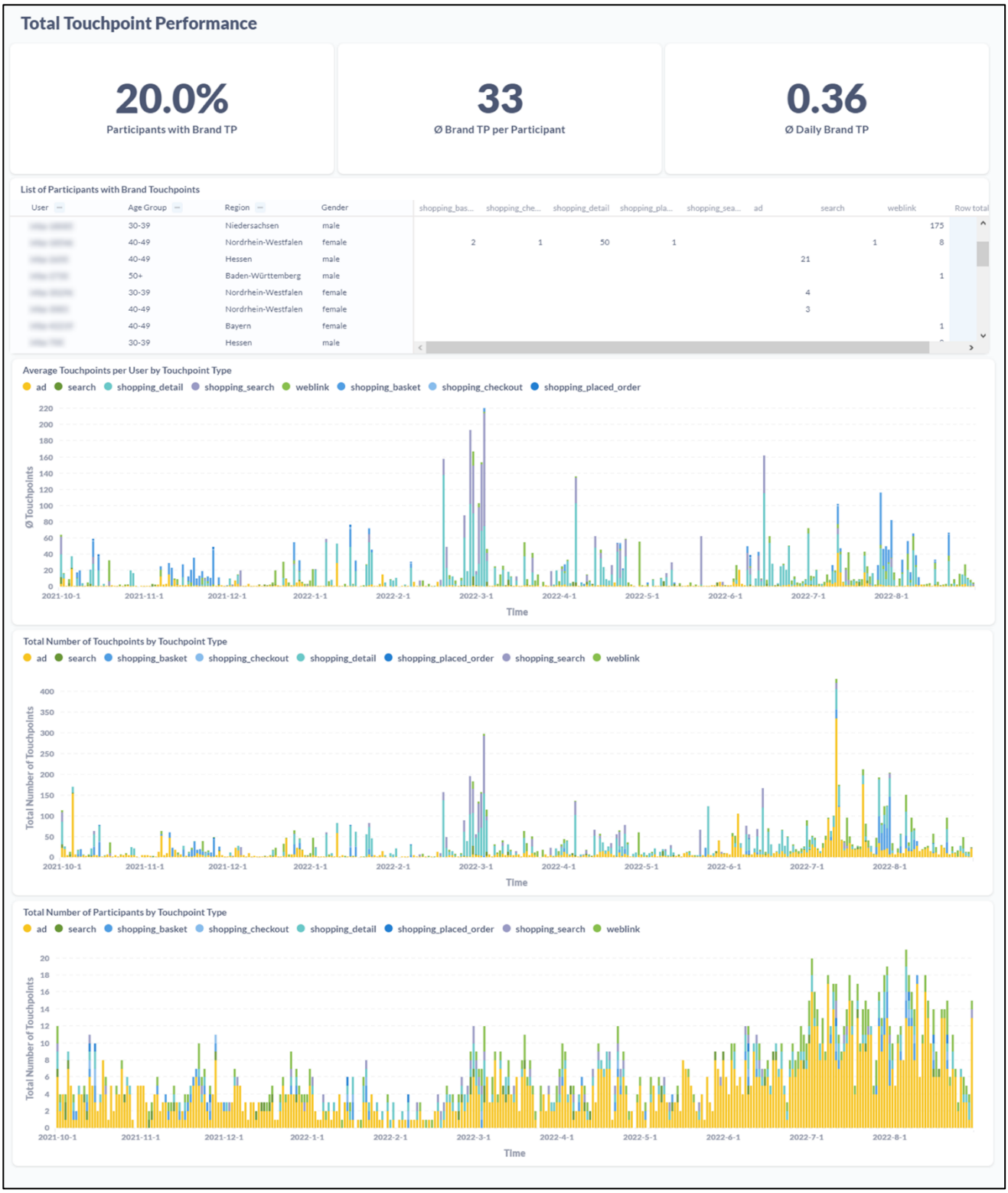


Figure 20: Total Touchpoint Performance and Mobile Customer Journey analysis – Example Adidas (own analysis)

[154] The average daily touchpoints per participant are calculated in the last section of this dashboard. The result can be seen in Figure 26.

Next, the participant list is computed. The output is not primarily relevant for the aggregated brand performance analysis, as it is used for the individual mobile customer journey analysis. However, the list provides an overview of all study participants who have at least one touchpoint with the filtered brand. Regarding the analysis process it must be noted that the visualisation by using a PIVOT table takes more than two minutes loading time in the dashboard.[155] This is too long considering the fact that the dashboard should present insights efficiently. Since results are still shown, this issue is not essentially important for the analysis in this thesis. Nonetheless, it should be thought about a different visualisation in order to guarantee a fast insight generation.

Subsequently, the mobile customer journey analyses are presented in three bar charts below the general touchpoint performance indicators. In order to provide a better overview, no values are directly displayed in the charts. However, when hovering over the bars, values are displayed. An example is illustrated in Figure 21.

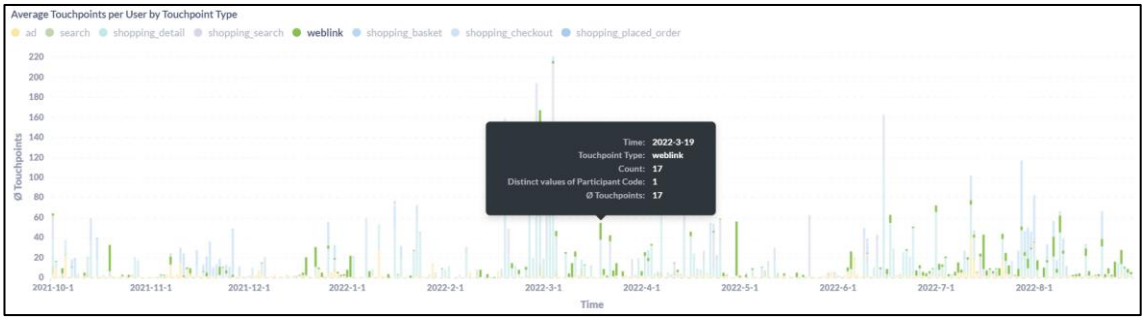


Figure 21: Detailed values in Mobile Customer Journey analysis (own analysis)

The first bar chart shows that Adidas touchpoints are captured across all touchpoint types, which means that the company's' performance can be assessed in all datasets. In particular, advertising touchpoints are continuously measured over the entire time period. On the 12th of July 2022, the average daily ad touchpoints were particularly striking as social media users have received 42 Adidas ads on average. As there have not been any recruitment of new participants at this time[156], it can be assumed that Adidas pushed a specific campaign to target groups that are represented in the sample.

Additionally, it can be said that shopping touchpoints are noticeably high, especially between 18.02.2022 to 25.04.2022 and 09.06.2022 to 10.08.2022. For instance, on the 4th of March 2022 every participant had 260 shopping-related touchpoints with Adidas on

[155] The query itself does not produce any timeouts and generates results in less than 60 seconds.
[156] For assessing this, the analysis for evaluating the sample stability in chapter 4.2.1.1 is used.

average. However, this seems rather unrealistic. When examining the absolute user number calculated in the third bar chart, it is noticeable that all touchpoints are measured on one device on this day. With regard to the dataset limitations, it is assumed that this issue is caused by a large number of duplications in the basis dataset. To verify this cause, the Amazon Shopping interaction dataset is exemplary analysed on the 04.03.2022.[157] The results show multiple duplications in the data captured on this day. It can be concluded that the anomaly occurred due to uncleaned data in the basis dataset. Since the data cleaning can only be performed in the pre-data processing step, touchpoints related to Amazon shopping data cannot be interpreted yet.[158] Nonetheless, the aggregated customer journey analysis still provides a useful overview on the captured brand touchpoints over time.

5.2.2 App Touchpoint Performance

In the following section the app performance indicators are described. Besides app usage time and frequency, the relative number of app users is calculated to gain an understanding of how common the brand app is used in the sample. In the first attempt all indicators are combined with a SQL analysis. However, the query results in a timeout. Considering previous analysis experiences, this could be caused by dashboard filters and calculating three different indicators across the entire dataset in one query. Consequently, it is decided to run singular analyses for each indicator. Thereby, the performance issue could be solved. The results are illustrated in Figure 22.

App Touchpoint Performance

Brand Apps - Relative Number of App User

App Name	App User %
adidas Running	3.2%
adidas	1.8%

Brand Apps - Average daily Usage Time

App Name	Ø Daily Usage Time in min.
adidas Running	7.34 min.
adidas	4.71 min.

Brand Apps - App Usage Frequency

App Name	Ø App Starts per User
adidas Running	24
adidas	9

Figure 22: App Touchpoint Performance – Example Adidas (own analysis)

It is observable that two Adidas apps are used: the Adidas app for shopping brand products and the Adidas Running app for tracking the own running performance.[159] Both

[157] The results are presented in Table 21 in the appendix.
[158] Q. Kasem (personal communication, October 16, 2022)
[159] Google Play (2022a,b)

apps are used by a relatively small number of participants as can be seen in the first analysis. Consequently, contacting the study participants via the apps is not efficient.

However, the app analyses show that the Adidas Running app is used longer and more frequent than the Adidas shopping app. Assumably, the Adidas app users have a particular interest in the brand, as they decided to download an app with only brand-related products and services. Hence, they are presenting a relevant target group for the company. It may be useful to analyse the mobile customer journey of Adidas app users to get a better understanding of how they are interacting with the brand on their phone.

5.2.3 Ad Touchpoint Performance

This part focuses on analysing the mobile advertising performance of Adidas. All results are displayed in Figure 23.

In order to get a better understanding of the data quantity, general numbers implicating how many brand touchpoints are captured on participants' phones are provided. For this, the absolute and relative number of brand ad touchpoints are calculated. For Adidas, 2,009 ad touchpoints could be counted. This represents only 0.1% of all ads in the dataset during the given time period. It is concluded that Adidas faces strong competition in the advertising environment on social media as their potential customers receive a fair amount of ads. However, for assessing the ad touchpoint performance of the brand more indicators need to be considered.

For this, the general ad performance is described in three analyses. According to the developed concept, the number of social media users reached at least once by the chosen brand is calculated. Adidas reached approximately 18% of all Facebook and Instagram users in the sample. Among Instagram users, only 8.7% have seen an Adidas ad, while in the Facebook app more than twice as many users are reached. Accordingly, the brand is more likely to reach their potential customers on Facebook. This is also evident from the reach analysis of each advertising account. The highest reach is generated by the official Adidas account on Facebook, followed by the same account on Instagram. Accounts with specific brand-related topics such as basketball or golf are reaching less participants on social media.[160] Nevertheless, it may be possible that Adidas has advertised more on this platform in the observation period. Thus, Adidas should use their

[160] The full results can be seen in File 3 in the digital appendix.

internal information on their advertising efforts to interpret the given ad performance indicators.

To determine how frequent the targeted users in the sample are contacted, the average number of ad touchpoints is calculated. On average, every reached participant has seen nine Adidas ads in the defined time frame. It is estimated that Facebook users view eleven brand ads on average, while Instagram users see only two. This is expected as the general advertising reach is higher on Facebook.

Figure 23: Ad Touchpoint Performance – Example Adidas (own analysis)

Next, an ad targeting analysis is developed in corporation with Murmuras' analytics team to get an overview on the advertising environment. The output displays a list of advertisers that are targeting the same social media users in the sample with their ad campaigns. First, the advertiser reach is calculated, similarly to the publisher reach. Hereafter, the brand reach is computed. It illustrates how many users are reached by a publisher within the group of people that were reached by the filtered brand, in this case Adidas. As an example, Adidas has reached 100 users in total. From these users,

the publisher Nike reached 50 users. This results in a brand reach of 50%. Combining both parameters, the reach proportion is given, which indicates how likely it is to receive a competitive ad from the displayed publishers.

When looking at the first ten publishers listed in the ad targeting analysis, it can be observed that Reebok reaches ca. 5% of the social media users in the sample. However, within Adidas' ad target group Reebok reaches approximately one quarter. With regard to the reach proportion, it can be stated that the probability of receiving a Reebok ad is more than five times higher for users who are targeted by Adidas. This is advantageous for Adidas as Reebok belongs to the Adidas group.[161] Nonetheless, in terms of advertising awareness both brands could be seen as competitors. Thus, it may be useful to examine the touchpoint performance of both brands in order to compare them.

Furthermore, the sports brand Snipes reaches more than one fifth of Adidas target group.[162] The probability for getting a Snipes ad in this group is 4.4 times higher than for the rest of the sample. Hence, this brand can be identified as a relevant competitor in the advertising environment of Adidas. It is recommended to observe this brand with the developed analyses as it may impacts the journey of potential Adidas customers.

The ad targeting analysis not only provides insights about relevant competitors, but further gives information on what ads the targeted users receive outside of the competitive industry. This helps a company to understand their entire advertising environment in the mobile customer journey context. In case of products and services being compatible, it is suggested to set up collaborations with these companies to extent their brand awareness in their target groups. As can be seen in the top ten publishers in the ad targeting analysis, other companies such as Superdry or Ahoj-Brause are targeting the same users as Adidas.[163] Since Superdry sells clothes, a collaboration may be beneficial for both brands.[164]

The last step in the analysis of the ads involves analysing the detailed content of each ad. With regard to the previous analysis, similar indicators are calculated to assess the individual ad performance. This includes the share of users who are reached by an ad as

[161] Adidas (2021), p. 74
[162] Snipes (2022)
[163] The full results can be seen in File 4 in the digital appendix.
[164] Superdry (2022)

well as the frequency they are reached. Based on this, the average ad impressions per user are computed. Since the dataset already counts the total number of likes, clicks, shares and comments, these indicators are also incorporated in the ad content analysis. The most seen Adidas ad in Facebook and Instagram has the ad text: “Cool, casual und immer up to date.”[165] This ad reached approximately 9% of all Facebook users and ca. 1% of all Instagram users. In total, the ad was seen 969 times. On average, every Facebook user has seen it around twelve times, while Instagram users have seen it ca. two times in the defined period. While on Instagram no interactions could be measured, the ad generated more than 370 clicks, 23 likes, one comment and has been shared by one participant. Among the sample participants, no other Adidas advertisement achieved such high results. Thus, it is identified as the most successful ad of the brand in the sample.[166]

5.2.4 Browser Touchpoint Performance

In this section, insights about the browser behaviour are generated. The results are presented in Figure 24. Aligned to the ad touchpoint performance part, the absolute number of brand-related browser touchpoints and the brand touchpoint share are calculated. Moreover, the relative number of users with touchpoints in the browser and the average number of brand touchpoints per participant is displayed. With regard to the example brand, it is observable that in total 2,663 browser touchpoints with Adidas could be measured, which accounts ca. 0.034% of all collected browser events. These touchpoints are measured from approximately 15% of all participants. In the given time frame, these users had 17 touchpoints with the brand Adidas in their mobile browser app on average. It can be argued that potential customers of Adidas do not show a strong browser search behaviour related to the brand.

Nevertheless, the brand referred browser searches, visited website domains and weblinks are analysed to further explore the browsing behaviour along the mobile customer journey. Because of the low sample size, the absolute numbers are calculated in all three analyses. When looking at the extracted brand-related website domains, it can be said that the Adidas website is the most frequent visited website. To make more precise

[165] For reference, the ad is shown in Figure 42 in the appendix.
[166] The full results can be seen in File 5 in the digital appendix.

statements about actual visits and users, further clustering of the website domains is needed, since all Adidas domains are listed separately.

Browser Touchpoint Performance

14.7%	17	0.034%	2,663
Total Browser Brand Reach	Ø Brand Browser TPs per Participant	Brand Browser Touchpoints Share	Total Brand Browser Touchpoints

Brand owned Website Domains

Website Domain	Source App	Absolute Website Visits	Absolute User
adidas.de	Chrome	875	51
google.com	Chrome	341	28
zalando.de	Chrome	33	13
click.link.adidas.com	Chrome	36	12
www.adidas.de	Samsung Internet	42	11
otto.de	Chrome	119	9
adidas.prf.hn	Chrome	11	7
adidas.de	Firefox	114	6

Rows 1-8 of 249

Brand related Searches

Search	Source App	Absolute Searches	Absolute User
adidas	Chrome	6	5
adidas	Google	5	3
adidas	Opera	1	1
adidas	Samsung Internet	1	1
adidas	Chrome	1	1
adidas	Google	1	1
Adidas	Chrome	1	1
adidas aa	Chrome	1	1

Rows 1-8 of 87

Brand related Weblinks

Link	Absolute Website Visits	Absolute User
adidas.de	180	29
adidas.de/cart	41	10
www.adidas.de	18	9
adidas.de/account-login	18	6
adidas.de/my-account	31	6
adidas.de/bestellverfolgung	7	5
adidas.de/wishlists	9	5
adidas.de/payment	6	4

Rows 1-8 of 1681

Figure 24: Browser Touchpoint Performance – Example Adidas (own analysis)

Besides the brand owned website, study participants are looking for adidas products on shopping websites such as Zalando, Otto or idealo. Second in terms of visits is google.com, which indicates that these users actively searched for the brand in the Google Chrome browser.[167] This can be verified by looking at the brand-related browser searches. It is shown that most participants directly searched for the brand name. Furthermore, it is searched for specific products, for example the adidas champions league ball, the adidas crossbody blau or adidas eqt csg 91 gore tex. These searches are of high interest for adidas, as they are indicating that the consumers are interested and may consider purchasing these items. With regard to the mobile customer journey model this already implies that the potential customers are in a prepurchase stage. However, it must be noted that similarly to website domains, there are duplications of search terms as a result of missing clustering. Thus, it is recommended to apply a clustering procedure to the weblinks dataset in order to produce aggregated results that are easier to interpret.[168]

When looking at the collected brand-related weblinks, purchase processes can be seen, e.g., *adidas.de/cart* shows that a website visitor has put a product in the basket.[169] This

[167] The full results can be seen in File 6 in the digital appendix.
[168] The full results can be seen in File 7 in the digital appendix.
[169] The full results can be seen in File 8 in the digital appendix.

information might already be available to the company because of their own tracking solutions on the brand owned websites. Nonetheless, these insights are still valuable for the individual customer journey analysis as the journey of a website visitor can be tracked backwards. Moreover, the data can be used to observe consumer behaviour on competitive websites.

5.2.5 Shopping Touchpoint Performance

The following section provides insights on the purchase performance of the selected brand, which are shown in Figure 25. Similar to the previous parts, general parameters about the shopping behaviour are generated. In general, 4,806 Adidas touchpoints are measured in the shopping app, which accounts for ca. 0.3% of all collected shopping events in the basis dataset. Additionally, it is detectable that approximately 7.8% of all Amazon Shopping app users in the sample have 64 touchpoints with Adidas on average. However, due to the duplication issue of the raw dataset, calculations based on the total number of touchpoints are not reliable yet. Accordingly, the following analyses have been adjusted to ensure accurate results and interpretation.

With regard to the analysis concept, the brand-related searches within the shopping app are analysed. For quantifying the searches, it is decided to calculate the total and relative number of brand searches. For this, the unique searches are considered to avoid duplications in the dataset. During the given time frame, 92 searches containing the brand name Adidas are captured. Considering all searches within Amazon, Adidas searches constitute 0.0022%. To have a more detailed view of the searches in the Amazon shopping app, a list including all brand-related searches is computed.[170] In addition, the relative number of Amazon users who used this search term is given. Amazon users are searching for a variety of Adidas products such as *badelatschen herren adidas, adidas adilette herren* or *adidas anzug damen*. It can be inferred that the Adidas mobile target group is primarily interested in clothing. Regarding the calculations, it is noticed that some search terms are written differently but refer to the same product. Hence, it is recommended to apply clustering to the searches based on the filtered brand.

