FH Vorarlberg
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Trust of Buyers in the DACH region in AI in E-Commerce in the Apparel Sector

The trust in AI recommendations from e-commerce apparel buyers.

Master Thesis
Submitted in Fulfillment of the Degree

Master of Arts

University of Applied Sciences Vorarlberg

MA International Marketing & Sales

Submitted to
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Handed in by
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Dornbirn, 07, January 2022

Abstract

Trust of Buyers in the DACH region in AI in E-Commerce in the Apparel Sector. The trust in AI recommendations from e-commerce apparel buyers.

The e-commerce market has been growing for years and this trend seems to be continuing. Online stores for clothing are very successful. It seems that hardly any company can afford not to have a digital presence. This goes hand in hand with the fact that the range of products on offer to customers is getting bigger and bigger. But it's not just the range that's getting bigger, it's also the effort customers have to make to find the right product. For this reason, many successful online stores are already relying on AI. In doing so, companies are creating opportunities for customers that an employee could hardly manage. Implemented on the website, AI can check inventory, update it in real time, predict trends and evaluate customer or user data and make suitable recommendations. This is important for the customer because with the huge choice available, for one thing, personalization is increasingly important and being presented with a relevant selection. A central question is whether the recommendations are trustworthy and whether they can be equated with a real salesperson advising the customer. After all, trust is relevant in long-term customer relationships in that it leads to loyalty and satisfaction, which in turn increases the intention to repurchase. The recommendation tools mentioned are also of particular interest for another reason. On the one hand, they help customers to get a relevant selection of the offer and thus to get faster to the desired one. On the other hand, they are relevant for companies not only because of customer satisfaction, but also because of the chance to reduce returns. The large online stores for clothing offer their customers very generous opportunities to return the goods free of charge. In doing so, the companies have responded to customer wishes, because hardly anything is more important to them when it comes to online shopping: free returns. In this way, customers have minimized the risk of having to keep goods that do not fit or please them. This thesis examines whether recommendation tools can help customers to better assess the sizes and properties of clothing, so that they receive more suitable clothing and do not even feel the need to order several sizes of the same item of clothing. It can therefore be assumed that trust in the recommendations of the AI tools reduces uncertainty, which in turn should reduce the intention to return goods. Another assumption to be tested is that of the perceived usefulness of the recommendation tools. As a prerequisite to get an assessment of these assumptions is the usage of the tools. Therefore, a survey was initiated in the DACH region to assess the extent to which usage influences the factors mentioned. It was found by means of a regression analysis that the frequency of online purchases, mediated by perceived usefulness, explains the influence on trust.

Keywords: Trust, Artificial Intelligence, E-Commerce, Recommendation Agents, Apparel, Uncertainty, Perceived Usefulness, Return Rate

Kurzreferat

Vertrauen von Käufern in der DACH-Region in KI im E-Commerce im Bekleidungssegment. Das Vertrauen in KI-Empfehlungen von Käufern von Bekleidung im E-Commerce.

Der E-Commerce Markt wächst seit Jahren und dieser Trend scheint sich fortzusetzen. Sehr erfolgreich sind Onlineshops für Bekleidung. Kaum ein Unternehmen kann oder möchte es sich leisten, digital präsent zu sein. Damit einher geht, dass das Angebot für die Kunden wird, immer größer wird. Doch nicht nur das Angebot wird größer, sondern auch die Mühen für die Kunden, das passende Produkt zu finden. Aus diesem Grund setzen bereits viele, erfolgreiche Onlineshops auf KI. Damit schaffen die Unternehmen Möglichkeiten für die Kunden, die ein Mitarbeiter kaum bewältigen könnte. Implementiert auf der Website kann KI-Bestände prüfen, diese in Echtzeit aktualisieren, Trends voraussagen und Kunden bzw. Userdaten bewerten und passende Empfehlungen machen. Das ist für den Kunden wichtig da bei der riesigen Auswahl zum einen die Personalisierung zunehmend wichtig wird und eine relevante Auswahl präsentiert zu bekommen. Eine zentrale Frage ist, ob die Empfehlungen vertrauenswürdig sind und ob sie gleichzusetzen sind mit einem echten Verkäufer, der die Kunden berät. Denn Vertrauen ist in langfristigen Kundenbeziehungen relevant, dass es zu Loyalität und Zufriedenheit führt und das Wiederum die Wiederkaufsabsicht erhöht. Die erwähnten Empfehlungstools sind auch aus einem weiteren Grund von besonderem Interesse. Auf der einen Seite helfen sie den Kunden eine relevante Auswahl des Angebots zu erhalten und so schneller an das gewünschte heranzukommen. Auf der anderen Seite sind sie für die Unternehmen aber nicht nur wegen der Kundenzufriedenheit relevant, sondern auch wegen der Chance, Rücksendungen zu reduzieren. Die großen Onlineshops für Bekleidung bieten ihren Kunden sehr großzügige Möglichkeiten die Ware kostenlos zurückzuschicken. Damit haben die Unternehmen auf Kundenwünsche reagiert, denn kaum etwas ist wichtiger für diese, wenn es um das Onlineshopping geht: kostenlose Rücksendungen. Damit haben die Kunden das Risiko minimiert, Ware behalten zu müssen, die ihnen nicht passt oder nicht gefällt. In dieser Thesis wird überprüft, ob die Empfehlungstools Kunden tatsächlich dabei helfen können, die Größen und Eigenschaften der Bekleidung besser beurteilen zu können, sodass diese zum einen passendere Kleidung erhalten und zum anderen gar nicht erst das Bedürfnis haben, gleich mehrere Größen eines Kleidungsstücks zu bestellen. Man kann daher annehmen, dass das Vertrauen in die Empfehlungen der KI Tools zum einen die Unsicherheit reduziert und das wiederum die Intention für Rücksendungen senken sollte. Eine weitere Annahme, die überprüft werden soll, ist die der wahrgenommenen Nützlichkeit der Empfehlungstools. Als eine Voraussetzung, um eine Einschätzung dieser Annahmen zu bekommen, ist die Nutzung der Tools. Daher wurde eine Umfrage in der DACH-Region initiiert, um zu beurteilen, inwieweit die Nutzung die genannten Faktoren beeinflusst. Es konnte mittels einer Regressionsanalyse festgestellt werden, dass die Häufigkeit der Onlinekäufe, mediiert durch die wahrgenommene Nützlichkeit, den Einfluss auf das Vertrauen erklärt.

Keywords in German: Vertrauen, Künstliche Intelligenz, Empfehlungsagenten, E-Commerce, Bekleidung, Unsicherheit, wahrgenommene Nützlichkeit, Retourenquote

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List of Abbreviations and Symbols

AI	Artificial Intelligence
API	Application Programming Interface
AR	Augmented Reality
CE	Consumer Electronics
CRM	Customer Relationship Management
CTR	Click-Through Rate
DAX	Deutscher Aktienindex
e.g.	exempli gratia
E-Commerce	Electronic Commerce
i.e.	id est
IoT	Internet of Things
OMS	Order Management System
RA	Recommendation Agent
RT	Recommendation Tool
SaaS	Software as a Service
SSO	Single Sign-On
TAM	Technology Acceptance Model
VR	Virtual Reality
3D	Three Dimensional

1 Introduction

This chapter first provides an overview of the relevance of the topic and then leads to the question of what role trust and AI play in this. It will be described what the term trust means. An example will be used to illustrate in what form and in what situations trust can be relevant and what role it plays in marketing. In addition, it will be clarified whether people can trust AI. This question is becoming increasingly important in the digitalized world.

1.1 Relevance of the Topic

This chapter describes how the topic is relevant. Starting with people's buying behavior on the Internet, the range of products and services offered by e-vendors and the search for information, and the extent to which e-vendors are increasingly supporting customers with AI.

Black, white, wide, extra short, cotton, or polyester, these are all things that people think about when shopping for clothing - some more, some less. In general, it can be observed that consumers are sometimes unable to evaluate all available alternatives in detail when making purchasing decisions. Many online stores simply have too much choice. For example, if you select pants under the women's clothing category at zalando.ch, you get 17,251 hits. This means that in a retail store you would have to look at 17,251 different pairs of pants. Online as well as in the store they are sorted of course. If you choose black as color, there are only 6,314 items. Selecting size leads to 1,680 items and specifying long for length reduces the whole thing again to 363 items (*Zalando.ch*, 2021).

Lots of people already buy their clothes online, and this number is increasing year by year and the trend for the next few years is also pointing in this direction (*E-Commerce weltweit*, n.d.). The large selection, the convenience, the independence from opening hours: there are good reasons to buy clothes on the Internet. But the large selection also brings problems with it, because the customer first must find what he or she is looking for (Häubl & Trifts, 2000; Urbany et al., 1989). And once they have found it, they may not know which pair of jeans is the right one. The color looks good, but in the picture the fabric seems a bit thin. Or is that just deceptive? The manufacturer is also unknown, so how sure can they be that the pants will fit (Urbany et al., 1989). Online retailers have found various solutions to steer the so called information overload into orderly channels (Häubl & Trifts, 2000; Lin et al., 2021; Xiao & Benbasat, 2007). On the one hand, product descriptions in most e-shops are very detailed (Kim & Krishnan, 2015), and on the other hand, customers do not run the risk of paying for something they do not like, as e-vendors offer generous return options, as will be described in more detail later. This is exactly a bane for the online retailers, especially those who offer clothing and footwear, because in no other industry are the return rates as high as for clothing (*eCommerce-Studie-Oesterreich-2021*, n.d.; *Retouren vermeiden*, 2019; Statista, 2020; Zapfl, 2019). And that costs money. Small businesses more than large ones (Friedrich et al., 2021; WELT, 2018). Capping the free returns option for customers isn't one, because without it, sellers have to worry about being stuck with the merchandise right away. At least, that's what customers in surveys consider important in an online store: free returns (PricewaterhouseCoopers, 2021).

As mentioned earlier, younger shoppers are the most avid online apparel buyers, but they also return the most (Statista, 2020; Zapfl, 2019). In other words, Generation Z, also known as the "digital natives". For some sources, these are the cohorts from 2001 to today. What distinguishes this group is that they are growing up in a networked world and spend a lot of time with their smartphones. Their enthusiasm for technology is great, but they are also less brand loyal and switch quickly between providers. The attention span of digital natives is considered very short. To cater to this, it makes sense to feed them relevant content right away (Kruse Brandão & Wolfram, 2018). Google, on the other hand, has coined the term Generation C, which ascribes the same attributes to this group of people as to digital natives, but does not ascribe these attributes to an age group per se, but rather wants to do this to reflect the mindset of this group, regardless of their biological age (*Vorstellung der Gen C*, 2013). What we don't know is whether this generation is returning more of the ordered clothes because they don't look deeply into the products before making a purchase decision due to the said short attention span, or if it's for other reasons. Either way, recommendation agents (RA) are likely to make a difference. More than in one study it was shown that the use of RA reduced the effort to find suitable product information. It also reduced the amount of deliberation. To the same extent, the quality of the considerations and the quality of the purchase decisions increased (Häubl & Trifts, 2000; Komiak & Benbasat, 2006; Lin et al., 2021).

Artificial intelligence in the form of a recommendation tool can support customers in making decisions or even take decisions away from them altogether. This is done, among other things, by calculating and deriving probabilities based on the data that is available. In this way, the tools implemented in online stores can help customers make decisions faster and more accurately (Rusnjak & Schallmo, 2018).

When making a purchase decision on the Internet, this is the classic way what is a two-stage process. In the first phase, people select a subset of the most promising alternatives by filtering. They then evaluate these alternatives in more detail, make relative comparisons between the products in terms of important features, and make a purchase decision. Given the different tasks to be accomplished in such a two-stage process, interactive tools that support consumers in the following respects are particularly valuable: first, the initial screening of available products, i.e., the classic filtering in online stores as described above, and second, the detailed comparison of the selected products before the actual purchase decision (Häubl & Trifts, 2000).

Another answer to this kind of information overload are recommendation tools. These have the potential to reduce information overload and complexity for consumers searching for the garment they want. Another positive effect is that the quality of the decision is also improved (Häubl & Trifts, 2000; Lin et al., 2021; Xiao & Benbasat, 2007).

This thesis aims to find out what influences the customer's trust in the recommendations and information provided by an AI in the online store as “artificial intelligence (AI) appears likely to influence marketing strategies, including business models, sales processes, and customer service options, as well as customer behaviors” (Davenport et al., 2020).

Another aspect is the relevance of the topic of online shopping. The trend of recent years is continuing, and more and more people are shopping online (*E-Commerce in Österreich*, n.d.-a; *E-Commerce-Markt für Bekleidung in Deutschland*, 2021; *Schweiz - Umsatz im Online- und*

Versandhandel 2021, n.d.). Recommendation tools are therefore likely to become increasingly important and could give companies that use them a competitive advantage over those that do not (Buchkremer et al., 2020). In general, online digitization continues to gain ground (Heinemann et al., 2016). With multi-channel, several sales channels are controlled and operated in parallel, whereas the term cross-channel describes the attempt to achieve a sales-stimulating link between the sales channels. Omnichannel extends the cross-channel by integrating all touchpoints with access capabilities via various devices, smartphones, and tablets (Deges, 2020). That is the reason that traditional brick-and-mortar stores are trying to grab a piece of the online business with digital innovations. For example, the well-known global cosmetics brand *MAC* recently introduced a virtual try-on for make-up (*Try Me On*, 2021). With the help of the camera on the laptop or smartphone, customers can see how the lipstick color suits them, whether the make-up matches the skin tone and, if in doubt, they can contact a make-up artist in addition to virtual make-up courses (*Virtual Services*, 2021). This kind of recommendation tools have an entertainment value in addition to the benefit for the buyer (Binckebanck & Elste, 2016).

AI still holds plenty of potential for innovation (Bruhn & Hadwich, 2021). More and more AI solutions can be found on the market to solve the problem of finding the right clothing size when buying clothes online. Here, presize.ai, meepl.com, *NeXR* and *ZyseMe* are worth mentioning:

- *Presize.ai* promises customers who implement the software to increase user confidence, reduce return rates by up to 5%, and increase the accuracy of recommendations by 20% in 6-12 months. The software makes accurate size recommendations using a body scan of the end customer (*Presize.Ai*, 2021).

- *Meepl.com* was acquired by *Zalando* and is also a virtual try-on (*Zalando*, 2020). More about this in the *Zalando* chapter.

- *Nexr* is cooperating with *H&M*, whose Virtual Try-on is still in the test phase. *H&M* has also launched *ZyseMe*, a project that allows customers to order customized clothing on demand. An algorithm that determines the body measurements based on the answers to 5 questions is supposed to be all that is needed (*H&M Lab*, 2021).

Implemented on the website of an online store, this is a recommendation tool. Such tools are, successfully applied, a solution where everyone benefits. The customer gets the right garment right away and the companies get less returns, which is a goal of many companies and should be achieved by RT's. As online retail continues to grow, the range of products available to customers will become even larger and thus more confusing (Fynn, 2020). As consumers also increasingly shop online with their smartphones, it will be even easier to implement applications with Virtual Reality and make them palatable to users (Hesse, 2021; Hürlimann, 2021).

SCAYLE, the B2B segment of ABOUT YOU, promises fabulous sales increases with the use of their technology. But it is also a fact that the most successful online stores for clothing have been using AI in their stores for a long time to optimally respond to customer needs. With the help of innovative technologies, customers can be shown the part of the assortment that is relevant to them. What we want to know is whether precise recommendations increase trust in continuing to precisely follow those recommendations.

This thesis, nonetheless, is at this point not concerned with what leads to greater customer satisfaction or increased sales. The researcher sees the enormous number of returns as a major problem in the industry and therefore want to find out which factors cause the number of returns to decrease. There is evidence that size advisors, for example, help customers find the right size better and return fewer garments (Dimoka et al., 2012; Häubl & Trifts, 2000; Urbany et al., 1989). We want to investigate what effect exactly it has when these tools are used by customers and when this becomes apparent.

Even though buying clothes online is becoming increasingly popular, the essential problem of fit remains. To counter this problem, online retailers have continued to develop their technologies. Starting with the Free return and shipping policies, to payment on delivery and virtual try-on (Tandon et al., 2020).

Research shows that interactive tools designed to assist consumers and facilitate comparisons between selected alternatives in an online shopping environment have a positive impact on the quality as well as the efficiency of purchasing decisions. Another benefit is that not only do they make better decisions, but there is less effort involved. Buyers can make much better decisions while expending much less effort. Recommendation tools are also changing the way consumers behave in online stores. The search for product information is changing and with it the way purchasing decisions are made (Häubl & Trifts, 2000).

1.2 The Relevance of Trust

There are numerous works on trust and marketing, especially in the context of sales and CRM (Abbass, 2019; Castaldo et al., 2010; Chiou & Droge, 2006; Crosby et al., 1990; Davenport et al., 2020; Fang et al., 2014; Gefen et al., 2003; Komiak & Benbasat, 2006; Moin et al., 2015; Moorman et al., 1993; Morgan & Hunt, 1994a; Oliveira et al., 2017; Overgoor et al., 2019; Puntoni et al., 2021; Sultan & Wong, 2019; Tandon et al., 2020; Verhoef et al., 2002; Verhoef, 2003). Trust itself is seen differently depending on the current context and discipline and is explained in more detail in the chapter *Overview Concepts of Trust*. There are also already good insights into the possible uses of AI in marketing; this has long since ceased to be future talk. There are also studies on consumer trust in AI in concrete applications such as chatbots. But most of the time, these studies involving AI have a focus on customer acceptance and are also strongly oriented towards the general technology acceptance of customers (Ashraf et al., 2014; Avramakis, 2020; Davis, 1989; Ewers et al., 2020; Kaufmann & Servatius, 2020; Kohne et al., 2020; Meyer-Waarden et al., 2020; Schlohmann, 2012; Venkatesh et al., 2003, 2012). Trust is usually also an issue, but not primarily. If we assume that AI will partially replace service or sales personnel in online stores, the technological component is not enough, and trust takes on a different significance. In trust research with a marketing context, there is also literature on the question of what characteristics, for example, sales personnel must have so that customers like to remain customers and are most likely to trust and be loyal to the respective company (Crosby et al., 1990). From this perspective, artificial intelligence, which takes over this part in the form of a recommendation tool, can also be viewed in the same way. This work therefore aims to establish a link between a technology and human characteristics. This under the aspect that this technology takes over in human tasks and thus the question of trust appears equally relevant.

Trust is a term that comes up frequently, not only in private life, but also in professional life, even if at first one might perceive the term as something very personal. Trust is also personal, but it does not stop where the private ends. Trust is there, or not there, in every interpersonal interaction. When one trusts, one takes a risk or more precisely: one makes oneself vulnerable (Mayer et al., 1995). Because trust is necessary where one's own competence ends. And then to trust that someone knows better than one, to trust that someone will help one decide, is fraught with personal risk. One does not know whether the counterpart is making the best decision for the customer, for example, and wonders whether a recommendation can be trusted. Very many decisions are based on trust, because the alternative would be to make no decisions at all if the person is not familiar with the situation, or to decide on good luck out of ignorance. Trust is often equated with risk, but the opposite of trust is mistrust and does not mean avoiding risk. By trusting, people make themselves vulnerable and the authors argue that trust represents the willingness to take risks (Mayer et al., 1995). If one considers trust as a behavioral intention, then no trust would be necessary where no vulnerability would be possible (Moorman et al., 1993).

Trust will now be illustrated by an example. When people aboard an airplane, they trust that the pilot is trained, that the airplane is maintained according to legal requirements, and that the mechanics would also detect a fault. What this example already shows is that there are several types of trust (Fladnitzer & Grabner-Kräuter, 2006). On the one hand, there is the pilot, whom people trust because they have seen the pilot on the way to the gate and he or she looks experienced and competent. A certain passenger even knows the pilot and know for whatever reason that he or she is a good pilot. The most passengers trust the pilot because they are trusting in the way they look at the world, which would be interpersonal trust (Mayer et al., 1995; Morgan & Hunt, 1994a; Rotter, 1967). Or people trust the pilot because they trust Lufthansa to hire only qualified pilots. Or customers trust Lufthansa as a company (both would be organizational trust) (Mayer et al., 1995; Möller, 2012; Pastoors & Ebert, 2019) or the authorities that only a safe aircraft is allowed to take off (systemic trust) (Fladnitzer & Grabner-Kräuter, 2006), this could be continued for a long time.

People can be expected to have more confidence in these things when boarding a Lufthansa plane in a Western country than when boarding a Malaysia Airlines plane that has lost two planes in a brief period and has slipped down in the ranking of safe planes (Ophüls, 2020) . What makes this example special is that a lot has been written and said about it in the press, so most have heard that the airline might be unsafe. But if a person boards an Air India plane now that is similarly poorly rated, one might not have any information about accidents, but still have a sinking feeling in one's stomach. When does that trust go out of the window? Or rather, how is trust created?

Now, the decision to take out a large loan or the decision to buy a dress on the internet are quite different in terms of trust. At least in terms of vulnerability. Taking on a financial risk has different consequences than finding out later that the dress does not fit, that it has been poorly made or that it simply does not suit the buyer, which briefly describes the involvement of customers (Garbarino & Johnson, 1999; Verhoef, 2003). Nevertheless, the latter should not be underestimated from a company's point of view, because unlike credit, many people around the world decide to shop for clothes online every day. The number of those is likely to be incomparably higher than those who take out a loan.

Now many do not know whether they can trust a seller. Surely everyone has heard that a seller wanted to "sell" something to someone, which often sounds like tricking, often when buying a used car. There are a lot of studies related to trust in Marketing and Sales and/or Customer Relationship Management and the chapter 3.2.1 describes them in more detail, but it turns out that some factors build trust and others do the opposite. Because trust becomes necessary only there, where e.g., the salesperson has a knowledge advantage over his customer (Crosby et al., 1990; Moorman et al., 1993). So, the car salesperson or mechanic and the ordinary car buyer. If one knew oneself what the desired car would have to be like for a certain price, then one would not have to rely on the statements of the salesperson or trust him to offer the car at a fair price.

For example, similarities between the seller and buyer promote trust, whereas opportunistic behavior on the part of the seller toward the customer negatively influences the latter's trust (Morgan & Hunt, 1994a).

In online stores, however, these salespeople are often completely absent, at least they are not as present as in a retail store and are more perceptible as customer service. Instead, the large online stores for clothing are increasingly relying on AI to make the vast selection accessible to customers and to support them in choosing sizes. This is not only done to make life easier for customers, but also for their own benefit. On the one hand, the selection of the product range is optimized (bonprix) and on the other hand, the online stores hope for fewer returns, because this branch is severely shaken in this respect (*Commerce-Technologie der nächsten Generation – SCAYLE*, 2021; *Geschäftsmodell*, 2021; *Zalando*, 2019b).

When we talk about trust in AI, a new, technical component is added (Rathje et al., 2021). Suddenly the question arises whether, and if at all, how, we can trust non-human intelligence (Puntoni et al., 2021). If we consider the significant role that trust plays in general in the areas of marketing, sales, and especially in CRM, the question of whether the positive effects of building trust between salespeople and customers can also be transferred to AI used in online stores is entirely relevant. In 2017, the major Swiss bank UBS commissioned a study on the excessive cost savings of flying airplanes without pilots. Technologically, this should be possible by 2025 and safety would also be increased as a result. However, the survey of potential customers revealed that more than half of these 8,000 respondents would not board a pilotless aircraft, according to their own statements. In Europe, even fewer people can imagine this than in the USA, but here, too, the younger generation is much more open to this topic overall than the 65+ generation (Bachmann, 2017) .

This paper therefore examines whether customers trust the recommendations of AI and what consequences a positive perception of AI entails. Conversely, it will also be examined what the possible reasons for a lack of trust might be and how this could be remedied. In this context it should be mentioned that there are several types of trust in the literature, which will be discussed in the further course.

1.3 Problem Definition and Aim of the Thesis

Trust is viewed as a key element of successful relationships (Morgan & Hunt, 1994a). It has always been a popular area of research across all disciplines, and so it is in marketing. It is interesting to see whether recommendation tools can also build a relationship of trust with customers, like some of as some AI solution providers promise. We know from trust research in marketing that trust leads to more lasting and loyal customer relationships and, moreover, to satisfaction and high quality. High relationship quality (trust and satisfaction) in turn leads to a higher likelihood with the customer for an exchange in the future (Crosby et al., 1990). Expertise has been found to be an important foundation for trust (Moorman et al., 1993).

It can be assumed that the return rate can be reduced if customers order matching garments more frequently. In general, this assumption is widespread, even if there are hardly any verifiable figures to support it. But considering that the main reason for return is "item does not fit", even before "I do not like item" or other reasons, it is a logical conclusion that at least the people who like and fit the item do not return it. (Weidemann, 2020), (*Retouren vermeiden*, 2019), (Zapfl, 2019). We also assume a certain level of trust in e-vendors, which are considered in this paper as they are among the most successful and well-known in the DACH region. The fundamental question that is addressed in this research project, is how to evaluate trust in the recommendations of AI tools. Another assumption, based on the literature, is that greater trust and usefulness reduce uncertainty, leading to higher decision quality (Häubl & Trifts, 2000) and thus fewer returns by customers. A look at perceived usefulness is also necessary, as it is relevant in the general acceptance of a technology (Davis, 1989; Gefen et al., 2003).

Companies like presize.ai already attribute declining returns to their tools (*Presize.Ai*, 2021). But we are still talking about assumptions here, as presize.ai, for example, states a 5% reduction in the retention rate, but no comprehensible information is provided on the website as to how this figure was determined.

Zalando writes about the implementation of AI Tools on the company website (*Zalando*, 2020):

> *"Solving the inherently very personal but prevalent problem of size and fit represents huge potential to transform fashion e-commerce for the benefit of both customers and brands. Customers will be able to generate precise body measurements which they can use to receive even more accurate size advice, and purchase items they know will fit. Brands, for the first time, can gain a deeper understanding of how well their assortment addresses the size and fit needs of a target audience which in the long run will enable them to produce better fitting garments."*

In surveys, the main reason for returns was "item does not fit" or "item is too small/too big", which amounts to the same thing. Another interesting observation is, younger customers are more likely to send back clothing than older ones, although sustainability is increasingly important to the younger generation. The latest Shell Youth Study from 2019 has already identified this trend. It states, that "many young people attach importance to a much more conscious lifestyle and are clearly and loudly articulating their demands for a sustainable environment and society" (*Summary Youth Study*, 2019)

They are also much more open to the use of new technical devices in surveys. The statement "I like to try out new technical devices" and "I know a lot about technical things" were answered positively by 53.3% and 43.8% of 14 to 24-year-olds, respectively. In contrast, only 43.6% and 39.8% of 25 to 29-year-olds and 34% and 30.2% of 40 to 54-year-olds were receptive to these topics (*Generationen - Technikaffinität und Kenntnisstand 2020*, 2020).

Not least because of this, we see an immense potential for recommendation tools to be a realistic answer to reducing the return rate. Based on the literature review, this is an expected outcome. Nevertheless, a prerequisite for the tools to work is that they are used. So, what does it take for the customer to use a recommendation tool? How often does he or she need to use it to find the recommendations trustworthy? Or does the trust come from the user finding the tools useful. Or do these processes take place simultaneously? Because, as we will see later, it is once about the acceptance of a technology, but also about trust. What we therefore also want to know is whether the recommendation tools can be like a salesperson in a classic customer relationship as a source of trust, to which one gladly returns and trusts in the competence and expertise (Crosby et al., 1990). We also assume that trust reduces customer uncertainty (Morgan & Hunt, 1994a), and that it is this reduction in uncertainty that will make returns obsolete. Only when the customer trusts that the recommendation is correct and that he feels confident that he or she has ordered the chosen garment in one, namely the correct size, will the customer be prevented from ordering five sizes of the same item. That leads us to our research questions.

- Does the use of the recommendation tools increase consumer trust in them?
- What role plays the technical antecedent perceived usefulness?
- Does a higher trust level reduce the customer's uncertainty?
- Does a decreased uncertainty lower the intention to send back ordered clothes?
- Is there a difference between customers who buy clothes online more often and those who do not? If so, which one?

The creation of a customer account is useful to benefit the most from AI, because it needs data. This depends on the extent to which one wants advice. At bonprix, as described, such data is collected based on experiences with different brands and their sizes. Within a brand, the sizes are namely quite constant, but there can be massive differences between the manufacturers (Dockterman, n/a; Kramper, 2018).

The question that arises with this topic is whether AI recommendation tools can make recommendations to the customers of online stores that can be trusted. That is, that fit so well that they no longer feel compelled to return goods.

Finally, it has been shown in general terms that the acceptance of technologies depends on only a few central determinants. These are perceived usefulness, perceived ease of use and intention to use. It was found that the higher the perceived usefulness and perceived ease of use, the higher the intention to use. As a result, the actual use of a technology is also higher (Pütz et al., 2021).

A look at what causes customers to return less items, there is the need to consider what the reasons are. As mentioned earlier, the most common reason for a return is that the garment does not fit, the second most common is not liking it. The latter is not very precise, but it is safe to assume that if the customer did not like the color or material in the store, they would have noticed it before they bought it.

While digitalization in online retailing is not an innovation per se, the ability of online retailers such as Zalando or ABOUT YOU to innovate is demonstrated by their focus on and further development of AI or data-driven technologies, completely displacing already existing technologies. The latter is something that characterizes an innovation among others (Heinemann et al., 2016). The rapid growth of fledgling companies such as ABOUT YOU could be an indicator of the success of the technologies used. In general, the three companies Zalando, bonbrix and ABOUT YOU show rapid growth, which is also in line with the trend of e-commerce. However, the fact that they themselves invest a great deal in the constant further development of technologies makes it seem as if these online retailers could maintain and further expand their market position and dominance (Goldmanis et al., 2010).

