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ABSTRACT

Keywords: B2C Online Transactions, Online Feedback System, Risk, Trust, Reputation, Arbitrations, Product Complexity

Despite the growing population of Internet customers, purchasing online can still be a confusing and overwhelming activity. Perceived risk plays a crucial role in online buying decisions. The mechanism of online customer feedback has been identified to improve trust and to reduce risk in online marketplaces. Feedback from previous customers greatly builds online vendor reputation and establishes trust, which positively influence the intent to purchase. This study aims to find out how a feedback system enhances vendor reputation and can thereby be used to mitigate product complexity and facilitate online purchasing decisions in the B2C environment. The cooperation with a feedback company creates an experimental setting that allows a relationship between positive feedback, conversion rate, arbitrations and feedback submissions to be inferred. The access to real feedback and transaction data allows the investigation of actual risk perception and the need for risk evaluation. This study considers both the user’s and the vendor’s interaction with the feedback system.

Nelson's (1970) product classification is used to divide product categories into different levels of product complexity. The study follows a positivist quantitative approach and applies deductive strategies and procedures to address the research objective. The author presents a number of hypotheses and has analysed data from 400 online stores that have implemented a feedback system. Transaction and feedback data were drawn from a feedback company database and have been analysed using linear regression and partial correlation.

The results of this research indicate that product complexity has an inevitable influence upon an online buying process. The greater the transaction value (average price) and the functional/technical complexity of the product (product complexity), the more the presence of feedback grows in importance. However, the aspect of trust, that emerged due to the percentage of positive feedback by past customers, only influences sales of highly complex products, which
means that product category matters with regard to the trust transference theory. The findings identified different risk types which corroborate the theory that risk is multi-faceted. Finally this study provides valuable insights about the vendor's strategic work with a feedback system.

The conclusions provide suggestions for online vendors as to how they can use online feedback systems as tools for dealing with the shortcomings associated with electronic commerce. It is important for vendors of complex products to invest in their reputation and to establish trust on the basis of feedback that is as positive as possible. By better understanding the relationships among positive reputation profiles and certain risk types (financial risk, product risk, physical risk, time risk), vendors may be able to take more appropriate actions in their efforts to make shopping online a less risky experience and motivate certain behaviour, such as purchasing. It is recommended that the vendor carries out proper complaint management in the form of arbitration procedures on negative feedback. A feedback system gives online vendors the advantage of protecting themselves against the negative opinions spread on the World Wide Web. The process of arbitrations enables vendors to show competence and has the ability to turn dissatisfied customers into satisfied customers. In order to enhance the online reputation, organisations should offer workshops on the efficacy of working with a feedback system and how to conduct arbitrations properly.
DECLARATION OF ORIGINALITY

'I confirm that the submitted work is my own work and that I have clearly identified and fully acknowledged all material that is entitled to be attributed to others (whether published or unpublished) using the referencing system set out in the programme handbook. I agree that the University may submit my work to means of checking this, such as the plagiarism detection service Turnitin® UK. I confirm that I understand that assessed work that has been shown to have been plagiarised will be penalised.'

Julia Bartels

July 2015
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Moreover, this research was only possible with the cooperation of eKomi, which develops and operates intelligent feedback systems.

Last but not least, I would like to thank my parents and my husband, Tom Bartels, for both their patience and support during the research project.
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### Abbreviations and Glossary

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<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>AGOF</td>
<td>Arbeitsgemeinschaft Online Forschung</td>
</tr>
<tr>
<td>AIS</td>
<td>The Association for Information Systems</td>
</tr>
<tr>
<td>ATM</td>
<td>Automated Teller Machines</td>
</tr>
<tr>
<td>BITKOM</td>
<td>Bundesverband Informationswirtschaft, Telekommunikation und neue Medien</td>
</tr>
<tr>
<td>B2B</td>
<td>Business-to-Business</td>
</tr>
<tr>
<td>B2C</td>
<td>Business-to-Consumer</td>
</tr>
<tr>
<td>B2G</td>
<td>Business-to-Government</td>
</tr>
<tr>
<td>BVDW</td>
<td>Bundesverband Digitale Wirtschaft</td>
</tr>
<tr>
<td>C2C</td>
<td>Consumer-to-Consumer</td>
</tr>
<tr>
<td>CEO</td>
<td>Chief executive officer</td>
</tr>
<tr>
<td>Cookie</td>
<td>A small text created by a website that is visited and stored on the computer. Cookies provide a way for the website to recognise visitors and keep track of their preferences. The cookie is often used to identify a particular event or transaction.</td>
</tr>
<tr>
<td>ECC</td>
<td>E-Commerce-Center</td>
</tr>
<tr>
<td>E-commerce</td>
<td>Electronic commerce</td>
</tr>
<tr>
<td>eWOM</td>
<td>Electronic Word-of-Mouth</td>
</tr>
<tr>
<td>HDE</td>
<td>Handelsverband Deutschland</td>
</tr>
<tr>
<td>ICIS</td>
<td>International Conference on Information Systems</td>
</tr>
<tr>
<td>IS</td>
<td>Information Systems</td>
</tr>
<tr>
<td>LN</td>
<td>Logarithmus Naturalis (Natural logarithm)</td>
</tr>
<tr>
<td>Ltd.</td>
<td>Limited Company</td>
</tr>
<tr>
<td>MIS</td>
<td>Management Information Systems</td>
</tr>
<tr>
<td>Term</td>
<td>Definition</td>
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<td>-----------------------------</td>
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<tr>
<td>MySpace, Facebook, Twitter, Friendster</td>
<td>A social networking service is a web-based platform to build social networks or social relations among people who interact over the Internet and share interests, activities, backgrounds or real-life connections.</td>
</tr>
<tr>
<td>SEO</td>
<td>Search Engine Optimisation</td>
</tr>
<tr>
<td>TRA</td>
<td>Theory of reasoned action</td>
</tr>
<tr>
<td>Unique Visitor</td>
<td>Individuals who have visited a website at least once in a fixed time frame.</td>
</tr>
<tr>
<td>Widget</td>
<td>It is an element of interaction in a graphical user interface, such as a button or a scroll bar. Controls are software components that a computer user interacts with through direct manipulation to read or edit information about an application.</td>
</tr>
<tr>
<td>WOM</td>
<td>Word-of-Mouth</td>
</tr>
<tr>
<td>Social Commerce SaaS Technology</td>
<td>Software-as-a-Service (SaaS) has become a common delivery model for many business applications. Social commerce is a subset of electronic commerce that involves using user contributions to assist in the online buying and selling of products and services. With this software eKomi collects customer feedback.</td>
</tr>
<tr>
<td>WWW</td>
<td>World Wide Web</td>
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1. Introduction

1.1 Research background

Electronic commerce (e-commerce) is a very important trading opportunity for vendors of different products, as it enables them to get in touch with their target buyers without having to make physical appearances at certain strategic trading locations. The Internet is usually the key facilitator of this kind of business since it is where most of the transactional interactions between the vendors and their target customers occur. With an online store a vendor is able to reach a broad audience. The relative ease with which vendors can sell their products on the Internet has led to an abundance of online stores offering all kind of products to a huge number of end consumers. Even though online sales have increased rapidly and are expected to have a 17% increase in turnover in 2014 (HDE, 2014), Internet customers complain about delayed or failed delivery and defective products (BITKOM, 2012). The online vendor and the customer are total strangers to each other. Online customers are unable to “touch” the product or to communicate with the salesperson. Customers who buy online for the first time are likely to be disappointed when they receive the products and to have difficulties returning the products (Bhatnagar et al., 2000). Customers perceive more risks in new online stores than in a traditional retail environment (Bhatnagar et al., 2000; Kim et al., 2008; Zhong and Shao, 2006). Perceived risks are a strong deciding factor in online buying decision-making.

Researchers acknowledge that perceived risks influence online purchasing behaviour (Jarvenpaa et al., 1999; Pavlou, 2001; Van der Heijden et al., 2003; Egeln and Joseph, 2012). Customers apply strategies to reduce the perceived risk until it is at an acceptable level. The perceived risk and the use of risk reduction strategies are also influenced by the complexity of products. More complex products, for which the quality or usage is difficult to assess, require an effective risk reduction strategy. This circumstance might explain why products with rather low levels of complexity, such as books, shoes and tickets were the three most frequently purchased online products in 2013 (AGOF and internet facts, 2014).
The Internet offers trust-building mechanisms that give unknown online vendors or vendors of complex products the possibility to reduce risk and to create trust among their potential customers. Tong (2010) suggests that it is vital for vendors to minimise the risks that consumers feel when making online purchases in order to be more successful.

In the Information Systems (IS) and marketing literature, the mechanism of online customer feedback has been identified as improving trust and reducing risk. Since consumer feedback reflects the history of online transactions in combination with their acceptance (in form of positive feedback) or rejection (in form of negative feedback) by previous customers, it plays a role in defining online vendor reputation and establishing a vendor’s trustworthiness, which, in turn, influence sales (Ba and Pavlou, 2002; Houser and Wooders, 2006; Resnick and Zeckhauser, 2002; Chevalier and Mayzlin, 2006; Bolton et al., 2008; Cabral and Hortacsu, 2010). Nevertheless, online reputation differs from reputation in offline markets in that online reputation is only connected to the virtual identity of a person, i.e., the username. On platforms like eBay, members can build up a good reputation by simply purchasing feedback (Dini and Spagnolo, 2009).

The following research aims to find out how a feedback system enhances vendor reputation, mitigates product complexity and facilitates online purchase decision-making in B2C online stores. This investigation reveals information about the relationship of the feedback system to both the online customer and the online vendor.

1.2 Framework of this thesis

1.2.1 Prior research

Although some products have intrinsic risks when purchased online, published research has mainly focused on product level and, with the exception of Chu and Li (2008), Huang et al. (2009) and Dai et al. (2014), thereby neglected to provide convincing evidence of the extent to which the risk perception of online
customers varies by product category or how risk perceptions influence online purchases for various product categories.

Despite the popularity of online customer feedback and its importance for online vendors, few studies have empirically investigated the effect of feedback in online stores (Cho et al., 2002; Huang et al., 2009). A large portion of the literature on online feedback mechanisms has primarily focused on marketplaces such as eBay and Amazon (Ba and Pavlou, 2002; Resnick and Zeckhauser, 2002; Houser and Wooders, 2006; Chevalier and Mayzlin, 2006; Bolton et al., 2008; Cabral and Hortacsu, 2010). The main questions that have been studied are how online feedback mechanisms may help build trust between vendors and buyers in the online markets, and how the positive or negative ratings of sellers impact the final prices, seller reputation, sales rank and number of bids received.

Empirical results confirm that consumer trust strongly increases the intention to make a purchase and that perceived risk reduces the consumer's intention to purchase (Kim et al., 2008). Resnick et al. (2002) discovered that the effect of eBay feedback profiles on the probability of sale is relatively higher for riskier online transactions and more expensive products. Offering customer feedback increases the likelihood that consumers will make a purchase. This is greater for products that can only be evaluated with certainty after their purchase and usage than for products that can be evaluated prior to purchase and use (Huang et al., 2009).