Next, all products viewed on the product detail page in the app are analysed. For this, the total and relative number of viewed brand products are calculated. Amazon app

[170] The full results can be seen in File 9 in the digital appendix.

users looked at 330 different Adidas products, which accounts for approximately 0.4% of all product views. Additionally, the relative number of viewed brand products is computed by category. For Adidas, most products are viewed in the categories clothing, shoes & handbags and sports & freetime activities. This is logic because Adidas offers products in these product segments.[171]

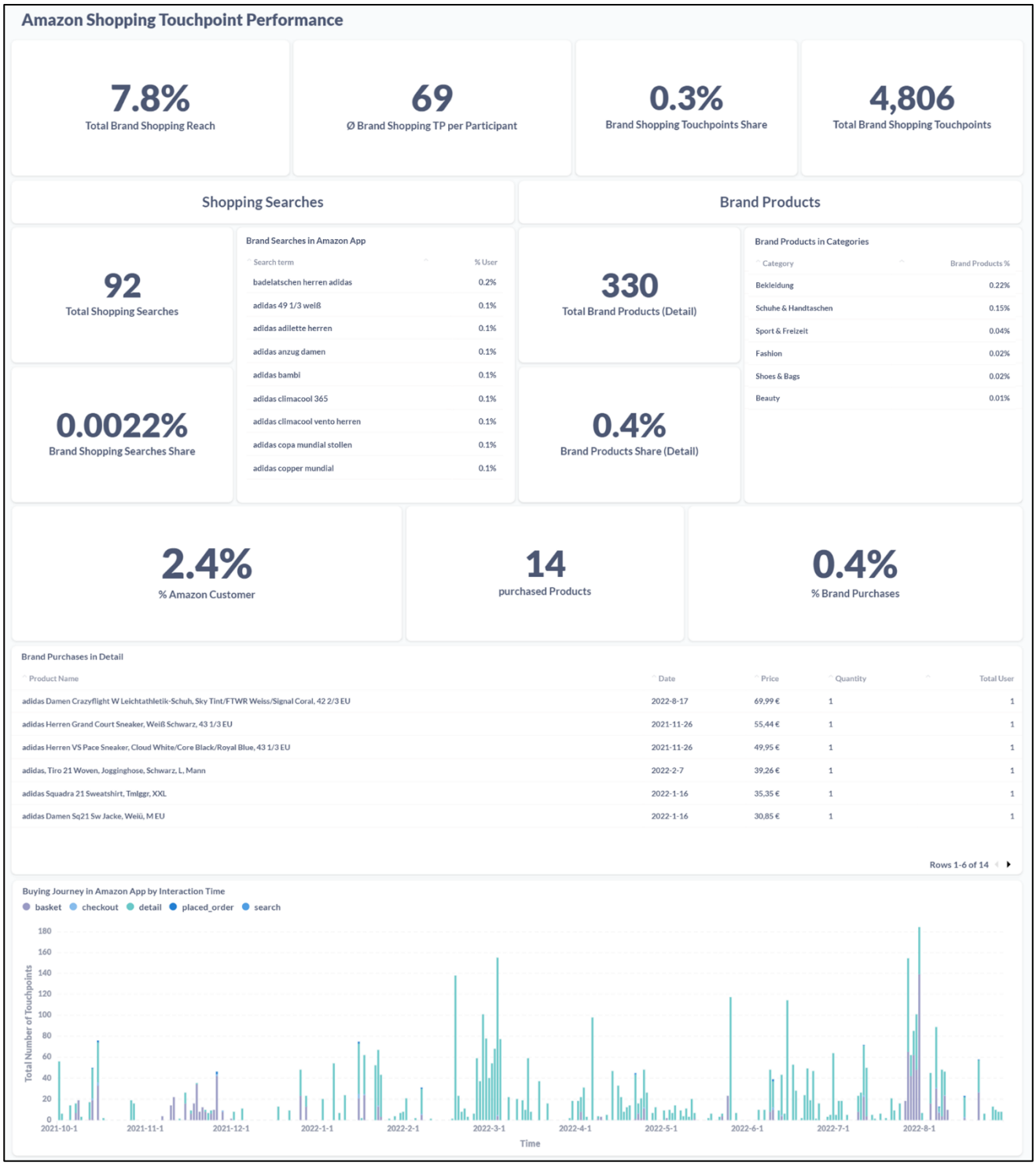


Figure 25: Shopping Touchpoint Performance – Example Adidas (own analysis)

[171] Adidas (2021)

As a next step, the purchase behaviour within the Amazon Shopping app is assessed. First, the relative number of users who purchased a brand product is computed. Furthermore, the absolute and relative amount of brand purchases are analysed. Within the given time frame, 2.4% of Amazon users, who purchased at least one product, ordered an Adidas product. In total, 14 brand products are bought. That makes 0.4% of all captured buying events in the app. In addition, all purchased items including the purchase date and exact price, the quantity and the total number of customers are displayed.[172] All items are ordered once. The most expensive product was a unisex sneaker for adults, which was purchased for 109.99 Euro in size 44. It can be concluded that pre-purchase behaviour in a shopping app is indicating shopping interests or even a purchase intention. Consequently, it is important to observe the brand-related shopping behaviour throughout the entire in-app shopping process. For this reason, the aggregated in-app buying journey is displayed, including all events derived from the column *interaction type* in the basis dataset. With reference to the previous statements about the duplication limitation, it must be stated that this overview is not meaningful yet. Nevertheless, it still provides information on when users are showing actions attributed to the filtered brand. In order to further estimate the shopping performance of Adidas, it is recommended to compare the indicators with sales figures regarding the distribution platform Amazon. Besides this, it may be useful to generate the analyses for competitive brands that are listed on Amazon to assess Adidas' position in the competition.

5.2.6 Total Sample Structure

In the last dashboard section, the sample structure is displayed as seen in Figure 26. Based on the theoretical concept, all analyses are implemented. In total, 1,702 smartphone users participated in the defined time frame. Of these, 340 people had at least one touchpoint with the brand Adidas. On average, every study participant sent approximately 59 in-app events per day. All relevant apps are used by more than 800 device owners.

[172] The full results can be seen in File 10 in the digital appendix.

Figure 26: Total Sample Structure (own analysis)

Gender, age and region distribution are analysed both with and without missing entries to estimate the sample structure in both cases. However, for 67% of the sample, the demographic distribution can be described. As it is outlined in the preliminary considerations regarding the time frame definition, the sample consists of slightly more male participants and is dominated by people over 40. Additionally, it can be seen that most participants are from North Rhine-Westphalia, followed by Bavaria and Lower Saxony.

5.3 Target Group Analytics Dashboard

In the following subchapters the target group analysis is performed based on the developed theoretical concept.[173] First, the time, brand and user filters are implemented as in the touchpoint performance analysis. The user filter is not applied yet, because the individual user analysis is conducted later. Furthermore, the target group filter is integrated based on the different touchpoint types that are generated in the *study touchpoint* dataset.

[173] For reference see chapter 4.2.2.2

Following the same analysis proceeding as in the first dashboard, all dashboard filters are tested with the first explorative analyses. The time and user filter are applied without any performance issues. Regarding the brand and target group filter, it must be said that all analyses are resulting in timeouts.[174] It is assumed that the connection of the analyses with the *study touchpoint* dataset significantly extents the query as two steps are required: First, the study touchpoint table is filtered by *brand* and *touchpoint type* to identify all relevant study participants. This prefiltered dataset is then used as basis for conducting the aimed analysis. This proceeding may lead to the observed performance issues. Thus, it is suggested to create a table that captures all brands and companies that participants have contact with through their phone. Further, these touchpoints should be sorted to a touchpoint type, similarly as in the *study touchpoint* dataset. Moreover, the timestamp should be integrated for time filtering. As this table uses less information than the *study touchpoint* dataset, the performance of the target group analyses should improve considerably. However, this process requires pre-data processing and testing before it can be implemented into the dashboard. Consequently, this solution cannot be used for the analysis conducted in this thesis. In order to provide insights on which analyses can be performed to describe the mobile phone behaviour, all analyses are computed based on the total sample. Hence, only the time filter is applied to the defined period.

5.3.1 Demographics

The first section of the target group dashboard provides basic demographic information about the target group. Aligned to the first analytics dashboard the age, gender and region distribution are displayed. As the results are illustrated for the total sample, the insights have been already described in the last section of the touchpoint performance analytics dashboard. Figure 27 presents how the demographics are shown in this dashboard. It is noted that further sociodemographic traits such as income, household size or education could be requested from the panel provider and added to this dashboard part to get deeper insights into the target group structure.

[174] Error documentation can be seen in the analysis documentation in the digital appendix. See analysis "4.1. Demographics".

Figure 27: Demographics – Total Sample (own analysis)

5.3.2 Smartphone Usage Habits

The next section analyses smartphone usage habits. As a first step, the average daily phone usage is calculated based on the *daily apps aggregation* dataset. In order to see usage differences over time, the smartphone usage is displayed on every day in the defined period. The total daily phone usage is integrated in the bar chart as a line to assess, if and when the device usage deviates from the total average. As a result, differences in the target group are more visible. In general, each participant in the sample uses their phone ca. four hours per day. Furthermore, seasonal effects can be observed. For instance, the lowest phone usage can be seen during Christmas on the 25th and the 26th of December 2021 and on new year eve on the 31st of December 2021. Additionally, it can be observed that the phone usage declines over the last half year. It is assumed that this is attributed to the summer season, during which people may spend more time outdoors than on their phones. To get evidence for this suggestion, the phone usage could be analysed in the third and fourth quarter of 2022 to see if the phone usage increases.

For more detailed information on what the participants are doing on their phone, it is analysed which apps are mostly used by calculating the relative amount of app users and the daily average app usage time. Both parameters are combined in one analysis. However, it must be noted that the data processing is causing a timeout. With regard to the experiences made in the app touchpoint performance analysis, both parameters are calculated in two different analyses to resolve this issue. The final results are illustrated in Figure 28.[175]

[175] The full results can be seen in File 11 and 12 in the digital appendix.

Figure 28: Smartphone Usage Habits – Total Sample (own analysis)

The most app users are measured for Chrome, Whatsapp, the Google Play Store, the Google Browser app and YouTube. In the sample, Whatsapp is used every day for approximately 28 minutes. The Google Play Store is only used less than two minutes, which is logical, because this app is mainly used for downloading android apps.[176] Besides this, it is observable that participants are browsing for almost half an hour per day on average. YouTube is also used for around 29 minutes on an average daily basis. It can be concluded that YouTube and Chrome offer good opportunities to reach sample members with advertisement. With regard to specific target groups, it is stated that these analyses are useful to identify relevant apps for communication purposes.

Besides that, the category usage is illustrated by computing the relative number of participants who are using an app in this category. Most category usage can be seen in communication, followed by productivity, tools and photography. All categories are used by more than 95% of the sample. This analysis may be particularly useful to observe target groups who use a wide range of apps. In this case, a better overview on the app usage habits could be provided, as the category usage aggregates the app usage.[177]

[176] Google Play (2022c)
[177] The full results can be seen in File 13 in the digital appendix.

5.3.3 Shopping Behaviour

In the third section of the dashboard the mobile shopping behaviour is analysed. As a first step, the most used shopping apps are assessed within the sample. For this purpose, the relative amount of app users of the top 20 most downloaded shopping apps in the Google Play Store in Germany is calculated.[178] However, the analysis is resulting in a timeout. In order to resolve this issue, the query is simplified by calculating the absolute number of app users. Hereafter, still no results are shown. Consequently, results cannot be generated with the developed analysis proceeding. Nevertheless, it is possible to use the app reach calculation from the prior section to manually calculate the app users.[179] The results are shown in Table 17.

Table 17: Top 20 Shopping Apps in the total sample (own analysis)

Shopping App	Reach in Sample	Rank Germany	Rank Sample	Rank Diff.
Amazon Shopping	39.3%	2	1	1
eBay Kleinanzeigen	32.0%	6	2	4
eBay	22.5%	14	3	11
Lidl Plus	17.2%	11	4	7
Mein dm	11.2%	12	5	7
Kaufland	10.1%	8	6	2
Vinted	8.7%	20	7	13
OTTO	7.7%	1	8	-7
Klarna	6.8%	3	9	-6
Zalando	6.8%	4	10	-6
AliExpress	5.7%	15	11	4
idealo	5.3%	5	12	-7
mydealz	4.0%	16	13	3
kaufDA	3.7%	9	14	-5
SHEIN	3.5%	7	15	-8
Etsy	2.5%	18	16	2
C&A	1.1%	13	17	-4
MeinProspekt	0.8%	10	18	-8
Zara	0.7%	19	19	0
Trendyol	0.3%	17	20	-3

In general, the Amazon Shopping app is the most used app in the sample, followed by both eBay apps. The top shopping app Otto is only owned by ca. 8% of the sample. Moreover, it can be observed that the second-hand shopping apps eBay Kleinanzeigen

[178] Similarweb (2022); In order to increase the analysis performance, the analysis is limited to the top 20 Shopping Apps for Android devices.
[179] Error documentation can be seen in the analysis documentation in the digital appendix. See analysis "4.3.1. Top Shopping Apps".

and Vinted are significantly more common among the sample users compared to the general app ranking in Germany. Thus, it is assumed that the study participants value sustainability in their mobile shopping. Additionally, it can be said that apps from clothing companies such as Shein, C&A, Zara and Trendyol are less popular. With regard to the shopping touchpoint performance for Adidas it can be suggested that participants are rather using digital marketplaces like Amazon or OTTO for buying clothes via their phone. To verify this, the in-app shopping data is further analysed in this dashboard section. The results can be seen in Figure 29.

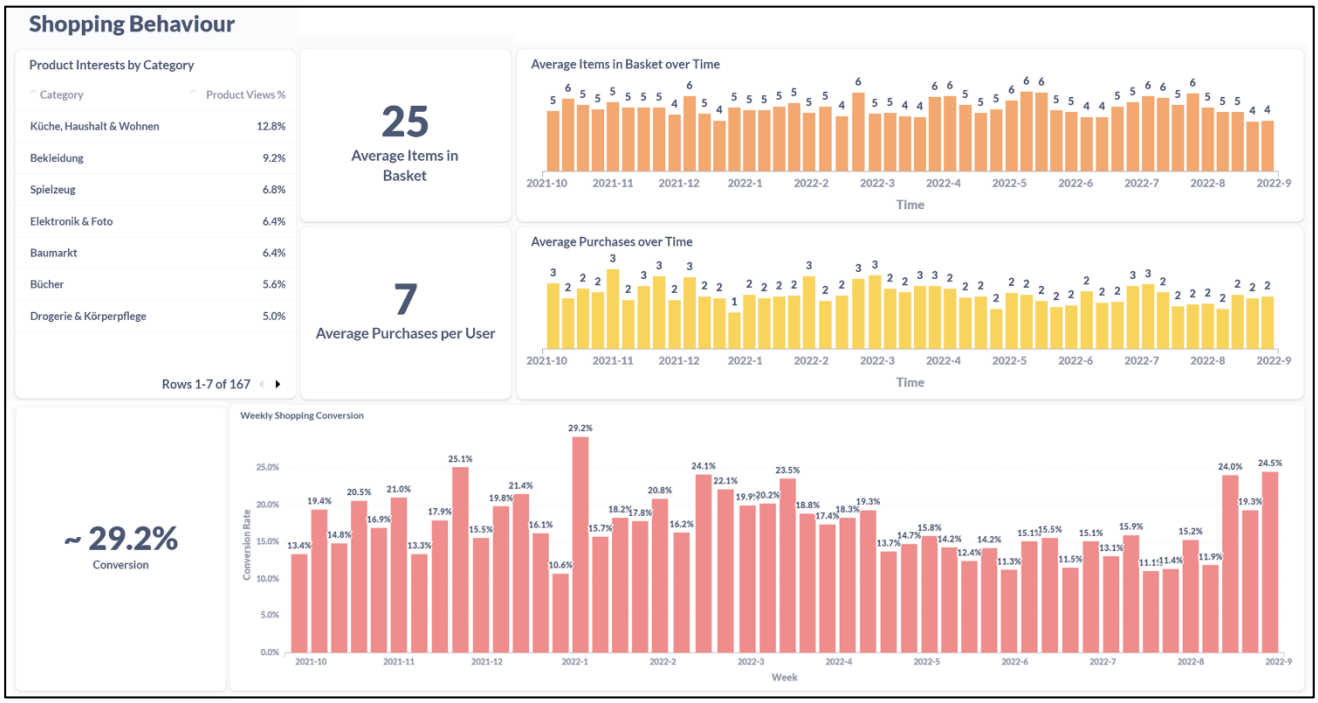


Figure 29: Shopping Behaviour – Total Sample (own analysis)

The theoretical concept proposes to calculate the average spendings in the target group. With regard to the format issue of the price column, this analysis cannot be performed in Metabase. Previous spending analyses have shown that data cleaning and analysis procedures can be conducted in Excel if the dataset contains less than one million rows. Otherwise, performance issues are produced. Therefore, the average spendings cannot be analysed on the basis of the total sample, because the dataset contains more than 1.5 million rows in the defined time frame.[180] Nevertheless, the data proceeding will be conducted when focusing on the individual mobile journey analysis in the third analytics part as it is expected that the dataset for one participant is relatively small. For this, a cleaning procedure is proposed in the analysis documentation.

[180] An exemplary analysis and cleaning proceeding can be found in File 14 the digital appendix and in the analysis documentation. See analysis “4.3.2. Ø Brand Spendings in Amazon”.

Next, product categories are analysed to determine which products the target group is mainly interested in. Among all Amazon app users in the sample approximately 13% of all viewed products are in the category *kitchen, household & living*, followed by *clothing* (ca. 9%) and *games* (ca. 7%). It can be seen that participants are mostly looking for products of daily use such as kitchen supplies or decorative products. Moreover, clothing such as underwear, baby clothes or active wear is of interest as well as games and games supplies such as board games and articles for children's birthday.[181] In reference to the previous remarks, it can be stated that participants are shopping for clothes in the Amazon app, which supports the suggestion about their mobile fashion shopping behaviour.

Furthermore, products in the basket of the Amazon app users are analysed to gather insights on what potential products are currently considered for purchasing. Initially, the average number of products in the basket is calculated. Preliminary, it can be noted that duplications are not occurring in the basket. In the given time frame every Amazon app user has 25 products in their basket on average. Whenever a target group is analysed, the total sample result will also be displayed, so that differences between the own target group and the total sample can be seen. Additionally, this analysis is displayed over time on a weekly basis for observing changes in the basket quantity. Among all study participants no striking anomalies can be seen. The average number of products in the basket in a week is six, while the lowest number is four. Thus, no seasonal effects such as Christmas shopping are observable for Amazon in this sample.

As a next step in the analysis, the average number of purchases are computed. Over the entire period, every Amazon customer bought seven products on average. On a weekly basis, it can be stated that three products are ordered at most per week and per participant. For further interpretation it is recommended to compare these results among different target groups and competitive brands.

Combining the results of the basket and purchase analyses, the conversion rate from the step of putting a product in the basket to the last step of placing an order is calculated. In total, almost 30% of all products in the basket are purchased. It can be concluded that Amazon app users are putting more products in the basket than they order.

[181] The full results can be seen in File 15 in the digital appendix.

This is particularly observable in the weekly conversion rate in the summer period of 2022 from the beginning of April to the beginning of August. In this period, smaller conversions are calculated. In comparison, in the winter period from October 2021 to beginning of January 2022 more products in the basket get purchased. Both observations can be interpreted as seasonal effects, as in winter Christmas shopping is done and therefore people are ordering more items via Amazon. Since the sample structure changed over the course of this thesis, these observations need further verification.[182] Moreover, it must be mentioned that the calculated conversion does not consider orders that are placed with the direct-purchase function in Amazon, because these purchases are not captured in the interaction type *basket* in the dataset. Hence, the conversion only covers the classic ordering process with *basket* and *placed order*. This should be considered when interpreting the results.

5.3.4 Total Sample Structure

In the last section of the target group analytics dashboard the total sample structure is illustrated. This part includes all analyses that have been already performed in the touchpoint performance analytics dashboard. Thus, the data proceedings can be copied for each analysis. Since the results have been described in the first analytics part, no further explanations are given here. For reference, the results can be seen in Figure 27.

5.4 Individual Mobile Customer Journey Analysis

Based on the developed analytics dashboards, the mobile customer journey of one exemplary study participant is analysed in this chapter to get insights into the consumption behaviour along the mobile brand journey. This is done by applying the user filter to generate all analyses on an individual level. It may be possible that not all analyses integrated in the dashboards are valuable for the user perspective. Thus, analyses without useful results are left out.

Align to the previous chapters, results are provided for the brand Adidas. As a first step, the participant list is generated in the first section of the total touchpoint performance dashboard with only including study participants who have at least one brand touchpoint in the given time frame.[183] Next, the participant is chosen based on three requirements. First, the smartphone user should have had several touchpoints across all

[182] For reference see chapter 4.2.1.1
[183] The results can be seen in Figure 20 in chapter 5.2.1

touchpoint types to illustrate the analysis based on all sensing datasets. Second, the user should have bought at least one Adidas product in the Amazon Shopping app. This, in turn, would classify the participant as brand customer and the entire mobile journey could be displayed. Besides this, demographic information should be available for better interpretation of the results. In order to secure the privacy of the participant, the participant code is hashed in the following analyses. In accordance with the created dashboards, the individual brand touchpoints are analysed at first, followed by the user information extracted from the target group analytics dashboard.

5.4.1 Individual Touchpoints

Initially, the individual brand touchpoints are analysed based on the touchpoint performance analytics dashboard. Since the structure of the dashboard has been outlined in the previous chapters, the results are displayed in the Figures 43 to 47 in the appendix.

The chosen participant is female, between 30 and 39 years old and lives in Berlin. This information is included in the participant list. Before proceeding with the touchpoint analysis, it should be reviewed how long the user is participating in the mobile tracking sample, as the participation period influences the analysis results. The person considered in this case is constantly sending data since the 20th of June 2022.[184] Thus, brand touchpoints are only measured between the 20.06.2022 and 31.08.2022. For comparing the mobile behaviour of this participant with the total sample, the time filter is adjusted on both dashboards for the total sample and individual analysis.[185]

In general, the user has had 165 contact points with Adidas during the defined period. Compared to the total sample with an average of 28 Adidas touchpoints, this woman had more than six times as many interactions with the brand. In addition, she has ca. one mobile contact with the brand per day on average. Accordingly, it can be concluded that this individual demonstrates strong brand affection as well as loyalty to the brand.

When analysing all touchpoints between the user and Adidas over time, it is visible that the first and last touchpoints are on the first and last day of the filtered time period. Both brand touchpoints are Adidas advertisements in social media. Besides this, a brand

[184] This is determined by an additional analysis. The result can be seen in File 16 in the digital appendix. The analysis proceeding can be found in the analysis documentation. See analysis “5.1. Participation Period”.

[185] The detailed results for the total sample in the adjusted time frame can be found in Figures 48 to 53 in the appendix.

purchase is captured on the 8th of August 2022. It takes approximately seven weeks from the first measured mobile brand contact until a brand product is ordered in the Amazon app. Considering these insights, it is possible to categorise all brand touchpoints into the three stages of the mobile customer journey model. Figure 30 shows all touchpoints and their categorisation to each stage. This gives a first overview of the individual customer journey. Moreover, it illustrates a first practical implementation of the mobile customer journey model. However, with further analysis of the touchpoints in the prepurchase stage, it may be possible to limit the time frame of this customer journey.