1.4 Structure of the Thesis

The first section of the main part clarifies what is meant by the terms trust, AI, and e-commerce in general, which are to be related in this thesis. This section is at the beginning general and leads then to a more exact delimitation of the main topics. That is, the results of a further literature research on the topic of trust in marketing, the description of recommendation tools with the reference to the technological aspect of the work. An overview of e-commerce specifically in the DACH region for the apparel sector is also provided. The online stores that are of particular interest for this work are described in more detail, including which recommendation tools are available on the respective website. AI Recommendation Tools are a technology that have an innovative character (Bruhn & Hadwich, 2021). The selection of tools explained in more detail here is limited to the tools used by the largest online stores in the DACH region.

The second part of the main section is devoted to the development of the research model, here called the trust model. The hypotheses are individually derived step by step from the theory and explained.

The third and last part of the main section deals with the evaluation of the trust model. It describes how the quantitative survey was developed and which statistical tests were used for the evaluation and why. This is followed by an evaluation of the results.

At the end of the thesis, the main points of the work are summarized again, and it is discussed whether and which hypotheses were confirmed, and which were not. The limitations of the trust model are explained, but also the results are put into perspective for potential future research.

2 Subject of Investigation

In this part of the paper, the object of study is delineated. After a definition of the term recommendation agent or recommendation tool, it is described how these are used specifically in marketing. After a general description of the technology, it is explained to what extent it is an innovative media technology. Furthermore, in the following subchapters, online stores for clothing will be closely examined regarding their use of AI and AI recommendation tools. All areas in which AI tools are intended to make shopping easier for the customer are analyzed in detail. However, we limit ourselves to the three online stores in the DACH region that have the highest sales and use such AI tools. We also only consider companies that conduct their major business online. Although the industry giant Zalando has now also opened stores and is therefore multichannel, fashion houses such as H&M have many stores and have intensified their online business, thus further expanding their omnichannel strategy, but as we will briefly explain later, the sales and websites are not easily comparable, which is why we want to limit ourselves to the online stores.

The theory of consumer search for information about the quality of goods is also relevant here in two respects (more information on this theory can be found in the Uncertainty chapter) (Nelson, 1970). First, recommendation tools provide more opportunities for consumers to obtain more information regarding the quality or fit of clothing prior to purchase, which reduces user uncertainty. However, Nelson's theory also includes experience as an alternative to search. If consumers use their experience by buying clothes from brands they know and whose quality they value, they can also determine their subsequent use. i.e. they can determine the quality of brands by buying them and then using them. Transferred to a recommendation tool, the user would do both. First, he receives all the information through detailed images and product descriptions, also through user ratings. If the users have a customer account and have stored the sizes there, combined with the brands they wear, the RT also builds up its wealth of experience with each customer order, from which the customers also benefit. Furthermore, the positive experiences made with the recommendation tool should lead to further use (Nelson, 1970).

2.1 Overview E-Commerce Apparel in the DACH Region

E-commerce is defined by the fact that trade in goods and services takes place electronically. The transaction, i.e. the initiation, conclusion and execution of the purchase or sale, takes place via the Internet using interactive information and communication technologies (Deges, 2020).

2.1.1 Facts and Figures DACH Region

Online shopping is big business, as the figures also tell us. In the DACH region, e-commerce sales are increasing year after year. Globally, the top free e-commerce service in 2018 was free returns, 65% indicated this option (*E-Commerce weltweit*, n.d.).

For the sake of clarity: Distance selling purchases include purchases on the Internet and purchases by mail order. When e-commerce is mentioned, only internet trade is meant and no other distance trade purchases such as teleshopping or purchases via a catalogue. The important key figures have been summarized in Figure 1 (*E-Commerce in der Schweiz*, 2021; *E-Commerce in Deutschland*, 2021; *E-Commerce in Österreich*, n.d.-b; *E-Commerce-Markt für Bekleidung in Deutschland*, 2021; *E-Commerce - Online-Umsatz nach Branchen in Deutschland 2020*, n.d.; *Österreich - Online-Anteil in einzelnen Produktsegmenten 2020*, n.d.; *Top 10 Online-Shops in der Schweiz im Jahr 2020*, n.d.).

Table 1: E-Commerce Facts & Figures 2019

E-Commerce Facts & Figures 2019

	Germany	Austria	Switzerland
Population in million	83,5	9	8.6
E-commerce users in million	62	6	6
E-commerce users in %	74%	69%	69%
Interest in clothing (1st)	73%	72%	75%
E-commere net sales* in bn US$	74	6	9
Biggest category	Fashion	Fashion	Electronics & Media
Share of shoppers that returned clothes	34%	32%	38%
Main reason	Article does not fit (58.2%)	Article does not fit (70.6%)	N/A

* net sales is the turnover at which discounts or returns and advertising adjustments have already been deducted

2.1.2 Market Switzerland

In Switzerland, the second strongest online shop is one for clothing, namely Zalando.ch. In general, the share of the apparel industry in the overall market in Switzerland increased from 10% in 2014, to 20% in 2019 and to 29% in 2020. The Corona epidemic is also likely to have played a large part in this strong increase: in 2019, online and mail order sales amounted to 10.3 bn, In a consumer survey conducted in March 2021, 74% of respondents said they had bought clothing and footwear, followed by sporting goods and clothing accessories.

In Switzerland, there is no source with information on the reasons, but here too there are clear differences in the age groups regarding returns. As a rule, it can be said that the younger the online shoppers are, the more they return.

2.1.3 Market Austria

Overall, the number of online shoppers and the proportion of Austrians who bought online increased significantly in the first Corona year 2020 compared to previous years. Since 2013, purchases had only increased by 1-2 percentage points annually, but in 2020 they had already increased by 6% points compared to the previous year.

The Austrian Trade Association describes the apparel industry as a "problem child" when it comes to returns. In this respect, the apparel sector is the sad front-runner with a return rate of 47% in 2021.

Spent e-commerce 10.4 billion in 2021, up 7.4% from 8.7 billion a year earlier in 2019 (8.1 billion). This means that sales have increased by 28.4% in just two years.

With 31.2% of total e-commerce spending in Austria, the clothing sector ranks third, behind film and photo equipment and photo books (35.8%) and books and magazines (33.9%).

It's also interesting to note that free delivery is important to 94% of online shoppers surveyed. If we then look at the fact that most of the returned items are from the clothing sector, we get an idea of what returns cost the clothing industry. In fact, 75% said that the category they have already returned products from is apparel/shoes/accessories. In second place, at 14%, is the consumer electronics category. The apparel segment is thus the sad front-runner in terms of returns. The number 1 reason in Austria 2020 with 70.6%: "Item does not fit", followed by "Item does not like" with 38.1% and 30% "Item does not correspond to the description / picture".

2.1.4 Market Germany

Unsurprisingly, Germany has the largest market in the DACH region based on population alone. In 2020, 62 million consumers were e-commerce users, 68% of whom also research online before making purchases. The Corona pandemic also brought not only sales growth in all three countries, but significant shifts could also be observed. Supermarkets benefited with an increase of 35% in global web traffic, whereas the fashion sector initially lost traffic (-10%).

In Germany, a total of 280 million parcels were returned in 2018, up from 315 million two years later. Apparel and accessories was the second strongest online category in terms of sales with 16.8 billion, behind CE/Electrical (CE = Consumer Electronics) with 17.8 billion. The leisure and hobby category ranked third with sales of 11.1 billion.

The figures have already shown that the apparel sector was already strong in e-commerce before Corona. The industries that benefited from the shift were those where people tended to shop offline in the pre-Corona phase, such as food. However, this does not mean that sales in the fashion sector have declined overall.

Figure 2 shows the importance of online stores in the respective country in the apparel sector and overall in e-commerce (*E-Commerce in der Schweiz*, 2021; *E-Commerce in Deutschland*, 2021; *E-Commerce in Österreich*, n.d.-b; *E-Commerce-Markt für Bekleidung in Deutschland*, 2021; *E-Commerce - Online-Umsatz nach Branchen in Deutschland 2020*, n.d.; *Österreich - Online-Anteil in einzelnen Produktsegmenten 2020*, n.d.; *Top 10 Online-Shops in der Schweiz im Jahr 2020*, n.d.).

Table 2: Facts | Top Online Stores Fashion

Facts | Top Online Stores Apparel

Ranking Top 5 Fashion Online Stores *		net sales** in 2019 in million US$	Growth from previous year in %
	Germany		
3	Zalando.de	1816	18%
7	bonprix.de	704	16%
13	aboutyou.de	588	16%
14	hm.com	559	24%
18	baur.de	473	20%
	Austria		
2	zalando.at	388	22%
3	universal.at	125	15%
7	hm.com	79	24%
17	bonprix.at	44	10%
18	aboutyou.at	43	31%
	Switzerland		
1	zalando.ch	883	8%
19	globus.ch	77	38%
21	hm.com	67	24%
22	bonprix.ch	66	13%
18	lehner-versand.ch	50	-3%

*Ranking of the top 5 apparel online stores out of the Top 40 of all online stores

2.1.5 Return rates

As already mentioned, one of the main problems of the fashion industry is the high rate of returns. It is assumed that each return, which is free for the customer at Zalando, for example, costs the company an average of €10. The reason for this is the administrative effort, with small shops suffering even more. Large companies like Amazon have often been criticized for (not only) destroying returns, as this is more economical than returning the goods to stock, some of which are unfortunately no longer in perfect condition. The most common reason given for returns is that the clothing ordered "doesn't fit," followed by "don't like." (*Österreich - Gründe für Rücksendungen von Online-Bestellungen 2020*, 2021; *Retouren - Gründe in Deutschland 2019*, n.d.; *Rücksendungen*, n.d.). It is also noticeable that younger buyers in particular return more (*eCommerce-Studie-Oesterreich-2021*, 2021), who on the other hand are more environmentally conscious. In the derivation of the corresponding hypothesis “Return Intention”, this topic will be discussed again in more detail. Detailed product descriptions and accurate product presentation used to be the basis for low returns, yet returns remain high in the industry, even though most online apparel stores offer very detailed product descriptions, as shown in the appendix (Lockhauserbäumer & Mayr, 2015).

2.2 Recommendation Tools

In this thesis, we specifically want to consider those recommendation tools that provide product recommendations to online apparel shoppers and use artificial intelligence to do so. Therefore, we will first clarify what can be understood by a recommendation agent in the first place.

RT's are used in a wide variety of domains: e-commerce, education, and organizations. In e-commerce, there are two areas of application. Recommendation tools can help either in finding the most suitable product or the most suitable supplier (Xiao & Benbasat, 2007). This paper deals exclusively with Recommendation Agents in e-commerce, which are already implemented on websites of certain online retailers for clothing and are intended to support users in their product and information search.

2.2.1 Definition

Recommendation Tools (RT's) are a software or software agents that can provide recommendations to users. They recognize the interests or preferences of individual users, based on which the product recommendation is made. The term AI Recommendation Tools, or RT's for short, is used here to describe software that is specifically designed to help users buy clothing online and select the right item of clothing. By suitable, several things are meant. First, the customer should find what he is looking for. Let us say black pants. But besides the color, there are many other factors that can influence the decision. There is certainly the price, the shape, the quality, the material and especially important, the right dress size. In their study, Xiao & Benbasat (2007) called these tools recommendation agents and defined them as follows: „Recommendation agents (RAs) are software agents the interests or preferences of individual user 's for products, either explicitly or implicitly, and make recommendations accordingly" (Xiao & Benbasat, 2007, p. 138). They also can be described as "a *personalized*, advice-giving technology" (Komiak & Benbasat, 2006, p. 942). The authors have further gathered designations from the literature that can be used interchangeably, such as *recommender systems*, *recommendation systems*, *shopping agents*, *shopping bots* und *comparison shopping agents*. In this thesis, the term AI recommendation tools is used because the most successful online retailers of apparel (Zalando, Bonprix) have more than one recommendation tool in use. The most important ones, which also use AI, are described in more detail below (Xiao & Benbasat, 2007).

2.2.2 Recommendation Agents for apparel

The research interest in AI techniques to solve decision-making problems in the the apparel industry has attracted increased attention in recent years. In fact, AI is used in the retail industry not only for customer service but also for other stages of value creation, which are, for this thesis, not considered. When consumers face decision-making problems, various AI-based techniques are available to find solutions that are effective (Guo et al., 2011). In the following, we will present recommendation agents in terms of how they are able to solve which problems and afterwards we will present the applications of the respective online stores.

Other sources also call recommendation agents digital assistants. This does not only refer to applications implemented on the website, but also to digital assistants on the sales floor provide advice. These are supposed to advise the sales consultant or the customer individually about the characteristics of the respective customer. It should be possible to use them by having the customer log in to the app or online store with his customer profile logging in. However, usable data is only available to the AI once the user has answered questions on specific topics. A self-learning algorithm is then able to create a product selection based on the customer's personal characteristics and preferences (Huang & Rust, 2021; Kruse Brandão & Wolfram, 2018). In principle, voice-controlled assistants work in the same way, but they are not considered in this paper because they are not yet relevant in the largest online stores for clothing and other aspects need to be considered with this topic. Digital voice assistants could also provide size advice and recommend cross-selling products and enable inventory queries. The same is true for chatbots or other technologies. The data basis for AI is not different because of this, only the method of delivery is different. For the recommendation agents considered here, many recommendations made in the webshop are implicit.

In principle, the tools for making recommendations work according to the following rule (Xiao & Benbasat, 2007):

1. The AI or RA receives its **input**, where user preferences, explicit or implicit, are requested.
2. The next step is the **process**. Here the recommendations will be generated for the users.
3. The last step is the **output**. Now the recommendations are presented to the user. Depending on the application, this can be in the form of a voice output, as just mentioned, or in the form of text and images, as in the online stores we are looking at in more detail.

2.3 AI Recommendation Tools in selected online stores

Many fashion companies that are successful online have already started as digital companies and have extended their lead over the years. Zalando is the first to be mentioned here, as the company is the absolute leader in terms of sales revenue in the DACH region. Zalando has also been relying on AI for some time now to offer customers a better sales experience.

The core of this thesis is to relate the field of fashion in e-commerce and artificial intelligence to the topic of trust. As already mentioned, trust is elementary in interpersonal relationships. However, since this interaction is severely limited online, this paper will look at the extent to which customers or consumers can or want to trust artificial intelligence instead of the sales-person. This inevitably raises the question of what characteristics a salesperson must have for the consumer to trust his or her advice.

If customers have the feeling that the salesperson only wants to talk them into buying the garment to earn commission, and does so, but we do not know that, then this is referred to as opportunistic behavior. In various trust studies, opportunistic behavior, i.e. behavior that one party believes to be opportunistic, has been identified as a negative factor influencing trust and has an impact on customer uncertainty (Aurier & N'Goala, 2010; Chiou & Droge, 2006; Crosby et al., 1990; Dimoka et al., 2012; Fladnitzer & Grabner-Kräuter, 2006; Gefen et al., 2003; Morgan & Hunt, 1994a).

Is it possible that AI is more to be trusted because it does not lie in the true sense of the word and is free of prejudice (the fact that AI can also learn prejudices has already been described several times in the literature and will receive more attention in the following) and purely pragmatically suggests the clothes that fit in terms of color or style and do not depend on the dubious taste of the salesperson? Can AI be the better advisor in the end?

The largest fashion online shops already use AI, how and to which will be described in more detail later. The question of trust is interesting because it has not yet been asked in this context. A closer look shows that many users are still skeptical about AI. However, since trust is also important in terms of customer loyalty and thus repurchase, trust is an aspect that should be considered when implementing AI. Customer loyalty is an important construct and is a means of developing relationships with customers, which in turn leads to more business and customer loyalty (Kumar & Shah, 2004). If you incorporate AI in such a way that it also creates trust, it could be much more than lowering the return rate because consumers find the right size. Or the other way around: If some customers still do not trust AI, e-vendors can gain loyal customers with trust, who also will not send anything back because they were well advised. Only the data from the customers of Zalando, bonprix and ABOUT YOU and H&M are considered regarding the use of AI, as it is not clear in the other stores whether and how it is used. But also because they are the strongest in the market. Especially Zalando is the market leader in all three countries, as can be seen in table 4.

As described at the beginning, most consumers who shop online are also buyers of clothing and shoes or have already bought clothing. If one then looks at which are the largest online shops for clothing, the same large companies crystallize in all countries. Zalando SE is the absolute leader in the DACH region. In Germany, the top 10 online shops (2019) include fashion retailers Zalando and bonprix. In the top 18 according to the highest net sales of online shops, ABOUTYOU, H&M and baur are added. Larger shops such as Amazon or otto are not included here, as they are not purely fashion online shops, thus ensuring a better differentiation. Amazon also does not have a service in Switzerland, for example (*E-Commerce in Deutschland*, 2021; *E-Commerce-Markt für Bekleidung in Deutschland*, 2021; *E-Commerce - Online-Umsatz nach Branchen in Deutschland 2020*, n.d.) .

In Austria, the top 10 online shops (2019) in the fashion sector included zalando, universal and H&M. In the top 18 of the shops with the highest net sales, bonprix and ABOUT YOU are also included here (*E-Commerce in Österreich*, n.d.-b).

In Switzerland, the picture is similar: zalando leads the top 10 list (2019) of the largest e-shops in Switzerland. For this, no other fashion store can be found in the top 10, just as little in the top 18. According to the highest net sales of the online shops, globus ranks 19th, H&M in 21st place, directly followed by bonprix. Lehner-Versand ranks 32nd and the shop ABOUTYOU, which is strong in the other countries, lands on 36th place as the sixth among the fashion stores. But this with a rapid growth of 24% in 2019 to 2020, while Lehner-Versand has lost 3% points in the same period (*E-Commerce in der Schweiz*, 2021; *Top 10 Online-Shops in der Schweiz im Jahr 2020*, n.d.).

“Customers also bought”, “This goes with that” or “You might also like” - all these topics belong to recommendation engines or, depending on the case, to recommendation AI (*Typen von Empfehlungsmodellen | Recommendations AI | Google Cloud*, 2021).

On the websites of ABOUT YOU, bonprix and Zalando we can see that such recommendation AI tools are used, and all three companies develop the software in use themselves[1]. Therefore, an overview of the functionality of the recommendation engines will be given here. Google, for example, also offers this technology and states that such personalization is important for customer loyalty.

The designations are not the same in every web store, but they are remarkably similar. To describe the purpose of them, we will use Google's designation and show the implementation methods. Google names the recommendation types as follows (*Typen von Empfehlungsmodellen | Recommendations AI | Google Cloud*, 2021):

- "What else you might like"
- "Frequently bought together"
- "Recommended for you"

"What else you might like". this is a prediction tool that predicts what product the customer is likely to look at or buy. The prediction is based on the shopping cart history, the user's made page views and relevance. The click-through rate (CTR) is given as the standard optimization target.

“Frequently Bought Together” recommendation is used for shopping cart expansion. This means that the tool displays which items are frequently purchased with a certain other product during a session. It is useful to use this type of recommendation if the user has already expressed the intention to buy something specific. It gives the provider the opportunity to suggest complements (not substitutes). The goal is increased sales per order.

"Recommended for you” makes predictions about the product a user is most likely to view or buy next. Based on the shopping cart history of the respective this user or the previously viewed pages, it is possible to make these predictions. Contextual information of requests is also used for this purpose, e.g. timestamps. The optimization target that makes the most sense here according to google is again the click-through rate (CTR) (*Typen von Empfehlungsmodellen | Recommendations AI | Google Cloud*, 2021).

Since the major online stores are already successfully using AI, the most important points are briefly explained below.

[1] Zalando's and bonprix's press releases often talk about new, self-developed AI models that have been implemented in the web stores (*Zalando*, 2019b). Also, as recently as August, Zalando lost its AI (data analytics and machine learning) expert, Ralf Herbrich, who was poached from Amazon at the time (Benrath, 2021). External companies are not mentioned regarding new developments. ABOUT YOU has also developed its own software. But not only that. Their SaaS infrastructure is marketed by the subsidiary SCAYLE in the B2B sector.

2.3.1 Zalando

Zalando was founded in 2008 in Berlin, Germany. The company was a pioneer in a new business area, an online store for shoes. In the DACH region, Zalando is now the biggest player in e-commerce in the apparel sector. In just a few years, the online shoe retailer has become the most important fashion platform in Europe, as the figures clearly show. There are around 1.2 million items on the platform. Zalando now also has a private label, but with 4,500 brands represented on the site, that is hardly worth mentioning. With more than 16,500 employees, the platform operates in 23 markets. Zalando's turnover amounted to around 8 billion euros in 2020. With more than 46 million active customers and more than 560 million monthly hits on the website, 90% of which are via smartphone or mobile, it is no surprise that the company made it into the DAX this year (Gründerszene, 2021; *Zalando*, 2021). Zalando uses AI to provide customers with a "better shopping experience" (*Zalando*, 2019a).

As early as 2019, Zalando's Research Lead, Urs Bergmann, described AI as a "current focus topic". At that time, the company could already count 120 employees in the field of machine learning. Besides business optimizations, the other focus is on customers. According to Zalando, this includes article recommendation systems, size recommendations, personalization, search, or the outfit recommendation system (*Zalando*, 2019a).

Zalando has implemented the AFC Algorithmic Fashion Companion in its online store. This AI was fed with data from real stylists and thanks to machine learning it can suggest personalized outfits (*Zalando*, 2019b).

Zalando announced in October 2020 that it has acquired Swiss company Fision. Fision has developed the app *meepl*, which serves as a virtual fitting room and is intended to enable customers to find suitable items of clothing. This is to avoid returns and to find an answer to the differences in the masses of the various brands. With the customer data, it should be possible to reconcile the individually different body measurements (3D scan based on two photos) of the customers and the different fits of the manufacturers with a personalized recommendation (*Zalando*, 2020). Since this app is not integrated into the Zalando online store, yet it would make more sense to survey the users of this app, specifically in a different context. In this work and the survey, only the tools implemented in the online stores can be considered.

It must also be considered here that the recommendation systems must access customer data to enable personalization. In the customer account, for example, the customer can indicate in the order history how well garments have fitted. New customers can also choose from a list of manufacturers and indicate which garments in which size have fit well so far. Zalando's AI can then recommend a garment selected in the shop in the right size.

2.3.2 bonprix

bonprix is not a purely digital company, with a store in Hamburg and clothing that can still be ordered via the catalog, but the offline segments are negligible, as the company makes 88% of its sales in e-commerce (*Otto Group*, 2021a). Like *ABOUT YOU*, the company is part of the

Hamburg-based OTTO Group and currently employs around 4,000 people worldwide (*Otto Group*, 2021b). In the 2020/2021 fiscal year, bonprix generated sales of 1.76 billion euros. According to the company, bonprix uses AI in the areas of product range design, size recommendations for customers and the personalized approach to customers.

This concept is working. The company has customers in around 30 countries (Europe, Russia, and North and South America). At the same time, bonprix generates 60% of its total sales outside Germany. The focus of the business model is on e-commerce and mobile shopping. The focus is on the customer, which is why bonprix tries to make shopping "appealing and inspiring" in the app and the webshop. With the help of technical innovations, the goal is to provide customers with optimal advice and help them quickly find the garment they want. Supporting this are many detailed views of the fashion, size and fit filters, and advice tools. The company is also active on social media such as Facebook and Instagram to exchange ideas with customers. New forms of digital marketing are used to offer customers what they like. We conclude from this that individualization or hyperpersonalization is also the goal here (*Geschäftsmodell*, 2021).

Only in mid-December 2021, bonprix presented a new AI tool with which the company says it wants to offer its customers an even better service. Based on the so-called product potential forecast model[2], which was developed in-house, bonprix creates the basis for a daily updated product ranking in all assortment categories of the bonprix webshop. This can be seen as an implicit recommendation tool, as customers are shown the products at the top that are currently the most popular, which makes customers aware of trends, and are also available in all sizes. For this purpose, an innovative method originally used in image recognition is applied: a Convolutional Neuronal Network. Previously, there was also a product ranking, but it was based on a different technique. Registered customers receive even more suitable products in first place. This is done by clustering. This is based on five different age groups and so customers can be shown the products that are particularly popular not just in general, but in the respective age group (Bonprix press release, 2021)

The company also uses AI in its Fit Finder. The Fit finder supports customers with specific size recommendations. This is a development of the Berlin-based company Fit Analytics. The recommendations are based on information from customers and purchase and product data. According to the company, this tool in the web store helps to increase customer loyalty and reduce the number of returns. The higher quality or accuracy of fit also avoids orders of multiple sizes. The company also announced that the Fit Finder has been used significantly more often since Corona than before the pandemic (*KI Steigert Attratktivität*, 2020). However, bonprix does not indicate whether this increase correlates with customer growth.

2.3.3 ABOUT YOU

ABOUT YOU was founded in 2014, as a subsidiary of the OTTO Group, with a with a data driven strategy from the start. According to the company, ABOUT YOU see itself as particularly successful with young customer groups (e.g., digital natives). The company has put a great

[2] The German term is *Produkt-Potenzial-Prognose Modell*. The English designation was translated from German into English ourselves.

deal of effort into improving the digitization of the business, taking a mobile-first approach, which is confirmed by the app download figures: since 2015, it has been downloaded more than 26 million times and the fact, that around 85% of user sessions were in the web store via mobile devices in fiscal year 2020/21. In fact, ABOUT YOU is Europe's fastest growing fashion platform. With more than 30 million monthly active users, the company has become one of the largest fashion and lifestyle platforms in Europe (*ABOUT YOU bündelt ihr B2B-Geschäft unter der neuen Marke SCAYLE*, 2021). The fashion online store is represented in 26 European markets and is currently most successful in the DACH region. More than half of net sales are generated there which amounted to €660 million in fiscal year 2020/21. ABOUT YOU, with an average annual net sales growth rate of over 90%, has had a robust growth profile since its foundation. This growth continues and ABOUT YOU's B2B division was also profitable for the first time. In this segment, for example, the company sells software solutions developed in-house, which are explained in more detail in the Technology section (*ABOUT YOU Holding SE*, 2021). In its web store, ABOUT YOU offers a range of more than 400,000 items from over 2,000 brands.

The web shop is driven by AI and relies heavily on creativity and personalization, working with over 10000 influencers. This is seen as a success factor for the use of the platform by the younger generation.

In fact, the company's strategy relies heavily on technological solutions. The B2B segment of the company operates under the name SCAYLE and offers a SaaS Infrastructure. However, its developments are not only used on the About YOU site. The company also makes its three-part service portfolio available to other retailers, consisting of Commerce Technology, Online Marketing and Commerce Operations (*ABOUT YOU bündelt ihr B2B-Geschäft unter der neuen Marke SCAYLE*, 2021).

SCAYLE's offer for the optimization or scaling of websites in e-commerce is so extensive that it would go beyond the scope of this work to list all functions and possibilities. In summary, one can say that, if one wants to as a provider, no step of the user remains unobserved or unaccompanied. There is no black box. What we want to know in the work and in the survey - how customers feel about using the Fit Finder, for example - is just the beginning. These things only represent what you can see as a user. About all the other, less obvious functions of a web store, we can only make assumptions from a certain degree. What is obvious is that the information and recommendations that a web store presents to the respective customer must come from somewhere. If we look at what solutions SCAYLE has to offer, we get an idea of how data-driven online stores already are but also must be if hyper-personalization is desired. Therefore, here is a brief selection of the possible positive outcomes for companies to implement such technologies in the web stores (*Commerce-Technologie der nächsten Generation – SCAYLE*, 2021).

SCAYLE offers customers innovative technologies that are modular and can thus be adapted to the needs of each customer. The focus is on scaling the digital D2C business. By using the technology, SCYALE's customers are expected to achieve an average increase in revenue of 40% and a 50% increase in profit. This is achieved by significantly reducing IT expenses using this technology in the e-commerce sector. However, these are processes where the AI works in the background and the customers of the web store only get to see a part on the surface, for example in the form of product or outfit recommendations. In the retail sector, AI is increasingly being used for the OMS (Order Management System), which can be particularly relevant for companies with an omnichannel strategy, as all inventories are updated in real time across all channels. This should illustrate that the use of AI is more far-reaching than consumers can see.

ABOUT YOU offers its potential customers the option of logging in with their Facebook or Apple account. We would like to briefly explain this possibility of so-called single sign-on here, since this thesis has trust in AI as its main topic and AI needs data to be useful for customers. And if you log in with your Facebook profile, you not only save time because the annoying registration is omitted, but you also give the web store a direct insight into a lot of information about yourself. It is not only that ABOUT YOU receive a lot of information, but Facebook receives at least as much information "back". The user profile can therefore be further refined as information is added about what they buy and how much they spend on it. Users would have to check the privacy policy to see what data is shared, but it remains doubtful that many users do. This way of logging in, single sign-on, is convenient, and before reading the privacy policy, one might as well create a user account (*Single-Sign-On*, 2021).

In fact, Facebook has come under criticism again, because not only they receive this data about preferences, habits, but also third-party providers with the help of scripts. This can become problematic if users give their consent without knowing exactly what happens to the data. Since AI is also used for pricing, you may have to pay more than others if you have made higher-priced purchases in the past. However, this already goes in the direction of the misuse of data but could contribute to the fact that users remain skeptical of innovative technologies since it remains difficult to assess who handles the data and how uncertainty causes insecurity. In principle, it is important to at least use the two-factor authentication to counter misuse. If, for example, the Facebook account used to log in to other websites via SSO were to be hacked, the attackers would also have access to these websites and third-party providers (Newman, 2020).

2.3.4 H&M

We would like to briefly introduce another high-revenue company that is also investing heavily in digital infrastructure and will certainly continue to expand its position in e-commerce in the coming years. Although H&M has a clear omnichannel strategy, it still generates a great deal of revenue from its retail stores. Due to its infrastructure with stores worldwide, the business model is also different (for example, pickup or returns in the store of clothing ordered online). Nevertheless they have implemented AI tools on their website and therefore, the comparability with Zalando, bonprix and ABOUT YOU is given.