So far the data in the literature has been collected mostly either through experiments or surveys. Further from the reviewed literature a common research method was content analysis. Very often researchers collected feedback comments on eBay or Amazon and analysed the negative and positive content (Pavlou and Dimoka, 2006; Ghose, 2009). The research on online feedback systems so far has focused on venues such as eBay with a bilateral feedback system, where vendors can be buyers and vice versa. So far less investigation has been carried out on one-sided customer feedback.
systems based on actual consumer behaviour within Business-to-Consumer (B2C) online stores.

### 1.2.2 Research focus

The main focus of this study is to determine how online customers and online vendors adopt the features of a feedback system and if this feedback system enhances vendor reputation, mitigates product complexity and thus positively influences the user's decision to purchase online. Customers can reduce their risk perception by checking the reputation profile of the vendor and can foster trust by providing future customers with positive feedback. Online vendors can establish their trustworthiness and reduce risks by taking customer feedback seriously, reacting to it and maintaining a high volume of positive feedback. This will be tested with respect to three different product categories, which differ in their functional complexity and transaction value. Using literature about risk, trust and reputation in the Internet environment as well as online feedback and purchase decision-making for search and experience products in an online store, hypotheses were developed to ascertain the degree to which users want to assess the recognised risk due to the transaction value (average price in EUR) and level of product complexity, as well as how far they trust the feedback profile, and how seriously online vendors care about their reputation profile.

The literature to date focuses on risk perception, which refers to the perceived likelihood of gains and losses when transacting with the online vendor. No studies could be found that investigated real consumer click behaviour with regard to risk evaluation. Results, already confirmed through the literature, shall be compared with the real browsing behaviour analysed in this study. The company eKomi, which provides and controls a feedback system for B2C online stores, extracted system-generated data from their own company database, which is used for this investigation. With the help of these transaction and feedback logs, the real behaviour of online customers and online vendors is tested. Surveys, too, are a popular method to measure trust and the social influence of others before making a purchase. However, possible bias can arise from measuring self-reported behaviour derived by asking individuals directly
about their communication habits (Dellarocas and Narayan, 2006). It is important to emphasise that this research cannot be directly compared to the literature on the eBay feedback system. In the present setting, there are no private sellers, but rather commercial vendors with their own online stores. Moreover, all prices are fixed rather than determined by bids, as is the case with eBay auctions.

1.3 Research objectives
This thesis will develop the existing theory of risk, trust and reputation in online transactions. Based on a quantitative approach with actual browsing data for three different product categories, relationships between average transaction value, feedback profile access, feedback submission, positive reputation profile, arbitrations and conversion rate will be identified. This study seeks to examine the degree to which customer feedback provided by a third party (eKomi) plays a role in enhancing vendor reputation, mitigating product complexity and facilitating online purchase decision-making. The following research questions will be specifically addressed:

- Do products with higher transaction values and complex functionality evoke greater risk perception, and therefore the need for risk evaluation?
- How important is the vendor’s reputation in online purchases of low, medium and high product complexity?
- Does trust (profile of a trustworthy vendor) influence online purchases of low, medium and high product complexity?
- How do vendors react to negative feedback based on the complexity of the product?
- Does a vendor’s positive reputation influence the feedback submission of low, medium and high complexity purchases?

1.4 Scope and limitations of this thesis
This investigation was conducted to determine how a feedback system enhances vendor reputation, mitigates product complexity, and thus facilitates
the user’s decision to purchase online. In cooperation with the company eKomi, who develop and operate feedback systems for online vendors, an analysis was carried out on 400 German online stores. About 1,536,403 transactions and 447,201 feedback logs have been drawn from the eKomi database. The data have been split into three different product categories to investigate the impact of transaction value and functional complexity on risk, trust and reputation during an online purchase.

In order to reach a clear understanding of the user’s attitude towards online purchases, previous studies of risk and trust made use of questionnaires. This study does not seek to examine the attitudes or motivations of consumers, but rather to provide an insight into customers’ real search and purchasing behaviour in an online store. The results of this study, in comparison to results obtained from surveys, reflect that people in the real world behave differently than they claim to behave in their self-reported descriptions.

1.5 Structure of this thesis
This thesis consists of six chapters. The first chapter introduces the thesis’ main field of inquiry. Chapter 2 presents an overview of extant literature on the relevant topics associated with this research. This includes literature about e-commerce, buying behaviour with respect to various product categories, online risk, online trust, online feedback and online reputation. Chapter 3 describes the methodology of the research, which includes the introduction of eKomi, the company which provides actual transaction-based online feedback data from their own database, and the description of variables. Chapter 4 then goes on to describe the data analysis of 400 B2C online stores using linear regression and partial correlation. The discussion of the findings and the implications for researchers are presented in Chapter 5. And Chapter 6 provides the conclusions and limitations of the research, as well as its implications for managers in the industry and suggestions for further research. Finally, the Appendix contains some materials that provide more details on the data analysis.
2 Literature review

2.1 Introduction of the literature review

This chapter explains the focus of the literature review and the sources of the literature used for this review. It provides a general overview of the scope and development of online shopping, as well as various definitions of online buying behaviour with respect to search and experience products, risk, trust, online feedback systems and reputation with a focus on online transactions.

2.1.1 Structure of the literature review

Dividing the literature into six parts, the literature review discusses a number of areas that are both theoretically and empirically covered by current and past research:

- Electronic commerce with the focus on B2C online transactions
- Online buying decision-making process
- Risk theories with the focus on online transactions
- Trust theories with the focus on online transactions
- Online feedback system
- Reputation theories with the focus on online transactions

First, e-commerce is described and defined with a focus on B2C online transactions. Then, after clarifying the characteristics of B2C online stores, the online buying decision process is introduced. In this section comments are made about the buying behaviour of online customers considering different product categories and product prices, which leads to a distinguished product involvement. Nelson’s (1970) product classification is used to divide product categories into different levels of product complexity: (1) Search products are products with a lower level of product complexity for customers, whereas (2) experience products are characterised by a higher level of product complexity for customers. This will be followed by a discussion of risk and trust as important factors in predicting B2C e-commerce acceptance.
The literature review will then focus on online customer feedback systems, which reflect the reputation of an online store. A positive reputation helps to reduce risk and to build trust.

The second part of the literature review presents the conceptual framework and the proposed research model. Hypotheses are presented to test how a feedback system enhances vendor reputation, and thereby helps mitigate product complexity and facilitate online purchase decision-making.

2.1.2 Literature sources

This thesis studied the important pieces of literature published by global organisations for academics. These organisations, such as “The Association for Information Systems (AIS)” and “International Conference on Information Systems (ICIS)”, are specialised in Information Systems. These publications present scientific papers on the theory and praxis of the constantly changing field of Information Systems.
2.2 Electronic commerce
This section introduces the definition and the development of electronic commerce. Electronic commerce developed from solely online business activities to user-friendly and relatively more customer-driven online transactions. In what follows, the characteristics of online stores are described with a focus on B2C electronic commerce. The section concludes with some reflections on the limitations of electronic commerce.

2.2.1 Definition and development of electronic commerce
There are a variety of definitions available for the term “electronic commerce” (e-commerce). E-commerce can be formally defined as technology-mediated exchanges between parties (individuals, organisations, or both), as well as the electronically based intra- or inter-organisational activities that facilitate these exchanges (Rayport and Jaworski, 2001). Ba and Pavlou (2002) include the aspect of trust in their definition of e-commerce. They define e-commerce as a new form of online exchange in which most transactions occur between entities that have never met. It is important to keep in mind that many business partners in e-commerce exchanges are total strangers, who have to trust the other party in order to transact. This implies a lack in the expectation of performance. Thus, risk perception is a barrier to the successful completion of transactions in an online setting where anonymity is the norm.

From the definitions above, the author manages to define e-commerce as the use of an electronic-based medium, such as the Internet, to perform various activities or processes, mainly involving transactions, electronically.

E-commerce began in 1991, when websites were allowed to use Internet for business transactions. Today e-commerce has gained broad popular appeal as the technologies have become increasingly user-friendly and relatively more customer oriented. People can easily search through a large database of products to see actual prices and are able to shop literally everywhere - at their workplaces during lunch time or on the underground in rush hour. Potential customers have also been offered new ways of engaging with products online,
with 3D technology, for example, allowing the customer to ‘feel’ the product so that they can better understand its shape, size, and texture (Mohapatra, 2013).

Furthermore, social networking sites like MySpace, Facebook, Twitter and Friendster have emerged over the last 15 years. Usually, these social networking sites are integrated across a number of online portals to promote sales. Such integration connects customers to one another so that they can share, recommend products and services which will improve a company’s business. E-commerce in social networking involves customer-driven online transactions (Mohapatra, 2013).

E-Commerce has become a community-driven dialog trade (Haderlein and Krisch, 2008). This so-called “social commerce” involves e-commerce and social influence in the form of reviews from other customers, which, in turn, can play a mediating role between customers’ attitudes toward a product and their intention to buy it (Lee et al., 2006). This is especially the case when consumers are uncertain about making a purchase, because they are willing to place an enormous amount of trust in the opinion of former customers (Lim et al, 2006). Vendors present content on their websites showing that many other customers have already completed transactions and are satisfied with the outcome, i.e., that the transaction between customer and vendor fulfilled the expectations of both partners. Such user-generated content helps build both trust and reputation. Pioneers such as Amazon and eBay show potential customers that previous users were satisfied with their online transaction by displaying the feedback of people who have already bought the product or made a transaction with the vendor. The most popular categories of products sold online include music, books, computers and office supplies (Mohapatra, 2013).

E-commerce can be classified according to the type of transaction partners. These can be Business-to-Consumer (B2C), Business-to-Business (B2B), Business-to-Government (B2G) or Consumer-to-Consumer (C2C) (Mohapatra, 2013). This study will focus largely on the Business-to-Consumer (B2C) electronic business, and hence the way the role of customer feedback influences online transactions is taken into consideration.
Business-to-Consumer markets (B2C) and Consumer-to-Consumer markets (C2C) are the categories that are most frequently found in marketing research. Qu et al. (2008) describe the difference between an online B2C market and an online C2C market. According to their distinction, online vendors list their products on an online B2C electronic market such as yahoo.de as an intermediary, so that when a potential buyer clicks on the product he or she is forwarded to the specific website of the online vendor. In contrast to this, eBay sellers do not have their own online store. The complete transaction process takes place on the platform eBay.de (bidding, visiting the eBay shop of the seller, payment choice). Since the author focuses on B2C product retail transactions (exchange of products for money), all other online transactions in which administrators (electronic government), or solely consumers and businesses (C2C and B2B) are involved (to exchange information or informational goods or services), are not taken into consideration. Furthermore, mobile commerce, a sub-form of e-commerce, is likewise not considered in this work.

2.2.2 Definition of B2C e-commerce

B2C e-commerce is the activity through which consumers get information and purchase products using Internet technology. In other words, it is the trading and transactional relationship between a company website (online store) and an end user (Olson and Olson, 2000). These end users enjoy the convenience of purchasing products such as cameras, books and clothing at any time.