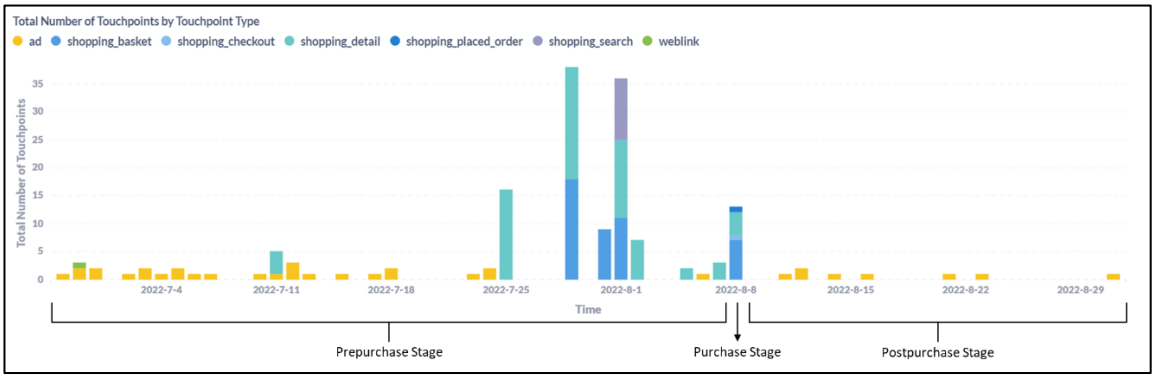


Figure 30: Individual Mobile Customer Journey (own analysis)

In the app performance section, no results are generated, which means that the female participant is not using an app from Adidas. Consequently, brand owned apps do not play a role in this customer journey.

The ad touchpoint performance part shows that the participant receives 28 Adidas ads over the entire customer journey only via the Facebook app. Among all mobile users with Adidas touchpoints, on average every participant gets nine ads in Facebook. Thus, the analysed user has almost three times more ad contacts than the total brand sample. This in turn confirms the brand affinity to Adidas and the relevance of this user for the company. Further, it can be analysed that all ads are sent from the publishers adidas and adidas Originals. Yet, the fact that the ads are only captured in Facebook may be explained in two ways: either the participant is not using Instagram, so in turn no ads can be collected in this app, or she is only targeted in the Facebook app by Adidas. This should be examined when analysing the smartphone usage habits in the target group analytics dashboard.

The ad targeting analysis cannot be interpreted on an individual user basis since the brand reach and reach proportion is calculated based on the sample size, which in this

case counts only one. Nevertheless, the list shows which other companies are targeting the mobile user. In total, she received advertisement of more than 3000 different publishers, for example from beauty companies such as *Glamourmed* or *Fmobeauty.de* or local companies from Berlin such as *EventConcept.Berlin* or *Hanoi Deli Berlin*.[186] It can be implied that she is interested in beauty products. Moreover, the demographic information provided by the panel provider can be verified by the Berlin located companies. Therefore, the ad targeting analysis can be used to discover interests, observe the competition, and verify external information about the participant. For this, a categorisation of the advertisers into industries is suggested to get a better overview of the advertising environment.

In the detailed ads analysis, it can be noticed that the female user has seen six different brand ads. The most ad impressions are counted for the Adidas ad with the following text: “Cool, casual und immer up to date”, which is also the most successful ad among of all captured Adidas advertisements.[187] Overall, this ad was seen 24 times and clicked once by the participant. In case the ad click led to a webpage, it should be identifiable which product in this ad caught the attention of the user. For this reason, the browser touchpoint analyses results are examined next.

In total, six browser touchpoints with the brand Adidas could be measured in the Chrome and Samsung Internet app. In the brand-related weblinks analysis, one link can be identified as the redirecting ad link caused by the click on the Facebook ad. Figure 31 shows a screenshot of the webpage that opens in the browser, when clicking on the ad.[188]

[186] A list of all publishers can be found in File 17 in the digital appendix.
[187] For reference see chapter 5.2.3
[188] The webpage is accessed by inserting the weblink collected from the user in the browser.

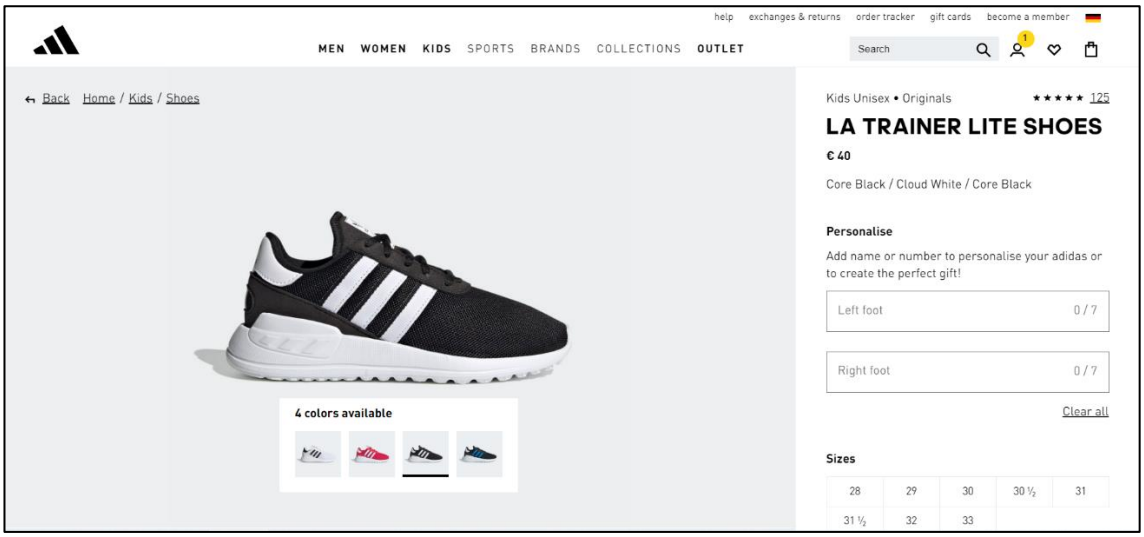


Figure 31: Screenshot of the redirecting webpage from an Adidas ad (Adidas, 2022)

It can be seen that the clicked Adidas ad promoted a sneaker for kids. Considering the fact that the shoe is for children, it could be assumed that the participant may be interest to purchase this product for a child, possibly her own child. Additionally, user visits the online shopping websites *asos.de* and *otto.de* to compare different Adidas sneaker for women here. Hence, it would be interesting to see whether the purchase consideration turned into a mobile purchase. Therefore, the amazon shopping data is analysed in the following section.

In general, 117 Adidas touchpoints are captured in the Amazon shopping app. However, duplications must be considered here. In order to get valid results for this user, the individual Amazon shopping data is manually cleaned in Excel.[189] After this proceeding, 35 Adidas touchpoints are counted. Moreover, one search for “adidas adilette herren” is captured. After the initial search, the participant looked at different variants of this Adidas product in the category *shoes & handbags* several times on different days. This leads to the assumption that she is informing herself about the product features and considers several options before making a purchase decision. Furthermore, the participant chose the shoe size 42 or 43 in all three products. Due to this and the fact that one viewed product is for men, it could be suggested that the product should be purchased for a man. The considered products can be seen in Figure 32.

[189] The cleaned dataset can be seen in File 18 in the digital appendix. The exact cleaning proceeding can be found in the analysis documentation in the digital appendix. See analysis “5.2. Cleaned Amazon Data - Individual User Analysis”.

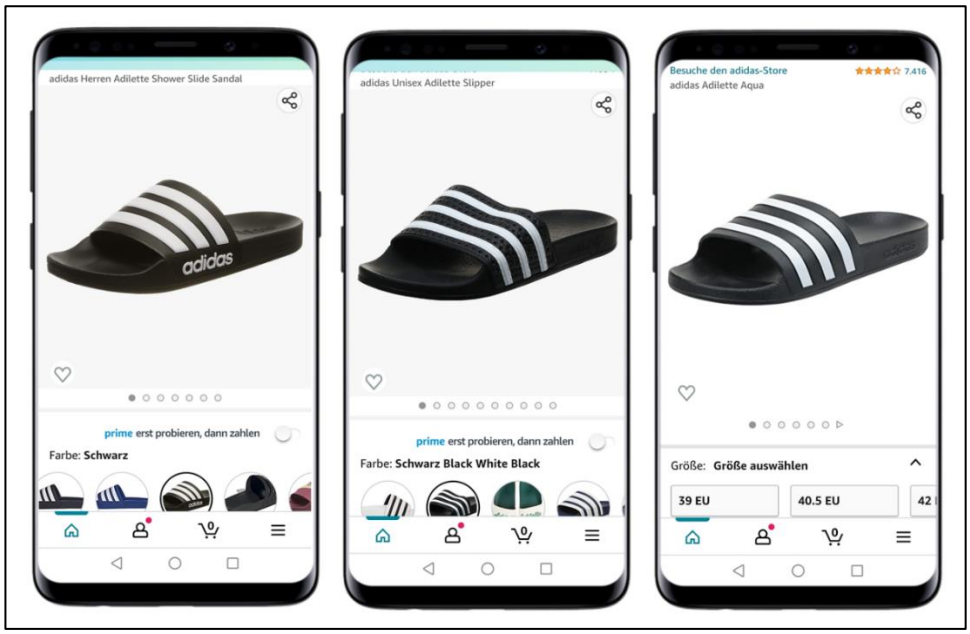


Figure 32: Viewed Adidas products in the Amazon Shopping app – Individual Analysis (own illustration)[190]

On the 8th of August 2022 it can be observed that the user puts the "Adidas Unisex Adilette Shower Slide Sandal, Schwarz, 42 EU" in the basket, continues the checkout process and completes the ordering process. The product is purchased for 21.96 Euros.[191] Considering the first brand contact in the Amazon app on 11.07.2022 it can be concluded that it takes the user approximately four weeks to make the purchase decision. Thus, this purchase could be classified as well thought and intentional.

As this product is not the promoted sneaker, this purchase cannot be directly connected to the prior touchpoints in the mobile journey. However, it can be assumed that all pre-purchase touchpoints with the brand potentially have influenced the decision making by strengthening brand awareness and a positive brand image. Nonetheless, it is possible that this user purchases the promoted sneaker in future. This in turn, could be assessed when observing the user for a longer period of time or by running a smart survey, which examines the purchase intention and buying motives.

5.4.2 User Information

Before drawing a final conclusion on the individual mobile customer journey analysis, general information about the user and her phone usage behaviour is analysed in the

[190] The Figure shows screenshots taken in the Amazon Shopping app of the viewed products.
[191] These information are derived from the cleaned Amazon data, which can be found in File 18 in the digital appendix.

target group analytics dashboard. All results for the individual user can be found in Figures 54 to 56 and the total sample insights are illustrated in Figures 57 to 59.

The basic demographic information is already known from the participants list in the first dashboard. With regard to the prior insights, it could be assumed that this woman is living in Berlin together with her partner and child. However, this suggestion needs further investigation for verification. This could also be assessed within a smart survey.

Next, smartphone usage habits are analysed. Primarily, it can be said that the participant most likely owns a smartphone of the brand Samsung. This can be derived from the usage of the Samsung Internet Browser app, which is mostly compatible with Samsung devices.[192] This information may be useful for further target group segmentation or competitive analysis based on the developed dashboard. The latter is especially interesting for smartphone selling companies, because the sensing data analyses allow to draw a precise picture on how people are using their device.

Subsequently, it can be observed that the analysed participant uses her phone 5.08 hours per day on average. Among all study participants the phone is used 3.68 hours, which is almost 1.5 hours less. It can be stated that the user shows an above-average phone usage behaviour. This is further emphasised in the daily phone usage displayed over time, as on most days the participants' smartphone usage is above the total sample average.[193] The highest phone usage with a duration of approximately eleven hours was measured on the 4th of July 2022. To determine what the user has done on her phone on this day, the app usage is analysed. It is observable that she used Chrome and the Samsung Internet app for more than eight hours in total.[194] When examining the collected Browser data of this user on this day, it can be seen that she participated in several online surveys over the day and played various online games, which explains the high phone usage.[195] However, this day can be classified as exception as no other day shows a phone usage this high.

[192] Samsung (2022)

[193] For this analysis, the total phone usage per day is calculated. Since no average is displayed, a new analysis is conducted. The analysis proceeding can be found in the analysis documentation in the digital appendix. See analysis "5.3. Daily Phone Usage over Time - User level".

[194] The full results can be seen in File 19 in the digital appendix and the analysis proceeding is documented in the analysis documentation. See analysis "5.4. App Usage Analysis on 04.07.2022".

[195] The full results are not displayed in order to protect the user's private browser usage on the analysed day. The analysis proceeding can be found in the digital appendix. See analysis "5.5. Browser Behaviour Analysis on 04.07.2022".

It is important to note that app and category usage cannot be interpreted on a user level because both apps and categories are ranked by the participants. For this reason, it is focused on the daily app usage calculation. The results show that the most daily used app is Instagram with an average usage of ca. 53 minutes, followed by Facebook with approximately 38 minutes per day. As the average Facebook usage in the sample accounts for ca. 22 minutes, it is assumed that this woman received more Adidas advertisement due to her relatively longer app usage. However, she is still considered to belong to Adidas target group, as the total number of brand touchpoints is significantly above the total sample average. With regard to the previously made assumptions about why this user only received Adidas ads on Facebook, it is now clear that Adidas is targeting this woman only on Facebook. Since she is using this app even longer than Facebook, Instagram is identified as relevant marketing channel for Adidas to interact with this user.

Besides social media apps, this user plays a mobile game called Gardenscapes for ca. 31 minutes on a daily basis.[196] Additionally, she is playing board games on her device for about nine minutes a day.[197] This participant appears to enjoy playing mobile games. Moreover, it is evident that the Browser apps Chrome and Samsung Internet are on the fourth and fifth place of the most used apps. With regard to the phone usage analysis, it can be suggested that she does not only browse online for brand products, but also uses her phone to browse in general.[198]

For more user insights, the mobile shopping behaviour is analysed next. First, it can be seen that most products in the Amazon app are viewed in the category *kitchen, household & living*, which shows that the user mostly looks for home supplies. Approximately 12% of all viewed products are viewed in the category *jewellery*, followed by *books* and *backpacks* which both account 10% of all product views. Shoes, handbags and clothes are not of particular interest for the participant. This implies that she normally does not shop items in these categories via Amazon on her phone and the Adidas purchase marks an exception.

[196] Google Play (2022d)
[197] Google Play (2022e)
[198] The full results for the individual user analysis and the total sample can be seen in File 20 and 21 in the digital appendix.

In the basket, purchase and conversion analyses the user shows similar shopping behaviour as the average study participant. It can be noticed that the participant has 13 items in the Amazon basket during the defined period. Further, it is observed that she purchases four products, which results in a conversion of approximately 31%. In the weekly conversions it is visible that this user orders all products in the basket on two days in the observation period. Thus, it is assumed that she is more likely to use the classic ordering process in the app by putting products in the basket, go to checkout and place the order.

Additionally, the total spendings are analysed in a manual analysis conducted in Excel.[199] In total, this participant spends 97.90 Euro on four products. For a deeper understanding of spending behaviour, it is suggested to observe in-app shopping behaviour over a period of at least one year to see seasonal effects and behaviour changes.

In summary, it can be said that the touchpoint performance analytics dashboard allows a detailed analysis of the user-based mobile customer journey for the brand Adidas along all captured touchpoints. Moreover, detailed user information can be generated. This knowledge helps a company to further understand the customer behaviour along their mobile journey. Further, these insights can be used to develop personas for the customer journey mapping. Figure 33 illustrates a customer journey map for this particular user by summarising all insights based on the framework of Nielsen.[200] In order to include observed user information, the framework is extended.

However, it should be considered that touchpoints are also happening outside the smartphone. In case of the adiletten purchase it can be assumed that other touchpoints such as a recommendation from friends, a TV spot or a store visit resulted in the mobile customer journey for this product. Therefore, the gathered insights should be used to complete the customer journey maps, which include all touchpoints online and offline.

[199] The results can be found in File 22 in the digital appendix. The proceeding is documented in the analysis documentation in the digital appendix. See analysis “5.6. Amazon Spending Analysis”.
[200] Kaplan (2016); For further reference see chapter 2.2.1

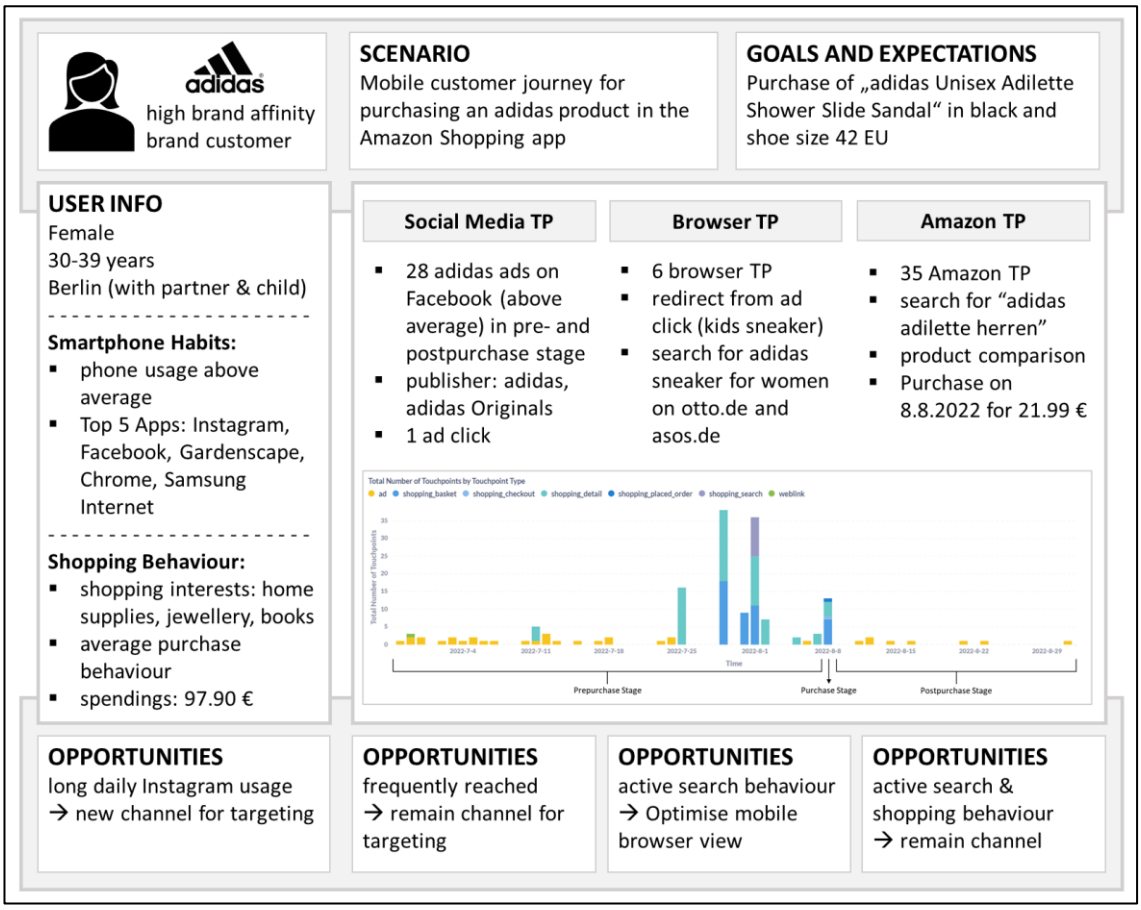


Figure 33: Customer Journey Map – User analysis (own illustration according to Kaplan, 2016)

5.5 Limitations

This final subchapter outlines the limitations of the sensing data analysis and suggests solutions if possible.

With regard to the sensing technology, sensing data analysis of in-app data can only be performed based on Android devices as of now, because iOS is highly restrictive in this manner. However, other companies developed an iOS solution to collect smartphone data. Nevertheless, these solutions cannot track the range of data that is collected on android devices due to the restrictions.[201]

In relation to this limitation, it should be repeated at this point that the sample on which the analysis in this thesis is based on is not representative for the German Android device users. As a result, no generalized statements can be made upon the collected data yet. This limitation would not appear when participants are recruited to represent a defined population with a quota, as it is mostly done for surveys.[202] Nevertheless, dropout

[201] For reference see chapters 3.2.1 and 3.2.2
[202] Meier and Hansen (2014), p. 197

and new recruitment during the field work complicates the comparability of results as could be seen in the definition of the time frame and in the later performed individual mobile customer journey analysis.[203] In order to remove this barrier from the analysis process, it is recommended to develop a constant and controlled recruitment process. This should include regular monitoring of dropped out participants with subsequent recruitment procedures. In addition, it should provide basic statistics on the total sample structure to keep the sample stable over the course of the study.

Another limitation can be seen in the availability of in-app data. This thesis is limited to Facebook, Instagram and Amazon Shopping app data, which is a relatively small amount of data considering how many apps are already used by a single user.[204] Additionally, it was determined during the analysis that intentions and motives for the observed mobile activities could only be partially seen. Thus, sensing data is limited in deriving reasons for a certain mobile behaviour. Consequently, a full picture of the mobile consumer cannot be drawn yet. Nonetheless, this only presents a temporary limitation because the sensing capabilities are continuously being expanded. Further, smart surveys could provide the missing insights into the motives and intentions of mobile users.[205]

A further limitation point should be discussed with regard to data ethics, particularly when capturing Browser data. As stated in chapter 3.2.3, no Browser data gets collected from the Menthal users, because the data is highly personal and they provide it on a voluntary basis without monetary incentives. Hence, results can only be generated for the Murmuras study participants. However, during the Browser data analysis, it could be seen that the weblinks contain sensitive information about the users. Thus, the question arises of whether and to what extent the collection of browser data in general is ethically acceptable. This should be discussed among sensing technology providers, researchers, analysts and device users to get all relevant opinions on this topic. Kargl et al. emphasised the importance of securing the privacy in mobile sensing by outlining the legal and technical aspects that must be considered when conducting mobile sensing studies. The authors also stated that the sole consent of a person is no longer sufficient for data collection, but a GDPR-compliant privacy concept must be integrated in the

[203] For reference see chapters 4.2.1.1 and 5.4
[204] For reference see chapter 5.4.2
[205] For reference see chapters 3.1 and 3.2.3

measuring process.[206] Such a concept was developed in collaboration with a data security legal expert for Murmuras' sensing technology.[207] However, further anonymisation processes regarding the data could be added. For instance, whitelisting presents a solution to circumvent the privacy problem in the Browser data. With whitelisting all entities that are relevant are marked, while the rest gets excluded.[208] By applying whitelisting to the Browser data collection process, exclusively consumption-related website domains that are relevant for customer journey analytics would be captured. The same proceeding could be used for Google searches.