H&M - the Swedish fashion group states in its 2020 annual report that it wants to focus more on digital growth because of or through Corona and the changes in customer behavior. In 2020, the group had 4429 physical H&M stores worldwide and online stores in 52 markets. While the company is already investing heavily in digital service capabilities, much of it is optimized for omnichannel presence or aimed at a seamless customer experience. For example, an increased number of stores is offering the option to return items shopped online to a store. Loyalty program members can (later) pay via the app whether they shop in-store or online. In 2021, H&M has also launched a styling app "Sorted by H&M", which uses AI to give tailored tips. Currently, the app is only available for men's fashion.

The app has also been on the market for too short a time and is only limited to men, so it can be assumed that no valid findings on usage can be expected in the survey. On the other hand, it might be suitable for control questions to see whether the users of the online shops use the AI, like the clothes that were ordered rather than those from H&M. So did the size fit or did the item look as described.

What is striking is that the use of AI in online stores is already more evident in the companies that started purely online. While Zalando also has stores and H&M has online shops, the sales figures clearly show where the companies originally came from, even if they offer their fashion across channels. They state in their annual report, that they continue *"to expand with a focus on increased omnichannel sales. In 2020 H&M opened online in Australia and consequently now sells online in 52 of its 74 markets"* (Annual Report, 2020, p. 37).

The company is also continuing to make investments in response to the fact that more purchases are being made from smartphones. They also want to pray the same shopping experience for their customers everywhere, whether that is in their stores, websites, digital marketplaces, or social media.

Overall, the net sales in SEK of the total company in 2020 show a minus 20% compared to the previous year, whereas in 2019 there was a plus of 11% compared to 2018, as in previous years could be referred to a plus between 4% and 6%. The decrease is due to Corona and is due to the closure of the stores, as the online business has grown in this period (*Annual Report*, 2020).

Trust and artificial intelligence are broad topics. Therefore, this chapter tries to break down the topic to the points relevant for this thesis, starting with AI and trust in general and the application areas of these topics in marketing.

2.4 Artificial Intelligence

Kaplan & Haenlein define, AI *"as a system's ability to interpret external data correctly to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation"* (Kaplan & Haenlein, 2019, p. 15).

Although it may seem new at first, artificial intelligence is not that new: in fact, it has been a concept in science and society since the 1950s (Bruhn & Hadwich, 2021). Some of the precursors of artificial intelligence can be traced back to the 14th century (Press, 2016).

However, the fact that AI has only now gained popularity is due to the following factors: Big Data, the availability of much cheaper computing power, and the development of new AI techniques. For AI to provide solutions or be trained, it requires substantial amounts of data, which were simply hard to come by in the past, i.e., before social media. Another problem was that only today's high-performance computers can process large amounts of data and parallelize processes so that AI can be trained. In the past, this process was simply too slow as well as too expensive (Overgoor et al., 2019).

Intelligence is a term that has undergone various definitions and has long been regarded as a human and innate ability. Today, a distinction is made between analytical, practical, and creative intelligence. Intelligence also implies adapting to certain circumstances and learning from them for the future. Who is intelligent, can deduce and find solutions for problems. (Bruhn & Hadwich, 2021).

Artificial intelligence imitates the way a human being acts and thinks. But artificial intelligence also refers to the different forms of intelligence mentioned above. A common classification is that of the subdivision into strong and weak intelligence. Accordingly, a weak Ki is one that only simulates human conclusions and ways of acting. A strong AI, on the other hand, can draw its own conclusions from its broader base of knowledge. This type of AI can also work out complex solutions (Buchkremer et al., 2020).

An extension of this view is the dimension of consciousness. This is AI that independently deduces from a problem to possible other fields of application. This could make AI superior to humans in terms of its competencies. AI is already capable of solving problems autonomously, even across different areas. Another form of AI, still in the future, is the super intelligent form that lies outside the control of humans and will no longer be comprehensible to them (Kaplan & Haenlein, 2019).

2.4.1 Kinds of Artificial Intelligences

Huang and Rust (2021) also divide artificial intelligence into three intelligences in the service area: mechanical, thinking and feeling intelligence. Depending on the task at hand, the authors recommend one of the intelligences.

Mechanical intelligence can be seen as the weakest and feeling intelligence as the strongest. Mechanical AI learns and adapts only to a small degree. The goal of this type of AI is to maximize efficiency and is therefore suitable for services that can be standardized, i.e., routine, and repetitive, human services. These can then be transformed with mechanical AI into self-service, for example. Other application areas may include fast-food ordering or customer service for some basic or routine matters. A service robot that replaces an employee to perform routine tasks would also fall into this category (Huang & Rust, 2021).

According to the authors' definition, AI-based recommendation tools fall into this classification of thinking AI. This type of artificial intelligence learns from the data and adapts to it. It can be analytical or intuitive. Analytical AI is there to identify meaningful patterns. A common term for this type of pattern recognition is data mining. Intuitive AI is already a step further and "is designed for maximizing decision-making accuracy" (Bruhn & Hadwich, 2021; Huang & Rust, 2021), which can mean solving problems or answering questions as accurately as possible. The capabilities of thinking AI are analytical as well as intuitive. This makes this form ideal for personalization. If a large base of customer data is available to the AI for this purpose, it can make exceptionally good predictions about which recommendations will be attractive to the customer in question. In complex purchasing decisions, these AI tools can learn what the consumer is prepared to purchase and can optimize the recommendations accordingly. Adapted to clothing, this could mean, for example, that the customer is willing to sacrifice the material in favor of the price but is not willing to order the product in red instead of black. The AI would then take these preferences into account when making recommendations. The term

Deep Learning is also to be located here. With Deep Learning, the AI tries to replicate the human brain and works according to the human brain with a virtual neural network. This human-like thinking capability enables a deeper and more adaptive personalization. AI assistants are becoming more valuable over time as a decision-making tool for users because they store and analyze every bit of information to make objective recommendations to consumers (Huang & Rust, 2021).

What makes sentient AI special is that it learns and adapts to experience. Experience can be defined in the AI context as specific data. Sentient AI is excellent for personalized relationships. Consequently, it is also suitable for customer satisfaction and retention, and is particularly applicable where customer relationship management or where all interpersonal aspects in a customer relationship are relevant. The uses of feeling AI have ranged from virtual agents and chatbots, which, however, in principle resemble mechanical AI customer service resemble, to dialog systems such as Alexa, Cortana and Siri that use natural language processing to interact with customers. Nevertheless, this type of communication still does not seem very natural. Advanced, feeling AI has a lot of potential for the customer service field, where empathy and understanding are required. This type of AI should be able to pick out the emotional state of the person speaking and respond to those emotions appropriately, like a human. Applications can be found in the areas of health or security (Huang & Rust, 2021). Others also speak in this context of “Human-Inspired AI”, which means that the AI has elements of cognitive and emotional intelligence, and “Humanized AI”, which has all the elements of human behavior, but is not yet available in this form (Kaplan & Haenlein, 2019, p. 18).

2.4.2 Big Data

What artificial intelligence needs to function, to learn is data. Big Data represents has enabled commercialization of artificial intelligence first (Kaplan & Haenlein, 2019). In this context, data, which can be of various natures, is being collected and stored by companies on an increasing scale (Cohen 2018). In the literature, these are divided into three dimensions of Big Data (Kaplan & Haenlein, 2019). Volume describes the amount of data underlying the dataset, Velocity is the speed of updating the data and Variety explains the form of the data which is text-based or numeric, but also or image-based (Bruhn & Hadwich, 2021)

Further specifications are possible, but at this point we just want to explain the term Veracity, which describes the unreliability of data with unknown background. This can be data that originates from social media, for example. An AI becomes capable of action if it can draw on input data of the most varied nature. An AI can receive data in several ways such as IoTs or social media. Companies can also store vast amounts of diverse data in their work processes (Lorenz, 2020). All data is then classified into structured data and unstructured data (Bruhn & Hadwich, 2021).

2.4.2.1 Machine learning

Machine learning is a subarea of artificial intelligence and is the most widespread so far. The AI is first trained by feeding it with data from which it derives information, be it patterns or rules or, in short, everything from which the AI can learn to be able to process new data at a later point in time. The AI thus collects experience that it can later use to solve tasks (*KI-basierte Kundenkommunikation*, 2020).

2.4.3 Artificial intelligence in the service sector

AI helps companies use collected data for the success of their own business. The insights gained in this way can support companies in various sub-areas. These include, for example, the personalization of services. This means that customers receive personalized services, but also at the right time. Companies can provide this service by collecting digital traces. In addition to the information provided during the purchasing process, this can also include data from social media, for example. Furthermore, campaigns can be targeted to the needs of users, customer segmentation or the identification of trends (*KI-basierte Kundenkommunikation*, 2020). Models can also be created for predictions and analyses. In part, for example, customers expect personalized services that they receive personally and individually at the right time. Companies such as Amazon or Netflix already work with cluster analyses that recognize the customer structure and divide it into segments. On this basis, suitable offers can be made to these customer groups and at the same time the search effort for these customers is reduced. This also allows trends to be identified at an early stage and companies can respond to them in good time. The basis is all data. that means data from real purchases but also older data. This allows assumptions to be made about how the respective customer will behave in the future (Bruhn & Hadwich, 2021).

With a recommendation tool, online providers offer their customers a service that only becomes relevant with use. Although they buy clothing, the recommendation tool with its immateriality is a classic service, even if the output is material when the recommended product arrives at the customer's home (Meffert et al., 2015). Regardless of this, offers such as recommendation tools involving AI perceived by customers must be accepted by them (Buchkremer et al., 2020). It has been found that people have different acceptance rates for the same offers from companies - depending on whether the service is provided by a human or AI. In certain situations, buyers have a reluctance to delegate to non-human decision makers, even when it is obvious that AI is superior to humans in many situations (Leyer, 2021) Some reasons for this are that humans are too confident in their own abilities or intuition.

Because AI system focuses on a concrete problem and works or thinks differently than a human (Broadbent, 2017), humans have difficulty establishing an emotional connection with AI. A positive attitude toward AI is evident when people feel that they retain some control (e.g., by having the underlying algorithm modified (Leyer, 2021). Experiments have also shown that laypeople are more likely to follow advice from AI than from people (Logg et al., 2019) and that people with a lower understanding of a situation are more likely to delegate to AI As quickly as trust in AI may emerge, it may also be lost compared to trust in other humans. However, trust in AI is also lost faster than trust in other humans. But acceptance also arises from context. For example, the intrusiveness of employees (credit cards) was rated negatively, which thus gave AI huge advantages in acceptability contexts in which AI can lead to a higher acceptance rate of the same offer. (Leyer, 2021)

So, context is an important parameter, but so is the offer or the perceived added value. How customers perceive such a service cannot be answered in a blanket way (Pütz et al., 2021).

This means that customers who use AI tools to find suitable clothing from the context could quickly gain confidence in AI tools. In particular, people who may not be well versed in fashion issues or are unsure what might suit them. In any case, the numerous blogs, and guides of the online stores on the subject of fashion point to this.

2.4.4 Hyper-personalization

The term personalization takes on a new dimension with the use of AI, which is explained by the term hyper-personalization. This means that customers are not only addressed personally, but individually. This requires that the information should have as much relevance as possible for the customer and the AI processes the data in real time to be able to do this. The aim is to ensure that each individual customer receives maximum benefit from the personalized customer approach. Then there is talk of a hyper-personalized approach. Without the use of AI, these volumes of data could not be processed efficiently. The authors complain that the terms personalization and individualization are becoming increasingly blurred, which is why the terms are classified again at this point (Gouthier & Kern, 2021):

- **Personalized** customer approach: this speech is based only on a superficial understanding of the customer. understanding of the customer. This includes, for example, mentioning the name when addressing the customer.
- **Individualized** customer approach: this is based on a deeper understanding of the customer. understanding of the customer. The basis for this is, for example, data from the customer's purchase history, on which the communication is adapted.
- **Hyper-personalized** customer approach: here, customers are addressed context-specifically and in real time based on comprehensive data. This data is derived from purchasing behavior and from browsing behavior.

Only the multitude of digitally available customer data has opened far-reaching opportunities for companies to address customers directly and individually. As the highest stage of evolution at present, hyper-personalization is based on the use and analysis of big data analytics. It is not only the data that customers leave behind when they buy online that is relevant, but also their individual browsing behavior. (Shukla/Nigam 2018). This 360-degree view of the customer is therefore a holistic, consistent, and constantly updated understanding of the customer. The focus is on need satisfaction whereby proactivity additionally comes into play. Proactivity here means that content can address a potential need on the customer side without this need having been actively demanded by the customer (Narver et al. 2004). Hyper-personalization builds on the fact that consumers ignore information provided by companies if it is deemed irrelevant or does not provide added value. Accordingly, hyper-personalization aims at designing the customer approach in such a way that the customer is targeted and proactively approached with relevant product offers (Shukla/Nigam 2018). At this point, the "information overload" should be mentioned again. The hyper-personalized approach can certainly be seen as information selection for the customer. The quality of this selection is also perceived as higher, since clearly structured and individually adapted information is rated qualitatively higher than a large, undifferentiated quantity of data. Standardized or simple, personalized communication policies are no longer sufficient to differentiate from competitors. It is becoming apparent that individualized recommendations with AI are becoming increasingly important, as they represent a key component for the customer in the evaluation of the overall customer experience. (Gouthier & Kern, 2021).

2.4.5 Conclusion Artificial Intelligence

The interrelationship between society and the economy has seen repeated upheavals. The economy of today is based on data, its currency is information, and this shift is based primarily on the fact that companies now have technologies to collect, store, process and use large amounts of data. This has opened a whole new set of opportunities for personalized engagement marketing. Individual customer information can be used to offer tailored products and services using AI. This will provide ever greater value to customers, becoming the basis for customer loyalty and a sustainable competitive advantage for businesses (Kumar et al., 2019).

2.5 Overview General Concepts of Trust

There is no universal definition of trust. This section will briefly show the different approaches between the concepts of trust but at a later stage, in the literature review section, the researcher will look at the studies relevant for this thesis with a marketing context, that are usually using one of the concepts with adaptations according to the research question.

We show which aspects that are considered in the relevant research area. Trust is relevant through all disciplines and is used in the following fields (Fladnitzer & Grabner-Kräuter, 2006):

- Psychology,
- social psychology,
- sociology,
- economics and
- business administration.

Furthermore, trust is not only defined differently in different disciplines, but also the context plays a role. In the following, interpersonal trust and systemic trust are described, which at first glance are clearly different, but these are also not always easily separated from each other (Möller, 2012).

2.5.1 Interpersonal Trust

In this chapter, we delve a little deeper into interpersonal trust, as it forms the basis of much-cited research related to trust and marketing (Crosby et al., 1990; Garbarino & Johnson, 1999; Moorman et al., 1993; Morgan & Hunt, 1994a)

2.5.1.1 Definition

Interpersonal Trust can be defined as "an expectancy held by an individual or a group that the word, promise, verbal or written statement of another individual or group can be relied upon" (Rotter, 1967).

Simplified, this means that the person who trusts assumes that the other party will behave in a certain and, in this case, desirable way, even though the person would have the option to behave differently. However, trust also becomes necessary only where control of actions is either not feasible or there are reasons to voluntarily to do without it. Thus, both parties take a risk. The trust recipient can be just as disappointed as the trust giver (Möller, 2012).

Interpersonal trust belongs to the field of psychology and is widely used in research. (Fladnitzer & Grabner-Kräuter, 2006).

2.5.1.2 Interpersonal Trust Scale

Since a survey was conducted in this paper based, among other things, on the interpersonal trust scale developed by Rotter, a brief summary of it is provided in this section.

The gold standard in trust research (in psychology) is the paper "A new scale for the measurement of interpersonal trust" by Julian B. Rotter in the Journal of Personality (Rotter, 1967). In this context it should be mentioned that there are several types of trust in the literature. In his work, Rotter constructed the interpersonal trust scale which consists of Likert format items or an additive scale. In addition to specific trust questions such as trust in parents or teachers. A basic tendency was also queried in which Rotter attempted to query the general optimism towards society. Filler questions were used to disguise the intention of the questionnaire. Also, with the Marlowe-Crowne Social Desirability Scale the items were removed in the first run, which correlated for example too strongly with this. In general, the questions on trust were asked in such a way that about half were to be answered with "I agree" and the other half with "I disagree" if they implied trust. Demographic key points were also asked, as well as questions about family situation, such as the number of siblings. In this first run, students answered the questionnaire as described. To validate the confidence scale, another survey was conducted with students. In this part, they were asked to rate interpersonal trust with themselves and with their classmates on a scale (Rotter, 1967).

A summary of the results of Rotter's study (Rotter, 1967):

- People at the highest economic level trust more than those with a low economic level.
- Lower trust scores were shown by the group whose parents belonged to different religions, but also the students who felt themselves to be atheists, agnostics or not belonging to any religion had lower scores than those who belonged to any other religion.
- Those who are the youngest of the siblings show lower values than children in a different position in the family.

- Trust and trustworthiness are significantly related. Trust is also positively related to humor, friendship, popularity, and trustworthiness (results from the Sociometric analysis).

2.5.2 Systemic Trust

For simplification, systemic trust is used here as a term to distinguish it from personal trust. A further classification would be possible by considering trust in systems (observance of norms and rules), in institutions or companies separately (Pastoors & Ebert, 2019), but this is not relevant here because these forms can also contain components of personal trust and these types of trust are not different (Mayer et al., 1995) (McKnight et al., 1998). Trust in RT's will furthermore be discussed in more detail in a later chapter.

2.5.2.1 Definition

In the literature on organizational trust is the following definition representative for other, similar definitions in this context (Mayer et al., 1995):

> *"The willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other part."*

This type of trust is less about the development of trust and more about its function in existing systems and the trust in them. So, in contrast to interpersonal trust, here an organization or institution is trusted; this can be, for example, a company or a department in an institution (Möller, 2012), (Fladnitzer & Grabner-Kräuter, 2006). Except for the fact that systems are not persons, this kind of trust is not fundamentally different from interpersonal trust and cannot be profoundly distinguished from interpersonal trust. One reason for this view is that a system, or a recommendation tool as in our case, cannot *trust us back* which would eliminate a relevant factor for the emergence of trust. Another reason is that there are also people behind the system. Be it the CEOs and other employees of Zalando, the software developers or more precisely, the developers of the recommendation tools (Schilcher et al., 2012). Also given is that such a trust relationship consists of "a trusting party (trustor) and a party to be trusted (trustee)" (Mayer et al., 1995, p. 711).

Another important finding is that if one party has taken a risk on the other party and the outcome is positive, the perception of the other party is improved. If the outcome is negative, the perception decreases accordingly (Mayer et al., 1995). It is believed that the duration of a relationship is relevant. For example, if one person has not had any bad experiences in the ongoing time, the greater the trust in the other person (Pastoors & Ebert, 2019). Trust is seen as a process that needs to be developed (Möller, 2012). With respect to Recommendation Agents, different approaches of trust are applicable to RT's, whether from the interpersonal trust or organizational trust perspective. More on this in chapter 3.2.

2.5.3 Initial Trust

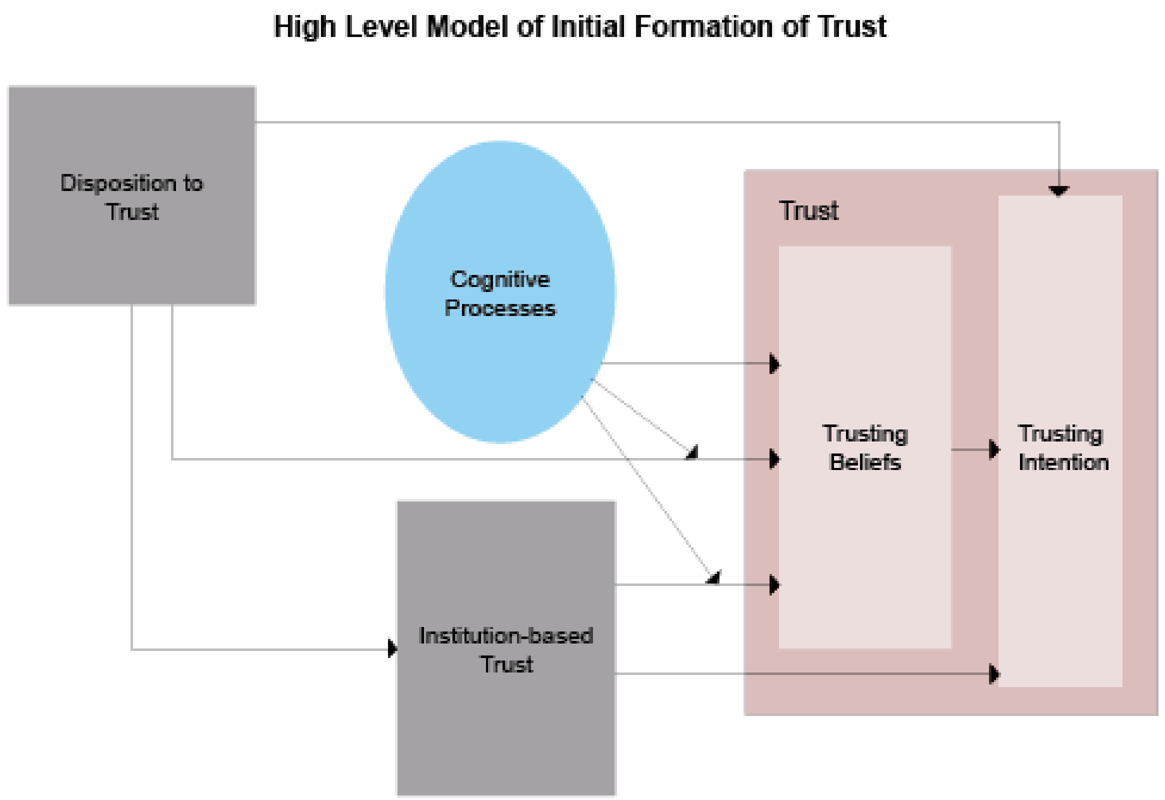
A different aspect worth mentioning here is initial trust. In a study, researchers found that trust does not always develop over time, as previously assumed (McKnight et al., 1998).

In contrast to this the initial trust. Initial trust means that trust occurs already in the first meeting or interaction between two parties. Initial trust between parties is not based on any first-hand experience or knowledge. Reasons to be cited here are the general willingness of the individual to trust or on institutional cues that enable the trusting person to trust another, as shown in Figure 1. This depicts the model of initial trust formation. It includes cognitive processes and factors that lead to initial trust and describes interpersonal, initial interactions. The authors have developed a model that brings together various constructs from four divergent strands of research. It has also been found that the temporal dimension is useful (McKnight et al., 1998).

The authors (McKnight et al., 1998) have created a model to illustrate the prerequisites for high initial trust. Three different research streams play a role: personality-based, which is according to Rotter (1967) the basic tendency of a person to trust others, systemic/institution-based trust, which shows how secure a person feels due to the given structures, and cognition-based trust. The latter is based on first impressions.

An interesting conclusion of the study is that the components through which trust is initially formed are different from those through which it is later formed. If trust in the other party exists over a longer period, experiential knowledge becomes relevant, while assumptions and predispositions fade into the background. With the temporal component, it is easy to see how trust is formed at the beginning of a relationship (McKnight et al., 1998).

Figure 1: High Level Model of Initial Formation of Trust (McKnight et al., 1998); own illustration.



2.5.4 Short Summary Trust Concepts

These examples are an effective way to describe how trust can occur in diverse ways depending on perspective, research direction, and subject matter. In this work, we cannot consider whether the people who have a high level of trust in the recommendations of the recommendation tools have a greater tendency to trust or know how the RT's work. We also do not ask about trust in the company and therefore cannot assess whether pre-existing trust in an e-vendor favors the use of RA's or not.

We want to find out whether the use alone can have a positive effect on the trust in the recommendations. Perceived usefulness is considered in parallel, because for it to influence reducing customer uncertainty and in turn lowering the return rate, it can be assumed that usefulness also contributes to usage.

2.6 Trust in Marketing and AI

This section explains how trust is viewed in marketing on the one hand and in the context of AI on the other. The most important studies are briefly explained to reflect the general views on this topic and to explain the approach of the research question of this thesis.

2.6.1 Trust in Marketing

In general, there are two views of trust in marketing. On the one hand, it is "as a belief, confidence, or expectation about an exchange partner's trustworthiness that results from a partner's expertise, reliability, or intentionality" and on the other hand "as a behavioral intention or behavior that reflects a reliance on a partner and involves vulnerability and uncertainty on the part of the trustor" (Moorman et al., 1993, p. 82).

Their study on trust concludes that trust influences relationship commitment. **Morgan & Hunt (1994)** came to this conclusion in their commitment-trust theory in relationship marketing. They found significant relationships between trust and similar values, communication, uncertainty, opportunistic behavior, and functional conflict. Fruitful communication and similar values increase trust, whereas opportunistic behavior decreases trust. Trust, in turn, reduces a partner's uncertainty in decision making. As already mentioned, trust in the model also showed a strong influence on relationship commitment, which in turn lowers the propensity to leave, increases cooperation and acceptance, to name just a few correlations (Morgan & Hunt, 1994b).

Based on Rotter, **Moorman, Deshpandé and Zaltman (1993)** defined trust as "a willingness to rely on an exchange partner in whom one has confidence" (Moorman et al., 1993, p. 82). The authors investigated which factors affect trust in market research relationships. What distinguishes this work from Rotters' framework is that they have included a sociological component in addition to the psychological component of trust. They conclude that trust is not necessary if the trusting party has, among other things, the knowledge or control. Furthermore, they estimate that trust depends more on interpersonal factors than on individual factors. The perceived integrity of the researcher was the most important indicator of trust in their study. Besides that, another indicator is important: reduce research uncertainty as well as confidentiality. This research concludes, as generally accepted, that expertise is an important foundation for trust. In the work, the power of the researcher was also a factor that increased trust, whereas other research had found a negative effect on trust regarding power imbalance. The authors reasoned that with a researcher, power stands for expertise, and not for controlling and threatening. (Moorman et al., 1993)

The relationship between trust and customer satisfaction has been widely researched and confirmed. So also in the study of **Garbarino & Johnson (1999),** which examined the relations between satisfaction, trust, and commitment to the behavior of satisfied customers (of a Broadway theater) and their future actions. Overall satisfaction was chosen as the mediating construct once (for occasional patrons), but trust and commitment were chosen for regular patrons (based on Morgan & Hunt's model). In fact, the groups differ significantly, especially for trust and commitment. While satisfaction regarding the actors was a key factor for overall satisfaction among occasional visitors, satisfaction with the actors had the greatest impact on trust. Physical facilities, furthermore, had no effect on trust or commitment, but did have an effect on satisfaction and future actions of casual visitors. It is interesting to ask whether the survey of e-shop users also reveals a difference in trust depending on the frequency of shopping (Garbarino & Johnson, 1999).

In the study by **Crosby, Evans & Cowles (1990)**, "Relationship Quality in Services Selling: an Interpersonal Influence Perspective", the extent to which relationship quality (= trust and satisfaction) influences purchasing behavior was examined. From the customer's perspective, the quality of the relationship between the customer and the salesperson was examined with the help of a model. The model was designed to show which characteristics emerge in ongoing sales relationships.

The outcome variates are sales effectiveness and anticipation of future interactions. The study surveyed customers who had taken out life insurance. Out of 296 completed questionnaires, 151 could be analyzed. The main findings were as follows (Crosby et al., 1990):

- Future purchasing decisions depend heavily on relationship quality.
- To convert opportunities into sales hinges more on similarity and expertise.

The researchers identified the aspect of uncertainty (which is relevant when it comes to trust) as particularly important where buyers face intangibility, complexity, lack of service familiarity and long-time horizon of delivery (Crosby et al., 1990).

While these points are quite different for life insurance than for buying clothes, especially the time aspect, these things still apply when buying online, especially when you compare buying clothes online to buying clothes in a store. Clothes online are intangible, at least until delivery, which means the customer must refer to the description, pictures and possibly customer reviews. Touching or trying on like in a store is not possible.

As far as complexity is concerned, it can be argued that with very large online shops with a huge selection like Zalando, it is not very easy to filter out the right garment without help.

The point lack of service familiarity could be understood as unfamiliarity with applications, namely RT's designed to help find the right garment. For example, it can be assumed that the virtual fitting certainly requires a little more practice than a filter on the website and involves a certain amount of effort.

The long-time horizon of delivery is not to be underestimated compared to the purchase in the store. In the store the customers have the part immediately after the purchase, with the online shop this is not the case. Even if the online shops nowadays promise a fast delivery, the delivery service also has a share in the delivery. Also, customers may have to pick up the package at the post office, because they were not at home and are there again dependent on the opening hours (Crosby et al., 1990).

The results of another research on trust and e-commerce investigation suggest that certain consumer characteristics, such as trust and attitude towards online shopping or interactions, such as service quality and customer satisfaction, mainly affect the three dimensions of consumer trust. These three dimensions are competence, integrity, and benevolence. Overall trust has a direct impact on consumers' online purchase intention (Oliveira et al., 2017).

What all work related to the focus on relationship management has in common is that trust plays a central role. Trust is the element that makes any relationship successful (Berry, 1995; Morgan & Hunt, 1994a; Zeithaml et al., 1985). Therefore, the extent to which the increasing use of AI as RT's has an impact on customer trust is of interest to this paper.

2.7 Trust in Technologies and AI

As things stand, there is a lot of literature on the topic of trust and in AI services in general (Davenport et al., 2020, 2020; Guo et al., 2011; Huang & Rust, 2021; Jarek & Mazurek, 2019; Kaplan & Haenlein, 2019, 2020; Kumar et al., 2019; Longoni & Cian, 2020; Puntoni et al., 2021). When it comes to the use of innovative technologies, most studies focus on the acceptance of these technologies than on trust in them. In the case of AI, however, the term trust is used more often, which could be because artificial intelligence applications imitate, or at least often try to imitate, human characteristics. The question of trust has been asked in many contexts in marketing. As described earlier, trust is considered by many to be the cement in interpersonal interactions. Having already described the concept of trust in general, in this chapter we will review the key findings from our literature review in the relationship between trust and AI or technologies in general. Be it in terms of business relationships (Castaldo et al., 2010) customer satisfaction (Chiou & Droge, 2006) relationship age (Verhoef et al., 2002) or service relationship maintenance (Aurier & N'Goala, 2010). The relationship between AI and trust has already been addressed, but often the AI used was integrated in an application, such as a chatbot.