According to Koufaris et al. (2001), the B2C environment requires two types of transformation to occur. The first is the transformation of the consumer into an Internet user, and the second is the transformation of a physical store into an online store, i.e. a website.

From the standpoint of user behaviour, getting product information and purchasing products are generally viewed as the two key online consumer behaviours (Gefen and Straub 2000). Choudhury et al. (2001) argue that online
users do not just make one decision, but rather focus on two distinct phases: finding product information and then buying the product.

2.2.3 Characteristics of B2C online stores

For the purposes of this study, an online store is defined as a website that enables online consumers to search and transact in order to pay for products and services. For the purposes of this thesis, the terms online store and (company) website will be used interchangeably. Running a successful online store involves getting potential customers to visit the store, helping them to understand their problem, providing evidence that the store’s products and services can solve their problem (trust), and making it uncomplicated for them to acquire the solution (purchasing the desired product without any risk).

According to Huizingh (2000), the content and the design of a B2C website constitute its key characteristics. While content refers to the information, features or service offered by a B2C website, the design refers to the way in which the content is presented to the consumer. Both content and design influence purchase behaviour (Ranganathan and Ganapathy, 2002). The content provides the necessary information for the consumer, such as brands, variety, quality and prices, while the design provides tools in order to navigate the consumer to the relevant information with ease.

B2C websites differ in the amount of information they make available to the user. In order to attract more customers, owners of a B2C online store will have to employ modern customer-oriented technologies for their businesses to become successful in e-commerce over the long run (Mohapatra, 2013). Thus, a B2C website should give enough information to positively influence the purchase decision, whilst carefully avoiding an information overload (Keller and Staelin, 1987). An effective B2C online store should serve as a major source of relevant information and allow quick access to that information. Apart from products and prices, consumers also look for information about the company and vendor that they are dealing with. A means of interactivity with the consumers is, therefore, essential (Ranganathan and Ganapathy, 2002). The
authors Häubl and Trifts (2000) have argued that interactive decision aids, such as recommendations, are designed to help consumers in the initial search for information. Consumers rely on such feedback because it is based on consumer experience and is relevant to product purchase.

2.2.4 E-commerce limitations

Although e-commerce has its own limitations, it is growing exponentially in today’s electronic and network economy. Trust always becomes a priority when it comes to doing business in virtual environment where the other party to the exchange is unable to be directly seen or heard. In this sense, the e-commerce situation is more risky than the more traditional setting for economic transactions (Zhong and Shao, 2006).

The following factors influence customers’ online purchasing habits (AlGhamdi et al., 2013):

- Lack of trust due to security / privacy concerns
- Involvement with the product
- Quality of e-commerce websites
- Lack of product trial / inspection by hand
- Prices
- Products / vendor's good reputation

Dishonest and criminal behaviour by online vendors can occur, and the main victims of these unethical activities are consumers who participate in Internet activities. This risk has come to factor in to consumers deliberations about engaging in any online transaction or purchasing activity.
2.3 Buying behaviour of Internet users

2.3.1 The online buying decision process model

Internet users make the choice and decision in any online transaction. Customer decisions are decisions that they make on the Internet as buyers (the person who makes an actual purchase), payers (the person who pays for an actual purchase) and consumers (the person who consumes or uses a product). These decisions include whether to purchase, what to purchase, when to purchase, from whom to purchase and how to pay for it (Sheth and Mittal, 2004). The process of making decisions culminates in a purchase made in response to a problem (Solomon et al., 2006). The Internet affects customer decision-making behaviour in all three stages: pre-purchase, purchase transaction and post purchase (Sheth and Mittal, 2004).

Based on empirical evidence, behaviourists have developed models of the online buying process. These models portray the buying decision as having several discrete stages. The classic online buying decision-making process in an online store consists of five cognitive stages: (1) problem recognition, (2) information search, (3) alternative evaluation, (4) purchase decision and (5) post-purchase behaviour. This buying decision process model (figure 2.1) demonstrates that when a customer purchases a product, the purchase event is a forward-moving process which begins long before the actual purchase and continues even after the purchase is made (Comegys et al., 2006).

**Figure 2.1: Five stage buying decision process model**

- **Pre-Purchase**
  - Problem recognition
  - Information search
  - Evaluation

- **Purchase**
  - Purchase decision

- **Post-Purchase**
  - Postpurchase behaviour

Source: Comegys et al. (2006)
The buying decision process starts with problem recognition, which occurs when potential consumers recognise a need that is activated by internal or external stimuli (Comegys et al., 2006).

In the next stage, they use the Internet to search for information related to the recognised need. One factor affecting the amount and type of information search is the perceived risk involved with the purchase (Comegys et al., 2006). For some products, it is relatively difficult to obtain the product quality prior to interaction with the product. The key attributes may be subjective or difficult to compare, and there might be a need to first use the product in order to evaluate the quality. Then there are products for which it is relatively easy to obtain information on product quality prior to interaction with the product. Here the key product attributes are standard product specifications (e.g. colour, shape) (Huang et al., 2009). For a product with standard product specifications and easy to compare, it is not necessary for the customer to test the physical product to evaluate its quality (Mudambi and Schuff, 2010). Huang et al. (2009) conclude from their empirical results that differences regarding the ability to assess product quality before and after purchase provide important insights into consumer behaviour in the online environment. There are differences between the type of information consumers seek for products where evaluation is not of great importance prior to the purchase, and the type of information they seek for products whose evaluation might be important for the consumer before making the transaction (Huang et al., 2009).

Users need to evaluate alternatives and reduce these alternatives to a choice set. They first acquire information about the products and then compare and evaluate between products available on the basis of the information provided to them. As no consumer has unlimited time at their disposal, a line must be drawn regarding how much information to search for and when to stop the evaluation process and choose the one that best fits their criteria for meeting the felt need (Comegys et al., 2006). At this stage, the purchase intention has been formed. However, there are two factors that come between the evaluation and purchase-decision stages. On the one hand, there are the attitudes of friends or communities that might influence the purchase decision. On the other hand,
there can be unexpected events that can intervene between intention and action, such as the price of the product going up, having less disposable income than expected or method of payment. However, when the intention turns into the actual purchase, then post-sales services are provided (Li and Zhang, 2002).

Evaluation of the purchase process continues even after the actual purchase has occurred. If online vendors want to retain customers then they must understand their behaviour after the purchase as well (Huang et al., 2009). According to Kotler and Keller (2006), post-purchase behaviour can be divided into two subgroups: post-purchase satisfaction as an attitude, and post-purchase actions. Evanschitzky et al. (2004) replicated a study by Szymanski and Hise (2000) and concluded that the single most important factor determining satisfaction in electronic commerce is shopping convenience, which has already been mentioned in 2.2.3 as a typical advantage of online shopping over traditional shopping. Typically, if a customer is not satisfied with the purchase, there is a chance that they will complain about the product. And post-purchase actions can have an impact on brand preference and repurchase intentions.

The whole decision-making process for the online purchase usually involves several events of data exchange. The first step involves basic information exchange from the online vendor to the potential consumer that supports browsing, gathering information, and making product and price comparisons available for user consideration. The next step, which occurs after the user has chosen a product, involves him or her providing some personal information, by registering an e-mail address, describing product preferences, etc. The final step in the transaction involves the entry of additional personal information and payment details, such as credit card information, in order to complete the purchase of a product (Pavlou, 2003).
2.3.2 Product involvement in buying decision

2.3.2.1 Definition of product involvement

A major influence on buying behaviour is the degree of involvement the customer has with the product (Shirin and Kambiz, 2011). In general, involvement is described as a state of motivation, excitement or interest. Involvement can be driven by external variables, such as the situation or product (Rothschild, 1984). Lilien and Wong (1981, 1984) suggested that the type of product affects decision-making. The higher the involvement users experience, the more effort they are be willing to invest in their decision-making and search for information (active information search) (Kroeber-Riel and Weinberg, 2003).

When speaking of product involvement, the higher the degree of product involvement, the higher the personal meaning of the product to the online customer. The perceived personal relevance of a product is determined by the needs and values of the persons concerned (Kuss and Tomczak, 2000). Users’ risk perception of making a purchase is the main driver for the degree of product involvement they experience online. The higher the risk perceived by the user, the higher the motivation to search for additional information before making their final purchase decision (Neibecker, 1990; Kroeber-Riel and Weinberg, 1999). Chaudhuri (2000) identified a correlation between the search for information and product involvement. In his analysis, consumers with high product involvement are also likely to have high levels of intention to collect related information online. In a recent study, Lian and Lin (2008) similarly found that product involvement can influence consumer acceptance of online shopping, but that this influence varies according to high and low involvement products.

2.3.2.2 Differentiation of high and low product involvement

Although involvement can be described as a process of continual increase, most studies usually distinguish between high and low levels of involvement (Deimel, 1989). High involvement purchases tend to be purchases that are very important for the consumer. These purchases may entail a financial risk for the
consumer due to a high transaction value. The user experiences a more complex decision-making process in a situation where they have to make a high involvement purchase (Assael, 1995; Meffert, 1992). Consumers typically go through a longer buying process for infrequently purchased, high-involvement products, and consumers in these website categories are typically engaged in a problem-solving task of moderate to high complexity (Bart et al., 2005). These consumers are generally swayed by information coming from other customers (Ha, 2002). Examples of high involvement products include many kinds of electronics and jewelry (Zaichkowsky, 1987).

In contrast, the low involvement purchase is a transaction that is not very important for the customer. According to Assael (1995), the perception of financial risk is substantially lower here than for high involvement purchases. Low involvement purchases involve only a limited decision-making process. A low involvement product is often not evaluated before the purchase decision is made, and sometimes the evaluation takes place only after the purchase process has occurred (Neibeker, 1990; Mühlbacher, 1988). Low involvement products are often mass-produced goods such as beverages or hand creams (Korgaonkar and Moschis, 1982).

2.3.2.3 The impact of product involvement on information behaviour
The level of involvement influences the information search and information processing of the consumer. With respect to high involvement, the customer searches actively and critically for information, while low involvement is accompanied by a more passive search for information (see table 2.1) (Trommsdorff, 1995).

Where user involvement with the product is high, customers will generally collect and use more information during the decision-making process. The cognitive information processing then takes longer time to reach a decision on a product (Deimel, 1989; Bleicker, 1983).
Table 2.1: The impact of involvement on information behaviour

<table>
<thead>
<tr>
<th></th>
<th>High Involvement</th>
<th>Low Involvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information Search Effort</td>
<td>Active information search and analysis</td>
<td>Passive information behaviour</td>
</tr>
<tr>
<td>Processing Intensity</td>
<td>High processing depth</td>
<td>Low processing depth</td>
</tr>
<tr>
<td>Persuasiveness</td>
<td>High persuasive impact</td>
<td>Low persuasive impact</td>
</tr>
<tr>
<td>Reactiveness</td>
<td>Cognitive reaction</td>
<td>No cognitive reaction</td>
</tr>
<tr>
<td>Assessment of Alternatives</td>
<td>Less acceptable alternatives</td>
<td>Many acceptable alternatives</td>
</tr>
<tr>
<td>Social Influence Impact</td>
<td>Lots of social influence</td>
<td>Less social influence</td>
</tr>
</tbody>
</table>

Source: Trommsdorff (1995)

Research by Lin and Chen (2006) has shown that product involvement positively influences the customer’s intention to search for information. Customers with a higher product involvement tend to search for more information and to view the searched information for a longer time. Customers are more dependent on information from other individuals when the product is complicated and when the perceived risk is high (Ha, 2002).