Besides this, limitations within the used datasets are outlined with regard to the performed analyses.[209] It can be stated that the Amazon shopping interactions dataset particularly caused problems in the analysis process. First, duplications distort the results. Second, uncleaned brand and price information cannot be used for analyses among a large sample due to the high effort required for manual cleaning. As a consequence, shopping KPIs cannot be calculated correctly yet. Thus, it is necessary to apply an automatic cleaning procedure in the pre-data processing to assess the full potential of this data.

[206] Kargl, van der Heijden, Erb and Bösch (2022), pp. 13 and 18
[207] Q. Kasem (personal communication, December 9, 2022)
[208] Bacik (2012), p. 15
[209] Observed limitations before conducting the analysis are described in chapter 3.2.3

6 Conclusion

Modern consumers are shaping a new mobile era: they are highly flexible in consumption, connected to social media communities, and have unlimited access to information via smartphone use. Consequently, it is more important than ever to understand the mobile consumer behaviour along the dynamic customer journey.

For this reason, customer journey models have been adapted to the complex consumer behaviour and tools such as the customer journey mapping for capturing the customer perspective on the path to purchase were established by researchers and practitioners in this discipline. Furthermore, new research methods were introduced in order to gather the necessary insights about modern consumers. However, customer journey analysts face great challenges in implementing new data sources and analytics processes in this fast-changing environment. Therefore, this thesis introduced a first approach in analysing independent mobile data generated with Murmuras sensing technology to examine which insights about mobile consumers can be generated to understand their behaviour along the customer journey.

Initially, a mobile customer journey model was developed which illustrates a general view of multiple customer journeys. Moreover, the model gives implications on relevant touchpoints and influencing factors in the journey. During the individual user analysis, the practical implementation of this model could be demonstrated. Nonetheless, further research is required to prove the general applicability of this model to all potential customer journeys on smartphones.

Subsequently, analytics concepts have been developed to evaluate the touchpoint performance of a company or brand, describe its mobile target groups, and derive mobile customer journeys. Most analyses were successfully implemented in dashboards. In turn, this enabled flexible filtering and insights generation for different companies, target groups, and time periods. Thus, the designed dashboard concepts served as an efficient base for performing the data analysis.

In the first analysis, the touchpoint performance was examined across all collected sensing datasets. The brand Adidas was used as an example to generate the results. It was possible to identify all brand-related touchpoints in total and within general app usage data, in-app Facebook and Instagram advertising data, Browser data and Amazon

Shopping data. In order to evaluate Adidas' general and app-related touchpoint performance, KPIs were calculated. Additionally, the integrated mobile customer journey could show an overview of all brand touchpoints over time, while detailed ads, browser, and shopping analyses provided deeper insights into the interactions between the brand and potential customers. These insights answered relevant research questions regarding touchpoints within the customer journey analytics for the group of mobile consumers. Thus, sensing data is suitable to assess the touchpoint performance of a brand or company in the context of customer journey analytics. Although a complete picture of all mobile touchpoints cannot be drawn yet due to a limited amount of sensing data, sensing capabilities are already being expanded. It is expected that sensing data analytics will be able to provide a complete overview of the mobile touchpoint performance in the near future.

Next, the target group analyses were conducted. The created dashboard was supposed to give information about the mobile behaviour of different target groups. Due to performance issues, though, the conceptualised analyses were only computed for the total sample. Besides basic demographic information, smartphone usage habits were analysed. Using these insights, it was possible to gain a better understanding of how people use their smartphones. Furthermore, relevant channels in which the study participants could be contacted by a company were identified. In addition, behavioural patterns regarding mobile shopping in Amazon were determined, e.g., general shopping interests and preferences were derived and basket content and purchases were analysed. Also, behavioural changes were observable when considering the time perspective. This led to a broad understanding of mobile consumer behaviour, which enables a company to derive new customer segments for better addressing their mobile customers. Additionally, the dashboard design allows to compare different target groups among a selected company and its competitors.

In the last part of the analysis, both dashboards were used to conduct a deep analysis of an Adidas customer. All relevant touchpoints as well as interactions between the brand and the participant along the individual mobile customer journey were identified. Further, an exact time course of the journey was drawn, which allowed the allocation of all touchpoints to the three stages of the mobile customer journey model. Moreover, intercorrelations between touchpoints were observed and the users’ phone and mobile

shopping habits were analysed, which led to a deeper understanding of the consumers mobile life. Based on this, a customer journey map was created and opportunities for the brand Adidas were derived.

Although a broad range of insights were generated, there were also limitations regarding the technology, the sensing data and the analyses. It can be concluded that further data cleaning processes and aggregation steps are required to be able to further explore the sensing data. Furthermore, deeper analysis and adding external data from smart surveys are necessary to draw a complete picture of the mobile consumer. In addition, a representative sample of the German Android users should be tracked to draw generalisable statements on the results.

In summary, it could be proved that sensing data presents a big opportunity for companies to follow their customers along their journeys in the mobile world. However, the vast amount of sensing data and the complexity of its analysis in the context of customer journey analytics still remains a challenge. As sensing technology and sensing capabilities as well as smart devices are constantly improving, it is expected that companies will face the challenge of decoding the mobile journeys of their customers by using mobile sensing data in the near future.

References

Abdullah, S., Matthews, M., Frank, E., Doherty, G., Gay, G. and Choudhury, T. (2016). Automatic detection of social rhythms in bipolar disorder. *Journal of the American Medical Informatics Association*, 23(3), pp. 538-543. http://dx.doi.org/10.1093/jamia/ocv200

Adidas (2022). La Trainer lite shoes. https://www.adidas.de/la-trainer-lite-shoes/FW5842.html [accessed on 30.11.2022]

Adidas (2021). Geschäftsbericht 2020. https://report.adidas-group.com/2020/de/serviceseiten/downloads/files/annual-report-adidas-gb20.pdf [accessed on 15.10.2022]

ADM (2022). Assoziierte Mitglieder – Murmuras GmbH. https://www.adm-ev.de/project/murmuras-gmbh/ [accessed on 14.08.2022]

Amazon (2022). Buy Now ordering. https://www.amazon.de/-/en/gp/help/customer/display.html?nodeId=GU224Z5TL5RBQTJA [accessed on 14.11.2022]

Andone, I., Błaszkiewicz, K., Eibes, M., Trendafilov, B., Montag, C., and Markowetz, A. (2016). Menthal: a framework for mobile data collection and analysis. *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct,* pp. 624-629. https://doi.org/10.1145/2968219.2971591

Angus, A. and Westbrook, G. (2022). Top 10 Global Consumer Trends 2022. https://go.euromonitor.com/white-paper-EC-2022-Top-10-Global-Consumer-Trends.html [accessed on 19.08.2022]

Apple (2021a). Sicherheit des Laufzeitprozesses bei iOS und iPadOS. https://support.apple.com/de-de/guide/security/sec15bfe098e/web [accessed on 19.11.2022]

Apple (2021b). Data Privacy Day at Apple: Improving transparency and empowering users. https://www.apple.com/newsroom/2021/01/data-privacy-day-at-apple-improving-transparency-and-empowering-users/ [accessed on 19.11.2022]

Bacik, S. (2012). Whitelisting. In M. K. Nozaki and H. F. Tipton (Eds*), Information Security Management Handbook – Volume 5.* (6th ed.) New York: Auerbach Publications, pp. 15-18. https://doi.org/10.1201/b11250

Baumeister, H., and Montag, C. (2019). Psychoinformatics – A Rapidly Evolving Interdisciplinary Research Endeavor. In H. Baumeister and C. Montag (Eds), *Digital Phenotyping and Mobile Sensing – New Developments in Psychoinformatics.* Switzerland: Springer Nature, pp. xiii-xx. https://doi.org/10.1007/978-3-030-31620-4

BMBF (2021). SanePhone – Künstliche Intelligenz und dynamische Benutzeroberflächen zur Reduktion von digitalem Stress. https://www.interaktive-technologien.de/projekte/sanephone [accessed on 14.09.2022]

BMDV (2022). Optimierung der ÖPNV-Planung durch die Analyse von Smartphone-App Aktivitäten und dem realisierten Mobilitätsverhalten – SSPT. https://bmdv.bund.de/SharedDocs/DE/Artikel/DG/mfund-projekte/sspt.html [accessed on 07.08.2022]

Bonsai (2021). Bonsai und Gemius decodieren Customer Journey neu. https://www.bonsai-research.com/pressemeldungen/bonsai-research-wird-exklusiver-forschungspartner-des-panel-anbieter-gemius-pressemittteilung [accessed on 17.09.2022]

Bonsai (2022a). Bonsai Shopper Research. https://www.bonsai-research.com/bonsai-shopper-research [accessed on 16.11.2022]

Bonsai (2022b). Customer Experience & Mystery Research. https://www.bonsai-research.com/mystery-shopper [accessed on 16.11.2022]

Brand Finance (2022). Apparel 50 2022 – The annual report on the most valuable and strongest apparel brands. https://brandirectory.com/download-report/brand-finance-apparel-50-2022-preview.pdf [accessed on 18.11.2022]

Bremer, V., Chow, P. I., Funk, B., Thorndike, F. P., and Ritterband, L. M. (2020). Developing a Process for the Analysis of User Journeys and the Prediction of Dropout in Digital Health Interventions: Machine Learning Approach. *Journal of Medical Internet Research*, *22*(10), e17738. https://doi.org/10.2196/17738

Byrne, M. L., Lind, M. N., Horn, S. R., Mills, K. L., Nelson, B. W., Barnes, M. L., Slavich, G. M., & Allen, N. B. (2021). Using mobile sensing data to assess stress: Associations with perceived and lifetime stress, mental health, sleep, and inflammation. *DIGITAL HEALTH*, *7*. https://doi.org/10.1177/20552076211037227

Canzian, L. and Musolesi, M. (2015). Trajectories of depression: unobtrusive monitoring of depressive states by means of smartphone mobility traces analysis. *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pp. 1293-1304. https://doi.org/10.1177/20552076211037227

Chen, Z., Chen, Y., Hu, L., Wang, S., Jiang, X., Ma, X., Lane, N. D. and Campbell, A. T. (2014). Context Sense: unobtrusive discovery of incremental social context using dynamic bluetooth data. *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication,* pp. 23-26. https://doi.org/10.1145/2638728.2638801

Ciordas-Hertel, G. P., Rödling, S., Schneider, J., Di Mitri, D., Weidlich, J. and Drachsler, H. (2021). Mobile Sensing with Smart Wearables of the Physical Context of Distance Learning Students to Consider Its Effects on Learning. *Sensors*, *21*(19), 6649. https://doi.org/10.3390/s21196649

Court, D., Elzinga, D., Mulder, S. and Vetvik, O. J. (2009). The consumer decision journey. Marketing & Sales Practice. *In: Mc Kinsey Quarterly 3/2009.* https://www.mckinsey.com/business-functions/growth-marketing-and-sales/our-insights/the-consumer-decision-journey [accessed on 26.09.2022]

Dlugosch, S. (2019). Effiziente Analyse der Customer Journey durch Online Communities. In B. Keller and C. S. Ott, *Touchpoint Management – Entlang der Customer Journey erfolgreich agieren.* (2nd ed.) Freiburg: Haufe Group, pp. 97-106

Edelmann, D. C. and Singer, M. (2015). Competing on Customer Journeys. *Harvard Business Review,* (11). pp. 88-100. https://hbr.org/2015/11/competing-on-customer-journeys [accessed on 16.06.2022]

Ferdous, R., Osmani, V. and Mayora, O. (2015). Smartphone app usage as a predictor of perceived stress levels at workplace. *Proceedings of the 9th International Conference on Pervasive Computing Technologies for Healthcare*, pp. 225-228

Fulford, D., Mote, J., Gonzalez, R., Abplanalp, S., Zhang, Y., Luckenbaugh, J., Onnela, J. P., Busso, C. and Gard, D. E. (2021). Smartphone sensing of social interactions in people with and without schizophrenia. *Journal of Psychiatric Research*, *137*, pp. 613-620. https://doi.org/10.1016/j.jpsychires.2020.11.002

FZI (2022). DeFaktS – Desinformationskampagnen beheben durch Offenlegung der Faktoren und Stilmittel. https://www.fzi.de/project/defakts/ [accessed on 16.11.2022]

Gemius Global (2022). TikTok's advertising champions #GemiusTurkey. https://www.gemius.com/advertisers-news/tiktoks-advertising-champions-gemiusturkey.html [accessed on 17.09.2022]

Gemius Audience (2022). Methodology. https://audience.gemius.com/en/methodology/overview/ [accessed on 18.09.2022]

GfK (2016). GfK drives its global digitalization through acquisition of digital panel specialist Netquest. https://www.gfk.com/press/gfk-drives-its-global-digitalization-through-acquisition-of-digital-panel-specialist-netquest [accessed on 02.10.2022]

GfK (2022a). GfK Consumer Journey – Decode the purchase decision-making process. https://www.gfk.com/de/produkte/gfk-consumer-journey [accessed on 26.10.2022]

GfK (2022b). Consumer & Shopper Intelligence – Entschlüsseln Sie den Shopper in allen Phasen des Kaufprozesses. https://www.gfk.com/de/produkte/consumer-and-shopper-intelligence [accessed on 04.11.2022]

Github Metabase (2020). Adjust the error message of "Your question took too long" #12423. https://github.com/metabase/metabase/issues/12423 [accessed on 26.10.2022]

Google Developers (2022a). Accessibility Service. https://developer.android.com/reference/android/accessibilityservice/AccessibilityService [accessed on 25.11.2022]

Google Developers (2022b). Accessibility Event. https://developer.android.com/reference/android/view/accessibility/AccessibilityEvent [accessed on 25.11.2022]

Google Play (2022a). Adidas app. https://play.google.com/store/apps/details?id=com.adidas.app&hl=de&gl=US [accessed on 27.11.2022]

Google Play (2022b). adidas Running Lauf App. https://play.google.com/store/apps/details?id=com.runtastic.android&hl=de&gl=US [accessed on 27.11.2022]

Google Play (2022c). Google Play Store App öffnen. https://support.google.com/googleplay/answer/190860?hl=de [accessed on 29.11.2022]

Google Play (2022d). Gardenscapes. https://play.google.com/store/apps/details?id=com.playrix.gardenscapes&hl=de&gl=US [accessed on 18.11.2022]

Google Play (2022e). Board Games – Brettspiele. https://play.google.com/store/apps/details?id=com.jellybtn.boardkings&hl=de&gl=US [accessed on 18.11.2022]

Hagiu, A. and Wright, J. (2020). When Data Creates Competitive Advantage. *Harvard Business Review,* January-February 2020 issue. https://hbr.org/2020/01/when-data-creates-competitive-advantage [accessed on 03.10.2022]

Haije, E. G. (2021). Die 20 besten Tools zum Customer Journey Mapping: Ein Überblick. https://mopinion.com/de/tools-zur-customer-journey-mapping/ [accessed on 15.06.2022]

Halscheid, I. (2021). Black Week 2021 – Werbung und Shopping in Smartphone Apps. https://murmuras.com/de/blog/black-week-2021 [accessed on 18.09.2022]

Halscheid, I. (2022). Shopping-Verhalten in Handy-Apps: Männer geben mehr Geld aus bei Amazon. https://www.marktforschung.de/marktforschung/a/shopping-verhalten-in-handy-apps-maenner-geben-mehr-geld-aus-in-amazon/ [accessed on 17.09.2022]

Harari, G. M., Lane, N. D., Wang, R., Crosier, B. S., Campbell, A. T. and Gosling, S. D. (2016). Using Smartphones to Collect Behavioral Data in Psychological Science. *Perspectives on Psychological Science*, *11*(6), pp. 838-854. https://doi.org/10.1177/1745691616650285

Harari, G. M., Müller, S. R., Aung, M. S. and Rentfrow, P. J. (2017). Smartphone sensing methods for studying behavior in everyday life. *Current Opinion in Behavioral Sciences*, *18*, pp. 83-90. https://doi.org/10.1016/j.cobeha.2017.07.018

Harari, G. M., Müller, S. R., Stachl, C., Wang, R., Wang, W., Bühner, M., Rentfrow, P. J., Campbell, A. T. and Gosling, S. D. (2019). Sensing Sociability: Individual Differences in Young Adults' Conversation, Calling, Texting, and App Use Behaviors in Daily Life. *Journal of Personality and Social Psychology.* http://dx.doi.org/10.1037/pspp0000245

Harari, G. M., Vaid, S. S., Müller, S. R., Stachl, C., Marrero, Z., Schoedel, R., Bühner, M. and Gosling, S. D. (2020). Personality Sensing for Theory Development and Assessment in the Digital Age. *European Journal of Personality*, *34*(5), pp. 649-669. https://doi.org/10.1002/per.2273

Hedewig-Mohr, S. (2022). Mit innovativer Werbewirkungsmessung die Cookiecalypse meistern. *planung&analyse.* https://www.horizont.net/planung-analyse/nachrichten/annalect-und-murmuras-mit-innovativer-werbewirkungsmessung-die-cookiecalypse-meistern-197680 [accessed on 17.09.2022]

Infas Quo (2022). SMARTPHONE TRACKING – Wir messen, wer was sieht! https://infas-quo.de/smartphone-tracking/ [accessed on 18.11.2022]

Innofact and Murmuras (2022). Competitor App Analytics – Wettbewerbs-App im Real-Life-Check. https://innofact-marktforschung.de/loesungen/datenanalyse/competitor-app-analytics/ [accessed on 17.09.2022]

Jones, S.L., Ferreira, D., Hosio, S., Goncalves, J. and Kostakos, V. (2015) Revisitation analysis of smartphone app use. *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pp. 1197-1208. https://doi.org/10.1145/2750858.2807542

Kantar and RealityMine (2019). Understanding GB Smartphone News Consumers. https://www.ofcom.org.uk/__data/assets/pdf_file/0025/174085/bbc-news-review-kantar-report.pdf [accessed on 18.11.2022]

Kantar (2022). Reimagine your customer journeys to drive growth. https://www.kantar.com/-/media/project/kantar/global/expertise/customer-experience/cx-customer-journey-mapping-brochure.pdf [accessed on 11.10.2022]

Kaplan, K. (2016). Journey Mapping in Real Life: A Survey of UX Practitioners. https://www.nngroup.com/articles/journey-mapping-ux-practitioners/ [accessed on 25.09.2022]

Kargl, F., van der Heijden, R. W., Erb, B., Bösch, C. (2022). Privacy in Mobile Sensing. In H. Baumeister and C. Montag (Eds), *Digital Phenotyping and Mobile Sensing – New Developments in Psychoinformatics.* Switzerland: Springer Nature, pp. 13-23. https://doi.org/10.1007/978-3-030-31620-4

Keller, B. (2019). Die Reise(n) durchs Touchpoint Management. In B. Keller and C. S. Ott, *Touchpoint Management – Entlang der Customer Journey erfolgreich agieren.* (2nd ed.) Freiburg: Haufe Group, pp. 35-70

Keller, B. and Ott, C. S. (2020). Einführung in das Thema. In B. Keller and C. S. Ott, *Touchpoint Culture – Alle Bereiche des Unternehmens konsequent auf den Kunden ausrichten.* Freiburg: Haufe Group, pp. 17-43

Kleindienst, J. and Halscheid, I. (2022). Messung der Marketing-Performance in TikTok, Instagram & Co. https://www.marktforschung.de/marktforschung/a/messung-der-marketing-performance-in-tiktok-instagram-co/ [accessed on 17.09.2022]

Kolle, S. (2020). Operative Excellence im TPM: CX messen und managen. Einführung in das Thema. In B. Keller and C. S. Ott, *Touchpoint Culture – Alle Bereiche des Unternehmens konsequent auf den Kunden ausrichten.* Freiburg: Haufe Group, pp. 287-389

Kress, D. (2021). GraphQL – Eine Einführung in APIs mit GraphQL. Heidelberg: dpunkt.verlag

Kuß, A., Wildner, R. and Kreis, H. (2018) Marktforschung – Datenerhebung und Datenanalyse (6th ed.) Wiesbaden: Springer Gabler-Verlag. https://doi.org/10.1007/978-3-658-20566-9

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

Lidl (2022). Wie funktioniert Lidl Plus? https://www.lidl.de/c/wie-funktioniert-lidl-plus/s10011363 [accessed on 25.11.2022]

Li, J., Abbasi, A., Cheema, A. and Abraham, L. B. (2020). Path to Purpose? How Online Customer Journeys Differ for Hedonic Versus Utilitarian Purchases. *Journal of Marketing,* 84(4), pp. 127-146. https://doi.org/10.1177/0022242920911628

Liu, M. (2013). A Study of Mobile Sensing Using Smartphones. *International Journal of Distributed Sensor Networks*, *9*(3), 272916. https://doi.org/10.1155/2013/272916

Ludwiczak, A. (2021). Using customer journey mapping to improve public services: A critical analysis of the literature. *Management,* 25(2), pp. 22-35. https://doi.org/10.2478/manment-2019-0071

Lu, H., Yang, J., Liu, Z., Lane, N. D., Choudhury, T. and Campbell, A. T. (2010). The Jigsaw continuous sensing engine for mobile phone applications. *Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems*, pp. 71-84. https://doi.org/10.1145/1869983.1869992