There is an informative short paper by **Zierau, Hausch, Bruhin and Söllner (2020),** who have dedicated themselves to this topic in a Conference Paper in 2020. During their literature review, the authors found a lack of trust in service-oriented chatbots (among other things, because they were not oriented towards the needs of the user and were not developed to take the trust issue into account). Therefore, they formed principles on how a chatbot should be designed to increase or create trust in the chatbot by the user. In a next step, the testing and implementation of a chatbot was announced, according to the previously developed principles (Zierau et al., 2020).

On the topic of AI chatbots, there is also a recent paper by **Ashfaq, Yun, Yu and Loureiro (2020)** that attempts to correlate the satisfaction of chatbot users and determinants of their continued use. While only customer satisfaction was studied here and not trust, it shows that this customer satisfaction increases when the chatbot provides up-to-date and reliable information, which can be seen as expertise. In trust research, expertise is an important influencing factor for trust, so that parallels can certainly be drawn here (Ashfaq et al., 2020). As mentioned earlier, while a chatbot can also act as an RT as the technology behind it is basically the same, chatbots are scripted tools and moreover, customers need to be active to use them. therefore, they are not included in the consideration of RT's in the present work, but they are certainly interesting as well as far as the service perspective is concerned (Ashfaq et al., 2020).

Komiak & Benbasat's (2006) study, the first to examine emotional trust in information technology (instead of the relationship of trust a technology adoption), found that the higher a customer's dependence on RA, the greater the role emotional trust plays. The results on emotional trust and acceptance of recommendation tools can be explained by the fact that users' knowledge of how an Rt works is incomplete. Emotional trust therefore enables users to block out their concerns about unfamiliar technologies, which makes it easier for them to engage in the use of RT's (Komiak & Benbasat, 2006).

Abass (2019) has identified three dimensions related to AI, that influence vulnerability. For example, that of a customer as a trustor[3].

- The first dimension is the capability of the trustee.
- The second dimension is the ability that the trustor gives to the trustee.
- The third dimension is the intention of the trustee.

These dimensions fit very well with AI since the capability of the AI equates to its skills and competencies and thus for the degree of automation of that AI. Opportunity is representative of the degree of autonomy with which the AI is allowed to perform its actions and its powers. The intentions of AI agents that learn and adapt may change during interactions. Therefore, the trust between humans and Artificial Intelligence (AI) could be measured via the two dimensions of degree of automation and degree of autonomy could be mapped. However, the prerequisite for this is that the intentions of the AI and the human's match. If this is not the case, the AI may make decisions that disappoint humans and cause them to distrust the AI. In this case, the trustworthy AI is capable of successfully completing the tasks, but the costs are then disproportionate to the benefits. According to this logic, the ideal state is reached when the

[3] Trust is not equally distributed between two parties. One party must trust the other more. The trustor is the party that is willing to trust the other party (to a certain extent). The trustee is the party that receives this trust from the trustor. The trustor is influenced by factors such as the trustee's ability, benevolence, and integrity with respect to his willingness to trust. For example, the mentor would be the trustee and the student the trustor; or the seller is the trustee and the buyer the trustor (Mayer et al., 1995).

degree of automation is equal to the degree of autonomy. Then the AI is also considered trustworthy (Abbass, 2019).

The study by **Puntoni, Walker Reczek, Giesler** and **Botti (2021)** provides remarkably interesting insights, and we draw particular attention from this study to the so-called “AI delegation experience” (Puntoni et al., 2021). A delegation experience is what consumers experience when they incorporate an AI solution into a production process and has it perform tasks that the user would otherwise have performed themselves. These tasks can be a wide variety of decisions, such as when AI makes a phone call at the consumer's request and using the consumer’s calendar to make an appointment. But it could just as easily be a task in the digital world or, in fact, a physical task. For example, the thermostat in the smart home can learn the consumer's preferences and act to "please" the user. Because consumers do not have to participate in such tasks that AI performs for them, delegation experiences can benefit consumers in two ways. First, consumers can use their time for things they find more satisfying and meaningful than booking appointments at the repair shop (Puntoni et al., 2021).

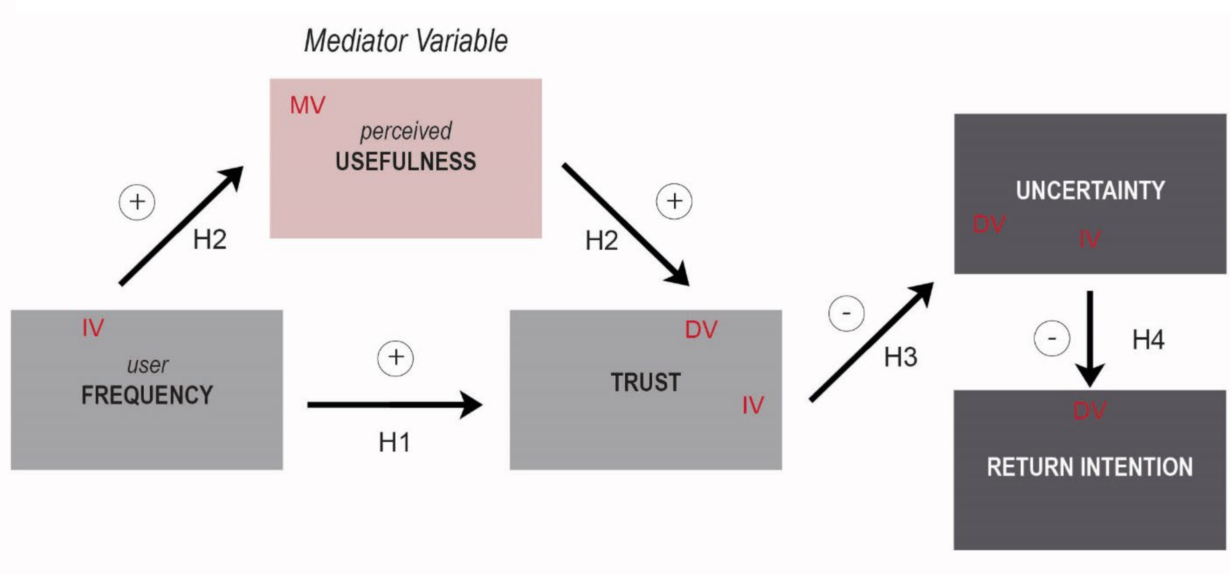
By delegating extrinsically motivated tasks to AI and keeping intrinsically motivated tasks to themselves, they can feel happier. Second, consumers can focus on activities that better match their skills and let AI handle those tasks leave to the AI those tasks that consumers would do less well. In this way, they can strengthen their self-efficacy[4] (Puntoni et al., 2021). It can be concluded that customers need to have used RT's first to perceive the benefits and develop trust in the recommendations.

[4] Self-efficacy can be defined "as the belief that one is capable of mobilizing physical, intellectual, and emotional resources to achieve success" (Paul & Moser, 2015, p. 276). Own translation from German.

3 Development of the Trust Model

In this chapter, the trust model for recommendation agents in e-commerce is developed. The derivation of the individual hypotheses, based on the previous literature review and other research results discussed here, also takes place and leads to the developed trust model. Figure 2 shows a summary diagram of the proposed structural model for online apparel shoppers. The components are frequency, trust, uncertainty, intention to return, and mediation of perceived benefit on trust. We hypothesize that customers who frequently purchase clothing online and use recommendation tools are more confident, less uncertain, and therefore return fewer items compared to the group that is more unfamiliar with the use of recommendation technologies because they do not frequently purchase online.

Figure 2: Model of Trust with Perceived Usefulness as Mediator, own design and illustration



3.1 Hypothesis Development

Based on literature review, the following for hypotheses have been formulated:

Table 3: Hypotheses

H1	The more frequently the AI recommendation tools are used, the greater the user trust in them
H2	The perceived usefulness has a mediating effect on the relationship of frequency of use and trust
H3	Trust in AI recommendations reduces user uncertainty
H4	The lower the uncertainty the lower the user intention of product returns

These Hypotheses are discussed in more detail below.

3.2 Frequency and Trust (Hypothesis 1)

Those who do not use AI tools cannot convince themselves of their usefulness and thus cannot develop trust in their recommendations. Frequent use with a positive result, i.e., a recommendation that meets the demands and needs of the customer, should increase the perceived usefulness, and thus also increase trust in these support services.

The frequency is also relevant because users sometimes lack experience in dealing with artificial intelligence. The KPMG study of 2021 found that familiarity and understanding of AI are the key driver of trust in AI (Gillespie et al., 2021). On the subject of technology acceptance, other studies have also shown that familiarity with the use of recommendation tools has an influence on trust and perceived usefulness ((Xiao & Benbasat, 2007) or that trust must be given the same importance in online shopping as the PU and EOU factors of the widely used technology acceptance models (Gefen et al., 2003).

In short, it could be said that people must learn how to use AI, they must experience the tools. And experience is gained through trial and error. Learning happens through things like repetition (Franken & Franken, 2020).

Learning new things can happen on different levels. There is success learning, which can be equated with conditioned learning. This means that repeated experiences have a learning effect. This can be positive or negative, depending on which experiences are constantly repeated. From this we can conclude that positive experiences with AI, which gives recommendations in the area of clothing, also has a positive learning effect (Franken & Franken, 2020; Tippelt & Schmidt-Hertha, 2018). That one thus, after repeated good recommendations, puts trust in the AI, in the recommendation tools, that this AI tool will again give a good recommendation the next time it is used. However, in order for this learning experience to be positive and for the trust to become stronger and not diminish, the usefulness of the recommendations seems to be relevant (Davis, 1989).

"Motives, goals and abilities" play a role in learning. Learning through insight could also have relevance here (Franken & Franken, 2020, p. 58). All these findings lead to the assumption that trust in AI recommendations also happens on the basis of frequency of use. It can be assumed that increasing usage solves users' problems and that they thus recognize the usefulness.

The relationship between usefulness, frequency and trust will be examined here. Without using the AI tools, their usefulness can become less apparent. While it is quite possible that the usefulness of a tool can be recognized without having used it, it can be assumed that only actual use, i.e., experience with it, will bring about the fulfillment of needs. Finding the AI recommendations useful, in turn, is likely to result in more frequent use of the tools (Davis, 1989; Fang et al., 2014; Gefen, 2000). Trust comes into play here as follows: As described earlier, trust is needed where information is lacking. On the one hand, the AI of an online store "knows" the entire assortment and, if the users have deposited their data, these as well. And thus, the AI has a knowledge advantage, so to speak. If customers want to use this information, they have to trust the AI recommendations, otherwise this knowledge is basically useless. Since AI is a relatively new technology and many users have not yet learned how to use it (Avramakis, 2020; Schlohmann, 2012; Venkatesh et al., 2003, 2012), and the implementation in the online stores is also at various stages, we assume that its use can create trust and thus also increase the perceived usefulness. In the KPMG/Queensland University study (2021), the authors come to the conclusion that public AI literacy must be improved since “the public generally has low awareness and understanding of AI and its use in everyday life” and identified “familiarity and understanding of AI as a key driver of trust and acceptance of AI” (Gillespie et al., 2021, p. 56) .

Certainly, it could also be argued that only trust influences the frequency of use, but for the reasons mentioned above, i.e., the little experience and skepticism towards AI, we assume that, at least at this stage, only a use of AI creates trust and not vice versa, at least not at the beginning of the use. This is because this work is not about trust in the vendor, but trust in tools, some of which can be used, but do not have to be. Other things, such as recommendations like "this goes with that" cannot be turned off by the user.

It is also unclear whether users are even aware that the recommendations they make when buying clothes online come from an AI. In the above-mentioned KPMG study "Trust in Artificial Intelligence" from 2021, in collaboration with the University of Queensland, respondents from five countries (USA, CAN, GER, UK, AUS) indicated how willing they are to rely on information provided by an AI. Only 28% answered this question positively, 37% were unwilling, and 35% were neutral. In the specific area of HR and recruiting, even fewer were willing to rely on AI, down to 23%. It is interesting to note that when it comes to AI in healthcare, the tables are turned. There, more are willing to rely on AI, namely 37% versus 32% who are neutral and 31% negative (p.10). Another interesting finding from the study is the assessment of the use of AI in existing technologies. Various technologies were listed where respondents were asked to indicate whether they used them and whether the respective technology used AI. In the case of social media, 76% said they used this technology, while 59% were not clear that AI was used here. For chatbots, 43% of respondents did not believe AI was used here, compared to 37% who said they used chatbots. for product recommendations technology, 58% said they used it and 56% were not aware that AI was used here. p. 47 This shows that AI has not yet arrived in the everyday lives of most consumers. As a rule, based on the data from the study, it can be said that the younger and more educated people are, and if they are male, the higher their trust in AI (Gillespie et al., 2021).

One of the most important findings of the study for this paper is that trust is also central to the acceptance of AI here: “if people perceive AI systems to be trustworthy and are willing to trust them, this leads to the acceptance necessary to realize the benefits of AI” (Gillespie et al., 2021, p. 52). It was also found that people trust AI more when they know how and when AI is used. Familiarity with AI, i.e. also the knowledge of how AI is used, e.g. in common applications, has emerged as a key driver for trust (Gillespie et al., 2021).

That is, unlike shopping in a clothing store, there is no interpersonal interaction initially. However, the recommendation tool used can be seen as a substitute for a salesperson advising one. Trust is therefore an important variable in the deployment and use of recommendation tools. From this we draw our first hypothesis:

Hypothesis 1: The more frequently the AI recommendation tools are used, the greater the user trust in them.

Consumers who are less familiar with the products are willing to trust a salesperson if he or she provides advice and responds to the customer's needs. This effect was also found in a study of websites with RA tools, since there, too, the people who knew less about the products were more likely to use the websites with RA tools (Xiao & Benbasat, 2007).

In a study, Crosby was able to demonstrate that salespeople with a higher level of (perceived) expert and referent power were rated as more trustworthy by customers. The frequent contact with sales representatives was also a positive influencing factor on trust. If we now say that AI replaces a salesperson, frequent use of a recommendations tool could equate to frequent contact with a salesperson. Crosby's study showed that the relationship was of high quality if the customer could rely on the salesperson and was confident about future performance (Crosby et al., 1990).

Gefen also found that there is considerable overlap between the conditions for trust and perceived ease of use. The reason for this is that in online shopping, the vendor's website is the primary means of establishing familiarity with the vendor and assessing situational normalcy. Accordingly, familiarity with the vendor requires gaining experience with the vendor's website. This assumption can be applied to RA tools and therefore we conclude that experience with RA tools, i.e., more frequent use, has a positive, direct impact on PU and trust (Gefen, 2000).

Based on our assumptions that frequency of use is related to perceived usefulness as well as trust, we developed the model. The exogenous variables such as uncertainty and future intentions are based on the information from the literature that trust positively influences uncertainty and future intentions, but here we assume that only the reduction of uncertainty influences the users' actions regarding future returns and that this variable is not directly influenced by trust. The derivation of the other hypotheses is described individually in the following chapters.

3.3 Perceived Usefulness (Hypothesis 2)

Perceived usefulness is a technological determinant. It describes how much it helps users to achieve a certain goal, which can be derived from the definition of useful as *“effective; helping you to do or achieve something”* (*Cambridge Dictionary*, 2021)

What we want to know is what causes users to use a technology, i.e., the recommendation tools, and whether the usefulness of these RTs is influenced by the frequency of use. Previous research suggests two factors are particularly important in this regard. One of the factors is perceived usefulness, as customers tend to use or not use an application to the extent that it helps them get their work done. Their "job" in this case would be to find the right garment. This means that in addition to type, color, shape, material, they also have to judge whether the garment fits at all (Davis, 1989).

Social influences, characteristics of the system, and the task were factors in perceived usefulness in previous research. In cases where technology is the interface, as in the case of the present work where the recommendation tools represent a technological interface (besides the website itself) in the relationship between customers and providers, it is important to include also the trust characteristics (Gefen et al., 2003), which we have already considered.

When consumers are better able to appreciate the intangible attributes of a product, and consumers' perceived usefulness increases as a result, they feel more comfortable making purchases over time. As a result, consumers are likely to order more products (intangibles at the time of purchase) as this learning process reduces product-level uncertainty (Kim & Krishnan, 2015).

As explained in the section above, the frequency of use of AI recommendation tools, trust in them and their usefulness are related. in the study by Xiao and Benbasat (2007) on the use of recommendation agents, the authors found that alone the use of RT's had a positive effect on trust and on perceived usefulness. It can be assumed that perceived usefulness and trust experience an influence by the frequency of use (Xiao & Benbasat, 2007). Thus, in this paper we assume that the tools are used, but we are particularly interested in the extent to which the intensity of use plays a role. The assumption is that the user of the RT's only experiences a higher, perceived usefulness through use. It will also be examined whether the outcomes PU and trust increase to the same extent as the frequency of use. A common technology acceptance model (TAM), consisting of the factors perceived usefulness and ease of use has proven to be a model for the acceptance of information technologies (Gefen et al., 2003).

Models such as TAM explain that a person's reactions to using a technology contribute to their intention to use a particular technology. This in turn then determines the actual use of the technology (Xiao & Benbasat, 2007). Here, perceived usefulness is viewed as a belief that can be formed in two ways in the case of a recommendation tool. First, it can be perceptions that come from others, for example, colleagues, friends, or from magazines and television. However, this would only be the case if the users have not yet used RTs. Second, on their own experiences with the RT, which we also assume in this work (Fishbein & Ajzen, 1975; Xiao & Benbasat, 2007). According to Fishbein and Ajzen (1975), direct experiences “result in the formation of descriptive beliefs”. Furthermore the authors state, that this kind of beliefs are “held with maximal certainty” which can only weaken overtime through forgetting (Fishbein & Ajzen, 1975, p. 132).

However, a website can be both for the customers. On the one hand, a technology is used, not only the website, but in the case of the present work additionally the recommendation tools, on the other hand, however, one is a buyer of clothing and thus a customer. Therefore, the session of the RA s is also to be considered from two perspectives, a cognitive and emotional one (Komiak & Benbasat, 2006).

It remains to be noted here again that trust is a social determinant, and perceived usefulness is a technological determinant (Gefen et al., 2003).

In the learning research it was also determined that one learns best by doing. Although there are different types of learners and people react more to visual than to auditory stimuli and vice versa, a retention rate of 90% shows that people learn best when they do what they have to learn themselves. Unlike a computer, the human brain also stores only what it finds useful. Our brain works according to categories, processes absorbed impressions and links new and already processed experiences with each other. We learn and retain only what is important to us and what has meaning or makes sense for us (Franken & Franken, 2020).

Another theory sees interpersonal similarity as crucial to building trust. Thus, buyers are often said to judge the degree of their similarity to a seller based on observable characteristics (physical attributes and behavior) and internal characteristics (perceptions, attitudes, and values). In this regard, internal similarity increases a buyer's willingness to trust a seller and thus to follow his or her instructions to trust a seller and follow his or her instructions (Xiao & Benbasat, 2007).

It can be concluded that if the customer follows the RT's instructions, as a "substitute" for a salesperson, he or she will choose better fitting clothes, since the RT actually "knows" better what suits the customer in case of doubt. To build trust, it is important that the customer has positive experiences in this process. If he would have negative experiences after following the instructions, it would have a negative impact on trust and also on perceived usefulness. In principle, this logic follows classical conditioning (Franken & Franken, 2020).

Adapted from Gefen, the benefit to the customer can be divided into the usefulness of the technology itself, and a benefit for the future, such as receiving the clothing ordered (Gefen et al., 2003). Trust is a social antecedent. Perceived ease of use and perceived usefulness are technological antecedents. Similarity as well as familiarity have already been identified as influencing factors in the usage of RAs and the relationship between usage and Trust as well as PU (Xiao & Benbasat, 2007)

Another aspect is that people who perceive a high benefit from a technology also classify it as less risky than people who can hardly recognize any benefit in a technology (Siegrist, 2001). Häubl and Trifts (2000) find that the use of RA reduces consumers' search effort for product information, while improving the quality of their choices and thus the quality of their purchasing decisions (Häubl & Trifts, 2000).

It can be argued that a technology is only used if it has a benefit for the user, of whatever kind. The satisfaction of needs is the focus of use and determines the choice of (voluntary) use of a particular technology (Brandtzaeg & Følstad, 2017). If it is an innovative technology, it must benefit the user more than the previous one, otherwise there is not necessarily a reason to use a new technology (Schlohmann, 2012). In the case of recommendation bots with AI, we assume a higher usefulness since they provide more precise recommendations as described.

In Davis' study, perceived usefulness correlated significantly with both self-reported current use and self-predicted future use (Davis, 1989). Our hypothesis is that more frequent use not only increases trust in recommendation tools, but also has a positive effect on perceived usefulness. In previous research on the topic, trust has always had an impact on perceived usefulness, but never vice versa. In this paper we want to test whether perceived usefulness mediates the influence of frequency of use on trust. We assume that the use of RTs first reveals their usefulness, but also that the more frequent use has an influence on trust, which, however, might be different without the perceived usefulness. From this, we derive the following hypothesis:

> Hypothesis 2: The perceived usefulness has a mediating effect on the relationship of frequency of use of recommendation tools and trust.

3.4 Uncertainty (Hypothesis 3)

At this point, we would like to draw another distinction between customer satisfaction and trust. Whereas overall satisfaction is based on an evaluation of past experience , trust and relationship retention relate more to the future service relationship. Satisfactory experiences with the offerer strengthen the confidence, since the customer counts on it to be able to expect also in the future a positive exchange and can estimate beyond that the own vulnerability and uncertainty better (Aurier & N'Goala, 2010).

Pavlou and Fygenson's study also found that trust has the strongest influence on the relationship between information acquisition and product purchase. The authors demonstrated the process by which trust influences behavior. It functions first as an attitude and second as a control belief. Thus, trust is the antecedent of attitude, which is the buyer's confident expectation, and controllability, which is a reduction in uncertainty (Pavlou & Fygenson, 2006).

Jurado, Ludvigson, and Ng describe uncertainty as "the conditional volatility of a disturbance that is unforecastable from the perspective of economic agents" (Jurado et al., 2015, p. 1177). According to the authors, an increase in uncertainty can be the setting when stakeholders are risk averse or when financial constraints tighten in response to higher uncertainty.

When online consumers show uncertainty, it is mostly in relation to subjective product quality. This means uncertainty about the fit, feel and materials. The reason for this is a lack of experience, as shown in the study by Kim & Krishnan (2015). The researchers investigated the change in products purchased online over time in the presence of the uncertainty described above. One finding was that consumers with greater online shopping experience are better able to assess product quality and therefore purchase products with high levels of product uncertainty. It is also interesting to note that with a 10% increase in online shopping experience, the average and maximum prices of the shopping carts decreased by about 1%. This could indicate that high priced products are more likely to be purchased in-store after all whereas cheaper products (in the study these were products under $50) are also purchased with a high level of uncertainty (Kim & Krishnan, 2015). Product uncertainty and lack of experience can also be offset by consumers choosing a particular brand (Kim & Krishnan, 2015).

Another finding from this is that the perceived benefits of online shopping can promote the online purchase of cheap products, but the effect is limited for the online purchase of expensive products, which may seem wrong at first. The downward trend in the prices of products purchased online suggests that online consumers do not buy very cheap products in the initial stage of online shopping. Again, one would assume at first that it should be the other way around. The researchers explain this fact by saying that this could be due to shipping and handling fees, as consumers are sensitive to shipping costs and these have a significant impact on order receipt. because for the consumer, only the total cost is relevant at the end of the online purchase. Shipping costs are all the more noticeable for cheap products, which is why mid-priced products are more attractive to online shoppers. Since most successful online stores offer free shipping, the question is whether these effects would still be observed today. In our case, that is, when considering companies that offer free shipping as well as return shipping, this is irrelevant. Online retailers have already taken this form of uncertainty into account (Kim & Krishnan, 2015).

Customers who shop online try to reduce their uncertainty before they decide to buy. It is known that uncertainty is greater when the consumer has less knowledge about the product (Heiman et al., 2001). It is also possible that consumers face multiple types of uncertainty at once. For example, if a woman buys a new costume in an unusual color for work, she may experience both matching and response uncertainty. Moreover, the degree of uncertainty depends on the purchase situation; for example, it is different in the case of a purchase for oneself or when one is getting a gift (Heiman et al., 2001).

Table 4: Causes for Uncertainty (Heiman et al., 2001)

Causes for Uncertainty	
Type	***Description***
Technical Uncertainty	This can also be referred to as reliability. It refers to the failure rate of the product. It indicates the extent to which the product meets certain specifications and standards.
Performance Uncertainty	It may happen that a customer perceives the performance of a product to be different from what it is. This gap is referred to as performance uncertainty.
Matching Uncertainty	In this case, the consumer is uncertain about the extent to which the product can meet his or her own needs.
Response Uncertainty	This uncertainty (also) arises after the purchase. The consumer is not sure how the reactions of his environment to the chosen product will turn out.

At the product level, it was found that uncertainty also depends on several factors. On the one hand, how high or low the involvement is is relevant. With unknown products, the search for information is more intensive. If one has more experience, the effort of searching for information is reduced (Heiman et al., 2001). There are separate ways of classifying a product in the literature. Kotler has divided this into durable, nondurable, or service goods. Durables are long-lasting products such as clothing. Nondurables are according to this definition fast consumable products like food and service goods contrast with the other types intangible (Heiman et al., 2001 according to Kotler, 1994). A further classification of products took place by Nelson, who divided them into search goods and experience goods. Search goods are products from which consumers can learn all relevant information before making a purchase decision. Experiential goods are products whose quality can only be judged after direct experience. So the online purchase of clothing would fall into this category because the material, the fit or the color is learned only after the purchase of the product, namely when the package has arrived home. Experience goods therefore lead to greater uncertainty before purchase than search goods (Nelson, 1970).

This classification of products took place at a time when there were no web stores at all. Therefore, Kim and Krishnan consider an adaptation of this classification to an online setting to be appropriate. A dress, when purchased in a retail store, is a search product. The same dress, however, becomes an experience good in an online store because the fit and feel cannot be assessed before purchase (Kim & Krishnan, 2015).

There are two sources of information asymmetry in online markets that buyers face: the information asymmetry at seller level, i.e. seller uncertainty, and that at product level, product uncertainty (Dimoka et al., 2012).

The purchase decision for durables is more likely to be characterized by intensive information search, especially if the products are expensive, long-term purchases. it concerns expensive, long-term purchases the involvement is high (Heiman et al., 2001).

Urbany, Dickson, and Wilkie examined two different dimensions of consumer pre-purchase uncertainty: Knowledge Uncertainty (KU) and Choice Uncertainty (CU). CU describes the consumer's uncertainty about which alternative to choose from among the products under consideration. KU, on the other hand, describes the consumer's uncertainty about the available features and the importance of those features. When these two dimensions were considered in the research in the context of search, CU appeared to increase search. KU had a weaker negative effect on search than CU (Urbany et al., 1989).

All physical experiential goods that cannot be perfectly described online, the problem of uncertainty is exacerbated. IT-based solutions can counteract this and improve the ability to describe products online, thereby mitigating their lack of knowledge about the actual condition of the product. The effectiveness of these IT solutions should be further enhanced by innovative AI recommendation tools. Accordingly, we also do not want to query an overall reduction of uncertainty in the e-vendor, but measure the reduction of product uncertainty (Dimoka et al., 2012). From this, we derive the following hypothesis:

Hypothesis 3: Increased trust in recommendations of a RT reduces user uncertainty.

Thereby, there are nevertheless attributes of salespeople, which we can derive from in the context of trust in salespeople and uncertainty.

As mentioned earlier, online retailers have long responded to the problem of uncertainty among shoppers who store online by offering free shipping and free returns. Zalando, bonprix and ABOUT YOU advertise free shipping and returns directly on the home page (*aboutyou.ch,* 2021; a screenshot can be seen in the appendix). Zalando touts the 30-day return policy and ABOUT YOU can boast 100-day return policy and purchase on account (*Zalando.ch*, 2021). These examples clearly show that customers do not suffer any financial disadvantages because of buying online. It has also been shown that these concessions remove uncertainty from online shoppers (Heiman et al., 2001). We want to know if trusting product recommendations also reduces uncertainty, so that most returns eventually become unnecessary.

Online product descriptions, especially for physical experiential goods such as clothing, furniture, touchable products, and virtually all used goods, are helpful in reducing product uncertainty. If they also come from reputable sellers who are seen as credible by buyers, the effect of the descriptions is even more likely (Dimoka et al., 2012).

An important question that also arises is how to measure uncertainty. If we consider uncertainty as a purely psychological construct, which makes sense since uncertainty describes internal states, there are separate ways of measuring it, and there is no one right method. One can distinguish between direct and indirect methods (H. R. Pfister et al., 2017).

In indirect methods, the degree of uncertainty is inferred from certain behaviors:

- Ranking methods,
- decisions and
- betting.

Direct methods include the following:

- Querying numerical probability estimates,
- interrogation of frequency estimates and
- verbal evaluations.

For this thesis, we chose to use evaluations, based on other research.

These are reasons why in this work the forms of users' insecurity are considered from a distinct perspective. We want a better solution than free returns because they cost money and time. The ideal state would be no returns. With trust in the recommendation agents and not a purchase despite uncertainty because nothing can happen (having to keep and pay for clothes you do not like) but a purchase because of trust and security would be the goal (not returning clothes because they like and fit) (*Österreich - Gründe für Rücksendungen von Online-Bestellungen 2020*, 2021; *Retouren - Gründe in Deutschland 2019*, n.d.).