2.3.3 Product classification in online shopping

2.3.3.1 Definition of search and experience products

Whereas involvement is based on the customer’s perception of a product, this classification is based on the attributes of the product itself. Nelson (1970) developed a theory of the consumers’ ability to obtain information on product attributes, and classified products into two categories, search and experience products, depending on the benefits the consumer sought from the product. According to Nelson (1970), search products are those for which consumers have the ability to obtain information on product attributes prior to purchase. These are products such as shoes or household furniture (Leahy, 2005). Experience products, on the other hand, are products with attributes that require sampling or partial purchase in order to evaluate the product quality. Examples
of experience products include automotive parts, cameras and beauty and health products (Huang et al., 2009). Hence, consumer information behaviour will differ depending on whether the product is a search or an experience product.

The classification of products is often necessary and very important, with research showing that there is a change in online consumer decision-making behaviour when consumers are dealing with different levels of product complexity (Bhatnagar et al., 2000; Huang et al., 2009; Keisidou et al., 2011; Dai et al., 2014). Consider a vendor of books versus a vendor of medical products. A vendor of medical products should be more concerned about competence than a vendor of books for the simple reason that the risk from lack of “performance” is higher for the medical product consumer. The quality of books can be assumed to be consistent across B2C e-commerce companies (Smith et al., 1999). However, there might be some heterogeneity with respect to the quality of, e.g., medical or beauty mixtures, because product variability across manufacturers may be possible, meaning that the quality levels of different units of the same product may likewise differ (Roberts and Urban, 1988). This circumstance adds to consumer uncertainty (Erdem et al., 2004) and raises a problem for online consumers, as they cannot be sure of the quality of the product that is purchased in the online setting.

Following from the definition of product involvement and Nelson’s product classification, the degree of product complexity for online customers in this study depends on:

- Perceived personal relevance for the consumer
- Quality attributes of a product
- Product composition
- Technical features of a product
- Higher prices (in many cases product complexity involves the aspect of product costs, as products with many functions are more expensive than those with less)
There is no real definition for product complexity in the existing literature. In this study, the characteristics listed above will determine whether the products are of higher or lower complexity. The higher the personal relevance, the transaction value (price in EUR), and importance of product quality and technical features, for example, the greater the product complexity.

As for the online context in this study, a further product classification by Weathers et al. (2007) is worth mentioning. According to Weathers et al. (2007), seeing and touching a product, rather than reading manufacturer-provided information about product attributes, is a more adequate way to distinguish between them. This means that it is better for customers to examine complex products personally, while reading about the products’ attributes online usually suffices for products of lesser complexity.

2.3.3.2 Information search for search and experience products
Huang et al. (2009) found that consumers who look for experience products (higher product complexity) will view fewer pages but spend more time per page before purchasing than those looking at search products (less product complexity). Additionally, communication mechanisms, such as consumer feedback and experience simulation (i.e., consumer reviews, multimedia, etc.), increase the time spent in a domain, but only for customers looking at experience products. Schlosser (2003), for example, has demonstrated that an interactive presentation of product features leads to an increase of purchase intentions for digital cameras. Furthermore, a study by Bei et al. (2004) revealed that online information sources from other customers were used more often by buyers of experience products. These studies confirm that the level of involvement will influence the information search and information processing of the online customer. Based on the study results above, experience products require more information and social influence and can be seen as high involvement products. Low involvement products, in contrast, are accompanied by a limited decision-making process (Assael, 1995). For the most part, the product information on the vendor website is enough for search products and there is less need of social influence information from former customers (Bei et
al., 2004). Due to the “intangible” nature of online transactions, users may be uncertain about product functionality and quality. However, a well-designed website of an online store can provide much richer information in the form of expert opinions and consumer feedback than would be possible for a traditional retail shop to offer (Klein, 1998). Likewise, consumers searching for cameras can read feedback from other consumers, and thus can improve their “experience” of these products before actually making a purchase. Search attributes, such as price and performance metrics, are objective, diagnostic, and easy to compare on the Internet, whereas experience attributes, such as how easy or convenient a camera is to use, are inherently subjective, characterised by uncertainty and difficult to evaluate (Mudambi and Schuff, 2010). Such product uncertainty constitutes a dimension of risk for customers (Weathers et al., 2007).

Several researchers (Klein 1998; Weathers et al., 2007; Huang et al., 2009) are of the opinion that the Internet, with its increasing interactivity and communication, minimises the differences of risk perception between search and experience products. In particular, studies have shown that the Internet reduces the cost of gathering and sharing information (Bakos, 1997; Lynch and Ariely, 2000) and offers new possibilities to receive detailed information about products before a purchase (Lynch and Ariely 2000). However, in online shopping search products tend to have lower intangible characteristics and can be evaluated based on product descriptions on the website. For these products an actual test is not necessary.

Experience products, that mostly have technical features or affect the body or health of the customer, rely on actual check and therefore evoke a higher perceived risk when traded in the online environment. Due to these differences in search and purchase characteristics between search and experience products, Huang et al. (2009) emphasise the need for differences in website design for the two product types. For experience products, consumers benefit from more complex and informative websites that incorporate multimedia presentations and consumer feedback to illustrate product features. Vendors of
search products may benefit more from strategies that enable them to sell at lower cost than from informative websites (Huang et al., 2009).

2.3.4 Information asymmetry in the online buying decision process
An e-commerce situation taking place in a virtual environment is still more prone to uncertainty than the traditional setting for economic transactions. The previous chapter has shown the importance of searching for information by online customers. Unfortunately, customers often have to act on information that is less than complete and, as a result, some risk is always present in their purchasing decisions (Kim et al., 2008). Online trade partners have limited information about each other’s reliability or the product quality during the transaction. Because of this uncertainty regarding the product quality, Akerlof (1970) calls the World Wide Web (WWW) a “Lemons” market. The main problem pointed out by Akerlof, and later developed by other researchers such as Ba and Pavlou (2002), Ba et al. (2003), Dellarocas and Wood (2008) and Ghose (2009), about such markets is the inherent information asymmetry between the customers and vendors. In the research projects cited above, asymmetric information means that the trading partners do not have the same information about the product. For the customer, the true quality of the product is mostly unknown. In addition to the uncertainty associated with the product quality, the anonymous identity of the trading parties is also a major concern, and is closely related to online fraud (Chau et al., 2006).

Under conditions of information asymmetry, customers find it difficult to distinguish between high and low quality. Even if buyers try to pre-contractually assess vendors and product qualities, a true inference can only be made after the purchase has been completed and delivered. In many cases, customers must make a decision at the time of purchase without having access to all of the information (Huston and Spencer, 2002). Gefen (2000) adds that the extent to which a consumer is willing to commit to an online vendor is dependent on the complexity of the product under consideration.
While quality attributes of a search product, such as a particular book, can be assumed to be consistent across the various online vendors, there is considerable heterogeneity with respect to the quality attributes of the complementary goods such as service and delivery (Smith et al., 1999), as well as with respect to experience products such as a camera, for which the quality is difficult to observe in advance (Hunag et al., 2009). Hence, information asymmetry remains an issue in the B2C e-commerce market (Bakos, 2001). In this context, a decision for a first time purchase at an unknown online store is always attended by a certain degree of risk for customers. In comparison to traditional shopping, an online setting generally hinders customers from using social cues such as physical interaction and body language to further assess characteristics of vendor quality (Chau et al., 2006). When Internet vendors understand that risk and trust have direct relationships with the willingness to purchase (McKnight et al., 2002; Gefen and Straub, 2003), they might minimise the risk and maximise trust to improve online purchases.

2.4 Risk perception
As mentioned above, researchers (McKnight et al., 2002; Gefen and Straub, 2003; Dai et al., 2014) emphasise the important role of risk in online transactions. The following section describes the theory of perceived risk and defines risk itself. The concept of perceived risk is frequently discussed in marketing literature, and various types of risk have been identified. For this study, product risk and financial risk, among others, are brought into focus, as analyses are here carried out on three different product categories with different transaction values (average price) in order to determine any differences between these categories concerning risk evaluation (checking the feedback profile), purchase behaviour and post-purchase behaviour (submitting feedback).
2.4.1 Risk theory

“A consumers' perceived risk is an important barrier for online consumers who are considering whether to make an online purchase” (Kim et al., 2008, p.546). Internet users perceive risk in the purchase decision-making process, regardless of the nature of their reasons for making a purchase (planned versus impulse) (Chu and Li, 2008). As already mentioned in 2.3.4, online users often act on information that is incomplete, which entails that there is always some degree of risk present in their purchasing decisions (Kim et al., 2008). Risk has been conceptualised as the product of two dimensions: Researchers generally agree that consumers must understand that a perceived risk is a combination of an unfortunate event with a consequent loss. Should such an event occur, it needs to be corrected (Kaplan et al., 1974; Lopes, 1995; Garbarino and Strahilevitz, 2004). Adverse consequences may vary between product categories (Dowling, 1986). In the context of online purchasing, if perceived risk increases, it serves to decreases consumers’ willingness to carry out online transactions. Based on the information presented, it is assumed that increased information will decrease perceived risk. In this thesis, the author defines perceived risk as a consumer's awareness of the potential uncertain negative outcomes (that something goes wrong and leads to a financial loss) stemming from the online transaction activity.

Studies of perceived risk have focused on various aspects of consumer behaviour related to newness, including, e.g., the purchase of a new product, the diffusion of new product information (Yao et al., 2009), and the selection of a new store (Lee and Lee, 2006). Most studies from this stream show that people tend to engage in risk evaluation activities such as reviewing feedback (Ba and Pavlou, 2002; Pavlou and Gefen, 2004; Lee and Lee, 2006). Consumers tend to avoid transactions that seem to increase perceived risk. Furthermore, risk is of greater concern to potential customers considering an online purchase than it is for repeat customers (Kim and Gupta, 2009).
2.4.2 Types of risk in online transactions

Risk is a multifaceted concept (Bhatnagar et al., 2000). Scholars of risk have identified various types in the context of e-commerce. The first risk under consideration here is the economic risk, also known as financial risk. Consumers have to rely on electronic information and are afraid of losing money while performing online transactions (Kuisma et al., 2007). A financial loss may occur due to credit card fraud, which is a primary financial concern among online customers (Bhatnager et al. 2000; Andrews and Boyle, 2008). In the event of such an occurrence, the customer not only loses money but also control over the private information required for the transaction.

Another type of risk, as defined by Forsythe and Shi (2003), is time risk, which refers to the time and effort that the potential buyer is likely to waste as a result of engaging in an online shopping activity involving a particular type of product. This type of risk covers both the time the consumer needs to use a product and the time the fund transfer requires when a product does not perform as expected (Featherman and Pavlou, 2002).