Markowetz, A. and Kasem, Q. (2021). Smart Surveys – Neue Technologien bei Befragungen. https://www.destatis.de/DE/Ueber-uns/Kolloquien-Tagungen/Veranstaltungen/14-wissenschaftliche-tagung/10-kasem-markowetz-kurzfassung.pdf [accessed on 11.10.2022]

Marktforschung.de (2016). GfK kauft Panelanbieter Netquest. https://www.marktforschung.de/marktforschung/a/gfk-kauft-panelanbieter-netquest/ [accessed on 11.10.2022]

Marktforschung.de (2022). Murmuras GmbH. https://www.marktforschung.de/anbieter/marktforschungsdienstleister-finden/marktforschungsinstitut/murmuras/ [accessed on 02.11.2022]

McKinsey (2017). Ten years on the consumer decision journey: Where are we today? https://www.mckinsey.com/about-us/new-at-mckinsey-blog/ten-years-on-the-consumer-decision-journey-where-are-we-today [accessed on 17.09.2022]

Meier, G. and Hansen, J. (2014). Quotenverfahren. In ADM Arbeitskreis Deutscher Markt- und Sozialforschungsinstitute e.V., *Stichproben-Verfahren in der Umfrageforschung – Eine Darstellung für die Praxis.* (2nd ed.) Wiesbaden: Springer-Verlag, pp. 197-205

Mele, C., Russo-Spena, T., Tregua, M. and Amitrano, C. C. (2021). The millennial customer journey: a Phygital mapping of emotional, behavioural, and social experiences. *Journal of Consumer Marketing*, *38*(4), pp. 420-433. https://doi.org/10.1108/jcm-03-2020-3701

Meta (2022a). Platzierung von Instagram-Werbeanzeigen. https://www.facebook.com/business/help/404249243119055 [accessed on 14.09.2022]

Meta (2022b) Werbebibliothek. https://www.facebook.com/ads/library [accessed on 14.10.2022]

Metabase (2022a). Built for data - Made for everyone. https://www.metabase.com/product/ [accessed on 31.10.022]

Metabase (2022b). Data Sources. https://www.metabase.com/data_sources/ [accessed on 31.10.2022]

Metabase (2022c). Exploration and Organization – Collections. https://www.metabase.com/docs/latest/exploration-and-organization/collections [accessed on 31.10.2022]

Metabase (2022d). Asking questions. https://www.metabase.com/docs/latest/questions/query-builder/introduction [accessed on 31.10.2022]

Metabase (2022e). The query builder. https://www.metabase.com/docs/latest/questions/query-builder/introduction#the-query-builder [accessed on 31.10.2022]

Metabase (2022f). Joining data. https://www.metabase.com/docs/latest/questions/query-builder/join [accessed on 31.10.2022]

Metabase (2022g). Filtering. https://www.metabase.com/docs/latest/questions/query-builder/introduction#filtering [accessed on 31.10.2022]

Metabase (2022h). Summarizing and grouping by. https://www.metabase.com/docs/latest/questions/query-builder/introduction#summarizing-and-grouping-by [accessed on 31.10.2022]

Metabase (2022i). List of Expressions. https://www.metabase.com/docs/latest/questions/query-builder/expressions-list [accessed on 31.10.2022]

Metabase (2022j). Visualizing data. https://www.metabase.com/docs/latest/questions/sharing/visualizing-results [accessed on 31.10.2022]

Metabase (2022k). The SQL editor. https://www.metabase.com/docs/latest/questions/native-editor/writing-sql [accessed in 31.10.2022]

Meyer, C. and Schwager, A. (2007). Understanding Customer Experience. *Harvard Business Review*, No. 2. https://hbr.org/2007/02/understanding-customer-experience [accessed on 15.06.2022]

Micheaux, A. and Bosio, B. (2019). Customer Journey Mapping as a New Way to Teach Data-Driven Marketing as a Service. *Journal of Marketing Education,* 41(2), pp. 127-140. https://dx.doi.org/10.1177/0273475318812551

Middelberg, N. (2019). Die inhaltliche Bestimmung von Touchpoint und Customer Journey Management. In B. Keller and C. S. Ott, *Touchpoint Management – Entlang der Customer Journey erfolgreich agieren.* (2nd ed.) Freiburg: Haufe Group, pp. 195-208

Murmuras (2020). Welche Einblicke Smartphone-Daten über Verhaltensweisen gewähren - Chancen für Forsche. https://murmuras.com/de/blog/smartphone_daten_in_akademischer_forschung [accessed on 12.09.2022]

Murmuras (2022a). About Us – History. https://murmuras.com/de/about [accessed on 18.09.2022]

Murmuras (2022b). Study behavior with smartphone data. https://academia.murmuras.com [accessed on 17.09.2022]

Murmuras (2022c). Benchmark your mobile marketing performance. https://murmuras.com/de [accessed on 18.09.2022]

Murmuras (2022d). FAQ. https://academia.murmuras.com/faq/ [accessed on 18.09.2022]

Murmuras (2022e) Free Ads Dashboard Germany. https://murmuras.com/de/insights/free-ads-dashboard [accessed on 18.09.2022]

Murmuras (2022f) Social Media Ads in Summer 2022. https://murmuras.com/de/insights/social-media-ads-in-summer-2022 [accessed on 18.09.2022]

Murnane, E. L., Abdullah, S., Matthews, M., Kay, M., Kientz, J. A., Choudhury, T., Gay, G. and Cosley, D. (2016). Mobile manifestations of alertness. *Proceedings of the 18th International Conference on Human-Computer Interaction With Mobile Devices and Services*, pp. 465-477. https://doi.org/10.1145/2935334.2935383

Nenninger, M. and Seidel, M. (2021). Praxisleitfaden Customer Centricity Mit Kundendaten und Customer Experience die digitale Transformation erfolgreich meistern – mit Strategie-Framework und Umsetzungsplan. Wiesbaden: Springer Gabler Verlag. https://doi.org/10.1007/978-3-658-33495-6

Nepal, S., Wang, W., Sharma, B., & Paudel, P. (2021). Current practices in mental health sensing. *XRDS: Crossroads, the ACM Magazine for Students*, *28*(1), pp. 28-33. https://doi.org/10.1145/3481829

Netquest (2022) Insights auf Basis authentischer Daten. https://www.netquest.com/de/über-uns [accessed on 15.11.2022]

Nielsen Group (2022). Customer Journey Map Template. https://media.nngroup.com/media/articles/attachments/JMTemplate.pdf [accessed on 26.09.2022]

Nielsen (2022). Commspoint Journey – Use Cases. https://www.nielsen.com/de/solutions/media-planning/commspoint-journey/#use-cases [accessed on 02.11.2022]

Ott, Cirk S. (2019). Erfolgreich verkaufen in einer digitalisierten Welt – Paradigmenwechsel im Touchpoint Management. In B. Keller and C. S. Ott, *Touchpoint Management – Entlang der Customer Journey erfolgreich agieren.* (2nd ed.) Freiburg: Haufe Group, pp. 71-93

Perez, A. J. and Zeadally, S. (2021). Recent Advances in Wearable Sensing Technologies. *Sensors*, *21*(20), 6828. https://doi.org/10.3390/s21206828

Peteva, Violeta (2020). Modern Consumers and the Decision-Making Process in the Context of Digitalization. Izvestia Journal of the Union of Scientists – Economic Science Series, vol. 9, No. 2, pp. 32-42. accessible on: https://doi.org/10.36997/IJUSV-ESS/2020.9.2.32 [accessed on 16.06.2022].

Phan, L. V., Modersitzki, N., Gloystein, K. K. and Müller, S. (2022). Mobile Sensing Around the Globe: Considerations for Cross-Cultural Research. *Research*. https://doi.org/10.31234/osf.io/q8c7y

Plottek, K. and Herold, C. (2018). Micro Moments als entscheidender Moment im Rahmen einer zunehmend fragmentierteren Customer Journey. In A. Rusnjak and D. R. A. Schallmo (Eds), *Customer Experience im Zeitalter des Kunden – Best Practices, Lessons Learned und Forschungsergebnisse.* Wiesbaden: Springer Gabler Verlag, pp. 143-176. https://doi.org/10.1007/978-3-658-18961-7

Puhlmann, A. (2013). Reaching customers where it really matters. *P&A International Market Research 2/2013,* pp. 15–17.

Pumpurs, A. (2022). User Journey Map as a Method to Extrapolate User Experience Knowledge from User Generated Reviews. *Lecture Notes in Business Information Processing*, vol.462, pp. 205-218. https://doi.org/10.1007/978-3-031-16947-2_14

PwC, Omdia, IAB UK and Interactive Advertising Bureau Europe (2021). German Entertainment and Media Outlook 2021–2025. https://www.pwc.de/de/technologie-medien-und-telekommunikation/gemo/2021/german-entertainment-media-outlook-2021-2025.pdf [accessed on 5.10.2022]

Qualtrics (2022). What is predictive analytics? Your ultimate guide. https://www.qualtrics.com/experience-management/research/predictive-analytics/ [accessed on 17.11.2022]

Quiring, F. (2022). Shopper Journey Studie 2022: Wie ticken Kunden beim Einkaufen? https://www.rheingold-marktforschung.de/rheingold-studien/shopper-journey-studie-2022-wie-ticken-kunden-beim-einkaufen/ [accessed on 09.11.2022]

Rabbi, M., Ali, S., Choudhury, T. and Berke, E. (2011). Passive and In-Situ assessment of mental and physical well-being using mobile sensors. *Proceedings of the 13th International Conference on Ubiquitous Computing - UbiComp '11*, pp. 385-394. https://doi.org/10.1145/2030112.2030164

RealityMine (2022a) The simple way to add behavioural data to your consumer insights. https://www.realitymine.com/realitymeter/ [accessed on 14.09.2022]

RealityMine (2022b) Real Moments. Real Actions. Real Intelligence. Real Life. Revealed. https://www.realitymine.com [accessed on 14.09.2022]

Riedmann-Streitz, C. (2018). Redefining the Customer Centricity Approach in the Digital Age. *Design, User Experience, and Usability: Theory and Practice*, pp. 203-222. https://doi.org/10.1007/978-3-319-91797-9_15

Saeb, S., Zhang, M., Karr, C. J., Schueller, S. M., Corden, M. E., Kording, K. P., and Mohr, D. C. (2015). Mobile Phone Sensor Correlates of Depressive Symptom Severity in Daily-Life Behavior: An Exploratory Study. *Journal of Medical Internet Research*, *17*(7), e175. https://doi.org/10.2196/jmir.4273

Sagina, I. J. (2022). 7 Customer Journey Map Examples Across Industries. https://freshdesk.com/customer-journey/journey-mapping-examples-blog/ [accessed on 09.10.2022]

Samsung (2022). Samsung Internet nutzen. https://www.samsung.com/de/support/apps-services/wie-nutze-ich-samsung-internet/ [accessed on 25.11.2022]

Schweidel, D. A., Bart, Y., Inman, J. J., Stephen, A. T., Libai, B., Andrews, M., Rosario, A. B., Chae, I., Chen, Z., Kupor, D., Longoni, C. and Thomaz, F. (2022). How consumer digital signals are reshaping the customer journey. *Journal of the Academy of Marketing Science*, *50*(6), pp. 1257-1276. https://doi.org/10.1007/s11747-022-00839-w

Similarweb (2022). Top-Apps-Ranking. https://www.similarweb.com/de/apps/top/google/store-rank/de/shopping/top-free/ [accessed on 29.11.2022]

Snipes (2022). Snipes main page. https://www.snipes.com [accessed on 19.11.2022]

Statista (2021). National Brands IPX (Index): Ranking der 10 stärksten Modemarken in Deutschland im Jahr 2021. https://de.statista.com/statistik/daten/studie/1126364/umfrage/staerkste-modemarken-in-deutschland/ [accessed on 17.11.2022]

Statista (2022a). Anteil der Smartphone-Nutzer* in Deutschland in den Jahren 2012 bis 2021. https://de.statista.com/statistik/daten/studie/585883/umfrage/anteil-der-smartphone-nutzer-in-deutschland/ [accessed on 26.09.2022]

Statista (2022b). Anteil der Smartphone-Nutzer in Deutschland nach Altersgruppe im Jahr 2021. https://de.statista.com/statistik/daten/studie/459963/umfrage/anteil-der-smartphone-nutzer-in-deutschland-nach-altersgruppe/ [accessed on 26.09.2022]

Stocchi, L., Pourazad, N., Michaelidou, N., Tanusondjaja, A. and Harrigan, P. (2022). Marketing research on Mobile apps: past, present and future. *Journal of the Academy of Marketing Science* 50, pp. 195–225. https://doi.org/10.1007/s11747-021-00815-w

Superdry (2022). Superdry main page. https://www.superdry.de [accessed on 11.10.2022]

Suruliraj, B., Bessenyei, K., Bagnell, A., McGrath, P., Wozney, L., Orji, R. and Meier, S. (2021). Mobile Sensing Apps and Self-management of Mental Health During the COVID-19 Pandemic: Web-Based Survey. *JMIR Formative Research*, *5*(4), e24180. https://doi.org/10.2196/24180

Sutherland, K. E. (2021). Strategic Social Media Management – Theory and Practice. Singapore: Springer Nature. https://doi.org/10.1007/978-981-15-4658-7

Sünkel, B. and Weber, W. (2019). Ein Customer Intelligence Hub – Basis für emotionale Differenzierung und CX Messung und Steuerung. In B. Keller and C. S. Ott, *Touchpoint Management – Entlang der Customer Journey erfolgreich agieren.* (2nd ed.) Freiburg: Haufe Group, pp. 141-152.

Talkwalker (2022). Social Listening. https://www.talkwalker.com/de/social-media-listening [accessed on 17.11.2022]

Tiffert, A. (2019). Customer Experience Management in der Praxis – Grundlagen-Zusammenhänge-Umsetzung. Wiesbaden: Springer Gabler Verlag. https://doi.org/10.1007/978-3-658-27331-6

Trendresearch (2022). Trendfrage – our in-house online portal. https://trend-research.de/en/online-access-panel/ [accessed on 06.11.2022]

Tseng, V. W. S., Merrill, M., Wittleder, F., Abdullah, S., Aung, M. H. and Choudhury, T. (2016). Assessing mental health issues on college campuses. *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct*, pp. 1200-1208. https://doi.org/10.1145/2968219.2968308

Vollrath, M. D. and Villegas, S. G. (2021). Avoiding digital marketing analytics myopia: revisiting the customer decision journey as a strategic marketing framework. *Journal of Marketing Analytics*, *10*(2), pp. 106-113. https://doi.org/10.1057/s41270-020-00098-0

Wakoopa (2022a) How it works. https://www.wakoopa.com/how-it-works [accessed on 14.11.2022]

Wakoopa (2022b) About us. https://www.wakoopa.com/about [accessed on 14.11.2022]

Wang, Q., Guo, B., Peng, G., Zhou, G. and Yu, Z. (2016). CrowdWatch: pedestrian safety assistance with mobile crowd sensing. *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct*, pp. 217-220. https://doi.org/10.1145/2968219.2971433

Wang, Z., Xiong, H., Tang, M., Boukhechba, M., Flickinger, T. E. and Barnes, L. E. (2022). Mobile Sensing in the COVID-19 Era: A Review. *Health Data Science*, *2022*, pp. 1-13. https://doi.org/10.34133/2022/9830476

Wang, Z., Xiong, H., Zhang, J., Yang, S., Boukhechba, M., Zhang, D., Barnes, L. E. and Dou, D. (2021). From Personalized Medicine to Population Health: A Survey of mHealth Sensing Techniques. *IEEE Internet of Things Journal*, *9*(17), pp. 15413-15434. https://doi.org/10.1109/jiot.2022.3161046

Weber, W. (2020). Silogrenzen überwinden – CX-Management nachhaltig implementieren. In B. Keller and C. S. Ott, *Touchpoint Management – Entlang der Customer Journey erfolgreich agieren.* (2nd ed.) Freiburg: Haufe Group, pp. 60-76

Welke, P., Andone, I., Blaszkiewicz, K. and Markowetz, A. (2016). Differentiating smartphone users by app usage. *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pp. 519-523. https://doi.org/10.1145/2971648.2971707

Wen, H., Sobolev, M., Vitale, R., Kizer, J., Pollak, J. P., Muench, F. and Estrin, D. (2021). mPulse Mobile Sensing Model for Passive Detection of Impulsive Behavior: Exploratory Prediction Study. *JMIR Mental Health*, *8*(1), e25019. https://doi.org/10.2196/25019

Werner, M., Kessel, M. and Marouane, C. (2011). Indoor positioning using smartphone camera. *2011 International Conference on Indoor Positioning and Indoor Navigation*, pp. 1-6. https://doi.org/10.1109/ipin.2011.6071954

Wizdo, L. (2016). How Do Buyer Journeys Relate To the Customer Life Cycle? Blog Article. https://www.forrester.com/blogs/16-09-30-how_do_buyer_journeys_relate_to_the_customer_life_cycle/ [accessed on 11.09.2022]

Wolny, J. and Charoensuksai, N. (2014). Mapping customer journeys in multichannel decision-making. *Journal of Direct, Data and Digital Marketing Practice*, *15*(4), pp. 317-326. https://doi.org/10.1057/dddmp.2014.24

Yan, Z., Yang, J. and Tapia, E. M. (2013). Smartphone bluetooth based social sensing. *Proceedings of the 2013 ACM Conference on Pervasive and Ubiquitous Computing Adjunct Publication*. https://doi.org/10.1145/2494091.2494118

Zetetic (2022). SQLCipher. https://www.zetetic.net/sqlcipher/ [accessed on 15.09.2022]

Appendix

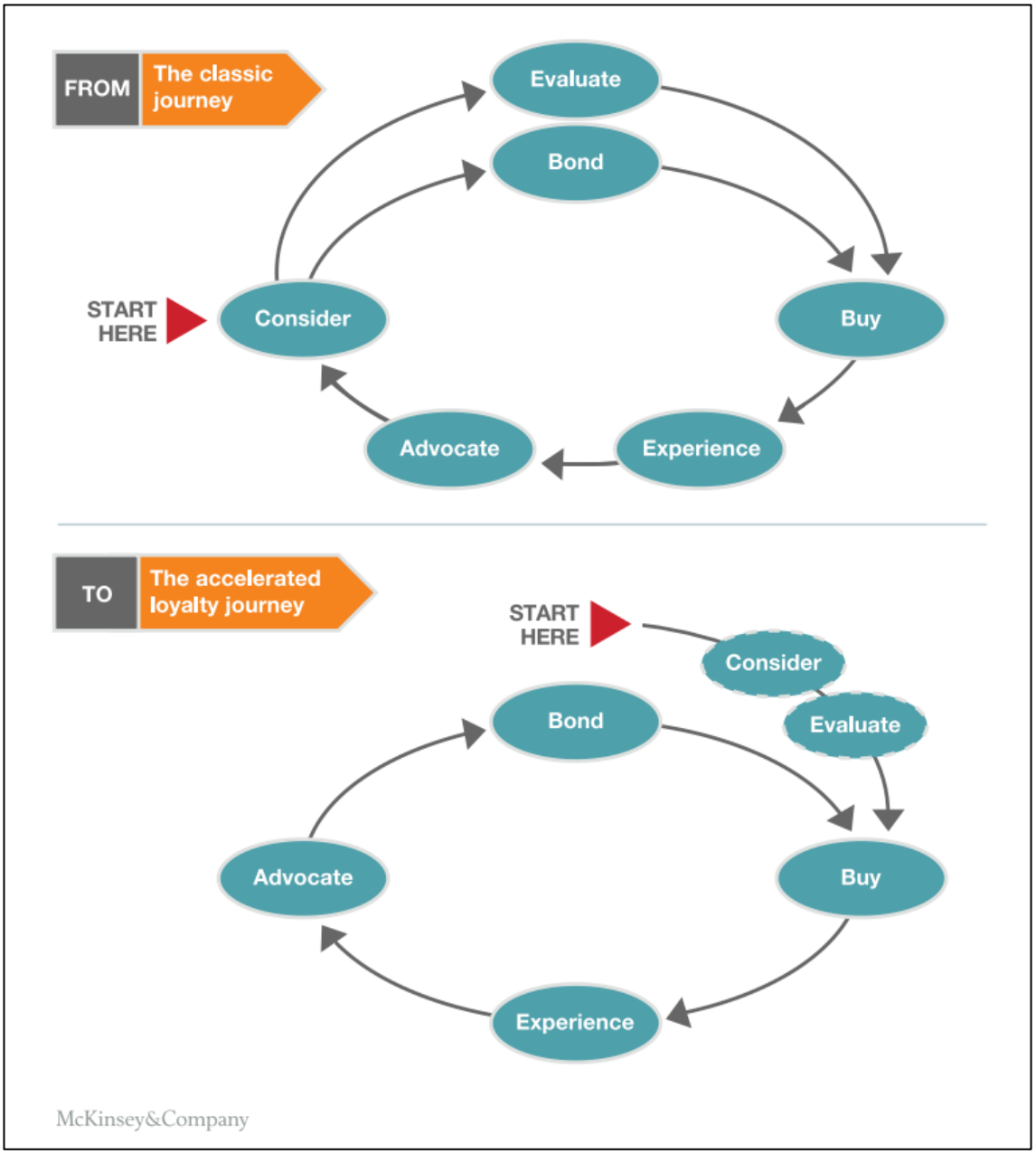


Figure 34: The Consumer Decision Journey Model by McKinsey (Edelmann and Singer, 2015, p. 90)