In the past, reputation and trust have emerged as the most crucial factors in reducing e-vendor uncertainty. In this paper, we do not ask the participants about trust in the providers, because that does not solve the problem of mismatched clothing at the first moment. Rather, we assume that the reputation is already given with the large online retailers that are the subject of this paper and that they have already proven this through their generous shipping policies. We view recommendation tools as representative of service personnel and examine trust in the tools' recommendations.

3.5 Intention of Returns (Hypothesis 4)

As has been discussed already in chapter 2, the high return rates are a major issue in the e-commerce for apparel. It is noticeable that the younger the shoppers are, the more they return.

Häubl and Trifts found as early as 2000 in their experimental study that certain tools that help present consumers with reduced but relevant choices increased decision quality (Häubl & Trifts, 2000, p. 4):

> *"In sum, our findings suggest that interactive tools designed to assist consumers in the initial screening of available alternatives and to facilitate in-depth comparisons among selected alternatives in an online shopping environment may have strong favorable effects on both the quality and the efficiency of purchase decisions-shoppers can make much better decisions while expending substantially less effort. This suggests that interactive decision aids have the potential to drastically transform the way in which consumers search for product information and make purchase decisions".*

As far as objective decision quality is concerned, it is relevant whether buyers change their mind after making a purchase decision and switch to another alternative if they have the opportunity to do so. A change, which we define as a return or exchange, both of which amount to a return of the goods, indicates poor initial decision quality. Subjective decision quality is the consumer's level of confidence in a purchase decision (Häubl & Trifts, 2000). We conclude that customers who return nothing or little have a high decision quality. Which, conversely, means that they have a low level of uncertainty about the purchase decision and a high level of confidence in the AI recommendations, as far as he uses them.

"When returns are too expensive, zero consumers will exercise the return option. Similarly, when there is no uncertainty about product fit, there will never be returns: all products shipped to a customer are kept" (Anderson et al., 2009, p. 410) .

From this information, the fourth and final hypothesis can be derived.

> Hypothesis 4: The lower the uncertainty the lower the number of product returns by the customers.

In the next chapter, the model will first be formalized to test it empirically and confirm or reject the a priori hypotheses.

4 Empirical testing of the developed trust model

This section first describes how the data was collected and who the questions are aimed at. This is followed by a description of the operationalization, i.e. the basis on which the indicators were formulated and the scales to which the items were combined. This part of the paper concludes with an empirical examination of the acceptance model and a description of the results of the study.

4.1 Research Methodology

In this first part of the chapter, the survey method is described in detail. The constructs and scales as well as the items are presented. In the second part of the chapter, we describe the procedure for evaluating the survey, including the selected test procedures, with an interpretation of the results at the end.

4.2 Description survey method and operationalization

The data comes from an online survey, designed by the researcher, of people living in the DACH region. The target group for the survey were people of all ages that purchase clothing online. Participants were made aware of the purpose of the survey and that the survey was anonymous. The questionnaire was available in German and English an the potential respondents had to agree to the privacy policy. 185 people completed the questionnaire, before we tested the data set for outliers. After correction, we had 182 questionnaires available for analysis.

The survey was aimed at people who buy clothing online, which requires Internet access. Therefore, we did not exclude any people with this online survey, which also requires Internet access (source?). The survey was online from December 06, 2021 to December 20, 2021 and respondents were approached through different channels. On the one hand, it was sent to students and employees of the University of Applied Sciences Vorarlberg, as well as shared via the social media channels Facebook and LinkedIn. More than 400 people started the questionnaire, but not all of them finished it.

First, respondents were asked whether they had already purchased clothing from one of the online stores indicated. Second, respondents could indicate how often they had shopped online in the last three months, as can be seen in . Those who indicated 0 were not excluded if they had already shopped online for clothing in one of the specified e-shops, as we wanted to check what differences there are between frequent and infrequent shoppers. How these are defined will be explained later.

When asked about the online stores from which respondents have already shopped, only the most relevant in the respective market were considered, as these already represent a considerable proportion of total sales in the apparel sector. In all three countries in the DACH region, Zalando ranked first by a wide margin among the most successful online stores for apparel in 2019, based on sales. In Germany, bonprix and ABOUT YOU follow in second and third place. In Austria, universal.at is second, h&m third, and bonprix and ABOUT YOU fourth and fifth, respectively. In Switzerland, the picture is different. There, Globus.ch is in second place, H&m also in third place, and bonprix in fourth place. Lehner-Versand was still in fifth place in 2019, but had to accept losses, whereas the other e-vendors mentioned were able to make strong gains, as can be seen in table 2. For this reason, the questionnaire only asked whether people had ever shopped in the following stores, where multiple answers were allowed as can be seen in figure 3.

Figure 3: Question 1 and 2 from questionaire, Source: www.unipark.de[5]

Have you already bought clothes online in one of the following online stores?

Please indicate all the answers that apply (multiple answers possible).

- ☐ zalando
- ☐ bonprix
- ☐ aboutyou
- ☐ universal
- ☐ h&m
- ☐ globus
- ☐ none of them

How often in the last three months did you buy clothes online?

Please enter a number. For "not at all" please enter 0.

We assume, even though ABOUT YOU was not among the top 5 in Switzerland (see table 2), that the above-mentioned companies show a good cross-section of the market in the DACH region. Zalando and Bonprix are strong in all three countries, ABOUT YOU is also strong in Germany and in Austria, in Switzerland the company was a bit further behind in 2019. The 2020 figures are not yet available but ABOUT YOU has strongly grown every year, so we assume it will see sales growth in Switzerland as well. In the consolidated financial statements, Switzerland is not listed individually in terms of sales. But the ABOUT YOU DACH segment, which covers Germany, Austria, and Switzerland together, grew strongly in the 2020/21 reporting year - by 29.3% to €660 million. Profitability also increased.

4.3 Measures

In addition to the frequency of online clothing purchases and the web stores from which purchases are made, 42 measures were used to capture the construct. All questions about

[5] Screenshot of the questionnaire created by the researcher in “Unipark” which is an online survey software

attitude were asked on a 5 point Likert-scale. The measures for perceived usefulness, trust and uncertainty were drawn or adapted from previous studies. Likert scales allow respondents to express their opinion on a question, and they can do so in direction and strength. Choosing a 5-point Likert scale allows us to evaluate on a metric scale level, which is important in this paper to test correlations. The distances of the 5-point Likert scale are always the same between the individual points (Döring & Bortz, 2016), here 1 means strongly disagree and 5 means strongly agree. In the questionnaire, however, each scale point was labeled as follows:

Figure 4: 5-point likert scale, own illustration einer likert scale wie sie im Fragebogen verwendet wurden

Missing values were avoided by declaring all questions as mandatory. Simple and unambiguous wording is important and it is equally important to avoid response bias. Therefore, positive as well as negative items were constructed. The internal consistency of each scale was checked with the item analysis. Elimination of items was not necessary because the result of the coefficient Cronbach's alpha. Cronbach's alpha was calculated for the scales trust (11 items), perceived usefulness (12 items), uncertainty (8 items), and intention to return (9 items). Internal consistency was acceptable, with Cronbach's alpha > .70 for positive affect (Hemmerich, n.d.-a).

Table 5: Results reliability test with Cronbach's α

Scale	Cronbach's α
Trust	0.7379294
Perceived Usefulness	0.7873868
Uncertainty	0.7143098
Return Intention	0.7526029

The items of the following constructs were all queried in a 5-point Likert Scale and were developed based on various theories from research, which are presented with each construct and source in the following table.

Table 6: Items, Constructs

Construct	Measurement Item	Source
Trust 11 items	I trust the accuracy of the size recommendations in the online store based on my data	Adapted from Gray-son, Johnson, and Chen (2008); Kumar, Nirmalya, Scheer, and E. M. Steenkamp (1995)*
	I trust that the recommendations are in my (customer's) best interest	
	I rely on the size recommendation of the online store	
	When choosing the right size I trust only my experience (reverse scored)	
	Since I rely on the recommendations of the online store, I can count on liking the ordered clothes	
	The recommendations of the online store are trustworthy	
	I generally do not trust the recommendations of an online store (reverse scored)	Adapted from Moorman, Zaltman and Despandé (1993)
	The recommendations of the online store always meet my expectations	Adapted

	I am worried that the recommendations I receive of the online store are wrong (reverse scored)	Kumar, Nirmalya, Scheer, and E. M. Steenkamp (1995)*
	In my experience the recommendations from a styling expert are more trustworthy than of an online store (reverse scored)	
	I cannot rely on the size information provided in the online store, so I always order several sizes of a product (reverse scored)	
Perceived Usefulness 12 items	Having a customer account allows me to find the clothes I am looking for faster	Adapted from Bosmans, Anick (2006), Kleijnen, Mirella, Ko de Ruyter, and Wetzels (2007); Voss, K.E., E.R. Spangenberg and B. Grohmann (2003)*
	The use of search filters helps me to find the clothes I am looking for faster	
	I find features like "this goes with that" or "complete the look" useful	
	I find the "other customers also bought" function useful	
	I know exactly what I need and buy only that (reverse coded)	
	When I shop for clothes online, the search function is very important to me	
	The "You might also like" function is important to me	
	I find it important to get tips from real stylists on the site (reverse coded)	
	The online shop provides me with a relevant selection of the range of clothes	
	The recommendations on the website make my shopping easier	
	Having a customer account allows me to find the clothes in the right size	
	The recommendations in the online shop are not useful (reverse coded)	
Uncertainty 9 items	When I order things based on a recommendation from the online store, I feel I have made the right decision	Adapted from Urbany, Dickson and Wilkie (1989)
	I am sure that the size recommendation is accurate and therefore I order only one size of the selected garment	New item
	When ordering I am certain that I have chosen the garment in the right size	Adapted from Urbany, Dickson and Wilkie (1989)
	I have confidence to make the right choices when using the recom-mendations of the online shop	New item
	To be on the safe side, I order multiple sizes of a garment (reverse coded)	New item
	With the help of the recommendation tools I am sure to find the clothes that best meet my needs	Adapted from Urbany, Dickson and Wilkie (1989)
	When I am unsure what goes with a chosen garment, I use recommendation tools like "this goes with that"	
	The recommendations in the online store give me certainty to find the clothes that fit my type	
	I am unsure that the recommendation tools on the website will help me choose the right size	
Return Intention 9 items	If the clothes I have ordered fit me, I do not send them back	New item**
	I always order several sizes of a garment and send back the pieces that do not fit (reverse coded)	Adapted from Harris, Lloyd C. (2008)*
	I make sure that I only order the right size of each garment	New item**
	I know even before the arrival of the ordered clothes that I will send back a certain part of it	Adapted from Harris, Lloyd C. (2008)*
	It is important for me to be able to return ordered clothing free of charge	Adapted from Harris, Lloyd C. (2008)*
	For reasons of sustainability, I generally find returns problematic	New item**
	It is important for me to order the clothes in the right size to avoid returning them	New item**
	I think it is fair that most online stores offer free returns	Adapted from Harris, Lloyd C. (2008)*
	I do not believe that returns are problematic for the environment	

*these scales were found in the Marketing Scales Handbook (Bruner & Hensel, 2012).

** the items from the *Return Intention Scale* were build based on the most frequent reasons for returns and the increasing importance of sustainability.

4.4 Analysis

This part contains the detailed evaluation. In five sub-chapters, we describe in detail how the evaluation of the questionnaire was carried out, systematically dividing this part of the paper into the following sections:

- Introduction
- Formulation of hypotheses for the evaluation
- Descriptive statistics
- Explorative statistics
- Inferential statistics
- Findings

4.4.1 Introduction

The analysis was performed in the statistical programs SPSS and R. The complete data of the evaluation is provided in the appendix.

As already described, 185 participants could be interviewed, which resulted in 53 partial answers to the questionnaire each. In the first step of the quantitative data analysis, the data set was cleaned. Here, N/A values should be deleted, which we do not have, because of the questionnaire design, as already explained in chapter 6.3. Further on, during descriptive statistics, potential outliers are removed, which represent a confounding factor on the testing of the hypotheses. Since this is a survey that is answered by marking the appropriate answer option and Likert scales, we do not expect many outliers due to, for example, mismeasurement. Duplications are also corrected for at this point.

4.4.2 Formulation of hypotheses for the evaluation

By means of the analysis of variance (here with the univariate analysis of variance ANOVA) one wants to examine the effect of an independent variable on one or also several dependent variables. The analysis of variance is considered the most important method in the evaluation of experiments (Backhaus et al., 2016).

Like any other statistical test, the one-factor ANOVA has a null and alternative hypothesis (H0 and H1 hypothesis). For simplicity we only formulate the null hypotheses. The specification of significance is based on these. In the following, we have formulated the null hypotheses that we want to test. The null hypothesis states that there is no difference between the means of each group, which means that there is no effect.

To be allowed to perform the ANOVA it is necessary to consider several aspects.

The measurements must be independent of each other. That is, the groups being tested must not occur more than once. This is the case here, since three groups were formed (those who have made few or no purchases online in the last three months, those who have made an average amount of purchases, and the last group, those who have made a lot of purchases) whose numbers and classification of the groups can be found in Table 6.

The dependent variable must be at least interval scaled and the independent variable must be nominal scaled. Both conditions are fulfilled. Additionally, there should be no outliers in the groups and the variances of each group should be similar. In the following, we have formulated the null hypotheses that we want to test. The null hypothesis states that there is no difference between the means of each group, which means that there is no effect (Döring & Bortz, 2016; *Einfaktorielle Varianzanalyse (ohne Messwiederholung)*, n.d.; Hemmerich, n.d.-b). Based on this theoretical foundation, we form the hypotheses 1.1 – 1.4 for the analysis of variance.

- Hypothesis 1.1:
  There is no difference in the scale PU regarding frequency grouping.
- Hypothesis 1.2:
  There is no difference in the scale trust regarding frequency grouping.
- Hypothesis 1.3:
  There is no difference in the scale uncertainty regarding frequency grouping.
- Hypothesis 1.4:
  There is no difference in the scale return intention regarding frequency grouping.

We use correlation analysis to discover relationships between the variables. To make the correlations measurable, the items were combined into scales and the averages per person were formed. In this way we obtained metric data. (Backhaus et al., 2016). Although correlations provide information about the direction and narrowness of a relationship, it must be considered that they do not explain the cause. The examination of causal correlations always takes place approximatively (Döring & Bortz, 2016). To ensure that all items answered the same, Cronbach's alphas were calculated as shown in the table 4. On this basis, we formulate the hypotheses for the Pearson correlation analysis (directed correlation test).

- Hypothesis 2.1:
  There is no positive correlation between frequency and perceived usefulness.
- Hypothesis 2.2:
  There is no positive correlation between frequency and trust.
- Hypothesis 2.3:
  There is no positive correlation between perceived usefulness and trust.
- Hypothesis 2.4:
  There is no negative correlation between trust and uncertainty.
- Hypothesis 2.5:
  There is no positive correlation between the uncertainty and the return intention.

To test for a mediator effect from perceived usefulness on the association between frequency and trust, we chose to use regression analysis. A mediator variable is called an intervening variable. It is causally influenced by the independent variable (frequency). The mediator variable (PU) then in turn causally influences the dependent variable (trust). The mediator variable is a necessary link in the causal chain. By including PU as a mediator variable in our trust model, we can theoretically and empirically investigate the causal effect processes in more detail (Döring & Bortz, 2016). For the mediator analysis, we undertake regression modeling.

- Hypothesis 3:
  A relationship between frequency and trust is not mediated by perceived usefulness.

4.4.3 Variable transformation

Since the data set has become large due to the many items, the response options to the 5 scales were evaluated into 5 row average scores. These scores are then used to examine the hypotheses to evaluate the model construct.

For this purpose, the demographic variables were first adjusted. In a further step, the inversely worded questions in the data set were adjusted by coding them in reverse.

For all further calculations, N/A values should be filled with the column mean. Since we do not have any NA values in our data set, as already noted, we do not need to consider this step.

Frequency groupings were then formed based on the data, with respondents having purchased inline apparel an average of 3.24 times.

Table 7: Grouping by frequency of purchase

Number of Purchases	Designation
0-1	Low buyers
2-3	Average buyer
>3	Frequent buyers

At this point, we also provide an overview of how many of the respondents have made purchases in which of the online stores.

Table 8: Purchases by online store

	Answers		
	n	**%**	**% of cases**
zalando	138	36.1	74.6
bonprix	25	6.5	13.5
aboutyou	74	19.4	40.0
universal	11	2.9	5.9
h&m	101	26.4	54.6
globus	5	1.3	2.7
none	28	7.3	15.1
Total	382	100	206.5

Since the questionnaire offered the option of multiple answers, we have 382 entries for online stores in which the respondents have already purchased clothing, minus the 28 who have not purchased from any of these online stores. The fact that Zalando is the market leader in e-commerce for clothing in all three countries is also reflected here. 74.6% of respondents have already shopped at Zalando, followed by 54.6% who have shopped at H&M and 40% at ABOUT YOU. It is interesting to note, considering that most respondents live in Austria, that universal.at has only been shopped at by 5.9%, even though this online store was statistically ranked the 2nd most successful online store for clothing in Austria (in 2019), behind Zalando. In the online store globus.ch also only 2.7% have shopped, but since this is a Swiss online store, this coincides with the small number of respondents from Switzerland

4.4.4 Descriptive Statistics

In this section we give an initial overview of the results of the analysis of the demographic data, the scales, the frequency, and an overview of the online stores in which the respondents purchased clothing.

4.4.4.1 Demographics

Demographic details were queried at the end of the questionnaire as individual indicators. These are manifest variables that do not require further explanation - they are assumed to have so-called face validity (p.265). These data were collected to describe the sample, to capture respondent characteristics, and to compare the sample with other studies as needed.

Table 9: Socio-demographic characteristics of the Respondents

		Total	**in %**
n		185	100
By Country	Germany	29	15.7
	Austria	132	74.4
	Switzerland	20	10.8
	other	4	2.2
Gender	male	56	30.3
	female	124	67.6
	diverse	4	2.2
Age	16-23 years	61	32.97
	24-30 years	59	31.89
	31-35 years	29	15.68
	37-42 years	15	8.11
	43-48 years	9	4.86
	> 49 years	12	6.49
Highest Level of Education	none	1	0.5
	Some high school	2	1.1
	Matric	73	39.5
	Technikon	68	36.8
	University degree	39	21.1
	Other post matric	2	1.1
Where the Respondents Live	Metro (+250.000)	20	10.8
	City/large town (40.000-249.999)	46	24.9
	Small town/village (500-39.999)	110	59.5
	Rural (<500)	9	4.9

The 185 respondents are on average 29.44 years old with almost 65% of the respondents in the age group16-30 years. More than half have a higher education degree and most respondents live in a small town or village.

Table 10: Overview Results Metric Scales

	mean	sd	median	trimmed	mad	min	max	range	skew	kurt	se
Frequency	3.84	3.37	3.00	3.16	1.48	1	20	19	2.78	9.56	0.25
Age	29.44	9.57	26.00	28.05	7.41	17	62	45	1.24	1.01	0.70
Trust	3.05	0.52	3.09	3.08	0.54	1.55	4.27	2.73	-0.38	-0.27	0.04
PU	3.08	0.60	3.08	3.09	0.62	1.58	4.33	2.75	-0.26	-0.34	0.04
Uncertainty	3.22	0.61	3.25	3.22	0.56	1.38	4.75	3.75	-0.08	0.04	0.05
Returns	3.40	0.69	3.44	3.40	0.66	1.67	5.00	3.33	-0.02	-0.27	0.05

For the four average scores of trust, PU, uncertainty and returns, boxplots were plotted in *R*[6] as descriptive statistics to detect outliers. In the relevant variables, which are needed in the following hypothesis tests, some conspicuous outliers are detected, which are winsorized. As a general rule, it cannot be said that outliers should be removed. Boxplots are first of all a suitable means to find outliers (Sauer, 2019). Thus, a few outliers could be identified in the survey, which were removed after careful consideration. While it is not always advisable to remove extreme values, we still chose to do so in order to make our analysis not susceptible to bias. A total of 3 outliers were identified, which doesn't make the sample much smaller. For verification, the boxplots were calculated again after winsorizing. As can be seen in Figure 11, the 5% winsorization cleaned up all the outliers.

Figure 6: Boxplots before winsorization

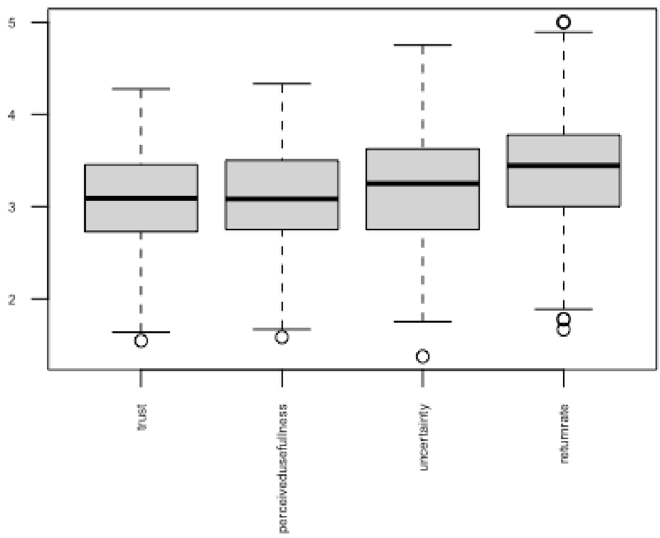
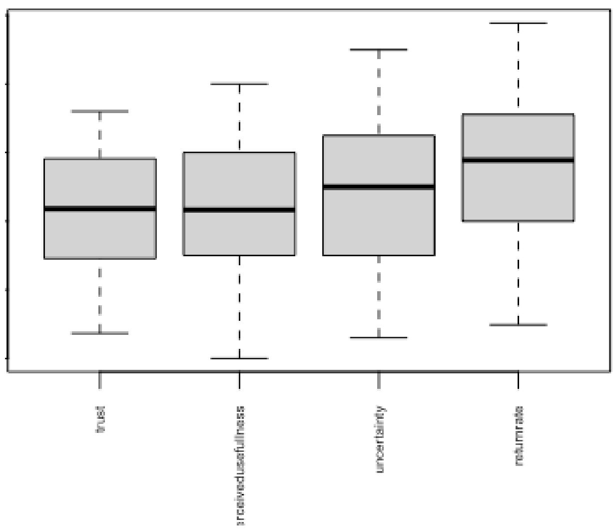


Figure 5: Boxplots after winsorization



[6] The graphs in Figures 10 and 11 were also created in the statistics program.

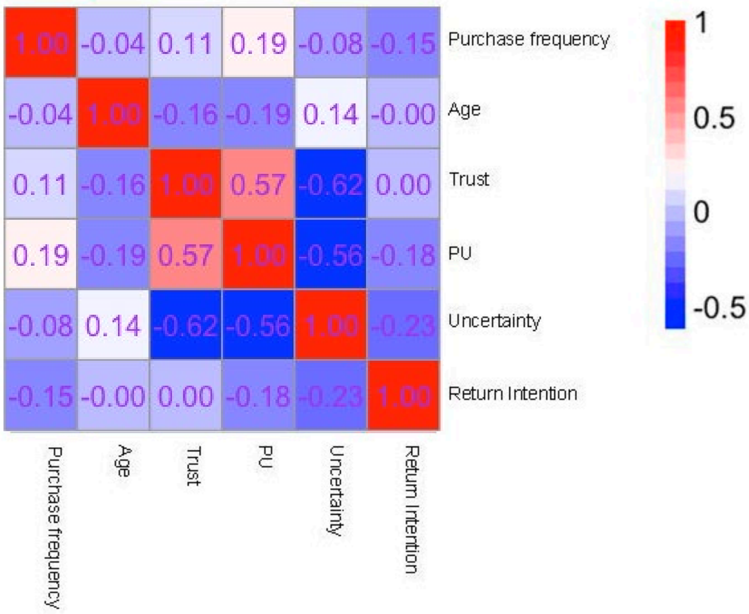
4.4.5 Explorative Statistics

For the previously formed scores, in this part we will look among other things at a Pearson correlation heatmap (created in *R*) to get a better understanding to the main questions. This heat map since we have formed row averages, which are artificially metric, we use Pearson correlations.

Pearson's correlation measures the strength and direction of the linear relationship between two metric variables. The range of values of the correlation coefficients extends from -A value of 0 indicates that there is no correlation; the closer the value is to -1 (negative direction) or 1 (positive direction), the stronger the correlation. It is calculated as the average deviation square of the z-transformed raw values (Sauer, 2019).

Each square in our heat map shows the correlation between the variables on each axis. The values closer to zero show that there is no linear trend between the two variables. The closer the correlation is to 1, the more positively correlated the two variables are, i.e., as one of the variables increases, so does the other, and the closer to 1, the stronger the relationship. A correlation closer to -1 is similar, but instead of both increasing, one variable decreases when the other increases. The diagonals are all 1 and red because these squares correlate each variable to itself and are therefore perfect. As a general rule for the heat map, the larger the number and the darker the color, the higher the correlation between the two variables. So, a weak relationship can be seen between age and uncertainty and a stronger relationship can be seen between trust and uncertainty.

Figure 7: Pearson correlation heat map



4.4.5.1 Reliability test

To test the questionnaire for internal consistency with respect to all main questions, we calculated Cronbach’s alphas, as already discussed in chapter 6.3 and can be seen in table 4. All 4 of the scales are internally consistent with a Cronbach's alpha of greater than 70%.

4.4.6 Inferential Statistics

In this section, we test the null hypotheses stated in Section 6.4.2 using a one-way ANOVA (ANOVA, difference in means) and assess the results.

- Hypothesis 1.1: There is no difference in the scale PU regarding frequency grouping.

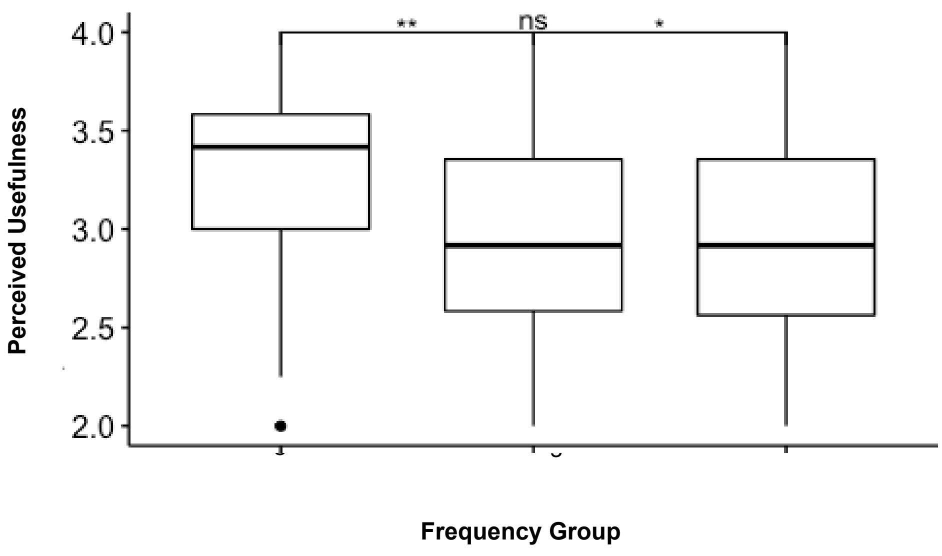
Table 11: Results ANOVA H1.1

	Df	Sum Sq	Mean Sq	F value	Pr(>f)
Frequency group	2	4.22	2.1103	7.216	0.000964[7]
Residuals	182	53.23	0.2925		

Preliminarily, a significant difference in perceived usefulness can be found according to Frequency grouping.

To adjust the observed significance level for multiple comparisons, a Bonferroni test is performed. This allows us to decide whether the significance is true (Döring & Bortz, 2016; Manderscheid, 2017). The test was made in *R* and a boxplot with p-values was created to visualize the result.

Figure 8: ANOVA Boxplot H1.1



The null hypothesis must be rejected because there is a difference between the PU regarding the different groups. Frequent shoppers have a significantly greater perceived usefulness than the other two group scales.

The following null hypotheses (1.2 to 1.4) are tested with the same method according to the same scheme.

[7] Common values for the significance level are 0.1, 0.05, or 0.01 (Rottmann & Auer, 2010). For this paper, we chose a significance level of 0.05.

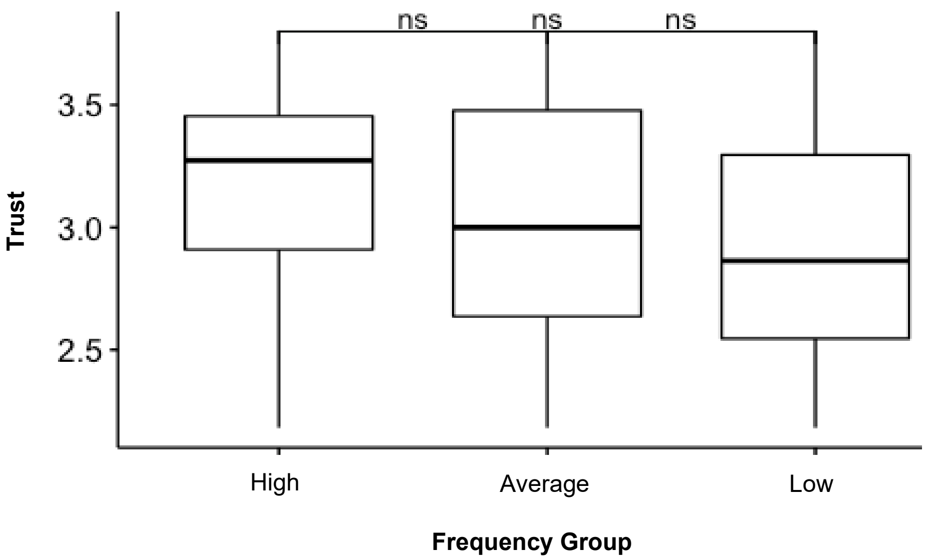
- Hypothesis 1.2: There is no difference in the scale trust regarding frequency grouping.