The worry that a product will not perform to expectations leads to product or performance risk. Product risks refer to situations in which the product purchased from an online store does not function, or its functionality does not conform to the product descriptions offered by the vendor (Peter and Tarpey, 1975; Featherman and Pavlou, 2002; Dai et al., 2014). In contrast to offline purchases, the potential online customer cannot touch, feel or test the product before deciding whether or not to purchase it.

Another important type of risk is the physical risk involved when buying products that affect the customer’s own body and health. If such products fail, they can be injurious to the customer (Roselius, 1971; Ko et al., 2004).

The above mentioned types of risk are those most often cited in studies on perceived risk in online transactions (Featherman and Pavlou, 2002; Cho, 2004; Ko et al., 2004; Chu and Li, 2008; Zheng et al., 2012; Dai et al., 2014). Financial, product, physical and time risk have also been chosen because these
types can be almost measured without asking for customer attitudes and opinions, by observing the actual purchasing behaviour of different products via transaction data logs coming from a database.

The findings of Dai et al. (2014) show that the impact of risk perceptions on purchase intention differs according to the types of risk or product categories. However, Chu and Li (2008) concluded from their study that customers perceive similar risks (product performance, financial loss, time-consuming, transaction security) regardless of the product type (search and experience products) when purchasing online. Nevertheless many studies have emphasised the need for the inclusion of product categories in order to generalise the multifaceted concept of perceived risk (Dowling, 1986; Dowling and Staelin, 1994; Stone and Gronhaug, 1993; Sweeney et al., 1999).

When looking at the different types of risk it becomes obvious that they are linked with one another. This means, e.g., that the financial dimension of risk automatically evokes product risk, and vice versa. Caterinicchia (2005) draws a similar conclusion when reporting that online customers fear financial losses (financial risk) if products purchased online fail to perform as expected (product risk). Both financial risk and product risk have shown significant negative influences on user’s willingness to purchase online (Forsythe and Shi, 2003; Bhatnagar and Ghose, 2004; Lu et al., 2005). Ha (2002) argued that the loss of money is an important consideration. When there is the possibility that the product may need to be repaired or replaced, or the purchase price refunded, financial risk is said to be high. Overall, financial risk has been negatively associated with online shopping (Bhatnager et al. 2000; Chang et al. 2005; Forsythe et al. 2006) and found to be a strong predictor of customers’ online shopping intentions. Liljander et al. (2009) researched perceived risk in the offline setting and concluded that a positive store image (store brand products and return policies) significantly helps to reduce consumers’ perceived financial risk.

Zheng et al. (2012) discovered in the course of conducting research on the chinese online market for clothing that, in addition to financial risk, time risk is
also important to online customers. In contrast to traditional shopping, consumers may lose time by researching and making the purchase, waiting for the delivery, or learning how to use a product only to have to replace it if it does not perform as expected. Bellman et al. (1999) propose that online consumers are very time oriented and concerned about the time they have to waste before they can actually use the product (Featherman and Pavlou, 2002; Zheng et al., 2012).

The above findings provide evidence that each risk type involves concerns that the product might not perform as expected. This is the reason that the performance or product risk associated with the product is ranked as the foremost dimension of risk (Zheng et al., 2012). Mitchell (1998) regards performance/product risk as the surrogate for overall perceived risk. For the customer it is important that the right product is sent to the right place, and that it is in working order when it arrives. If this is so, then financial risk and time risk automatically decrease. Performance/product risk also has an influence on the physical risk. It is important to know how safe the product actually is (Roselius, 1971; Kaplan et al., 1974).

It is suggested by Cho (2004) that it is useful to identify the significance of risk perceptions, as this can provide a more detailed insight for vendors into what needs to be done to reduce certain risk perceptions. Instead of treating risk as a unidimensional construct, this study attempts to examine perceived risk as a multidimensional factor (financial, product, time and physical risk) as suggested by Bhatnagar et al. (2000). Many studies fail to recognise the fact that the impact of perceived risk may differ for different categories and measure this construct without accounting for the effect of various product categories (e.g. Lee and Lee, 2006; Lim et al., 2006; Kim et al, 2008; Duan et al., 2008). Therefore, this study considers the impact of different product categories. The next section describes what characteristics of a product entail that it may present a risk to a potential customer.
2.4.3 Characteristics of products entailing risk
According to Bhatnagar et al. (2000), product risk is very present in online shopping. Since the potential online customer is not in a position to physically examine and test the product, some product categories evoke a higher level of risk than other categories (Garbarino and Strahilevitz, 2004). According to Bhatnagar et al. (2000), the risk is greatest when the product has the following characteristics: technological complexity, high price, or the satisfaction of ego-related needs (i.e., higher product involvement and products whose consumption is observable by others). While the risk of buying a book or software program (search products) is not very high, it is likely to be higher for stereo equipment or computers (experience products). A study by Tsiros and Heilman (2005) on grocery store products concluded that perceived risk is not significant because groceries are not considered as “status” goods, nor are the transaction values (prices) very high (Tsiros and Heilman, 2005). The examples given above show that product risk is often linked with financial risk.

Past research shows that more interactive purchases take place in product categories such as fashion. Here material and sizing are important, and there is a risk that the product characteristics, such as colour, material or size, are not what the customer expected. As already mentioned above, some products evoke more risk perception than others. In the case of brick-and-mortar retail stores, consumers can experience (touch and feel) the product before deciding whether or not to buy it. This personal experience automatically reduces the perceived risk. In contrast, when purchasing from an online store a customer can only hope that the transaction will be processed completely and accurately (Kim et al., 2008). In most cases, he or she has to wait for days until the product is delivered and the transaction completed. The inefficiencies resulting from such information asymmetry can be mitigated through trust and reputation (Jøsang et al., 2007).
2.5 Trust

E-commerce has always been faced with many challenges. Among the problems involved are difficulties in converting regular web page visitors into active customers. One fundamental factor to consider regarding this sector is the level of trust that exists between the vendors and their potential customers. This is one of the instrumental factors that define the success of any e-commerce activity. According to Arrow’s (1974) argument, trust is the instrument that enables healthy business cooperation between both the parties involved in any business transaction, and this is especially so for e-commerce. As the previous chapters have shown, online shopping always involves a level of risk for the consumer. When the risk increases that the vendor may not act as expected, the importance of trust increases (Swan et al., 1999). Therefore, trust and risk are important factors in predicting B2C e-commerce acceptance as demonstrated by Pavlou (2003).

Trust has been defined in many ways throughout the research literature. This thesis focuses on an initial customer-vendor-relationship, entailing that the user is still unfamiliar with the vendor and that his or her perceptions of risk concerning the vendor are particularly salient (McKnight et al., 2002). Many definitions for trust in a customer-vendor relationship have been proposed in the marketing literature. Ganesan (1994) suggests a definition of trust (for a customer-vendor relationship) with two different components: (1) cognition and (2) affect. The following section will introduce and define cognitive and affect-based trust.

2.5.1 Trust definitions in a customer-vendor-relationship

2.5.1.1 Cognitive trust definition

Cognitive trust (Rotter, 1971) refers to the positive expectations of the trusting party towards the trustee. Mayer et al. (1995, p. 712) define it as “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.” These definitions indicate that trust is perceptual, involving a subjective interpretation or a belief by one party regarding another. Sirdeshmukh et al.
(2002, p. 17) describe consumer trust as “the expectations held by the consumer that the service provider is dependable and can be relied on to deliver on its promises.” They specify the assumption of reliability while expecting that they can rely on the delivery promises of the vendor. Trustworthiness is based on the belief that the vendor possesses the required expertise to perform reliable and effective work. Reliability is defined as the attainment of the required result. Hence, trust is based on the competence and reliability of the transaction partner, which determines his/her objective trustworthiness (Ganesan, 1994).

Kim et al. (2008) have shown that cognitive trust in the online world can be established by displaying accurate and complete information on a vendor’s website, as well as by privacy and security protection in the form of policies and authentication practices.

2.5.1.2 Affect-based trust definition

According to Luhmann, trust can only occur in a social context, and thereby becomes irrelevant in a situation where ‘real’ people are absent (Luhmann, 1979). An electronic machine, for example, has no will of its own and therefore cannot be expected to willingly fulfil its commitments. For example, one can trust a bank clerk with whom one interacts, but it is meaningless to attribute such trust to an ATM machine even if it does exactly the same job.

According to McAllister (1995) trust is affect-based only when an emotional relationship between two individuals exists. While cognitive trust involves the aspect of reliability (the customer is convinced that the vendor possesses the requisite competence and motivation to rely on him), affect-based trust refers to the feeling of being certain or uncertain when relying on the vendor.

According to Swan et al. (1999), a customer’s trust of a salesperson partakes of both components, affective and cognitive.
2.5.2 Trust in online transactions

This thesis focusses on the trust between online customers and online vendors with their own B2C online store. The customers have no prior experiences with the vendor and no possibility to build trust on the basis of interpersonal experiences. In MIS literature, researchers (McKnight et al., 2002) speak of initial trust. Initial trust is particularly critical to the success of a vendor in attracting potential customers, and so vendors need to engender sufficient trust at the beginning in order to minimise consumers’ perceptions of risk and thereby persuade consumers to transact with them. Customers visiting an online store for the first time heavily rely on website cues to form their initial trust beliefs (McKnight et al., 2002).

In the context of e-commerce, there is no universally accepted definition of trust, or ‘e-trust’, but rather several different competing definitions (for example Gefen, 2000; Ba and Pavlou, 2002; Pavlou, 2003; Pavlou and Gefen, 2004). According to Gefen (2000), trust is the confidence a person has in his or her favourable expectations of what other people will do, and it is mostly based on previous interactions. However, the previous behaviour of the transaction partner cannot guarantee that they will behave as one expects.

According to market research conducted by Quelch and Klein (1996), trust has been determined to be a factor in boosting sales as well as a weapon that can be used to lure more regular Internet visitors into becoming active customers. They argue that the secret behind convincing their target customers into becoming actual buyers is giving them a reason to be able to believe in the vendors’ ability to keep their word and adhere to the agreements made between them and the customers. Gefen (2000) is of a similar opinion, but adds that the level of customers’ commitments to vendors and their willingness to go ahead conducting business with them depends on the cost involved, which, in turn, is a function of product complexity. Each consumer who visits an online store has different needs and intentions. Nevertheless, whether their intent is just to search for information about a certain product or purchase the product that fulfils their needs, it all depends on the level of trust built during their visit to the online store (Urban et al., 2000).
IS researchers (McKnight et al., 2002; Jarvenpaa et al., 2000) view trust as a general belief about an online vendor, i.e. that the trustee can be trusted. Brynjolfsson and Smith (2000), Resnick et al. (2000), McKnight et al. (2002) and Ba and Pavlou (2002) have all demonstrated that trust is crucial for e-commerce, often due to the impersonal nature of online transactions that occur between entities that have never met before. It is a very important factor in the success of online vendors. Trust is critical, especially when the transaction is not immediate and physical (Shin, 2008). Online transactions, in contrast to offline purchases, are more impersonal, anonymous and automated (Head et al., 2001).