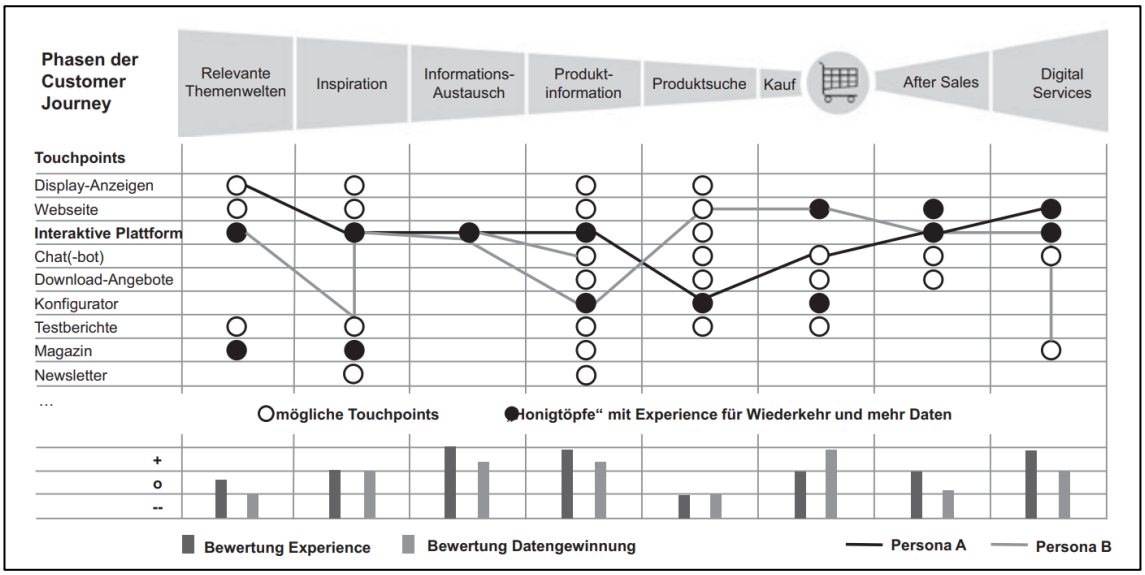


Figure 35: Exemplary Customer Journey Map with linear structure (Nenninger and Seidel, 2021, p. 75)

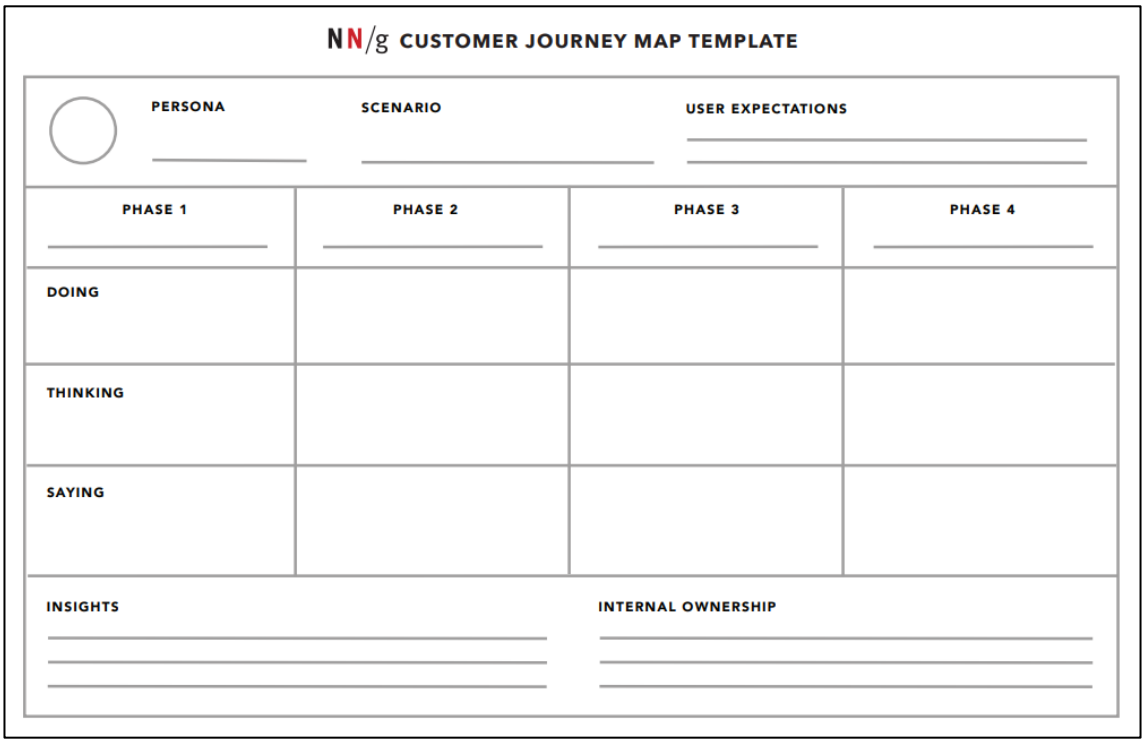


Figure 36: Customer Journey Map Template with Persona focus by Nielsen (Nielsen Group, 2022)

Figure 37: Menthal App Interface (own illustration)[210]

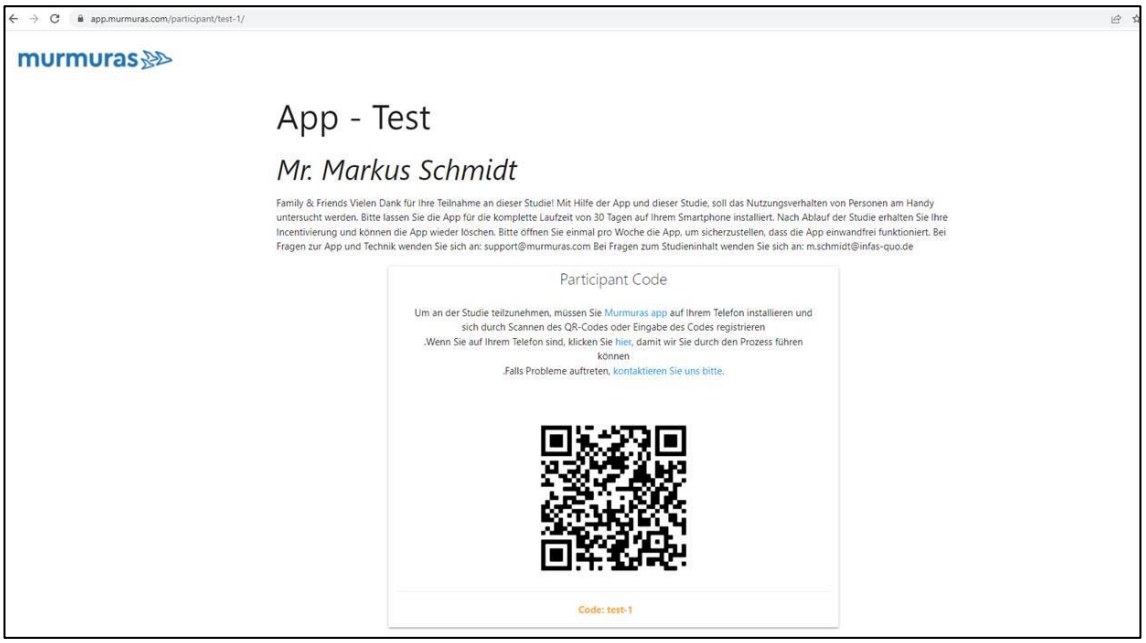


Figure 38: Exemplary onboarding email for the Murmuras App
(Q. Kasem, personal communication, August 31, 2022)

[210] The shown app screenshots and its content is generated from the own device usage.

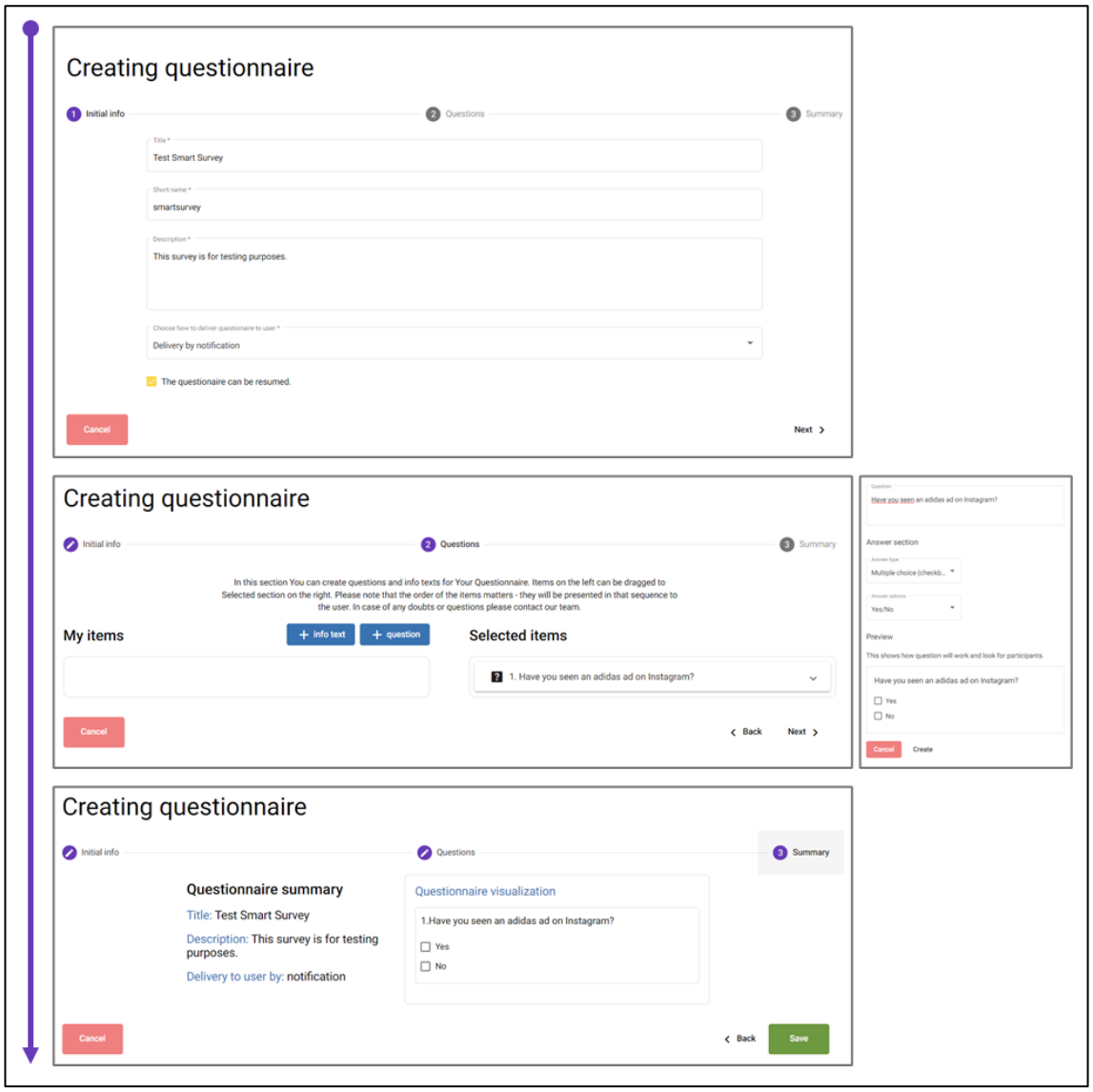


Figure 39: Exemplary Smart Survey set up process (own illustration)[211]

[211] The exemplary questionnaire is created with an own researcher account on the study management platform of Murmuras. This option can be accessed by students and academic members for free. For reference see the following website: https://academia.murmuras.com/pricing/

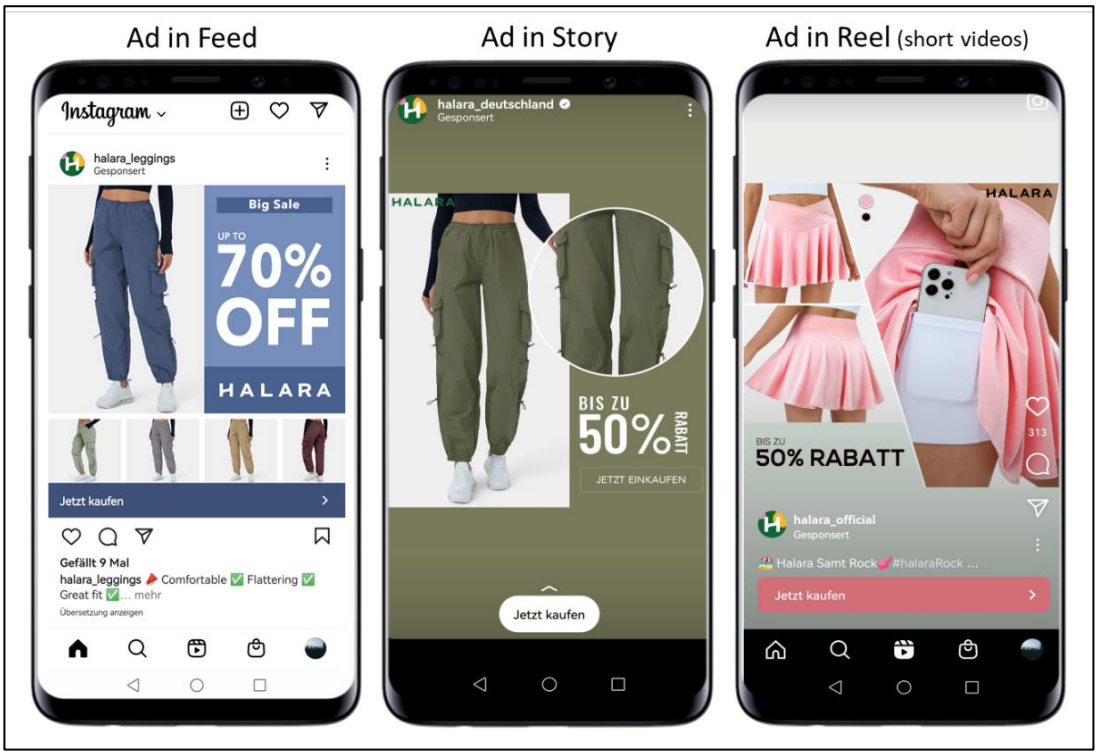


Figure 40: Ad placement options in Instagram (own illustration according to Meta, 2022a)[212]

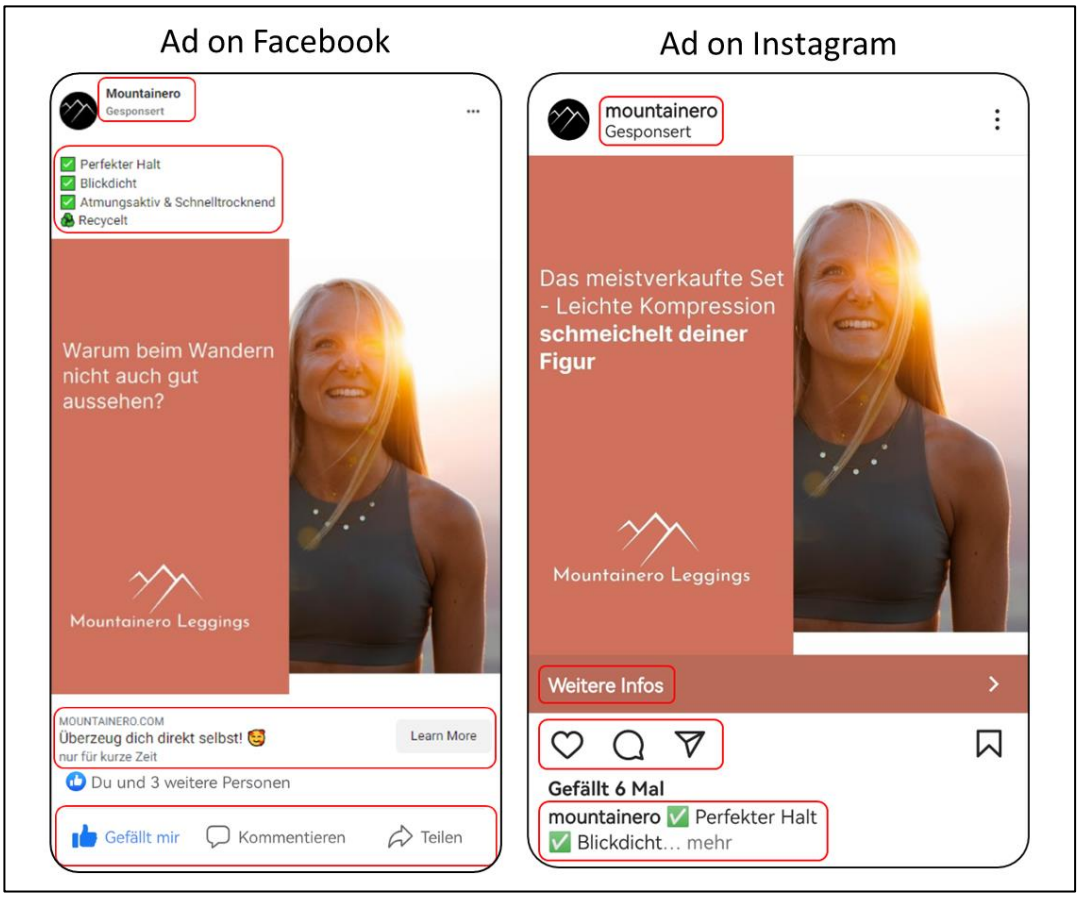


Figure 41: Captured Ad Content on Facebook and Instagram (own illustration)[213]

[212] The Figure displays screenshots of ads seen in the Instagram app on the own device.
[213] The Figure displays screenshots of ads seen in the Instagram app on the own device. Content that is captured in the sensing process is marked in red.

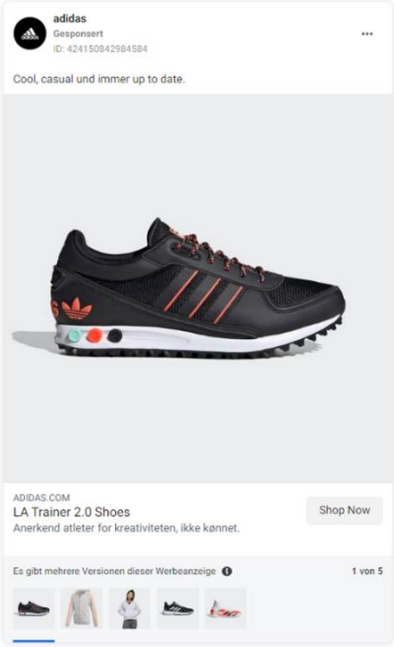


Figure 42: Adidas ad "Cool, casual und immer up to date." (own illustration according to Meta, 2022b)[214]

[214] All published ads on Facebook and Instagram are available online via the ad library. However, they are only accessible for a certain amount of time and get deleted regularly. For this reason, it may be possible that the Adidas ad cannot be seen in the ad library anymore.