Table 12: Results ANOVA H1.2

	Df	Sum Sq	Mean Sq	F value	Pr(>f)
Frequency group	2	1.14	0.5684	2.517	0.0835
Residuals	182	41.09	0.2258		

Preliminarily, no significant difference can be found in the trust scale according to Frequency grouping.

Figure 9: ANOVA Boxplot H1.2



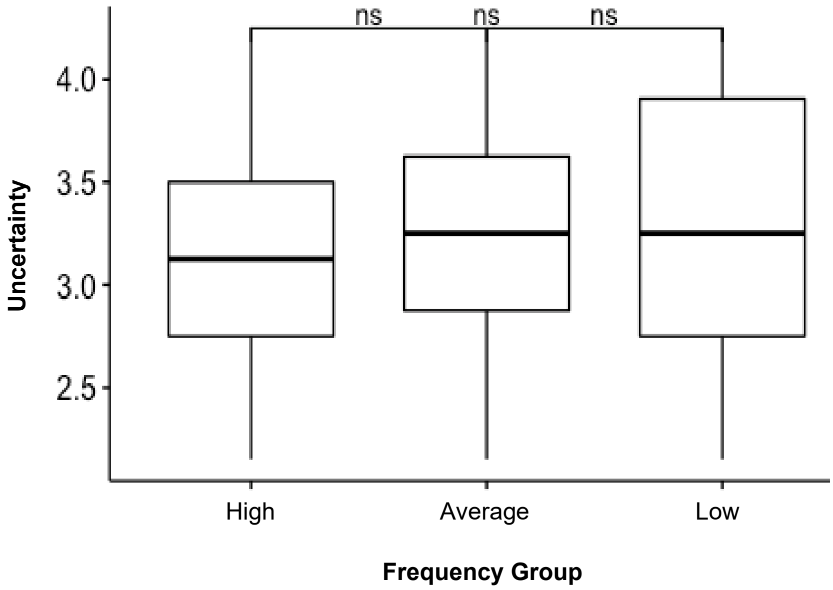
- Hypothesis 1.3: There is no difference in the scale uncertainty regarding frequency grouping.

Table 13: Results ANOVA H1.3

	Df	Sum Sq	Mean Sq	F value	Pr(>f)
Frequency group	2	1.03	0.5157	1.659	0.193
Residuals	182	56.58	0.3109		

Preliminarily, no significant difference can be found in the uncertainty scale according to Frequency grouping.

Figure 10: ANOVA Boxplot H1.3



- Hypothesis 1.4: There is no difference in the scale intention to return regarding frequency grouping.

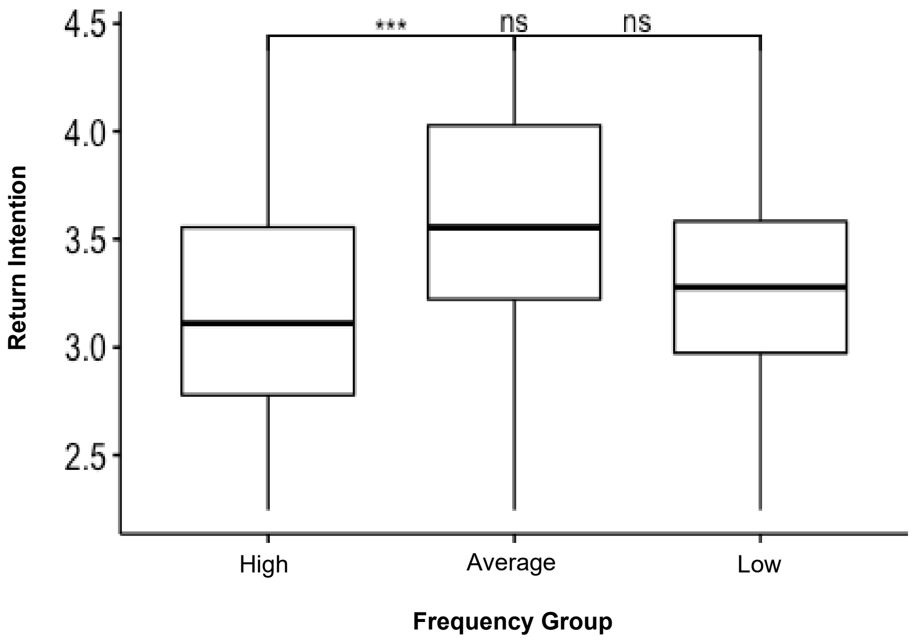
Table 14: Results ANOVA H1.4

	Df	Sum Sq	Mean Sq	F value	Pr(>f)
Frequency group	2	6.39	3.195	8.747	0.000236
Residuals	182	66.47	0.365		

Preliminarily, a highly significant difference in the return rate scale can be found according to the frequency grouping.

This means that the null hypothesis can be provisionally rejected. In fact, frequent shoppers show a significantly lower intention to return clothing than the other two groups of infrequent and average shoppers. However, this does not mean that this is due to a higher level of trust in this group.

Figure 11: ANOVA Boxplot H1.4



As can be seen also in the boxplot, frequent buyers have a significantly lower return rate or intention to return something than average buyers.

In a next step, we test the strength of the correlation between the variables, Frequency, perceived usefulness, trust, uncertainty and return intention. We are using the Pearson correlation test or Pearson's r (directed correlation test). Pearson's r is a parametric test and requires at least interval scaled data. Other requirements are that there are no outliers (we have already removed this one) and that both variables are bivariate normally distributed[8]. However, the relationship between the variables must be linear. We check the linearity by means of a scatterplot. A perfect correlation would be given at -1 (perfectly negative correlation) or +1 (perfectly positive correlation). The correlation coefficient r determines the strength of the linear correlation. It is important to know that this test by itself cannot be used to prove the direction of the correlation (Backhaus et al., 2016; Döring & Bortz, 2016; Hemmerich, n.d.-c).

[8] According to the "central limit theorem", we assume a bivariate normal distribution since our sample is n>30 (Döring & Bortz, 2016, p. 641).

- Hypothesis 2.1: There is no positive relationship between frequency and perceived usefulness.

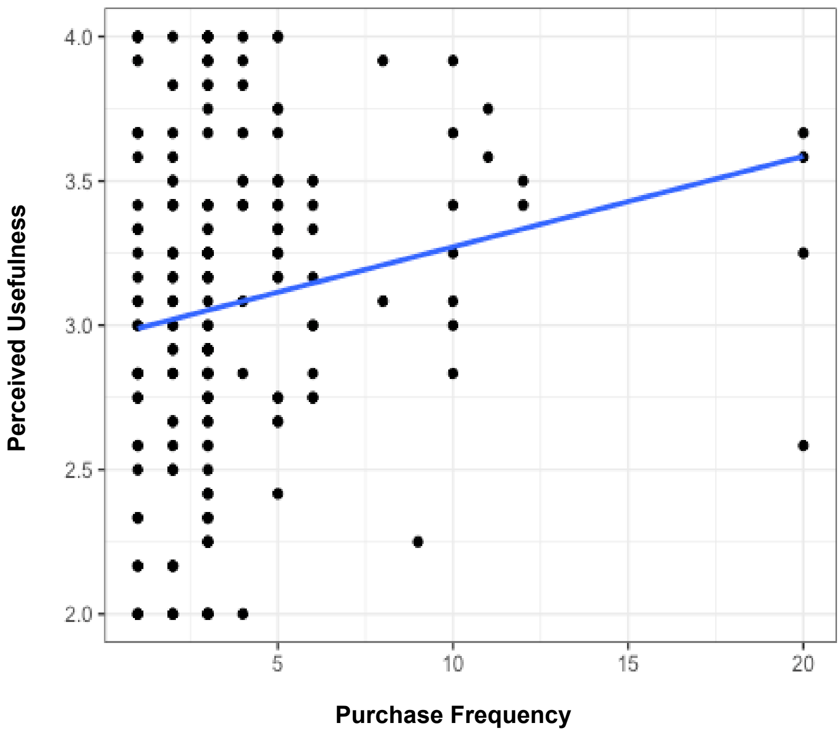
Table 15: Results Correlation H2.1

	t	df	p-value	cor	95 % CI[9]
Alternative hypothesis: true correlation is greater than 0	2.6119	183,	0.004876	0.1895726	0.06985521 1.00000000

The r value as well as the p-value are showing a significant correlation. The p-value of 0.004876 is strongly significant, the r or cor of 0.1895726 shows a correlation, albeit weak (Hemmerich, n.d.-c). The scatterplot shows a linear relationship of the variables.

It can be preliminarily confirmed that the positive correlation is significant.

Figure 12: Scatterplot H2.1



[9] A confidence interval (CI) of 95% was chosen. This means, that the range of characteristic values is marked in which 95% of all possible parameters are found that could have generated the empirically determined sample characteristic value (Backhaus et al., 2016; Döring & Bortz, 2016). The table shows the values of the lower and upper limits (in the 95% CI column).

- Hypothesis 2.2:
  There is no positive correlation between frequency and trust.

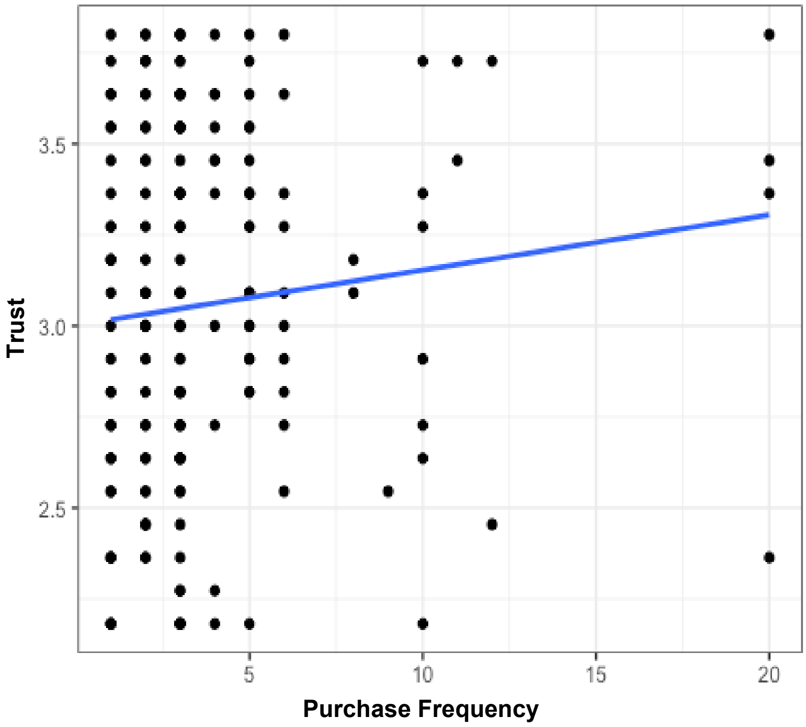
Table 16: Results Correlation H2.2

Alternative hypothesis:	t	df	p-value	cor	95 % CI[10]
true correlation is greater than 0	1.4511	183,	0.07423	0.1066574	-0.01485893 1.00000000

Although there is a weak correlation between the variables (cor = 0.1066574), the relationship is not significant (p = 0.07423).

Preliminary, it cannot be confirmed that the positive correlation is significant.

Figure 13: Scatterplot H2.2



[10] A confidence interval (CI) of 95% was chosen. This means, that the range of characteristic values is marked in which 95% of all possible parameters are found that could have generated the empirically determined sample characteristic value (Backhaus et al., 2016; Döring & Bortz, 2016). The table shows the values of the lower and upper limits (in the 95% CI column).

- Hypothesis 2.3:
  There is no positive correlation between perceived usefulness and trust.

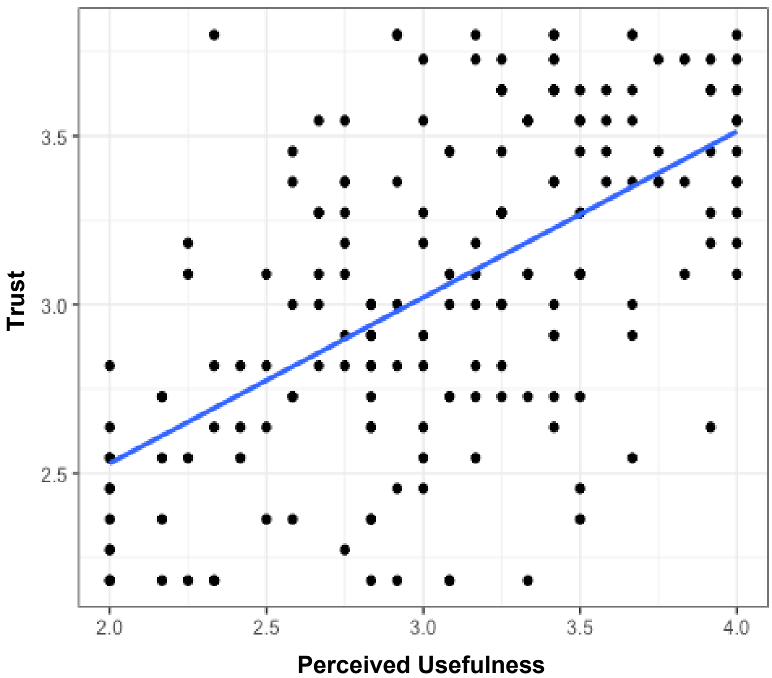
Table 17: Results Correlation H2.3

Alternative hypothesis:	t	df	p-value	cor	95 % CI[11]
true correlation is greater than 0	9.4846	183,	2.2e-16	0.5740794	0.4866504 1.0000000

Both the r -value and the p-value show a significant correlation. The p-value is close to zero and therefore highly significant, and the r or cor-value of 0.5740794 also shows a strong correlation (Hemmerich, n.d.-c) The scatter plot shows a linear relationship between the two variables.

It can be preliminarily confirmed that the positive correlation between trust and PU is significant.

Figure 14: Scatterplot H2.3



[11] A confidence interval (CI) of 95% was chosen. This means, that the range of characteristic values is marked in which 95% of all possible parameters are found that could have generated the empirically determined sample characteristic value (Backhaus et al., 2016; Döring & Bortz, 2016). The table shows the values of the lower and upper limits (in the 95% CI column).

- Hypothesis 2.4:
  There is no negative correlation between trust and uncertainty.

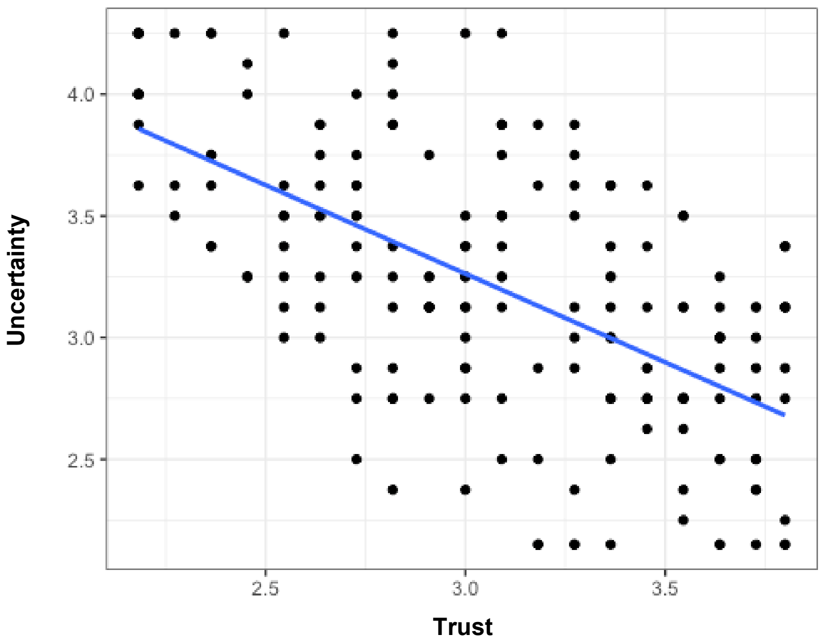
Table 18: Results Correlation H2.4

Alternative hypothesis: true correlation is greater than 0	t	df	p-value	cor	95 % CI[12]
	-10.774	183,	< 2.2e-16	-0.6229992	-1.0000000 -0.5426945

The r -value as well as the p -value show a significant correlation. The p -value is close to zero and thus highly significant. The r -value of -0.6229992 also shows a strong, negative correlation (Hemmerich, n.d.-c) The scatter plot shows also a linear relationship between the two variables.

It can be preliminarily confirmed that the negative correlation between trust and uncertainty is strongly significant.

Figure 15: Scatterplot H2.4



[12] A confidence interval (CI) of 95% was chosen. This means, that the range of characteristic values is marked in which 95% of all possible parameters are found that could have generated the empirically determined sample characteristic value (Backhaus et al., 2016; Döring & Bortz, 2016). The table shows the values of the lower and upper limits (in the 95% CI column).

- Hypothesis 2.5:
  There is no positive correlation between the uncertainty and the return rate.

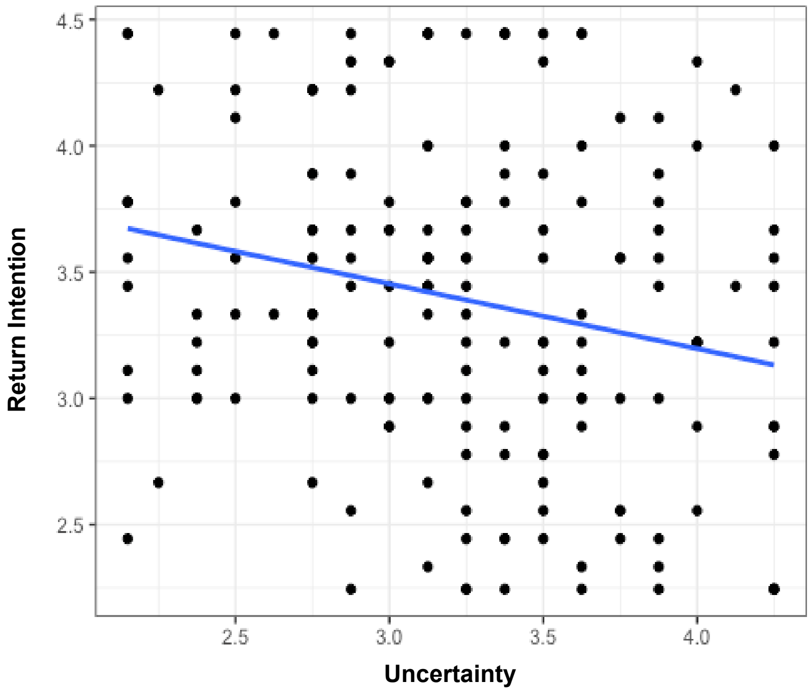
Table 19: Results Correlation H2.5

Alternative hypothesis: true correlation is greater than 0	t	df	p-value	cor	95 % CI[13]
	-3.1768	183,	0.9991	-0.2286135	-0.3404935 1.0000000

A weak, negative correlation between the variables can be observed (cor = -0.2286135), but the correlation is not significant (p = 0.9991).

Preliminary, it cannot be confirmed that the negative correlation between uncertainty and return intention is significant.

Figure 16: Scatterplot H2.5



[13] A confidence interval (CI) of 95% was chosen. This means, that the range of characteristic values is marked in which 95% of all possible parameters are found that could have generated the empirically determined sample characteristic value (Backhaus et al., 2016; Döring & Bortz, 2016). The table shows the values of the lower and upper limits (in the 95% CI column).

- Hypothesis 3:
  A relationship between frequency and trust is not mediated by perceived usefulness.

To check whether the relationship between frequency and trust is mediated by perceived usefulness, several steps are necessary. We start the test by setting up two different regression models. To check the mediator effect, PU is also added in the second model, while frequency is the predictor and trust the criterion in the first model. The regression analysis requires certain checks, mainly that of the residuals (since the confounders are not testable). (Backhaus et al., 2016) which are worked out in several steps. These points are checked to ensure an unbiased and efficient estimator. These attributes are also called BLUE which stands for "Best Linear Unbiased Estimators" (Backhaus et al., 2016, p. 98).

Model 1:

1. First, the relationship between Frequency and Trust is analyzed again.
2. The Durbin Watson test is used to check whether an autocorrelation exists. Autocorrelation is not desired since a linear regression model is based on the assumption that the residuals are uncorrelated (in the population) (Backhaus et al., 2016).
3. The Breusch-Pagan test is used to check whether heteroskedasticity is observed. Heteroscedasticity indicates that the predictive performance of the model is not uniformly good. This in turn may indicate a possibly more complex relationship between the explanatory variables than predicted by the model (Manderscheid, 2017).
4. The Shapiro Wilk Normality test shows whether the residuals of the base model are normally distributed. A normal distribution is desirable. If this is not the case, it is an indication that the predictors are not all complete. This would result in a part of the explanatory information being transferred to the residuals (Backhaus et al., 2016).
5. With the t-test on the mean value of the residuals one sees whether the residuals lie in the expected value zero (Backhaus et al., 2016). The reason is that the probability that the difference in the mean is random, so significance value should be as small as possible, close to zero (Döring & Bortz, 2016).

Table 20: Results Analysis H3, Model 1

Residuals	Min	1Q	Median	3Q	Max
	-0.97144	-0.33513	0.01336	0.42242	0.78302
Coefficients	Estimate	Std. Error	t-value	p-value	
(Intercept)	3.00184	0.05326	56.357	<2e-16	
Frequency	0.01514	0.01044	1.451	0.148	
Residual standard error: 0.4776 on 183 degrees of freedom					
Multiple R-squared: 0.01138 Adjusted R-squared: 0.005973					
F-statistic: 2.106 on 1 and 183 DF p-value: 0.1485					

As discussed earlier with the correlation test, the frequency of purchases has with a p-value of 0.148 no significant effect on the trust scale.

Table 21: Results Estimator Test H3, Model 1

Durbin Watson Test (D-W)	Autocorrelation	D-W Statistic	p-value
	0.1473697	1.701447	0.044
Breusch-Pagan Test (BP)	BP	df	p-value
	0.0046876	1	0.9454
Shapiro-Wilk Normality Test (W)	W		p-value
	0.96312		8.76e-05
One-Sample t-Test	t	df	p-value
	-1.0747e-15	184	1
	alternative hypothesis: true mean is not equal to 0	mean of x	95% CI
		-3.763647e-17	-0.06909559 0.06909559

- Interpretation Durbin Watson: The p-value of 0.044 (<5%) indicates that there is an autocorrelation in the residuals of the base model.
- Interpretation Breusch-Pagan Test: Likewise, it cannot be assumed that heteroskedasticity exists.
- Interpretation Shapiro-Wilk-Normality Test: For the time being, we cannot confirm that the residuals of the basic model are normally distributed because the p-value is close to 0 and the null hypothesis (values are normally distributed) must be rejected.
- Interpretation t-test: The t-test on the mean value of the residuals shows with almost 100% probability of error that they are equal to 0.

Since this means that our preconditions are not all verified, the Gauss-Markov theorem is to be regarded as invalid. Two conditions are violated, namely autocorrelation and normal distribution. Finally, this means that not all Gauss-Markov prerequisites for the basic model are fulfilled and the model is accordingly not BLUE (best linear unbiased estimator) (Rottmann & Auer, 2010).

Model 2:

In this model, we take the same steps to check whether our model is BLUE as in Model 1. But we include perceived usefulness in our model and check for a possible mediator effect of PU.

Table 22: Results Analysis H3, Model 2

Residuals	Min	1Q	Median	3Q	Max
	-1.0033	-0.2563	-0.0128	0.2867	1.1068
Coefficients	Estimate	Std. Error	t-value	p-value	
(Intercept)	1.5448289	0.1628202	9.488	<2e-16	

Frequency	-0.0003199	0.0087760	-0.036	0.971	
PU	0.4925807	0.0529993	9.294	<2e-16	
Residual standard error: 0.3944 on 182 degrees of freedom					
Multiple R-squared: 0.3296 Adjusted R-squared: 0.3222					
F-statistic: 44.73 on 2 and 182 DF p-value: < 2.2e-16					

As in the previous correlation test, we can preliminarily confirm that perceived usefulness has a significant positive influence on the trust scale (p-value is close to zero). Furthermore, we see that in the second model the influence of purchase frequency has become significantly smaller and even less significant. Accordingly, we can tentatively conclude that perceived usefulness explains the actual relationship to trust and mediates the influence of purchase frequency.

Table 23: Results Estimator Test H3, Model 2

Durbin-Watson Test (D-W)	Autocorrelation	D-W Statistic	p-value
	0.06116853	1.874148	0.358
Breusch-Pagan Test (BP)	BP	df	p-value
	0.022804	2	0.9887
Shapiro-Wilk Normality Test (W)	W		p-value
	0.9951		0.8093
One-Sample t-Test	t	df	p-value
	2.8205e-16	184	1
	alternative hypothesis: true mean is not equal to 0	mean of x	95% CI
		-8.134447e-18	-0.0568998 0.0568998

- Interpretation Durbin Watson: The p-value of 0.358 (>5%) indicates that there is no autocorrelation in the residuals of the base model.
- Interpretation Breusch-Pagan Test: The data does not confirm that heteroskedasticity exists. If homoscedasticity is present, the dispersion of the residuals is constant, which is desirable (Manderscheid, 2017).
- Interpretation Shapiro-Wilk-Normality Test: With a p-value of 0.8093 we can preliminarily confirm that the residuals of the base model are normally distributed.
- Interpretation t-test: The t-test on the mean value of the residuals shows with almost 100% probability of error that they are equal to 0.

In this model, all requirements according to Gauss-Markov for the basic model were thus fulfilled. The model is BLUE, a best linear unbiased estimator (Rottmann & Auer, 2010).

4.5 Conclusion

In this quantitative evaluation, we were able to determine that only the scale of perceived usefulness differs significantly regarding frequency grouping. We were able to preliminarily determine that frequent shoppers have a significantly higher perceived usefulness. Furthermore, we recognized that perceived usefulness has a significant positive influence on the trust scale and almost completely mediates a possible influence of purchase frequency on trust. It is important to note here that purchase frequency alone also did not have a significant effect on trust. However, there was a slight positive effect even without the mediator. The assumption that trust has an influence on reduced uncertainty could be confirmed. It was shown that with a higher value on the trust scale, uncertainty decreased significantly on average. For the time being, we could not confirm that the intention to send less items back correlated significantly with this.

Numerous e-vendors offer their customers the option of to return goods they have already purchased. The reasons for this are only covered superficially, but the literature shows how customers come to a decision online and that free returns are particularly important to them. The increasing implementation of AI-based tools to help customers make a better decision has moved the researcher to relate the use of these to trust, which is seen as a lubricant of successful customer relationships. Should the use of recommendation tools have a positive effect on trust, it can be assumed that uncertainty will decrease as often described in the literature. Since returns mean a cost and administrative effort for companies, the goal with better recommendations is to send customers only what they are likely to want to keep. If they are less uncertain about their decision, the assumption was, the intention to send something back would also decrease. Since the topic of technology acceptance focuses on perceived usefulness, among other things, this was also considered in. Furthermore, the researcher assumed that the customers would order clothes several times, for example with the help of the size advisor, the so-called Fit Finder, and they would out after delivery that the clothes fit. From this experience, it can be expected, albeit assuming that the experiences made are positive, that the trust in the recommendations increases and the uncertainty about whether one has made the right choice decreases at the same time. We further assume that a decrease in uncertainty because of increased trust increases the quality of decision-making, which results in fewer returns because customers no longer feel compelled to order several sizes of a product or feel confident in the color, shape, material, and size that they have chosen the garment they will like and will then keep it.

For the thesis a trust model was developed that correlates the variables Frequency, Trust, Uncertainty and Return Intention. Since perceived usefulness is one of the central issues in technology acceptance, it was also included in the model, but as a mediator. This was done because PU was previously considered an outcome of trust. In our main question about how much users trust the recommendations; PU was not included as an outcome of trust because in the model the assumption was made that uncertainty as an outcome of trust influences return intention. Estimating these relationships in the model was not without problems. In the first model we checked whether there is a relationship between frequency and trust, in the second model we checked whether PU as a mediator variable has an influence on this relationship.

Based on the data sample of the online survey, 185 data sets could be analyzed. The subjects were asked for their assessment on a 5-point Likert scale. Prior to this, the purchase frequency of clothing purchased online in the last three months was queried and completed. We note that there are differences between the frequent shoppers and the other groups of average and infrequent shoppers.

Frequent shoppers were defined as subjects who made purchases more frequently than the average, which was 3.84 purchases in the sample. Since only whole numbers could be entered, the average shopper was defined as the group that purchased clothing online 2-3 times. Fewer shoppers were therefore those who had shopped 0-1 times in the last three months. The average age of the test persons was 28.44 years. The subjects mainly live in a city with less than 40,000 inhabitants and most of them had a higher education level. 74.6% of our respondents had already shopped online at Zalando, which was to be expected since Zalando is the clear market leader. The results of the scales showed that all scales had a mean value of >3 (scale went from 1 do not agree at all to 5 agree completely). The Trust scale had the smallest standard deviation with a value of 0.52 and the largest of the four scales was the Return Intention with 0.69.

ANOVA revealed in a further step that frequent shoppers had a strongly significant higher PU than the other two groups. The questionnaire asked how useful the recommendation tools were perceived by the subjects. The Trust and Uncertainty scales showed no significant difference between the groups, so the corresponding null hypotheses had to be tentatively accepted. However, a highly significant difference was again seen in the Return Intention scale. It can be seen that frequent shoppers Return Intention is significantly lower than of the other groups.