This study adopts the definition of Gefen (2000), who states that trust is the confidence a person has in the expectations of what other people will do, and that this confidence is mostly based on previous interactions. A feedback system that reflects the vendor behaviour gives an idea of what a potential customer who is planning to purchase one of the vendor’s products can expect. Like Resnick and Zeckhauser (2002), the author of this study asserts that trust is fostered by the use of a feedback system. Furthermore, as Ba and Pavlou (2002) reported in their study, positive feedback is associated with greater trust in a vendor. For this study, this means that trust can be defined as the presence of positive reviews of the vendor within a feedback system. Credibility, as one dimension of trust, demands that the vendor is doing the job honestly and reliably, thereby fulfilling the customer’s expectations. This form of trust is mostly impersonal and relies on information coming from a trust-building strategy (Ba and Pavlou, 2002). A trust-building strategy will be introduced later in the section on online feedback.

According to Ba and Pavlou (2002), there is a further type of trust, which they call benevolence. Benevolence develops over the course of repeated buyer-seller relationships. The vendor and customer believe that each partner is interested in the other’s welfare and has motives and intentions beneficial to the other even under adverse conditions. This type of trust cannot be applied to many B2C-e-commerce transactions, since impersonal one-time transactions are often made and each partner must simply assume and hope for honesty.
and reliability of the other party (Brown and Morgan, 2006). Benevolence does not readily apply to the context of this study since it requires familiarity and prior interaction.

Trust in B2C e-commerce is established in a different manner than it is in business-to-business (B2B) e-commerce environments. Relationships in B2C environments are often shorter, of relatively lower value and orientated more towards the single transaction (Roy et al., 2001). It is difficult to think about exchange relationships, which are not based on trust in the other party (Salam et al., 2005). In the marketing literature, researchers studied trust both in terms of trust in the salesperson and in terms of trust in the seller organisation (Doney and Cannon, 1997). When the salesperson is absent from the buying process, as is generally the case with online stores, then the primary target of the consumer’s trust is the vendor of the online store (Lohse and Spiller, 1998). In such situations, the feedback mechanism becomes the main carrier of trust.

Several studies have looked at possible mechanisms to explain the relationship between trust and purchase intention in online stores (e.g. McKnight et al., 2002; Gefen and Straub, 2003). Kim et al. (2008) show that trust addresses the problem of risk in the online world in two ways: by reducing perceived risk, and by increasing purchase intentions. The present study aims to extend the understanding of the topic by analysing the relationship between trust in the form of positive feedback and the actual purchase. Positive feedback allows for the building of trust, which is then associated with a lower perceived risk of shopping in the online store (Kim et al., 2008). Especially those customers visiting an online store for the first time, as is the case for the customers in this study, rely on website cues such as feedback. As already seen in the chapter on risk, the factor of trust is influenced by the transaction costs of a product, which is itself usually a function of product complexity. This means that in order to convert online visitors into online customers trust will potentially play a more crucial role for experience products than for search products.
2.5.3 Vendor trustworthiness

It is vital for online vendors to help their potential customers to overcome risk by establishing the trustworthiness of their websites and of the Internet as a medium for transactions, particularly in initial customer-vendor-relationships (Shin, 2008). Many studies consider the perceived trustworthiness of a vendor as often being an important antecedent of trust (Lee and Turban, 2001). Mayer et al. (1995) looked at prior studies of trust and identified three frequently cited attributes of the trustworthiness of a trustee. The three attributes, illustrated in figure 2.2, are ability, benevolence and integrity. Ability relates to the skills, competencies and characteristics of the trustee. This suggests that the vendors’ products are of good quality. Benevolence, as already mentioned, is related to repeated buyer-seller relationships in which both the vendor and buyer have the intention to conduct transactions that satisfy the other party. Integrity refers to the consistency of the vendor’s former reliability in terms of credible communications. A customer feedback system reveals how well the vendor represents ability/competence and integrity.

Figure 2.2: Three principal dimensions of vendor trustworthiness

![Three principal dimensions of vendor trustworthiness diagram]

Source: Julia Bartels in accordance with Mayer et al. (1995)

Pavlou (2003) shows a positive impact of user trust on their perceptions in regards to the usefulness and ease of use of the web for commerce. The more
consumers trust a website, the less effort they have to invest to scrutinize the content of the site to assess the benevolence of the merchant. On a trustworthy site, where customers assume the benevolence and competence of the online vendor, they will not waste time and cognitive effort reading the privacy policy, the terms of use, and the conditions of sale, and thus will experience higher ease of use (Shin, 2008).

A study by Lynch et al. (2001) of 299 consumers across 12 countries in three broad regions of the world (North America, Western Europe, and Latin and South America) indicates that the critical factors that affect customer’s online purchase intention and loyalty are quality and trust. The study further reveals that the trustworthiness of an online store has a positive impact on purchase intention. Consequently, online stores have to take into consideration the importance of producing trust by providing mechanisms such as service guarantees, privacy policies, third parties and customer testimonials.

2.5.4 Trust transference theory
Andaleeb (1992) looked at the various aspects of trust transference. He wanted to identify any differences in attitudes and behaviours of the focal party when trust is transferred (e.g., when someone else says that member A is trustworthy or untrustworthy) compared to when trust is actually experienced. Much of our everyday decision-making is based on recommendations and feedback from others. Andaleeb (1992) presumes that trust is only transferable when the party providing the recommendation is trustworthy. Doney and Cannon (1997) claim that the trust-building transference process allows customers to trust vendors based on information they receive from other customers. To a potential customer, accordingly, other past customers are essentially trusted third parties insofar as they have nothing to gain by providing inaccurate feedback on vendors. In their empirical research they were able to prove this positive effect. Therefore, provided that other customers generally trust the vendor, this trust can be transferred (Stewart 2003). In the context of this study, the above finding allows for the assumption that a customer’s initial trust in the online vendor may be influenced by the online feedback of past customers.
In a study of over 130 students who acted as online shoppers in a book store, Lim et al. (2006) observed that when potential shoppers see the extent to which other customers trusted the online store, they would transfer their trust of the satisfied customers to the online vendor. Potential consumers trust those customers who are similar to themselves and who have bought from the same store. Thus, customer feedback is among the critical “social information” that assists in making purchase decisions by reducing risk and developing trust (Yao et al., 2009).

2.6 Online feedback system

2.6.1 Definition of online feedback systems

Online feedback systems provide a type of ‘word-of-web’ that transaction participants use to exchange information and opinions in order to reduce risk (Weinberg and Davis, 2005). Scholars (Ba and Pavlou, 2002; Resnick and Zeckhauser, 2002; Livingston, 2005; Lee and Malmendier, 2005) believe that a critical reason for the success of online auction sites such as eBay is the use of online feedback as a reputation system that helps sustain trust in online markets. This is in accordance with Shankar et al. (2002), and similar ideas are also documented by Wang and Emurian (2005).

Online customer feedback can be defined as a type of information on a product or service that is created by consumers based on personal usage experience (Chen and Xie, 2008). Helm and Günter (2000) define customer feedback as the negative or positive reporting of customers in their private and/or business environment on the objective and/or subjective perceived quality of the vendor’s performance. Stauss (2000) speaks of “Internet customer communication” as occurring when “customers report/interact about consumption-relevant circumstances on the Internet“ (p. 243). Hennig-Thurau et al. (2004) created the term “eWOM communication”, which means any positive or negative statement made by customers about a product or vendor that is made available to the public via the Internet.
One of the most important capabilities of the Internet is its bi-directionality. Through the Internet, not only can companies reach audiences of unprecedented scale at a low cost, but individuals can make their personal opinions and reactions easily accessible to other Internet users as well (Resnick et al., 2000).

According to Langner (2007), for a customer to give feedback it is necessary for them to have had an intensive individual interaction with the recommended product or service. This is an important thing to remember for online vendors when they try to determine the right moment to gather feedback from the customer. It would be disadvantageous to send it directly after the order is placed, because the customer has not yet had the possibility to assess the quality of the product and/or service.

Dellarocas (2003) claims that feedback mechanisms are poised to have a much wider impact on Internet vendors. Their growing popularity in times of social commerce might have important implications for management activities, such as reputation and brand building, customer acquisition and retention, product development, and quality assurance (Dellarocas, 2003).

Online feedback mechanisms are only effective if the participants believe that the feedback is an accurate and credible depiction of the online store. An effective feedback mechanism should act as an informal buyer-driven certification system for an online store (Pavlou and Gefen, 2004). Online feedback systems are a helpful mechanism to overcome information asymmetry (Wang et al., 2005).

The design of consumer feedback sites varies. Table 2.2 below shows possible designs of feedback systems. Websites can choose to integrate quantitative rating schemes, such as the star ratings used to assess hotel sites, qualitative free-response user feedback or a combination of quantitative and qualitative evaluations. eBay’s feedback system, for example, allows buyers to evaluate different criteria such as communication, item description, delivery time and delivery costs, and also provides an opportunity for the customer to leave a
short comment either to praise the seller for having provided good service or to punish the vendor for having provided bad service (Gerdes et al., 2008). Some other online vendors choose to buy customer reviews from Amazon or other sites and post the reviews on their own online storefronts (Mundambi and Schuff, 2010).

Table 2.2: Design of online feedback systems

<table>
<thead>
<tr>
<th>Design of Online Feedback</th>
<th>Utility</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>One-dimensional</strong></td>
<td>One scale (5 points) to rate the object</td>
</tr>
<tr>
<td><strong>Multi-dimensional</strong></td>
<td>Feedback consists of more than one mark. Different criteria can be rated, such as service, delivery time, product quality</td>
</tr>
<tr>
<td><strong>Supplement</strong></td>
<td>Feedback written by the customer in a comment box</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

Three different customer feedback environments can be identified for the various designs of online feedback systems:

1. In the corporate environment:
   In the corporate environment, reviews are meant to be expressed in a feedback system, which are displayed on the product page or on the page on which the purchase takes place. This includes feedback systems of manufacturers, as well as feedback systems of the vendors of products and services.

2. Within feedback portals:
   These are reviews that are published on websites that specialise in the supply of infrastructure for the preparation and organisation of feedback, such as HolidayCheck.de, epinion.com or tripadvisor.de.
3. On independent content platforms
This means feedback, which is expressed locally in the Internet on various external platforms, such as weblogs, wikis, forums, and social networks, or on own websites.

2.6.2 Characteristics of online feedback
What makes online feedback mechanisms different from previous forms of offline feedback is the combination of (1) their originality scale, achieved through the exploitation of the Internet’s low-cost, bipolar communication capabilities, (2) the possibility to control and monitor feedback, and (3) new challenges introduced by the characteristics of online interaction, such as the frequently changing nature of anonymous online identities and the almost complete absence of face-to-face communication that would aid in the interpretation of what is merely subjective information (Dellarocas, 2003).

The scope of spreading information is essential to the effectiveness and success of feedback systems. In an online marketplace, for example, vendors care about customer feedback, because they believe that feedback influences purchase behaviour, and hence, potentially, their future sales. This can only happen if enough feedback is submitted and communicated to a significant number of potential customers. Theory predicts that a minimum degree of feedback participation is required before reputation effects can induce any cooperation (Bakos and Dellarocas, 2002). The acceptance of feedback mechanisms is, therefore, an arrangement that promotes the success of vendors and online stores with a good reputation and hinders those with a negative feedback record.