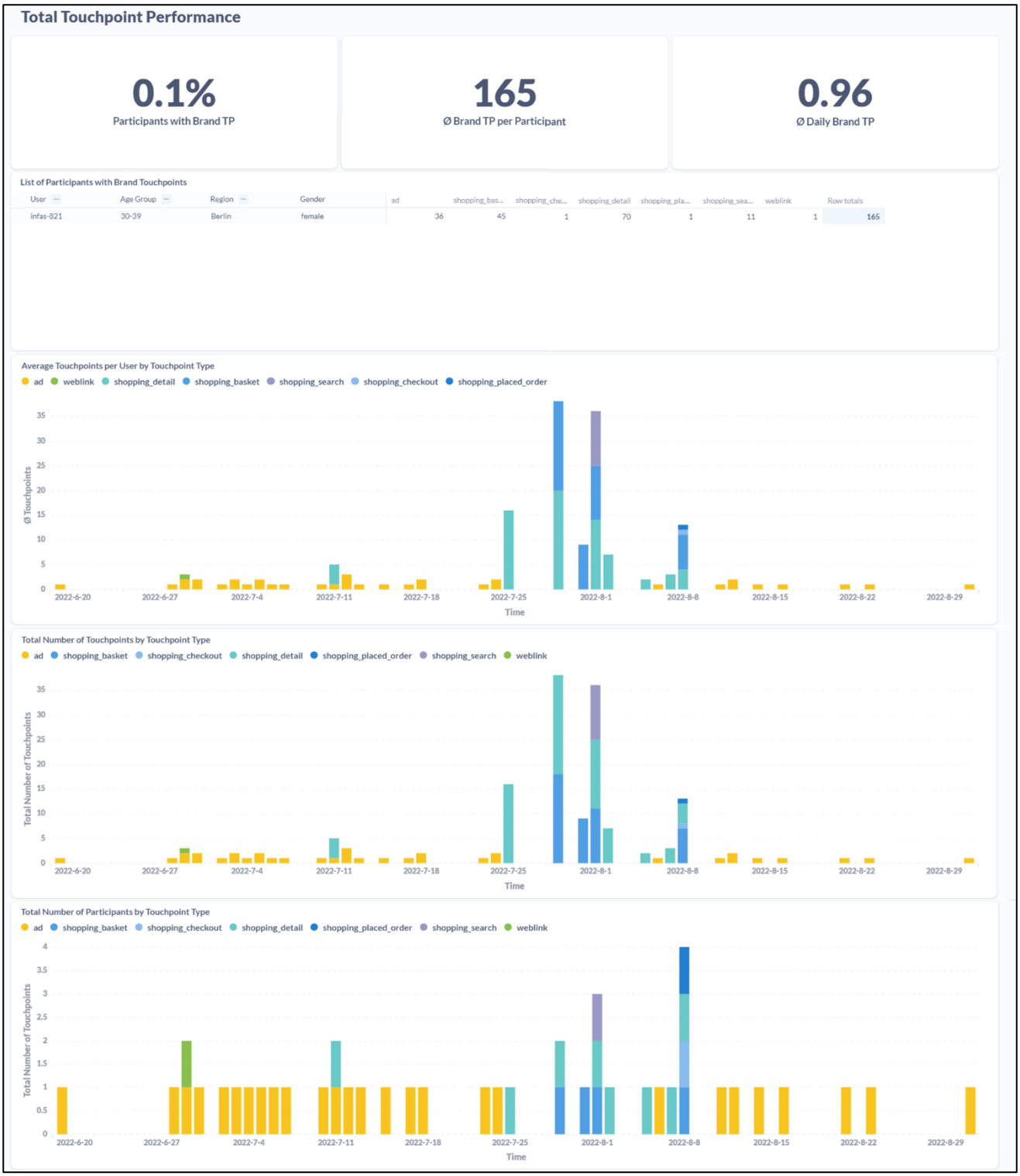


Figure 43: Total Touchpoint Performance and Mobile Customer Journey analysis – User Analysis (own analysis)

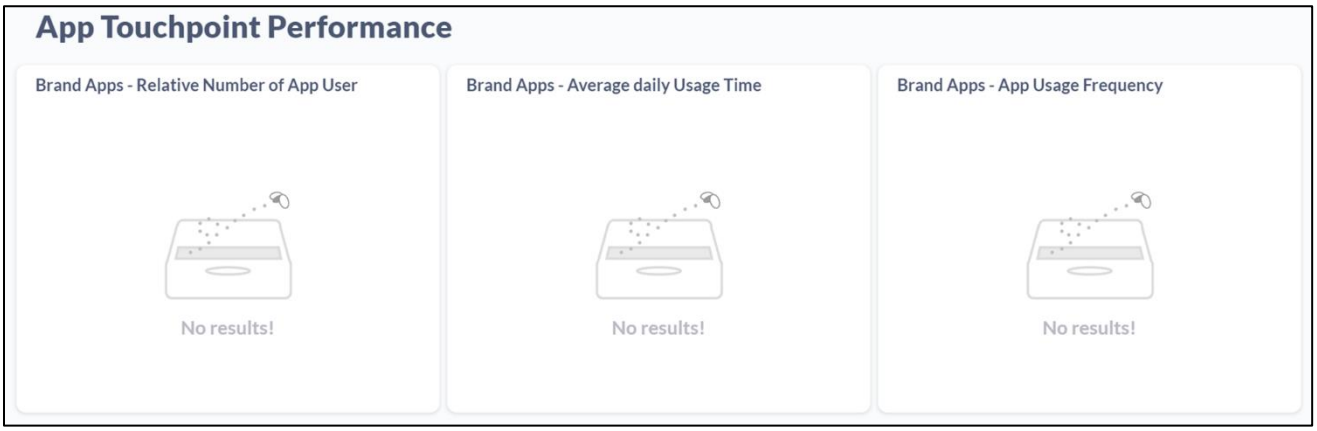


Figure 44: App Touchpoint Performance – User Analysis (own analysis)

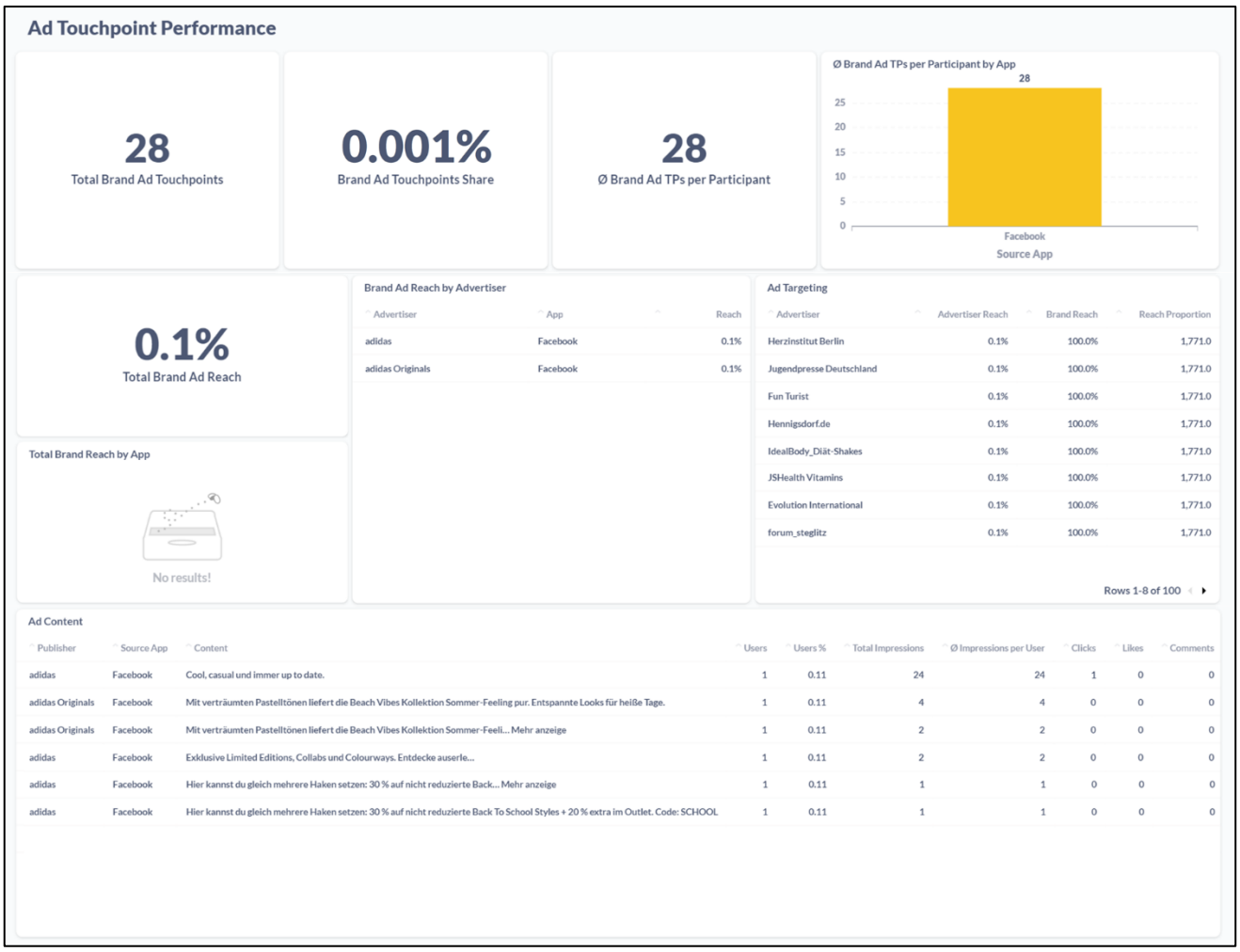


Figure 45: Ad Touchpoint Performance – User Analysis (own analysis)

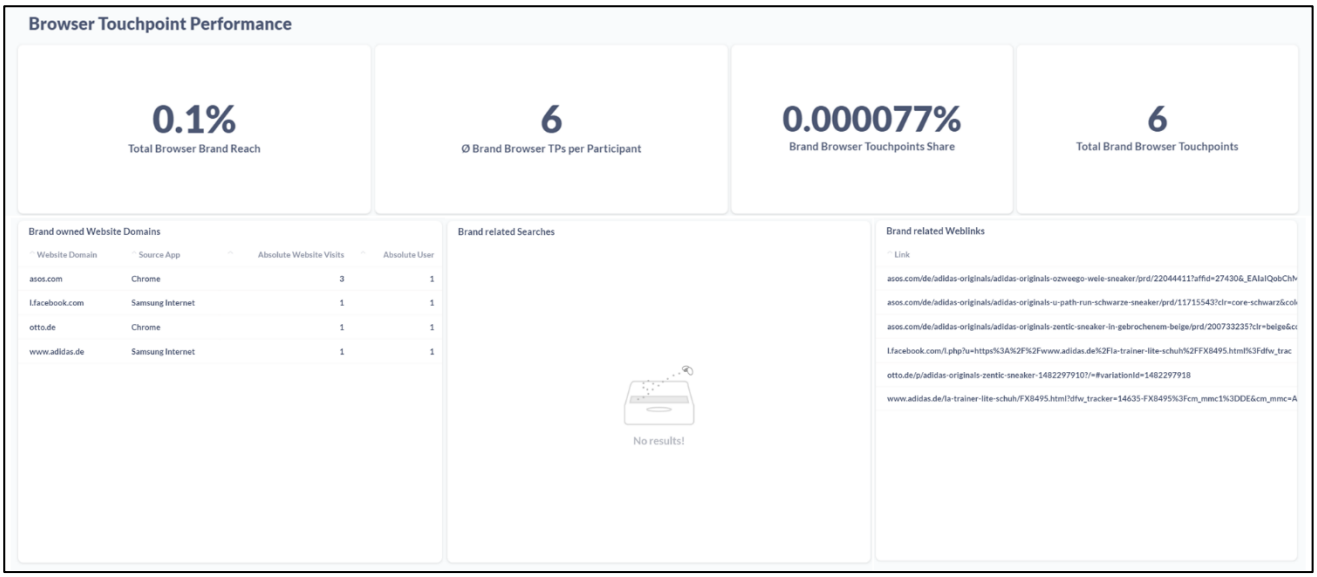


Figure 46: Browser Touchpoint Performance – User Analysis (own analysis)

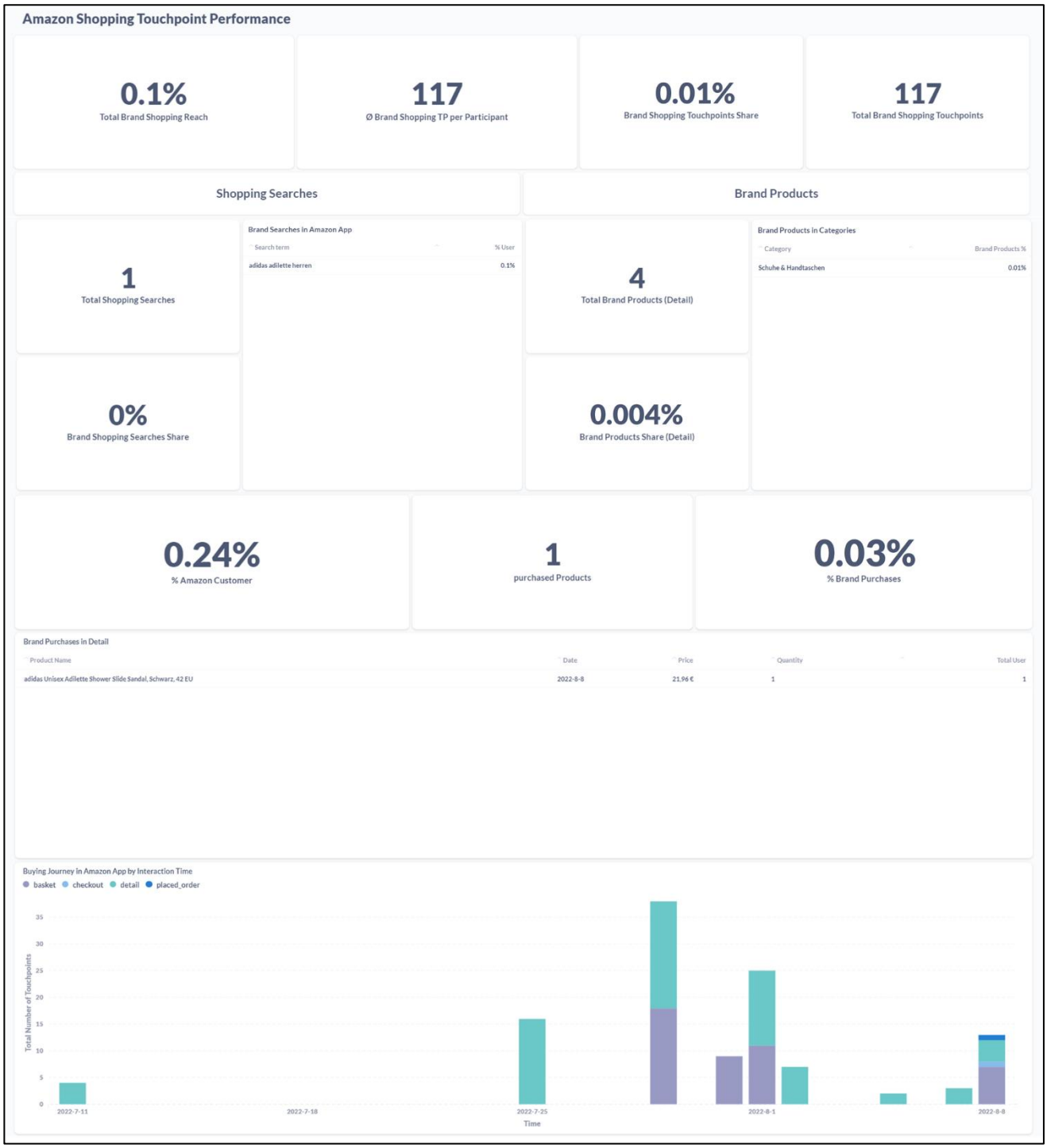


Figure 47: Amazon Shopping Touchpoint Performance – User Analysis (own analysis)

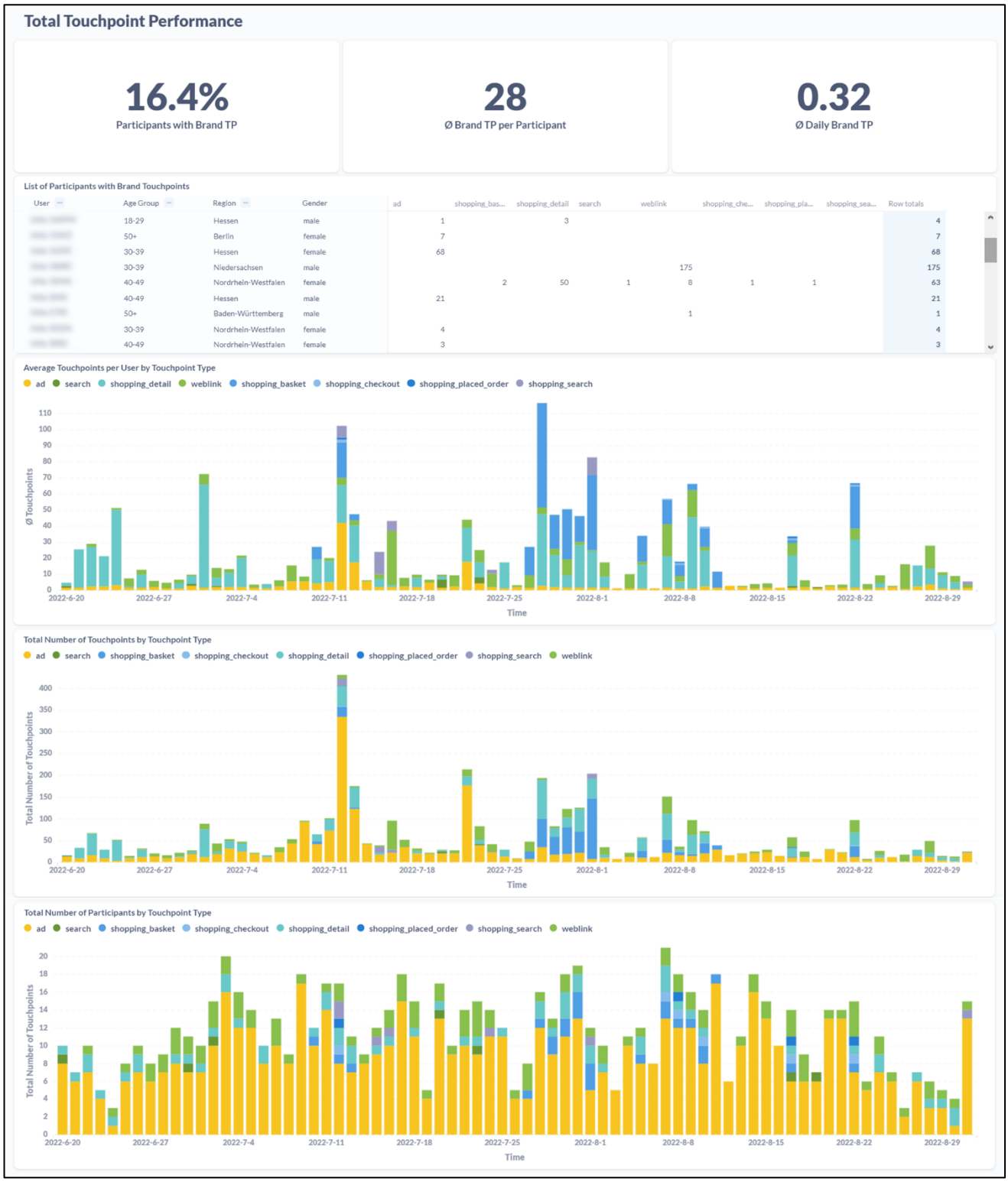


Figure 48: Total Touchpoint Performance and Mobile Customer Journey analysis – Total Sample in new time frame (own analysis)

App Touchpoint Performance

Brand Apps - Relative Number of App User

App Name	App User %
adidas Running	3.8%
adidas	1.6%

Brand Apps - Average daily Usage Time

App Name	Ø Daily Usage Time in min.
adidas Running	6.08 min.
adidas	5.53 min.

Brand Apps - App Usage Frequency

App Name	Ø App Starts per User
adidas Running	12
adidas	6

Figure 49: App Touchpoint Performance – Total Sample in new time frame (own analysis)

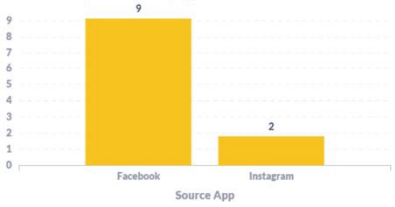
Ad Touchpoint Performance

933
Total Brand Ad Touchpoints

0.1%
Brand Ad Touchpoints Share

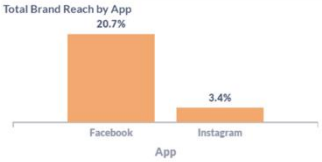
9
Ø Brand Ad TPs per Participant

Ø Brand Ad TPs per Participant by App



16.1%
Total Brand Ad Reach

Total Brand Reach by App



Brand Ad Reach by Advertiser

Advertiser	App	Reach
adidas	Facebook	20.0%
adidas Originals	Facebook	1.9%
adidas	Instagram	1.5%
adidas Golf	Facebook	1.3%
adidasoriginals	Instagram	1.1%
adidasgolf	Instagram	0.6%
adidasterrex	Instagram	0.4%
adidasfootball	Instagram	0.4%

Rows 1-8 of 10

Ad Targeting

Advertiser	Advertiser Reach	Brand Reach	Reach Proportion
Reebok	4.7%	36.7%	7.8
MELIÁ Hotels & Resorts	2.8%	22.0%	7.8
STOPPY	3.0%	22.9%	7.7
ERDINGER Alkoholfrei	2.7%	20.2%	7.6
AXE offiziell	3.4%	25.7%	7.5
Xbox	3.3%	23.9%	7.3
Cowboy	3.8%	27.5%	7.3
Davidoff Cool Water	3.2%	22.9%	7.3

Rows 1-8 of 1032

Ad Content

Publisher	Source App	Content	Users	Users %	Total Impressions	Ø Impressions per User	Clicks	Likes	Comments
adidas	Facebook	Cool, casual und immer up to date.	72	15.16	889	12.35	369	21	1
adidas	Facebook	Sommer, Sonne, Rabatte. Im Summer Sale gibt's jetzt 20 % Extra-Rabatt auf bereits bis zu 50 % reduzierte Styles. Code: EXTRA20.	9	1.89	48	5.33	47	0	0
adidas	Facebook	Hier kannst du gleich mehrere Haken setzen: 30 % auf nicht reduzierte Back To School Styles + 20 % extra im Outlet. Code: SCHOOL	8	1.68	35	4.38	25	1	0
adidas	Facebook	Entdecke die neuesten Styles im adidas Summer Sale – natürlich bis zu 50 % reduziert.	8	1.68	26	3.25	11	0	0
adidas Originals	Facebook	Mit verträumten Pastelltönen liefert die Beach Vibes Kollektion Sommer-Feeling pur. Entspannte Looks für heiße Tage.	6	1.26	16	2.67	1	0	0
adidas	Facebook	Mach mit und gewinne eine kostenlose Reise zu den Endspielen der FIFA Fußball-Weltmeisterschaft™!	5	1.05	6	1.2	0	0	0
adidas	Facebook	Cool, casual und immer up to date.	4	0.84	32	8	0	0	0

Rows 1-8 of 247

Figure 50: Ad Touchpoint Performance – Total Sample in new time frame (own analysis)

Browser Touchpoint Performance

15.1%	21	0.054%	1,163
Total Browser Brand Reach	Ø Brand Browser TPs per Participant	Brand Browser Touchpoints Share	Total Brand Browser Touchpoints

Brand owned Website Domains

Website Domain	Source App	Absolute Website Visits	Absolute User
adidas.de	Chrome	517	22
google.com	Chrome	55	10
www.adidas.de	Samsung Internet	17	7
zalando.de	Chrome	14	6
click.link.adidas.com	Chrome	25	4
idealo.de	Chrome	32	4
otto.de	Chrome	71	4
adidas.de	Firefox	16	3

Rows 1-8 of 125

Brand related Searches

Search	Source App	Absolute Searches	Absolute User
adidas	Chrome	2	2
adidas	Opera	1	1
adidascaps	Edge	1	1
adidas chamo	Chrome	1	1
adidas chamoni	Chrome	1	1
adidas champions league	Chrome	1	1
adidas champions league ball	Chrome	1	1
Adidas faust	Chrome	1	1