Regression modeling showed that Model 1 without PU as a mediator was to be rejected as not all conditions were met to be a good estimator. Even though the correlation test preliminarily confirms that the positive correlation between Frequency and PU is also significant here. However, there is no positive correlation between PU and the Trust and Frequency and Trust. A significant correlation was also found between Trust and Uncertainty. It was found that the greater the trust, the lower the uncertainty. However, there was also no significant correlation between reduced uncertainty and lower return intention.

The Model two was BLUE and therefore suitable as a good estimator. The null hypothesis for the mediator analysis was "the relationship between frequency and trust is not mediated by perceived usefulness". As in the previous correlation test, we were able to preliminarily confirm that perceived usefulness has a significant positive influence on the trust scale. Furthermore, we see that in this model the influence of purchase frequency has become significantly smaller and even more non-significant. Accordingly, we can provisionally conclude that perceived usefulness explains the actual relationship to trust and mediates the influence of purchase frequency. The perceived usefulness has a significant positive effect on the trust scale. It is important to note here that purchase frequency alone also had no significant effect on Trust, even though a slightly positive effect was shown without the mediator.

5 Limitations and Future Research

From the results, it can be concluded that a technology cannot be considered 100% like human-human interaction, as was assumed. Technology acceptance still seems to take the more central role, in terms of trust between humans and AI. The fact that the Uncertainty had no influence on the Return Intention can be due to different things.

For further investigation, it would be interesting to know to what extent greater awareness of how and in what situations data is used influences trust in applications using AI.

Ryan (2020) has shown in his paper why trust is not a concept that is applicable to AI since AI cannot be held accountable. He writes that AI is more about reliability and less about trust (Ryan, 2020). This is certainly an aspect that needs to be considered in further research, because one can argue that while AI cannot be held responsible, those who created or implemented it can. This is material that will continue to generate discussion. In the present thesis, at least trust has already played a role, but this was not to be derived from the use of the recommendations and the experience with online shopping; instead, the perceived usefulness component was a contributing factor, but this is located in the technology acceptance. Ryan (2020) argues that the organizations and individuals implementing AI can be trusted, but not the technology itself. This idea was taken up in the thesis by saying that the focus is on trust in the recommendations and not in the RT's themselves. This difference would need to be fine-tuned in further studies. A suitable experiment would be to divide customers into two groups, with one group using RTs and the other not over a longer period of time. This would allow us to measure whether the trust of the group of RT users is increasing and to what extent this could be observed within the group. As far as the returns are concerned, the selected scale may not have been suitable, since here too it was only a matter of the personal assessment of the respondents. In fact, a simple question such as "on a scale of 1-10, how likely is it that you will return clothing" would have been probably more appropriate. However, if customer data could be analyzed, this would also be ideal to directly assess how the use of RT's affects the return rate. Since the frequency of use had hardly any influence on trust, but PU did, it would be necessary to examine how the relationship between PU and Trust is to be classified in the use of these technologies. In studies, PU was mostly seen as an outcome of trust, which we cannot confirm here because PU showed a strong mediator effect on the relationship between frequency and trust. In this thesis, Trust has an impact on Uncertainty, as assumed, which decreased significantly, which is consistent with previous research. No relationship could be established between reduced Uncertainty and reduced Intention to return clothing.

A focus group could also be useful to better understand the motives of the users. In the survey, an email address was provided and some of the respondents came forward to express their dilemma about always trying to order the right size right away but knowing that they would be returning some of the clothes. In an interview, it would be easier to find out how this problem could be solved for the users or what they would need to refrain from returning the goods.

These results do not mean that the respondents do not trust these recommendations. However, it was not possible to clearly clarify what led to trust among our respondents. Perhaps they already have a basic trust in the renowned online stores as online shoppers, which is why their use had no influence on trust, but rather on usefulness. With the growing number of users, the topic is likely to remain interesting. In particular, it is likely to become important for smaller companies to implement recommendation tools so as not to lose out to the industry giants. When this technology of recommendation agents in any form is fully accepted and found in every web store, the question of trust will probably be more relevant than usefulness.

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Appendix

In the first part of the appendix, the results are presented as they were generated in the statistical programs SPSS and R in order to be able to understand them better. In SPSS a few basic evaluations were made, in R mainly the hypotheses were tested

Figure 17: Frequency of online purchases by age group | SPSS

Altersklasse

Verarbeitete Fälle

		Fälle					
		Gültig		Fehlend		Gesamt	
	Altersklasse	N	Prozent	N	Prozent	N	Prozent
v_12_häufigkeit	16-23 Jahre	61	100,0%	0	0,0%	61	100,0%
	24-30 Jahre	59	100,0%	0	0,0%	59	100,0%
	31-36 Jahre	29	100,0%	0	0,0%	29	100,0%
	37-42 Jahre	15	100,0%	0	0,0%	15	100,0%
	43-48 Jahre	9	100,0%	0	0,0%	9	100,0%
	älter als 49	12	100,0%	0	0,0%	12	100,0%

Figure 18: Frequency of online purchases by online store | SPSS

Häufigkeiten von $Auswahl_Onlineshops

		Antworten		Prozent der Fälle
		N	Prozent	
In welchen E-Shops kaufen Sie ein? [a]	v_18_zalando	138	36,1%	74,6%
	v_19_bonprix	25	6,5%	13,5%
	v_20_aboutyou	74	19,4%	40,0%
	v_21_universal	11	2,9%	5,9%
	v_22_h_m	101	26,4%	54,6%
	v_23_globus	5	1,3%	2,7%
	v_24_none	28	7,3%	15,1%
Gesamt		382	100,0%	206,5%

a. Dichotomie-Gruppe tabellarisch dargestellt bei Wert 1.

Figure 19: Distribution of educational level and place of living | SPSS

v_151_Abschluss

		Häufigkeit	Prozent	Gültige Prozente	Kumulierte Prozente
Gültig	kein Abschluss	1	,5	,5	,5
	Realschulabschluss	2	1,1	1,1	1,6
	Abitur/Matura	73	39,5	39,5	41,1
	Fachhochschule	68	36,8	36,8	77,8
	Universitätsabschluss	39	21,1	21,1	98,9
	anderer Abschluss nach dem Abitur	2	1,1	1,1	100,0
	Gesamt	185	100,0	100,0	

v_153_Einwohner

		Häufigkeit	Prozent	Gültige Prozente	Kumulierte Prozente
Gültig	Metropole (mehr als 250k)	20	10,8	10,8	10,8
	Stadt/Großstadt (mehr als 40k)	46	24,9	24,9	35,7
	Kleinstadt/Dorf (mehr als 500)	110	59,5	59,5	95,1
	Ländlich (weniger als 500)	9	4,9	4,9	100,0
	Gesamt	185	100,0	100,0	

Import survey data into R

```
df <- as.data.table(read.csv("daten.csv", sep=";"))
dim(df)

## [1] 185  53
```

Cleanup of the dataset

```
df <- na.omit(df)
```

Variable transformation

```
df$Geschlecht <- as.character(df$Geschlecht)
df[Geschlecht == 1] <- df[Geschlecht == 1][, Geschlecht := "männlich"]
df[Geschlecht == 2] <- df[Geschlecht == 2][, Geschlecht := "weiblich"]
df[Geschlecht == 3] <- df[Geschlecht == 3][, Geschlecht := "divers"]

df$Wohnort <- as.character(df$Wohnort)
df[Wohnort == 1] <- df[Wohnort == 1][, Wohnort := "Großstadt"]
df[Wohnort == 2] <- df[Wohnort == 2][, Wohnort := "Stadt"]
df[Wohnort == 3] <- df[Wohnort == 3][, Wohnort := "Kleinstadt"]
df[Wohnort == 4] <- df[Wohnort == 4][, Wohnort := "Ländlich"]

df$Abschluss <- as.character(df$Abschluss)
```

```
df[Abschluss == 1] <- df[Abschluss == 1][, Abschluss := "Keinen"]
df[Abschluss == 2] <- df[Abschluss == 2][, Abschluss := "Grundschule"]
df[Abschluss == 3] <- df[Abschluss == 3][, Abschluss := "Realschule"]
df[Abschluss == 4] <- df[Abschluss == 4][, Abschluss := "Matura"]
df[Abschluss == 5] <- df[Abschluss == 5][, Abschluss := "Technikon"]
df[Abschluss == 6] <- df[Abschluss == 6][, Abschluss := "Universität"]
df[Abschluss == 7] <- df[Abschluss == 7][, Abschluss := "Andere post Matur
a"]
```

Inverted the questions that were formulated inversely

```
# Neutralisiere Antwort 0
df[df == 0] <- 3

df$TRU4 <- (-1) * df$TRU4 + 6
df$TRU7 <- (-1) * df$TRU7 + 6
df$TRU9 <- (-1) * df$TRU9 + 6
df$TRU11 <- (-1) * df$TRU11 + 6

df$PU5 <- (-1) * df$PU5 + 6
df$PU12 <- (-1) * df$PU12 + 6

df$UNC1 <- (-1) * df$UNC1 + 6
df$UNC2 <- (-1) * df$UNC2 + 6
df$UNC3 <- (-1) * df$UNC3 + 6
df$UNC5 <- (-1) * df$UNC5 + 6
df$UNC6 <- (-1) * df$UNC6 + 6
df$UNC7 <- (-1) * df$UNC7 + 6

df$RR2 <- (-1) * df$RR2 + 6
df$RR4 <- (-1) * df$RR4 + 6
df$RR5 <- (-1) * df$RR5 + 6
df$RR8 <- (-1) * df$RR8 + 6
df$RR9 <- (-1) * df$RR9 + 6
```

For all further calculations, possible NA values should be filled with the column mean. However, we do not have any NA values in our data set and do not need to consider this step, as mentioned before.

```
# trust
trust <- replace(df[, c(21:31)], TRUE, lapply(df[, c(21:31)], NA2mean))
trust = apply(trust,1,mean)

# perceivedusefullness
perceivedusefullness <- replace(df[, c(9:20)], TRUE, lapply(df[, c(9:20)],
NA2mean))
perceivedusefullness = apply(perceivedusefullness,1,mean)

# uncertainty
uncertainty <- replace(df[, c(32:39)], TRUE, lapply(df[, c(32:39)],
NA2mean))
uncertainty = apply(uncertainty,1,mean)
```

```
# returnrate
returnrate <- replace(df[, c(40:48)], TRUE, lapply(df[, c(40:48)],
NA2mean))
returnrate = apply(returnrate,1,mean)
```

The Frequency Grouping has been formed:

```
df$frequencygruppe <- "Wenig Käufe"
df[HäufigkeitKäufe %in% c(2,3)] <- df[HäufigkeitKäufe %in% c(2,3)][, frequ
encygruppe := "Durchschnittlich"]
df[HäufigkeitKäufe > 3] <- df[HäufigkeitKäufe > 3][, frequencygruppe := "V
iel Käufe"]
```

Descriptive statistics for the demographics and the scales:

```
describe(df[, c(8,53:57)])

##                       vars   n  mean   sd median trimmed  mad   min   max range
## HäufigkeitKäufe          1 185  3.84 3.37   3.00    3.16 1.48  1.00 20.00 19.00
## Alter                    2 185 29.44 9.57  26.00   28.05 7.41 17.00 62.00 45.00
## trust                    3 185  3.05 0.52   3.09    3.08 0.54  1.55  4.27  2.73
## perceivedusefullness     4 185  3.08 0.60   3.08    3.09 0.62  1.58  4.33  2.75
## uncertainty              5 185  3.22 0.61   3.25    3.22 0.56  1.38  4.75  3.38
## returnrate               6 185  3.40 0.69   3.44    3.40 0.66  1.67  5.00  3.33
##                        skew kurtosis   se
## HäufigkeitKäufe        2.78     9.56 0.25
## Alter                  1.24     1.01 0.70
## trust                 -0.35    -0.28 0.04
## perceivedusefullness  -0.26    -0.34 0.04
## uncertainty           -0.08     0.04 0.05
## returnrate            -0.01    -0.26 0.05
```

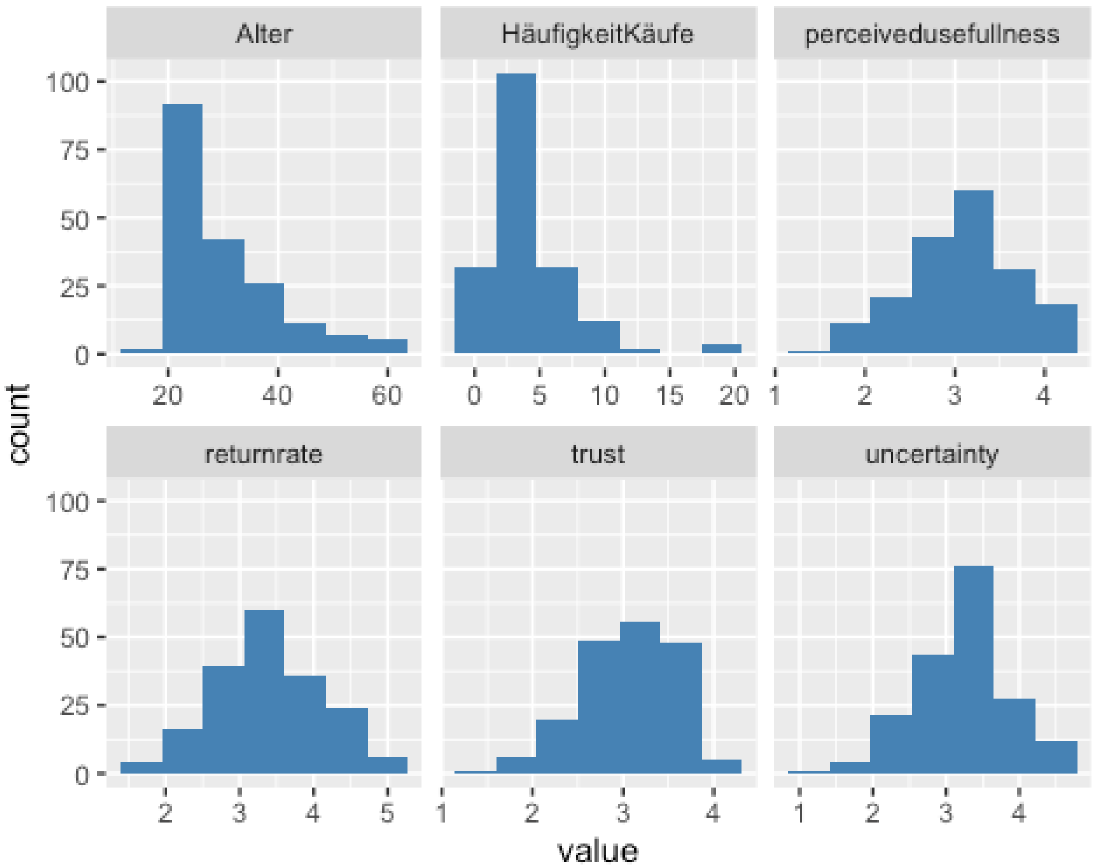
Subsequently, the non-parametric statistics are reported:

```
summary(df[, c(8,53:57)])

##  HäufigkeitKäufe      Alter            trust        perceivedusefullness
##  Min.   : 1.000   Min.   :17.00   Min.   :1.545   Min.   :1.583
##  1st Qu.: 2.000   1st Qu.:22.00   1st Qu.:2.727   1st Qu.:2.750
##  Median : 3.000   Median :26.00   Median :3.091   Median :3.083
##  Mean   : 3.838   Mean   :29.44   Mean   :3.053   Mean   :3.077
##  3rd Qu.: 5.000   3rd Qu.:35.00   3rd Qu.:3.455   3rd Qu.:3.500
##  Max.   :20.000   Max.   :62.00   Max.   :4.273   Max.   :4.333
##   uncertainty      returnrate
##  Min.   :1.375   Min.   :1.667
##  1st Qu.:2.750   1st Qu.:3.000
##  Median :3.250   Median :3.444
##  Mean   :3.216   Mean   :3.402
##  3rd Qu.:3.625   3rd Qu.:3.778
##  Max.   :4.750   Max.   :5.000
```

Histograms were formed for the metric variables and plotted in bundles.

```
df_metrical <- df[, c(8,53:57)]
ggplot(gather(df_metrical), aes(value)) +
    geom_histogram(bins = 7, fill = "steelblue") +
    facet_wrap(~key, scales = 'free_x')
```

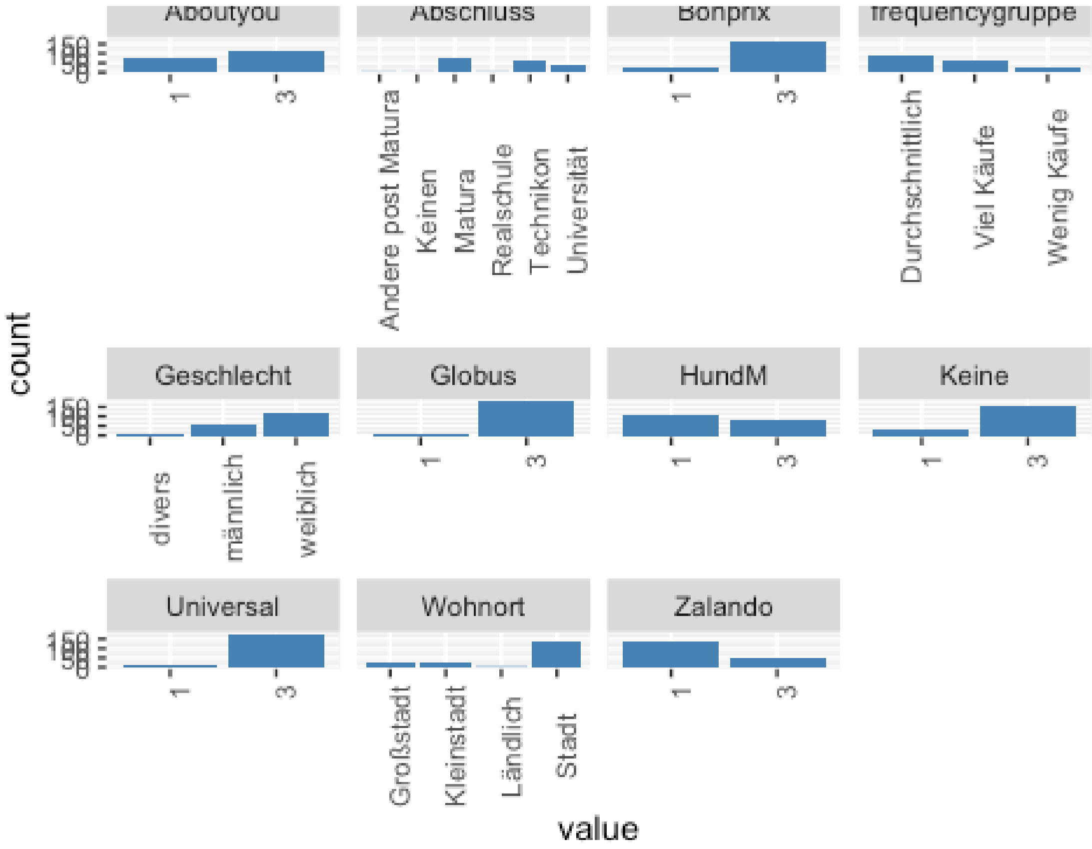
Figure 20: Histograms | R



The demographic data is visualized with barplots:

```
df_factor <- df[, c(1:7,49:51,58)]
ggplot(gather(df_factor), aes(value)) +
    geom_bar(stat="count", fill = "steelblue") +
    facet_wrap(~key, scales = 'free_x') +
    theme(axis.text.x = element_text(angle = 90))
```

Figure 21: Barplots demographic data | R



The 4 average scores were plotted as descriptive statistics to detect outliers (figure 5):

```
meltData <- melt(df[, c(54:57)])

## Warning in melt.data.table(df[, c(54:57)]): id.vars and measure.vars are
## internally guessed when both are 'NULL'. All non-numeric/integer/logical type
## columns are considered id.vars, which in this case are columns []. Consider
## providing at least one of 'id' or 'measure' vars in future.

par(cex.axis=0.5)
boxplot(data=meltData, value~variable, las = 2, xlab = "")

p <- ggplot(meltData, aes(factor(variable), value))
p + geom_boxplot() + facet_wrap(~variable, scale="free")
```

In the relevant variables, which were needed for the following hypothesis tests, some conspicuous outliers were detected, which were winsorized:

```
df$trust <- winsor(df$trust, trim = 0.05)
df$perceivedusefullness <- winsor(df$perceivedusefullness, trim = 0.05)
df$uncertainty <- winsor(df$uncertainty, trim = 0.05)
df$returnrate <- winsor(df$returnrate, trim = 0.05)
```

For verification, the boxplots were calculated again (figure 6):

```
meltData <- melt(df[, c(54:57)])

## Warning in melt.data.table(df[, c(54:57)]): id.vars and measure.vars are
## internally guessed when both are 'NULL'. All non-numeric/integer/logical type
## columns are considered id.vars, which in this case are columns []. Consider
## providing at least one of 'id' or 'measure' vars in future.

par(cex.axis=0.5)
boxplot(data=meltData, value~variable, las = 2, xlab = "")

p <- ggplot(meltData, aes(factor(variable), value))
p + geom_boxplot() + facet_wrap(~variable, scale="free")
```

A Pearson correlation heatmap was created to get a better understanding to the main questions. Since row averages were formed, which are artificially metric, a Pearson correlation was applied (figure 7):

```
cormat<-signif(cor(df[, c(8,53:57)], method = "pearson", use = "pairwise.c
omplete.obs"),5)
col<- colorRampPalette(c("blue", "white", "red"))(20)
HeatmapPlot <- pheatmap(cormat, display_numbers = TRUE, color = col,
                        cluster_rows = F, cluster_cols = F, fontsize = 15,
                        fontsize_row = 10, fontsize_col = 10, number_color
= "purple",
                        df = "CrossCorr-Heatmap der Skalen",
                        width = 15, height = 15, cellwidth = 30, cellheigh
t = 30)
```

In order to test the questionnaire for internal consistency with respect to all main questions, Cronbach alphas were calculated (reliability test):

```
# trust
psych::alpha(df[,c(21:31)])$total$raw_alpha

## [1] 0.742623

# perceivedusefullness
psych::alpha(df[,c(9:20)])$total$raw_alpha

## [1] 0.7873868

# uncertainty
psych::alpha(df[,c(32:39)])$total$raw_alpha

## [1] 0.6968684

# returnrate
psych::alpha(df[,c(40:48)])$total$raw_alpha

## [1] 0.7559772
```

Inferential Statistics

- Hypothesis 1.1: (ANOVA, difference in means) There is no difference in the perceived usefulness scale with respect to frequency grouping (figure 8):

```
anova_one_way <- aov(perceivedusefullness~frequencygruppe, data = df)
summary(anova_one_way)

##                   Df Sum Sq Mean Sq F value   Pr(>F)
## frequencygruppe    2   4.22  2.1103   7.216 0.000964 ***
## Residuals        182  53.23  0.2925
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

pwc <- df %>%
  pairwise_t_test(
    perceivedusefullness~frequencygruppe, paired = FALSE,
    p.adjust.method = "bonferroni"
    )
# Visualization: box plots with p-values
pwc <- pwc %>% add_xy_position(x = "frequencygruppe")
ggboxplot(df, x = "frequencygruppe", y = "perceivedusefullness") +
  stat_pvalue_manual(pwc) +
    theme(axis.text.x = element_text(angle = 90))
```

- Hypothesis 1.2: (ANOVA, difference in means) There is no difference in scale trust regarding Frequency grouping (figure 9):

```
anova_one_way <- aov(trust~frequencygruppe, data = df)
summary(anova_one_way)

##                   Df Sum Sq Mean Sq F value Pr(>F)
## frequencygruppe    2   1.14  0.5684   2.517 0.0835 .
## Residuals        182  41.09  0.2258
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
pwc <- df %>%
  pairwise_t_test(
    trust~frequencygruppe, paired = FALSE,
    p.adjust.method = "bonferroni"
    )
# Visualization: box plots with p-values
pwc <- pwc %>% add_xy_position(x = "frequencygruppe")
ggboxplot(df, x = "frequencygruppe", y = "trust") +
  stat_pvalue_manual(pwc) +
    theme(axis.text.x = element_text(angle = 90))
```

- Hypothesis 1.3: (ANOVA, difference in means) There is no difference in scale uncertainty with respect to Frequency grouping (figure 10):

```
anova_one_way <- aov(uncertainty~frequencygruppe, data = df)
summary(anova_one_way)
```

```
##                  Df Sum Sq Mean Sq F value Pr(>F)
## frequencygruppe   2   1.03  0.5157   1.659  0.193
## Residuals       182  56.58  0.3109
```

```
      pwc <- df %>%
  pairwise_t_test(
    uncertainty~frequencygruppe, paired = FALSE,
    p.adjust.method = "bonferroni"
    )
# Visualization: box plots with p-values
pwc <- pwc %>% add_xy_position(x = "frequencygruppe")
ggboxplot(df, x = "frequencygruppe", y = "uncertainty") +
  stat_pvalue_manual(pwc) +
    theme(axis.text.x = element_text(angle = 90))
```

Hypothesis 1.4: (ANOVA, difference in means) There is no difference in scale return rate with respect to Frequency grouping (figure 11):

```
anova_one_way <- aov(returnrate~frequencygruppe, data = df)
summary(anova_one_way)
```

```
##                  Df Sum Sq Mean Sq F value   Pr(>F)
## frequencygruppe   2   6.39   3.195   8.747 0.000236 ***
## Residuals       182  66.47   0.365
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
pwc <- df %>%
  pairwise_t_test(
   returnrate ~frequencygruppe, paired = FALSE,
    p.adjust.method = "bonferroni"
    )
# Visualization: box plots with p-values
pwc <- pwc %>% add_xy_position(x = "frequencygruppe")
ggboxplot(df, x = "frequencygruppe", y = "returnrate") +
  stat_pvalue_manual(pwc) +
    theme(axis.text.x = element_text(angle = 90))
```

- Hypothesis 2.1: (Correlation test, directed correlation test) There is no positive correlation between frequency and perceived usefulness (figure 12):

```
ggplot(data = df, aes(HäufigkeitKäufe, y=perceivedusefullness, group=1)) +
  theme_bw() +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE)
```

```
## `geom_smooth()` using formula 'y ~ x'
```

```r
cor.test(x = df$HäufigkeitKäufe, y = df$perceivedusefullness, alternative
= "greater")

##
##  Pearson's product-moment correlation
##
## data:  df$HäufigkeitKäufe and df$perceivedusefullness
## t = 2.6119, df = 183, p-value = 0.004876
## alternative hypothesis: true correlation is greater than 0
## 95 percent confidence interval:
##  0.06985521 1.00000000
## sample estimates:
##       cor
## 0.1895726
```

- Hypothesis 2.2: (correlation test, directed correlation test) There is no positive correlation between frequency and trust (figure 13):

```r
ggplot(data = df, aes(HäufigkeitKäufe, y=trust, group=1)) +
  theme_bw() +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE)

## `geom_smooth()` using formula 'y ~ x'

cor.test(x = df$HäufigkeitKäufe, y = df$trust, alternative = "greater")

##
##  Pearson's product-moment correlation
##
## data:  df$HäufigkeitKäufe and df$trust
## t = 1.4511, df = 183, p-value = 0.07423
## alternative hypothesis: true correlation is greater than 0
## 95 percent confidence interval:
##  -0.01485893  1.00000000
## sample estimates:
##       cor
## 0.1066574
```

- Hypothesis 2.3: (correlation test, directed correlation test) There is no positive correlation between perceived usefulness and trust (figure 14):

```r
ggplot(data = df, aes(perceivedusefullness, y=trust, group=1)) +
  theme_bw() +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE)

## `geom_smooth()` using formula 'y ~ x'

cor.test(x = df$perceivedusefullness, y = df$trust, alternative = "greater
")

##
##  Pearson's product-moment correlation
##
## data:  df$perceivedusefullness and df$trust
## t = 9.4846, df = 183, p-value < 2.2e-16
## alternative hypothesis: true correlation is greater than 0
```

```
## 95 percent confidence interval:
##  0.4866504 1.0000000
## sample estimates:
##       cor
## 0.5740794
```

- Hypothesis 2.4: (correlation test, directed correlation test) There is no negative correlation between trust and uncertainty (figure 15):

```r
ggplot(data = df, aes(trust, y=uncertainty, group=1)) +
  theme_bw() +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE)
```

```
## `geom_smooth()` using formula 'y ~ x'
```

```r
cor.test(x = df$trust, y = df$uncertainty, alternative = "less")
```

```
##
##  Pearson's product-moment correlation
##
## data:  df$trust and df$uncertainty
## t = -10.774, df = 183, p-value < 2.2e-16
## alternative hypothesis: true correlation is less than 0
## 95 percent confidence interval:
##  -1.0000000 -0.5426945
## sample estimates:
##        cor
## -0.6229992
```

- Hypothesis 2.5: (correlation test, directed correlation test) There is no positive correlation between uncertainty and return rate (figure 16):

```r
ggplot(data = df, aes(uncertainty, y=returnrate, group=1)) +
  theme_bw() +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE)
```

```
## `geom_smooth()` using formula 'y ~ x'
```

```r
cor.test(x = df$uncertainty, y = df$returnrate, alternative = "greater")
```

```
##
##  Pearson's product-moment correlation
##
## data:  df$uncertainty and df$returnrate
## t = -3.1768, df = 183, p-value = 0.9991
## alternative hypothesis: true correlation is greater than 0
## 95 percent confidence interval:
##  -0.3404935  1.0000000
## sample estimates:
##        cor
## -0.2286135
```

- Hypothesis 3 (Model 1): (mediator analysis, regression modeling) A relationship between frequency and trust is not mediated by perceived usefulness:

```
base <- lm(trust ~ HäufigkeitKäufe, data = df)
summary(base)

##
## Call:
## lm(formula = trust ~ HäufigkeitKäufe, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.97144 -0.33513  0.01336  0.42242  0.78302
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      3.00184    0.05326  56.357   <2e-16 ***
## HäufigkeitKäufe  0.01514    0.01044   1.451    0.148
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4776 on 183 degrees of freedom
## Multiple R-squared:  0.01138,    Adjusted R-squared:  0.005973
## F-statistic: 2.106 on 1 and 183 DF,  p-value: 0.1485
```

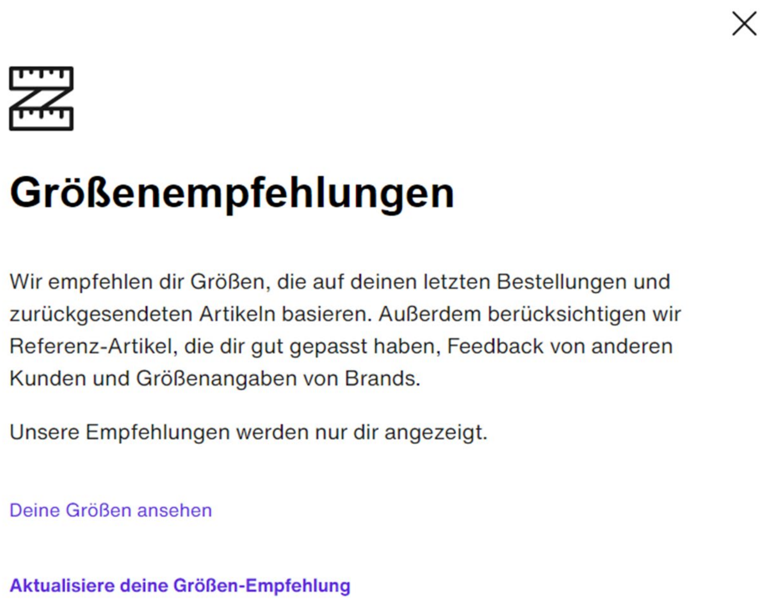
Tests whether BLUE is given:

```
durbinWatsonTest(base)

##  lag Autocorrelation D-W Statistic p-value
##    1       0.1473697      1.701447   0.044
##  Alternative hypothesis: rho != 0

bptest(base)

##
##  studentized Breusch-Pagan test
##
## data:  base
## BP = 0.0046876, df = 1, p-value = 0.9454

shapiro.test(base$residuals)

##
##  Shapiro-Wilk normality test
##
## data:  base$residuals
## W = 0.96312, p-value = 8.76e-05

t.test(x = base$residuals)

##
##  One Sample t-test
##
## data:  base$residuals
## t = -1.0747e-15, df = 184, p-value = 1
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.06909559  0.06909559
## sample estimates:
##     mean of x
## -3.763647e-17
```

- Hypothesis 3 (Model 2): (mediator analysis, regression modeling) A relationship between frequency and trust is not mediated by perceived usefulness:

```
h3 <- lm(trust ~ HäufigkeitKäufe + perceivedusefullness, data = df)
summary(h3)

##
## Call:
## lm(formula = trust ~ HäufigkeitKäufe + perceivedusefullness,
##     data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.0033 -0.2563 -0.0128  0.2867  1.1068
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)           1.5448289  0.1628202   9.488   <2e-16 ***
## HäufigkeitKäufe      -0.0003199  0.0087760  -0.036    0.971
## perceivedusefullness  0.4925807  0.0529993   9.294   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3944 on 182 degrees of freedom
## Multiple R-squared:  0.3296, Adjusted R-squared:  0.3222
## F-statistic: 44.73 on 2 and 182 DF,  p-value: < 2.2e-16

bptest(h3)

##
##  studentized Breusch-Pagan test
##
## data:  h3
## BP = 0.022804, df = 2, p-value = 0.9887

shapiro.test(h3$residuals)

##
##  Shapiro-Wilk normality test
##
## data:  h3$residuals
## W = 0.9951, p-value = 0.8093

t.test(x = h3$residuals)

##
##  One Sample t-test
##
## data:  h3$residuals
## t = 2.8205e-16, df = 184, p-value = 1
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  -0.0568998  0.0568998
## sample estimates:
##    mean of x
## 8.134447e-18
```

In the following, screenshots of the most successful online stores in the apparel sector in the DACH region are given as examples for recommendation tools.