The Internet allows for precisely measuring and controlling customer feedback through proper engineering of the information systems. A properly developed feedback system enables writing and reading online feedback and saves the data in a database. Designers or IT experts of such automated feedback systems specify who can participate, what type of information is required from customers and how it is collected and made available to the public. Through the
design of these online feedback systems, vendors can exercise control over a number of parameters that are difficult or impossible to influence in brick-and-mortar settings (Dellarocas, 2003).

The anonymous nature of the online environment presents some challenges related to the interpretation and use of online feedback. Brick-and-mortar settings have the advantage of being able to provide personal relationships, which means that customer and vendor are face to face, thus making it easier to interpret the opinion of the salesperson based on facial expression or familiarity. In the online environment most of these cues do not exist (Kim et al., 2008). Consequently readers of online feedback have to evaluate the opinions of complete strangers and to base their trust on their anonymous feedback. Furthermore, the nature of online feedback mechanisms makes it difficult to discern the trustworthiness of their operators (Dellarocas, 2003).

2.6.3 Online feedback participants

Customer feedback on a website has the potential to attract consumer visits, increase the time spent on the site ("stickiness") and create a sense of community among frequent customers (Mundambi and Schuff, 2010). Through customer feedback systems, feedback participants have the ability to let potential customers hear about their experiences with a product or service. In this way, the opinion of an individual can influence the behaviour of other customers (Dellarocas, 2003).

It is important to draw a distinction between social networks and participants of B2C feedback systems. Although customer feedback systems are associated with social influence and support the active participation of users on the website, this alone is not sufficient justification for comparing feedback participants with participants of social networks. The following section will attempt to demonstrate the difference between the two terms.

Several authors have defined a social network as being the point at which a computer network connects people (Wellmann, 1996; Kiesler et al., 1984;
Adamic and Adar 2005). In a social network, the focus lies on bringing people together. In such networks users can exchange information by sending messages via the Internet. A social network service focuses on the building of social relations among people who share the same interests and activities. Online social networks such as Facebook and Twitter essentially consist of a representation of each user, often through a profile, and a variety of additional services that are completely organised around users (Mislove et al., 2007).

Online customers participating in an online feedback system give their opinion about the same online vendors and their products. Hence online feedback participants in an online store are organised around one content. Furthermore, a feedback submission is mostly bound to a transaction.

2.6.4 Risk evaluation and trust transference in online transactions

As the previous sections have clarified, risk and trust are interlinked (McAllister, 1995), with both being based on perceptions (Hawes et al., 1989). In online transaction activities, there is always a residual risk. Online vendors have considerable influence on the variables of trust and risk. Through the implementation of a feedback system, online vendors can show their trustworthiness and mitigate risk at the same time (Pavlou, 2003). In assessing certain risks, consumers can look to the feedback of others to make up their minds and to establish a level of trust (Rao et al., 2001). Thus, trust-inducing features stimulate customer behaviour (Jarvenpaa et al., 1999; Karvonen, 2000; Kim et al., 2008).

Purchasing decisions are often strongly influenced by people who the potential customer knows or trusts (Kim and Srivastava, 2007). Empirical results emphasise the importance of trust and risk for explaining and predicting online purchase behaviour (Jarvenpaa et al., 2000; Van der Heijden et al., 2003). Customer feedback provides a means to learn about the experience of others. Potential customers form a level of trust according to the proportion of positive and negative experiences. This developed trust is an important predictor of the willingness to purchase a product (Godes and Mayzlin, 2004; Chevalier and
Mayzlin, 2006). A feedback system is based on the active participation of the customer and the communication of customers among themselves (Bauer et al., 2007). The output of these interactions is the trust that the next customer is looking for when purchasing products or services online (Decker, 2007; Moreno and Terwiesch, 2014).

Most online stores encourage customers to submit feedback. In order to capture data on customer feedback, vendors have to change their websites from a place that just sells products to a place that offers a kind of community as well as a product. Customer feedback, as an indirect interaction with the vendor, establishes a kind of affect-based trust (Kim et al., 2008). The interactivity is formed by consumers who purchase at the same store and share experiences or opinions about the product and the service of the store. Figure 2.3 shows that during the information search, and prior to evaluating the risk, consumers are motivated to gather information, such as feedback from previous customers, in order to satisfy their unmet need (Lim et al., 2001; Dellarocas, 2003). After the evaluation, consumers typically decide to buy. However, consumer behaviour does not stop there. Customers experience certain levels of satisfaction or dissatisfaction and tend to express their opinions in the form of feedback to others (Taylor, 1991). Again, this submitted feedback is helpful for potential consumers who want to learn more about the vendor’s reputation and associated products. The additional feedback stages build the potential for trust transference and are important because the success in B2C e-commerce depends not only on user acceptance of Internet technologies as feasible for transactions, but also on user recognition of online vendors as trustworthy salespersons (Pavlou, 2003). Insofar as the experiences submitted by customers in the form of feedback might affect the future decision-making processes of other customers, “decision-making is a cycle of feedback activities” (Chu and Li, 2008, p. 215).
Figure 2.3: Consumer decision-making in the online store

There are studies that confirm the critical role of prior feedback in shaping the customer perceptions of unfamiliar online stores (Lee and Lee, 2006). In online stores, positive customer feedback is used to build trust in the store. An online questionnaire (n= 1008) conducted by ECC (2012(a)) points out that 72% of the respondents admitted that they would have more trust in an online shop with a customer feedback system. Three quarters of them stated that they would rather purchase in a shop that has received positive feedback and is therefore more trustable (see figure 2.4).

Figure 2.4: Impact of trust on potential online customers

Source: ECC (2012(a))
Standifird (2001) examined consumer feedback to eBay sellers of 3Com Palm Pilots, and found that sellers with positive feedback ratings generated more sales than those with negative ratings. Ba and Pavlou (2002) confirmed that sellers with better ratings enjoy greater consumer trust and trustworthiness. Melnick and Alm (2002) analysed eBay sellers of 1995 U.S. $5 gold coins, and likewise confirmed a positive relationship between feedback and sales. Taken together, these studies, which have focused on the eBay marketplace, have examined how sellers’ reputations based on feedback can improve their future sales. Their findings generally support the view that online feedback profiles can influence customers’ behaviour and future sales (Resnick and Zeckhauser, 2002; Livingston, 2005; Lee and Malmendier, 2005). This is in accordance with arguments by Güth et al. (2006) and Cabral and Hortacsu (2010). Chevalier and Mayzlin (2006) and Duan et al. (2008), moreover, confirmed a positive influence between feedback and sales performance in the movie and book industry and showed that this relationship is not solely confined to the eBay marketplace.

A study conducted by Girard et al. (2002) showed that in cases of experience products whose quality cannot be tested before purchase and consumption, the online vendor’s reputation, as well as its ability to save consumers’ time and effort by providing detailed product information and third party reviews are very important vendor attributes.

In contrast to this, Huang et al. (2009) propose that for search products with attributes that can be easily evaluated before purchase, investments in online feedback mechanisms may not be as important. Vendors of such products may benefit from strategies that enable them to sell at lower cost in order to defy competition (Huang et al., 2009).
2.7 Reputation

2.7.1 Defining reputation

Reputation is public information, in the form, e.g., of feedback, about the past trustworthiness of an agent (Picot et al., 1998). For this thesis reputation is understood as an important trust building factor for online vendors (Fung and Lee, 1999), particularly in the initial trust phase.

In many games repeated over time it is said that it pays to have a reputation of being cooperative. The analyses and results in question have been cited by David Kreps as one of the successes of game theory (Morris, 1999). In contrast to classical decision theory, the game theory describes decision situations, in which the success of the particular individual depends not only on their own actions, but also on the actions of others (interdependent decision situation). Vendors have long claimed that it is worthwhile to be moral (Morris, 1999). In this context, reputation can be defined “as what is generally said or believed about a person’s or thing’s character or standing” (Jøsang et al., 2007, p.5). Reputation can be applied to individuals, products, professions, government agencies, companies and to entire industries (Fuller et al., 2007). A reputation is ultimately established by parties external to the vendor (Fombrun, 1996; Rindova and Fombrun, 1998; Standifird et al., 1999).

When feedback reports that a vendor is honest, this contributes to his or her reputation for honesty. However, the literature differentiates between vendors who only behave honestly when being observed (behaviour) and vendors who are actually honest (character). The latter believes honesty to be right and acts accordingly, the former only behaves honestly because it pays to do so. The “honest” vendors typically don’t cheat their customers. Dishonest vendors have an incentive to appear to be honest. This circumstance makes it difficult to distinguish between the two, thus presenting an epistemic problem.
2.7.2 Reputation and trust formation

The effect of reputation information on trust formation has been illustrated in existing marketing and IS literature (Doney and Cannon, 1997; Ba and Pavlou, 2002; Jøsang et al., 2007; Malaga, 2008). The research shows that reputation, defined as information that represents a publicly held perception of a specific vendor, can play a role in trust formation at various stages within the customer-vendor relationship. Herzig et al. (2008) argue that the main difference between trust and reputation is that trust is an individual belief of the trusting party (micro level), while reputation is a group belief of the evaluating agents (macro level). This means that trust is an evaluation of a given target by a certain agent, whilst reputation is a collective evaluation of a given target by a group of agents.

Reputation information is most critical when the consumer has only little or no experience with a specific vendor (Doney and Cannon, 1997). Studies on reputation in the field of economics have shown that evaluations of others are based on experiences or observation of the company's past actions in such a way that companies who have demonstrated reliability or ability to others have established a stronger reputation (Kreps and Wilson, 1982; Shapiro, 1983; Wilson, 1985; Weigelt and Camerer, 1988). In other words, the greater the number of people giving feedback (reputation building) the more trust is established (the percentage of positive feedback). A study by Kim et al. (2008) found that reputation is an important antecedent to affect-based trust, which means that customers develop trust when they see that the vendor has a positive reputation.

The following figure 2.5 illustrates that it is important to build a reputation based on positive and negative feedback from the beginning. When this reputation involves a high percentage of positive feedback, it conveys high integrity and ability. These characteristics illustrate the vendor's consistency and prove that the vendor would guarantee the quality of his products and services. This forms the trust that is essential for a transaction between a customer and a vendor (Mayer et al., 1995; McKnight et al., 1998). This link between reputation and trust reduces information asymmetry.
A good reputation is a valued asset (Chiles and McMackin, 1996) and a competitive advantage for a vendor. Improving the vendors’ reputation will also improve trust, because more feedback (reputation building) shows that one has positive intentions (positive feedback forms trust) (McKnight and Chervany, 2002).