Rows 1-8 of 13

Brand related Weblinks

Link	Absolute Website Visits	Absolute User
adidas.de	91	14
adidas.de/cart	32	6
www.adidas.de	9	6
adidas.de/account-login	9	3
adidas.de/my-account	23	3
adidas.de/adilette	4	2
adidas.de/bestellverfolgung	2	2
adidas.de/comfort-adilette/GW8754.html	3	2

Rows 1-8 of 687

Figure 51: Browser Touchpoint Performance – Total Sample in new time frame (own analysis)

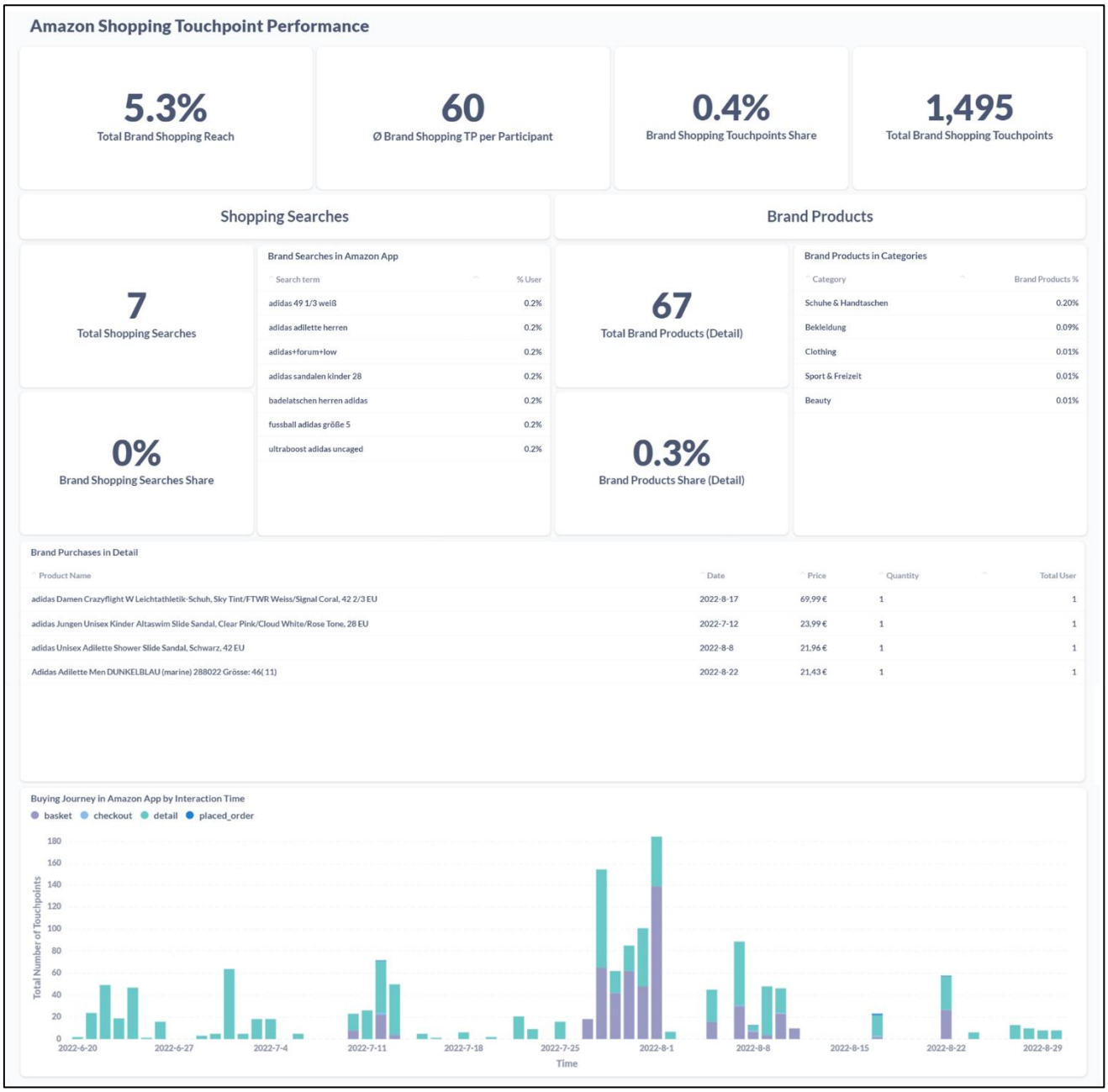


Figure 52: Amazon Shopping Touchpoint Performance – Total Sample in new time frame (own analysis)

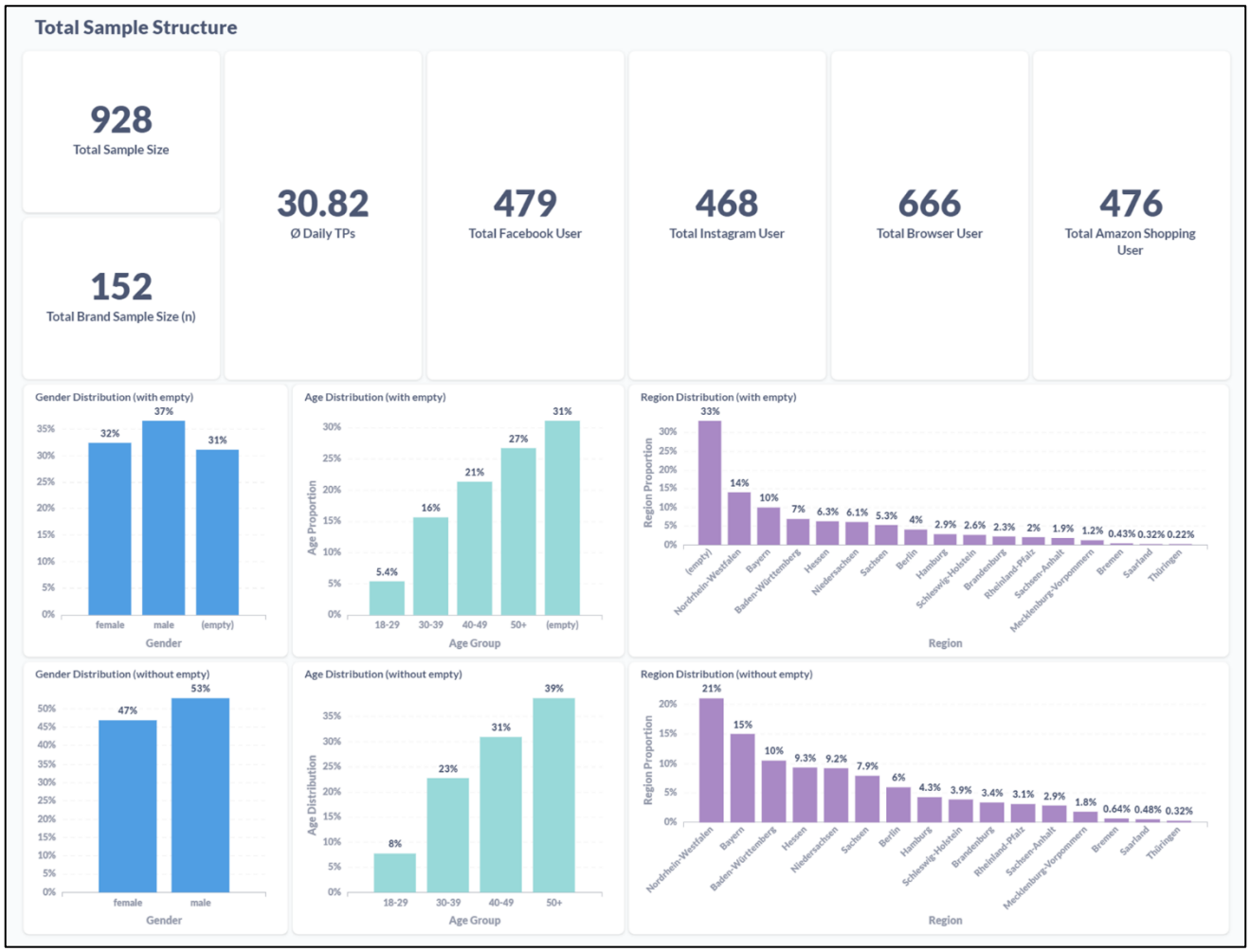


Figure 53: Total Sample Structure – User Analysis and Total Sample in new time frame (own analysis)

Figure 54: Demographics – User Analysis (own analysis)

Figure 55: Smartphone Usage Habits – User Analysis (own analysis)

Figure 56: Shopping Behaviour – User Analysis (own analysis)

Figure 57: Demographics – Total Sample in new time frame (own analysis)

Figure 58: Smartphone Usage Habits – Total Sample in new time frame (own analysis)

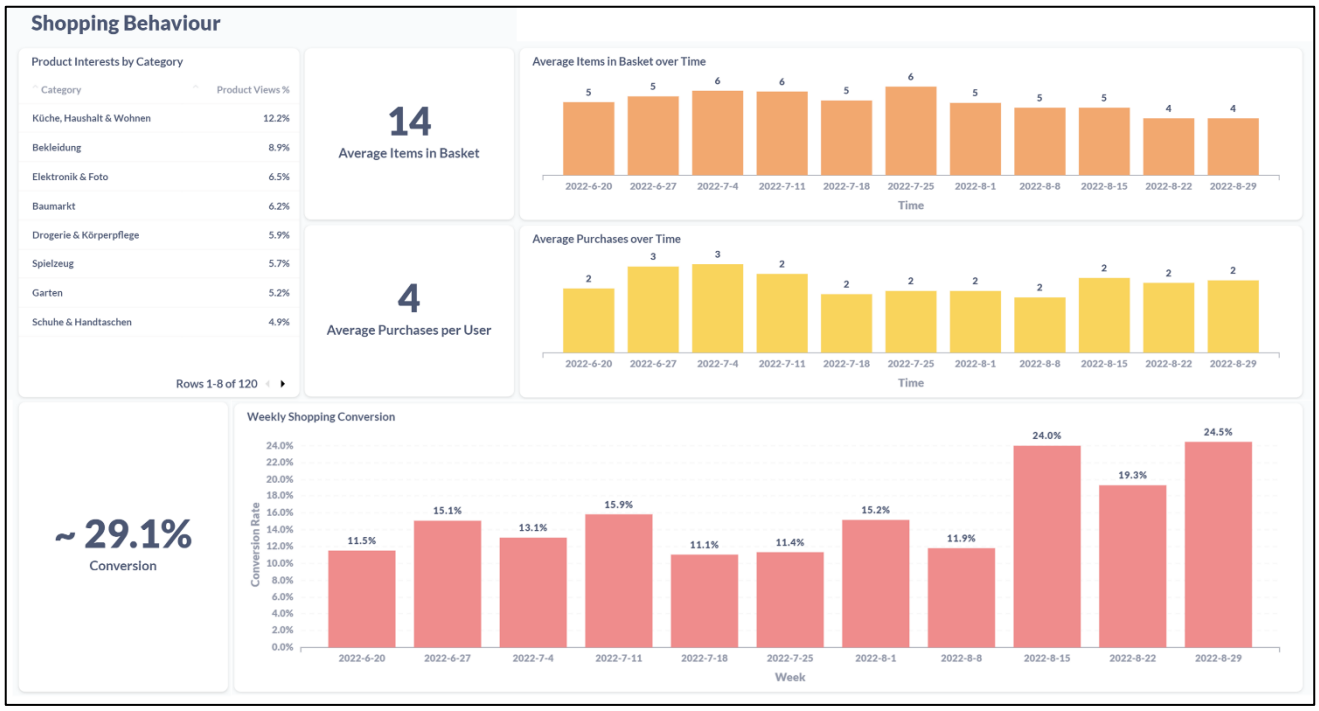


Figure 59: Shopping Behaviour – Total sample in new time frame (own analysis)

Table 18: Overview – Sensors and Behavioural Patterns
(own illustration according to Harari et al., 2016, p. 6)

Data Source	Behaviours				Research References
	Physical Movement	**Social Interactions**	**Daily Activities**	**Consumption Behaviour**	
Accelerometer	✓	X	✓	X	Tseng et al. (2016); Abdullah et al. (2016); Wang et al. (2016); Rabbi et al. (2011); Lu et al. (2010)
Bluetooth	X	✓	X	X	Chen et al. (2014); Yan et al. (2013)
Global-positioning- system scans (GPS)	✓	X	✓	(✓)	Fulford et al. (2021); Tseng et al. (2016); Abdullah et al. (2016); Wang et al. (2016); Canzian et al. (2015); Saeb et al. (2015); Lu et al. (2010)
Light sensor	X	X	✓	X	Tseng et al. (2016); Abdullah et al. (2016); Wang et al. (2016)
Microphone	X	✓	✓	X	Fulford et al. (2021); Harari et al. (2019); Tseng et al. (2016); Abdullah et al. (2016); Wang et al. (2016); Rabbi et al. (2011)
WiFi scans	✓	X	X	X	Abdullah et al. (2016)
Cameras	X	✓	✓	X	Werner et al. (2011)
Phone Usage Logs	X	✓	✓	(✓)	Harari et al. (2019); Tseng et al. (2016); Abdullah et al. (2016); Murnane et al. (2016); Wang et al. (2016); Saeb et al. (2015)
App Usage Logs	✓	✓	✓	(✓)	Harari et al. (2019); Andone et al. (2016); Welke et al. (2016); Wang et al. (2016); Ferdous et al. (2015); Murnane et al. (2016); Jones et al. (2015)
Accessibility Service scans	✓	✓	✓	✓	BMDV (2022); Murmuras (2020); Kantar and RealityMine (2019)

✓: Behaviour is captured.
(✓): Behaviour could be captured, but no research has been conducted yet.
x: Behaviour cannot be captured.

Table 19: Examples for wrong publisher entries in the dataset daily ads (own illustration)

Source App	Publisher	Error Description
Facebook	0,99€/Monat für drei Monate	Information from the ad text was incorrectly identified as publisher.
Facebook	1.714 Reaktionen	Information below the ad was incorrectly identified as publisher.
Facebook	18.07.2021•	Information about the published date was incorrectly identified as publisher.
Instagram	lisa_müller96	A private account was incorrectly identified as publisher*.
Instagram	#50plus1bleibt	A Hashtag in the ad text was incorrectly identified as publisher.
Instagram	3M	The number of followers was incorrectly identified as publisher.

* In order to protect the participants privacy this account is fictional.

Table 20: Advertising Accounts – Example Amazon (own analysis)[215]

Amazon Publisher (advertising accounts)	
Amazona.de	Amazon Kids+ De
amazona.de_official	Amazon Kinder & Familie
amazonads	amazonkindle
Amazon Ads	Amazon Kindle
Amazon Alexa	Amazon Kindle Direct Publishing
Amazon Appstore Developers	Amazon Latam
amazon_buch	Amazon Launchpad
Amazon Business	amazon.lean
Amazon.com	amazonlive
Amazon.com.br	Amazon Logistics EU
Amazon.co.uk	amazonluna
amazon.de	Amazon mini TV
amazonde	amazonmusic
Amazon.de	Amazon Music
Amazon Europe	amazonmusicde
Amazon Fashion	Amazon Music DE
amazonfashioneu	amazonmusicforartists
Amazon FBA for women	Amazon of Europe Bike Trail
Amazon Fire TV	Amazon Operations Life
Amazon Fire TV AU	amazonopslife
Amazon Flex Deutschland	Amazon-Partner in Deutschland
amazonfreevee	Amazon Pay
Amazon Freevee	amazonpets
Amazon Freight Partner - Deutschland	amazonphotos
Amazon Fresh	Amazon Photos
Amazonfreshde	amazonprime
amazonfulfillment	Amazon Prime
Amazon Fulfillment Jobs	Amazon Prime Video
Amazon Handmade	amazonprimevideo

[215] The analysis proceedings can be found in the analysis documentation in the digital appendix. See “6.1. Advertising Accounts – Example Amazon”

Table 21: Duplication analysis results on the 4th of March 2022 (own analysis)[216]

Participant Code	Time	Interaction Type	Product Name	Duplications
YGv2385jwp9	2022-3-4, 19:41	detail	adidas Tiro21 T-Shirt Black M	3
YGv2385jwp9	2022-3-4, 19:42	detail	adidas Tiro21 T-Shirt Black M	8
YGv2385jwp9	2022-3-4, 22:29	detail	adidas Own The Run Tee Damen-T-Shirt	1
YGv2385jwp9	2022-3-4, 22:30	detail	adidas Own The Run Tee Damen-T-Shirt	5
YGv2385jwp9	2022-3-4, 22:44	detail	adidas Damen Flashrunner Gymnastikschuhe, Schwarz (Core Black/FTWR White/Core Black), 38 2/3 EU	10
YGv2385jwp9	2022-3-4, 22:45	detail	adidas Damen QT Racer 2.0 Sneaker, Core Black/Cloud White/Grey, 42 EU	12
YGv2385jwp9	2022-3-4, 22:46	detail	adidas Damen QT Racer 2.0 Sneaker, Core Black/Cloud White/Grey, 42 EU	1
YGv2385jwp9	2022-3-4, 22:47	detail	adidas Originals Unisex FX7521_36 2/3 Sneakers, White, EU	3
YGv2385jwp9	2022-3-4, 22:49	detail	adidas Runfalcon 2.0 Running Shoe, Cloud White/Cloud White/Grey, 33 EU : adidas Performance	2
YGv2385jwp9	2022-3-4, 22:50	detail	adidas Runfalcon 2.0 Running Shoe, Cloud White/Cloud White/Grey, 33 EU : adidas Performance	6
YGv2385jwp9	2022-3-4, 22:51	detail	adidas Runfalcon 2.0 Running Shoe, Cloud White/Cloud White/Grey, 33 EU : adidas Performance	4
YGv2385jwp9	2022-3-4, 23:07	detail	adidas Damen QT Racer 2.0 Sneaker, Core Black/Cloud White/Grey, 40 EU	3
YGv2385jwp9	2022-3-4, 23:08	detail	adidas Damen QT Racer 2.0 Sneaker, Core Black/Cloud White/Grey, 40 EU	4
YGv2385jwp9	2022-3-4, 23:09	detail	adidas Damen Lite Racer CLN 2.0 Straßen-Laufschuh, Carbon Iron Met Core Black, 36 EU	1
YGv2385jwp9	2022-3-4, 23:09	detail	adidas Damen QT Racer 2.0 Sneaker, Core Black/Cloud White/Grey, 40 EU	3
YGv2385jwp9	2022-3-4, 23:10	detail	adidas Damen Puremotion Laufschuhe, Ftwbla Ftwbla Tonros, 36 EU	1
YGv2385jwp9	2022-3-4, 23:10	detail	adidas Damen Puremotion Sneaker, Ftwbla/Plamet/Gridos, 36 2/3 EU	7
YGv2385jwp9	2022-3-4, 23:10	detail	adidas Damen QT Racer 2.0 Sneaker, Core Black/Cloud White/Grey, 40 EU	3
YGv2385jwp9	2022-3-4, 23:11	detail	adidas Damen Flashrunner Gymnastikschuhe, Schwarz (Core Black/FTWR White/Core Black), 38 2/3 EU	2
YGv2385jwp9	2022-3-4, 23:12	detail	adidas Damen Run90s Sneaker, Schwarz 000, 42 2/3 EU	2
YGv2385jwp9	2022-3-4, 23:14	detail	adidas Roguera Sneaker, Crystal White/Crystal White/Cloud White, 38 2/3 EU	7
YGv2385jwp9	2022-3-4, 23:15	detail	adidas Roguera Sneaker, Crystal White/Crystal White/Cloud White, 38 2/3 EU	3
YGv2385jwp9	2022-3-4, 23:16	detail	adidas Roguera Sneaker, Crystal White/Crystal White/Cloud White, 38 2/3 EU	12
YGv2385jwp9	2022-3-4, 23:17	detail	adidas Damen Advantage Base Sneaker, Cloud White/Glow Pink/Core Black, 40 EU	7
YGv2385jwp9	2022-3-4, 23:18	detail	adidas Damen Advantage Base Sneaker, Cloud White/Glow Pink/Core Black, 40 EU	17
YGv2385jwp9	2022-3-4, 23:31	detail	adidas Damen QT Racer 2.0 Sneaker, Core Black/Cloud White/Grey, 40 EU	1
YGv2385jwp9	2022-3-4, 23:32	detail	adidas Damen Advantage Base Sneaker, Cloud White/Glow Pink/Core Black, 40 EU	10
YGv2385jwp9	2022-3-4, 23:33	basket	adidas Damen Advantage Base Sneaker, Cloud White/Glow Pink/Core Black, 40 EU	2
YGv2385jwp9	2022-3-4, 23:33	detail	adidas Damen Advantage Base Sneaker, Cloud White/Glow Pink/Core Black, 40 EU	1
YGv2385jwp9	2022-3-4, 23:37	basket	adidas Damen Advantage Base Sneaker, Cloud White/Glow Pink/Core Black, 40 EU	1
YGv2385jwp9	2022-3-4, 23:38	basket	adidas Damen Advantage Base Sneaker, Cloud White/Glow Pink/Core Black, 40 EU	1
YGv2385jwp9	2022-3-4, 23:38	checkout	adidas Damen Advantage Base Sneaker, Cloud White/Glow Pink/Core Black, 40 EU	1

[216] The table shows how many duplications are included in the Amazon shopping interactions dataset on the 4th of March 2022 of one participant. In order to secure the participants' privacy, the participant code is randomised.

Statutory Declaration

I hereby declare that I have written this thesis independently and without third parties and without the use of other than the stated resources.

Data and concepts taken directly or indirectly from other sources are marked with the correct reference. This also applies to sources from my own work.

I assure that I have not previously submitted this work or any non-quoted parts thereof in any other examination procedure.

I am aware that my work can be checked for unmarked adoption of other people's intellectual property for the purpose of a plagiarism check using plagiarism detection software.

Cologne, 20.12.2022

I. Halscheid

Isabelle Halscheid