In Zalando's online store, for example, the customer can specify how well the clothes from past orders fit or, alternatively, actively store sizes. ABOUT YOU makes it easy for customers to log in. Also, via SSO.

Figure 23: ABOUT YOU Screenshot Log-in

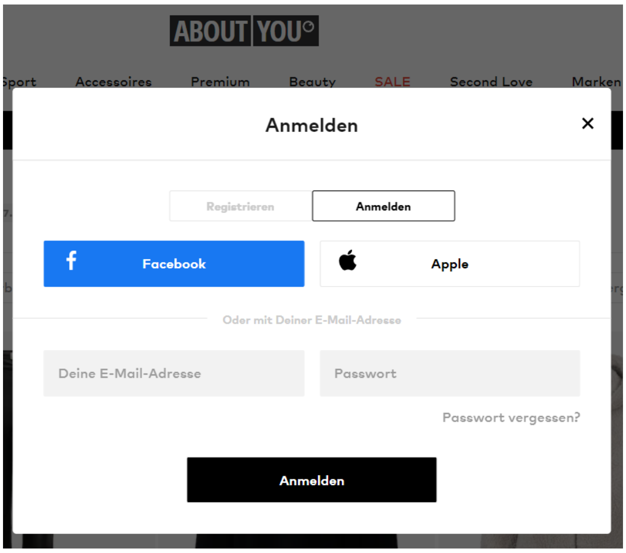
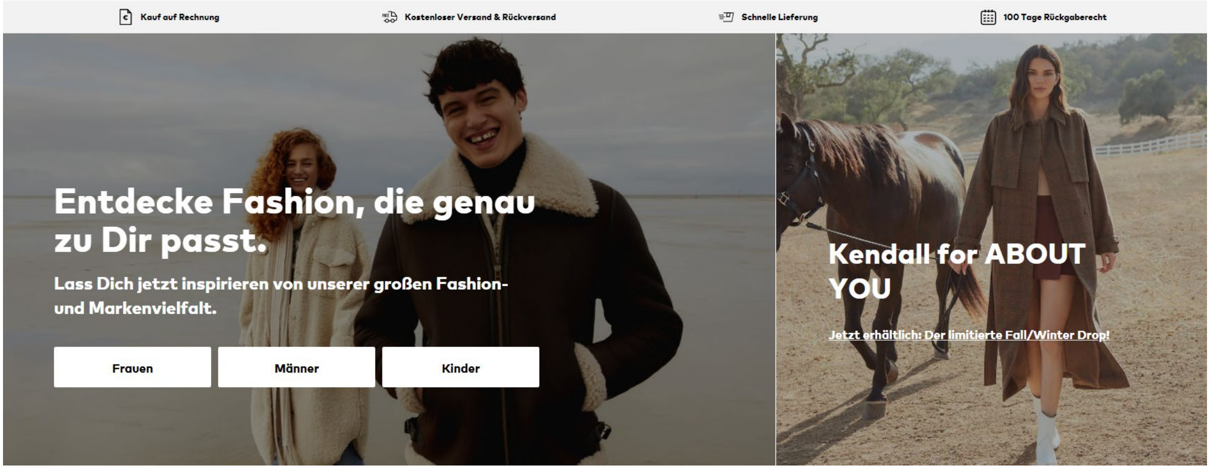
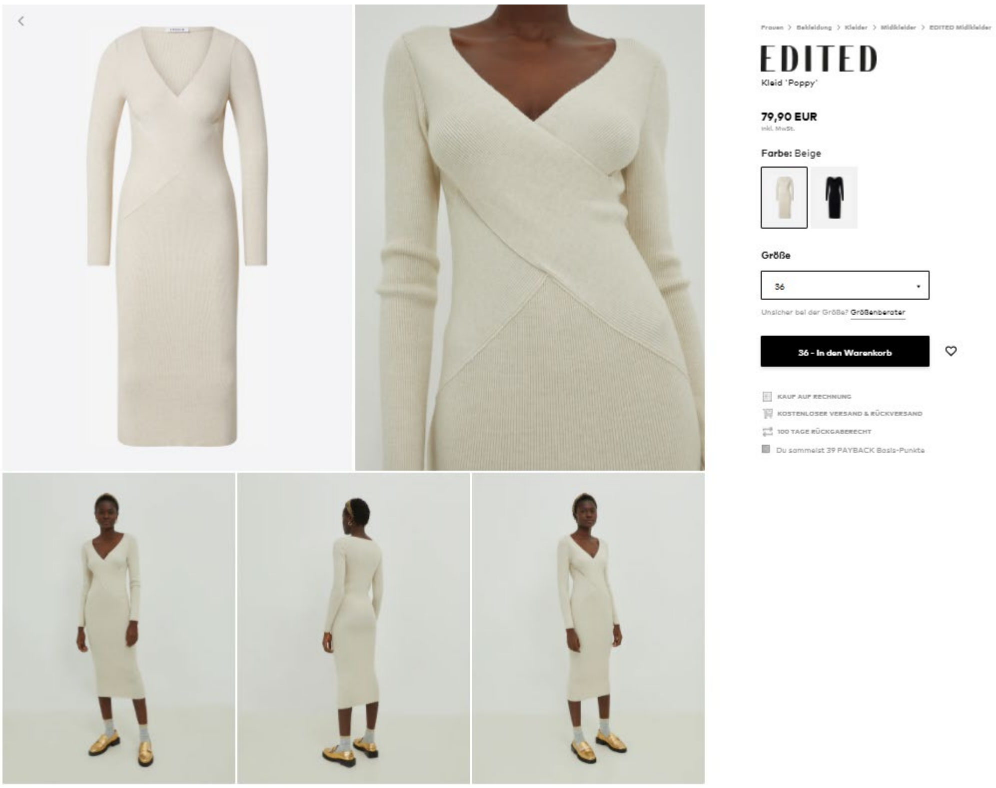


Figure 24: Screenshot Homepage ABOUT YOU



Influencers are displayed immediately on the home page (Figure 19).

Figure 25: Process of size determination via Fit Finder | Screenshots



Artikel Details   Versand & Rückgabe

EDITED Kleid 'Poppy' In Beige
Design & Extras

- Unifarben
- Viskose
- V-Ausschnitt
- Rippstrick
- Wickeloptik

Art.-Nr. EDT3811001000003

Größe & Fit

Ärmellänge: Langarm
Länge: 3/4-lang
Passform: Figurbetonte Passform
Ärmellänge: 59cm
Gesamtlänge: 116cm

Material & Pflege

Obermaterial: 52% Viskose, 26% Polyester, 22% Nylon
Materialart: Feinstrick
Ursprungsland: Spanien

Nicht trocknergeeignet
Trockenreinigung mit Perchlorethylen
Nicht heiß bügeln
Nicht bleichen
30 °C Feinwäsche

ABOUT YOU   FIT FINDER   Datenschutz

Ihre Angaben

Finden Sie Ihre passende Größe:

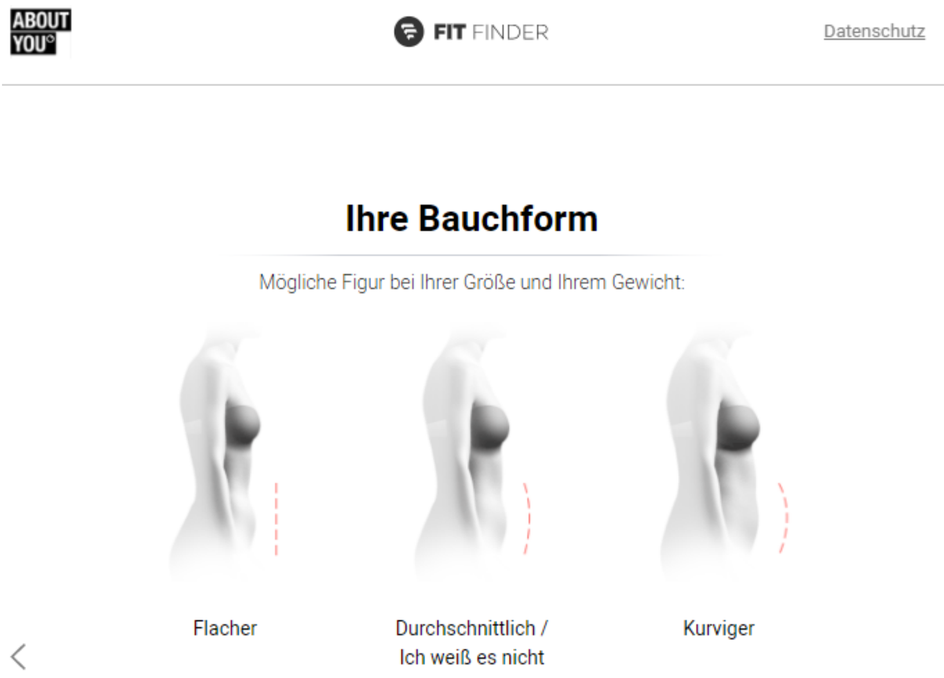
GRÖSSE

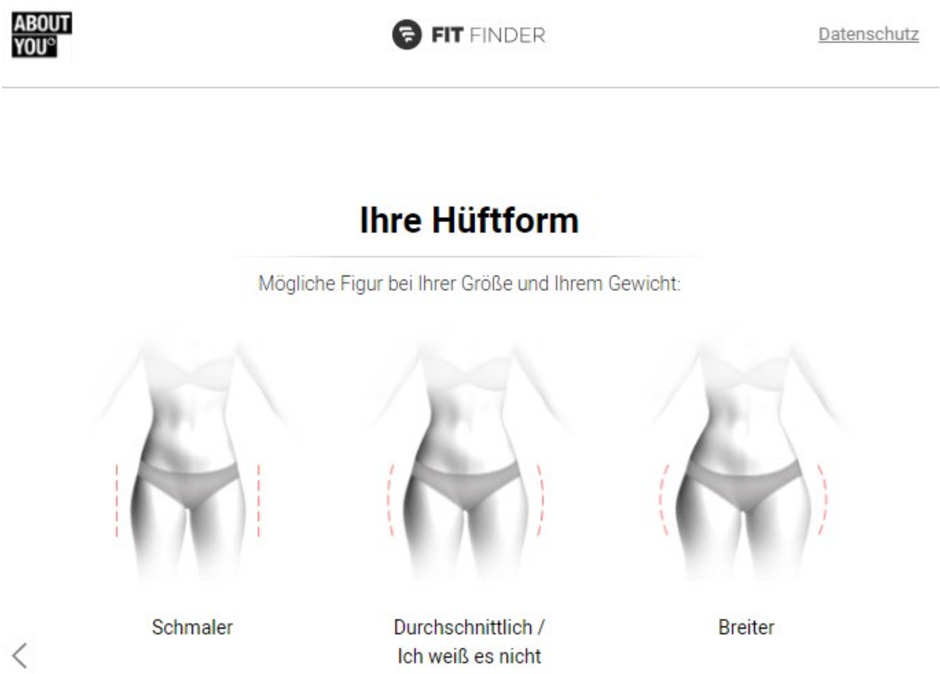
cm   cm in

GEWICHT

kg   kg lbs

Weiter >


FIT FINDER
Datenschutz
Ihre Bauchform
Mögliche Figur bei Ihrer Größe und Ihrem Gewicht:
Flacher
Durchschnittlich / Ich weiß es nicht
Kurviger


FIT FINDER
Datenschutz
Ihre Hüftform
Mögliche Figur bei Ihrer Größe und Ihrem Gewicht:
Schmaler
Durchschnittlich / Ich weiß es nicht
Breiter

ABOUT YOU

FIT FINDER

Datenschutz

38 scheint Ihre Größe zu sein. Noch 4 Fragen...

BH-Größe hinzufügen

Anzeigen: Europäische Größen

Brustumfang				Körbchengröße			
60	65	70	75	AA	A	B	C
80	85	90	95	D	E	F	G
100	105	110	115	H	I	J	K
120	125						

Weiter

ABOUT YOU

FIT FINDER

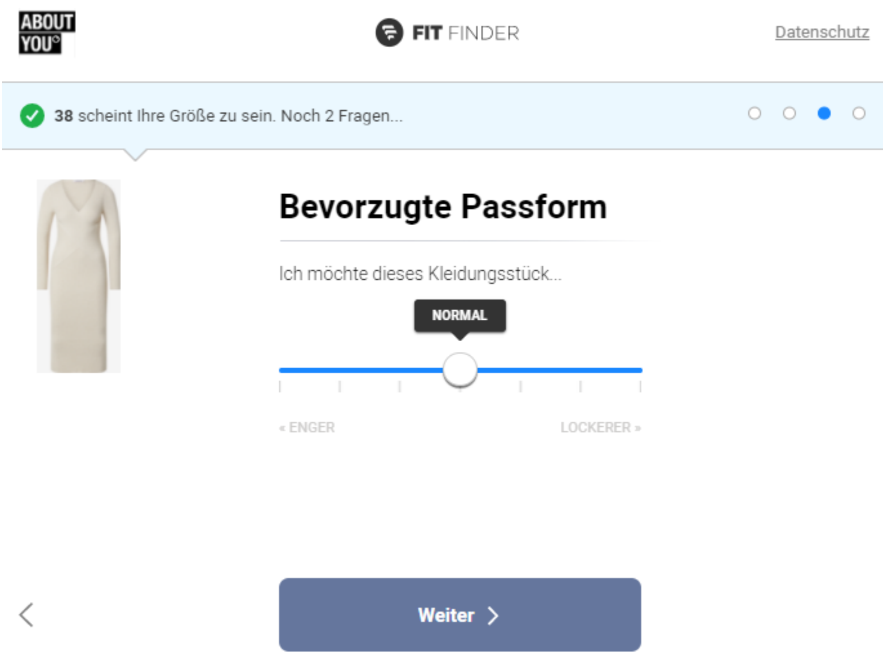
Datenschutz

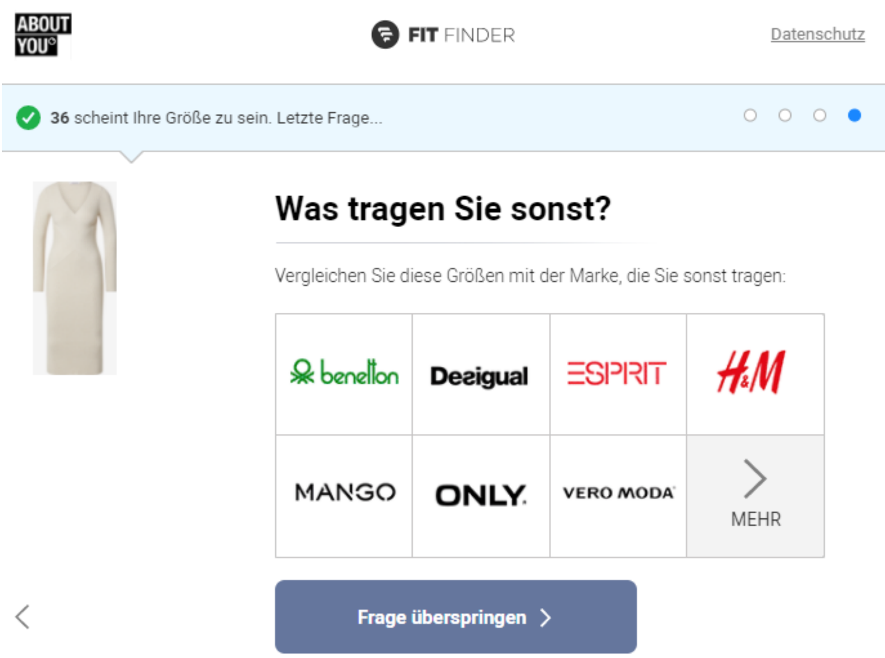
38 scheint Ihre Größe zu sein. Noch 3 Fragen...

Wie alt sind Sie?

Warum fragen wir nach Ihrem Alter? Das Alter beeinflusst die Verteilung Ihres Gewichts und hilft uns, Ihnen die passende Größe zu empfehlen.

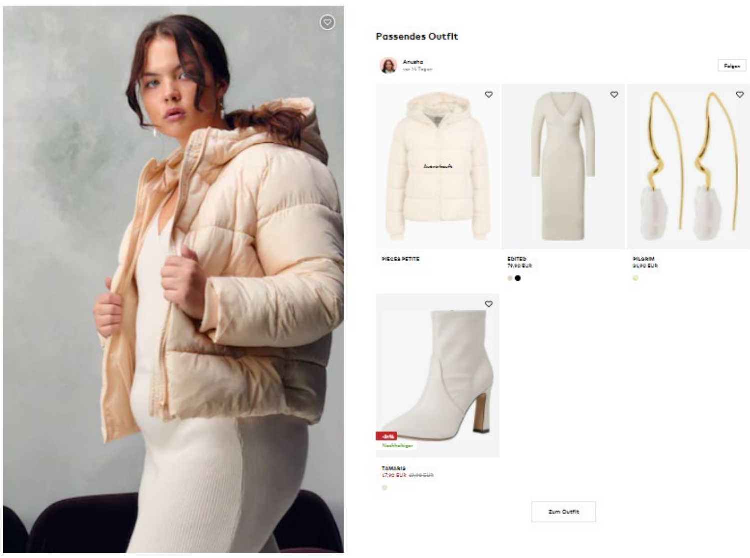
Weiter


ABOUT YOU
FIT FINDER
Datenschutz
38 scheint Ihre Größe zu sein. Noch 2 Fragen...
Bevorzugte Passform
Ich möchte dieses Kleidungsstück...
NORMAL
« ENGER
LOCKERER »
Weiter

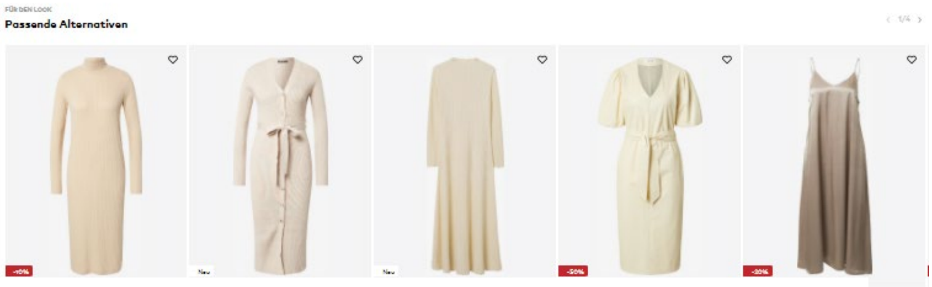

ABOUT YOU
FIT FINDER
Datenschutz
36 scheint Ihre Größe zu sein. Letzte Frage...
Was tragen Sie sonst?
Vergleichen Sie diese Größen mit der Marke, die Sie sonst tragen:
benetton
Desigual
ESPRIT
H&M
MANGO
ONLY
VERO MODA
MEHR
Frage überspringen

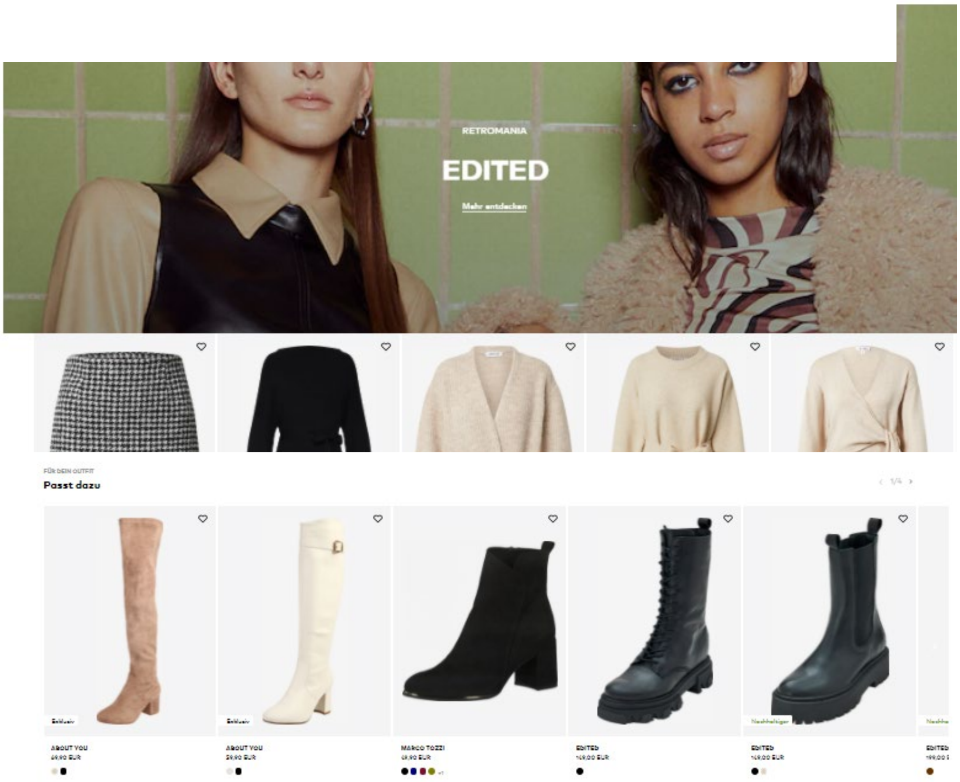
The next images show a randomly selected garment, with numerous images of the item available from all sides. All important information is also quickly visible, such as the material, washing instructions and initial information about the fit. If you click on the Fit Finder, it is possible to determine the right size. For this purpose, personal data such as height and weight are required, and even the shape of the body and hips are asked for. Bra size and age are also relevant. Last but not least, the customer is asked about the fit, i.e. whether the clothing should be more tight-fitting or not - only then is the size recommendation given. In addition, it is also possible to specify which clothes from which manufacturer have fit well so far. This was exemplified by a garment in the online store of ABOUT YOU, but can be found in a similar way at Zalando and bonprix.

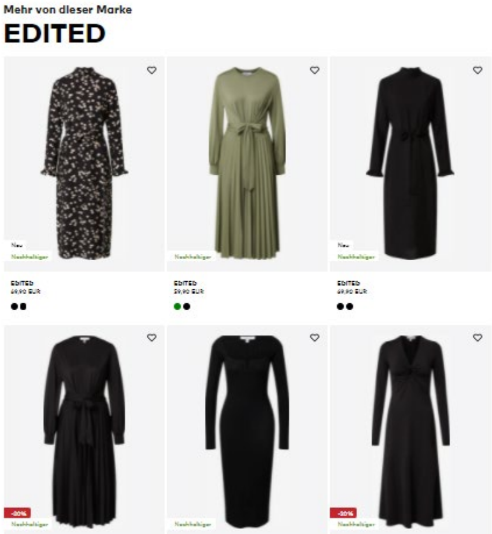
Figure 26: Screenshot "goes with" and other recommendations

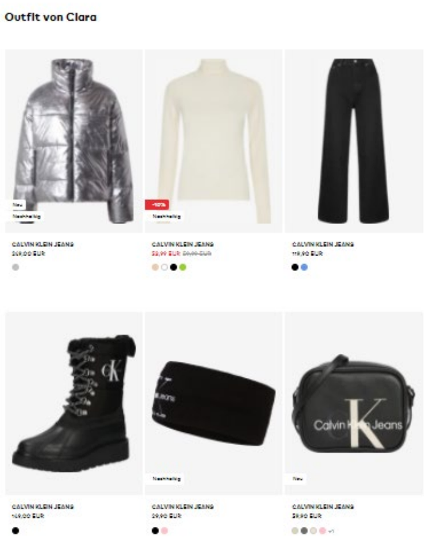


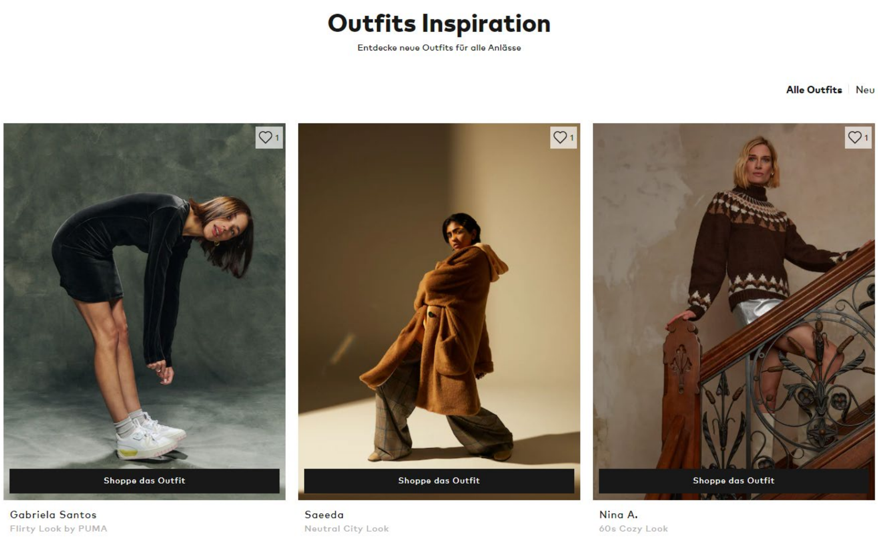
In addition, customers receive tips on what to wear or complete outfit recommendations. They also receive direct suggestions for alternatives or can look at what the influencers are wearing (the following screenshots).






Mehr von dieser Marke
EDITED


Outfit von Clara


Outfits Inspiration
Entdecke neue Outfits für alle Anlässe
Alle Outfits
Neu
Shoppe das Outfit
Shoppe das Outfit
Shoppe das Outfit
Gabriela Santos
Flirty Look by PUMA
Saeeda
Neutral City Look
Nina A.
60s Cozy Look

Statement of Affirmation

I hereby declare that all parts of this thesis were exclusively prepared by me, without using resources other than those stated above. The thoughts taken directly or indirectly from external sources are appropriately annotated.

This thesis or parts of it were not previously submitted to any other academic institution and have not yet been published.

Dornbirn, 7, January 2022 Danijela Galic