### 2.7.3 Dimensions of reputation

It is important to mention that the percentage of positive feedback is not the only decisive factor for a vendor to be successful. The quantity of feedback, on which reputation is based, also has to be taken into consideration. According to Rindova et al. (2005), the more prominent the vendor’s feedback is (i.e., many people perceive the vendor as trustworthy, which means high numbers of positive feedback), the greater his reputation is. Aside from prominence as a key component of reputation, Rindova et al. (2007) also conceptualised company or vendor reputation in terms of favourability (i.e. the ratio of positive to negative feedback). Favourability is distinct from prominence. For example, it is possible for a user to rate high on favourability (e.g. few people know vendor A but all of them think the vendor is trustworthy) but low on prominence (since
few people perceive vendor A as trustworthy) (Rindova et al., 2007). This means that a vendor with 100 entries of 100% positive feedback has less reputation than a vendor with 10,000 feedback entries, although only 95% of them are positive. This example emphasises the importance of the quantity of feedback. Although the electronic market places eBay and Amazon have made mistakes and disappointed their customers through failures, they still remain successful because they are established Internet brands and are considered as more reputable than other online markets.

2.7.4 Reputation in online transactions

Online reputation, which is the focus of this study, is a factor in any online environment where trust is important. For customers who are first-time visitors to a known online store they are unfamiliar with, the quantity of feedback from previous buyers is a potential resource for evaluating reputation and the possibility of developing trust for the vendor. The outcome of a feedback system can be used to build the reputation of the target online store. In fact, reputation-building can be seen as a social process dependent on past interactions (chronologically published in form of feedback) between customer and vendor. Whereas the customers’ voice is directly targeted to the vendor in the traditional marketplace, in the online market the customers’ voice on the feedback page is aired toward both the vendor and future customers, and is therefore accessible to the public. Additionally, customer feedback submitted in an online store might not only cause current customers to leave but also further block potential customers from entering into the initial relationship with the vendor. In the traditional market, leaving is an economic action and speaking out is considered more of a political phenomenon (Hirschman, 1970). When it comes to the online market, speaking out becomes a powerful economic action, which, in turn, can shape the decisions of other potential customers. Stores can potentially recover from damaged reputations through effective complaint management (Lee and Lee, 2006).

The role of reputation in the development of trust in electronic markets has been investigated by a number of researchers (Standifird, 2001; Ba and Pavlou,
2002; Resnick and Zeckhauser, 2002; McDonald and Slawson, 2002; Bolton et al., 2004; Güth et al., 2007; Ghose, 2009; Cabral and Hortacsu, 2010). However, most studies have focused either on the online auction market eBay, or the marketplace Amazon. A common finding was that a trustworthy reputation led to higher prices (Standifird, 2001; Ba and Pavlou, 2002; Ottaway et al., 2003; Houser and Wooders, 2006; Standifird and Weinstein, 2007).

Generally customer feedback systems operate on the basis of voluntary submissions by customers that leave feedback on their transaction. Therefore, the “reputation” developed through the feedback system may not be accurate and truthful. There is the possibility of users abusing their privileges of submitting (good or bad) feedback about a vendor; and comments as well as ratings can be manipulated. As was already mentioned in the previous chapter, a reputation system is only effective to the extent that honest and accurate information is submitted and disseminated. Such a system is an economic incentive system in the sense that when a reputation is bound to a fixed identity that cannot be easily changed or can be observed by a third party, then the reputation will have a stronger impact on the long-term payoff of a market participant. This ensures that vendors have an incentive to maintain a good reputation (Ba et al., 2003).

The reputation of an online store assists in reducing the complexity of the social world by providing a summarised statement of the probability that one’s expectations will be disappointed before one has actual dealings with the store. Consequently, reputation creates a willingness in people (such as potential customers) to trust the vendor in the absence of actual knowledge concerning the product quality, service and potential to fulfill the customers’ expectations. In order to reduce the perceived risk of a purchase, potential customers look for vendors of reputation endorsed by the feedback of former customers (Lim et al., 2006; Chu and Li, 2008).

A vendor’s positive reputation is considered a key factor for reducing risk (Resnick et al., 2000) and creating trust (Ganesan, 1994; Doney and Cannon, 1997; Jarvenpaa et al., 1999) insofar as it provides confirmation that the vendor
has met his/her obligations toward their customers in the past. A potential customer, seeing the positive history of a vendor, is likely to conclude that the vendor will continue to demonstrate the same behaviour in present and future transactions (Sharif et al., 2005). A positive reputation has the advantage of being associated with having a high level of ability and competence to deliver products or services at the promised terms. If a vendor has a positive reputation, the consumer believes that the vendor will honor their specific obligations and infer that the vendor is trustworthy (Kim et al., 2008).

If a vendor has a negative reputation, a customer may conclude that the vendor does not possess the competence and the willingness to meet their obligations. Consequently, the potential customer concludes that the vendor is not trustworthy. As a general rule, consumers tend to feel that it is risky to transact with a vendor who has a negative feedback history, whereas it is relatively less risky to transact with a vendor who has a feedback history of meeting the customer`s expectations (Kim et al, 2008). Perceptions of reputation have been tested empirically by Jarvenpaa et al. (2000) and Wetsch and Cunningham (1999). Both studies have reported that the perception of positive reputation is a prerequisite for establishing consumer trust in an online store.

Reputation building is characterised by a long-term investment of resources, effort, and attention to customer relationships (Jarvenpaa et al., 2000). Amazon did not establish itself simply by performing well in terms of deliverables, but by creating a reputation by means of cultivating good publicity in the traditional media. Examples of transference-based trust can also be seen in instances when new brands have established trust by associating themselves with existing well-known brands already in possession of a status of trust in either the world of traditional commerce, e-commerce, or both (Morrison and Firmstone, 2000).

On the whole, online reputation results from the total number of chronologically published positive and negative feedback, which is the basis for the development of trust.
2.7.5 Aspects of customer feedback that impact reputation

Although customer feedback is often described as a useful trust-building and risk-reduction strategy for online stores, existing research has uncovered some problems associated with customer feedback systems. Online feedback mechanisms rely on subjective experiences and voluntary feedback submissions. This introduces two important considerations: (1) inducing truthful comments, and (2) ensuring that sufficient feedback is submitted (Dellarocas, 2003). The most frequently discussed problems are the lack of incentives to leave feedback, dishonest submitted feedback, the manipulation of the feedback system and identity changing.

Incentives to leave feedback

As already mentioned in section 2.6.2, one challenge for feedback systems is that feedback information must come from the voluntary self-reporting of the customer’s own experiences with the online store. Yet feedback is a public good, and the effort a customer takes to submit feedback only benefits others, such as the vendor and other potential customers. Unsurprisingly, therefore, economic theory suggests that feedback is definitely underprovided. According to researchers (Resnick and Zeckhauser, 2002; Bolton et al., 2008) who have analysed the eBay online marketplace, only about 50% of the transactions on eBay receive feedback. It is widely accepted that people are more willing to disclose extreme experiences than average experiences (Tesser and Rosen, 1975). For example, the benefits of reading a book or buying an appliance are rarely affected by the number of other readers or buyers. The voluntary submission of feedback leads to a suboptimal supply, since many users do not consider the benefits that his feedback submission gives to others (Dellarocas, 2003).

Dishonest and unfair feedback

Since feedback is usually subjective, it must also be considered whether feedback is ever honest and fair. Feedback is often submitted by customers who want to punish the vendor by giving him unfairly poor ratings (Dellarocas, 2003). Such incidents have been observed on eBay. On platforms such as Holidaycheck and Tripadvisor, where it is possible to rate restaurants and
hotels, the identity of hotels and restaurants is published, but the identity of customers is concealed (Dellarocas, 2000). This gives rise to unfair customer feedback, because no retaliation or reciprocation can take place (Dellarocas and Wood, 2008).

**Manipulation of the feedback system**
There are companies who have introduced their own online feedback systems for their online stores. These companies can to a great extent control the amount and type of information that is made available to consumers (Dellarocas, 2003). For example, companies can hide the detailed history of past positive and negative feedback from customers and replace it with a summary statistic (such as the sum of past ratings). This possibility would create a more positive appearance to the customer, because it robs the potential customer of any detailed insight into any negative comments. Vendors can also simply delete negative or suspect feedback. In the online setting of imperfect information and anonymity, traditional reputation models predict that reputations are not sustainable (Dellarocas, 2003). One reason for this, as Dellarocas puts it, is that “Once firms build a reputation for trust, they are tempted to “rest on the laurels”; this behaviour, ultimately leads to a loss of their reputation” (Dellarocas, 2003, p. 27).

**Identity changing**
At first sight, identity changes seem to weaken the effectiveness of a feedback system. Dishonest behaviour or bad service by a vendor can be punished with negative feedback. But this feedback is pointless when the vendor can easily create a new identity and build a new reputation. Thus, real newcomers and vendors who have changed identity due to negative feedback become indistinguishable (Wibral, 2010). On online marketplaces like eBay or Amazon, reputation is only connected to the online identity of a person, i.e. the username and not the person. Vendors who are dissatisfied with their reputation profile can simply delete the old account and create a new account under a new username. As a consequence of this, customer trust is high in transactions with experienced vendors and low towards new vendors (Wibral, 2010), which creates a barrier for honest new vendors. Based on experimental research,
Wibral (2010) found reduced vendor trustworthiness and customer trust to be present in markets where identity changes are possible.

2.7.6 Strategies to minimise feedback problems

2.7.6.1 Third party feedback system

The well-known eBay feedback system still struggles with problems such as online identity changing. However, many feedback systems in the B2C e-commerce environment are provided by a third party. Third parties are considered to have some coercive power over the online vendor through explicit rules (Kim et al., 2008). The certificate or seal, which the online vendor receives from the third party when using the feedback system, bind the online vendor to a fixed identity—the real-world person. If an online vendor receives a large quantity of negative feedback, they cannot simply build up a new reputation profile. Therefore, many vendors are eager to fulfill the online transactions in a manner that fully satisfies the customer’s expectations.

2.7.6.2 Feedback arbitrations

Negative feedback in a reputation profile will seriously damage the potential customers' perception of trustworthiness vis-à-vis an online store and further damage the reputation of the online vendor (Lee and Lee, 2006). The primary target is to handle negative feedback effectively to achieve customer satisfaction and trust between customer and vendor.

Generally speaking, the online pioneer eBay encourages buyers to negotiate and try to work out their problems before simply leaving negative comments. Before May 2008, eBay permitted “revoking”, a process of removing negative feedback on the condition that the buyer and seller came to an agreement (Ye et al., 2014). The online vendor has the opportunity to apologise, explain the problem and ensure compensation. The customer, in turn, can then respond to the vendor’s competence and his ability to solve the problem. However, in May 2008 eBay banned the withdrawal of negative feedback. This policy change had a great impact on sellers who used the process of withdrawing negative
feedback to fix their reputation and to increase trust. Ye et al. (2014) analysed the behaviour of the sellers before and after the policy change and discovered that sellers who made use of revoking, displayed more efforts to improve their service in order to avoid negative feedback after the policy change went into effect. The noticeable increase of positive feedback confirmed this behaviour.

2.8 Conceptual framework: research model and proposed hypotheses

Online customers often act on the basis of incomplete buying information. As a result, they are often faced with risk in their purchasing decisions. In order to evaluate the risk of buying from an online store, consumers prefer to read the feedback of customers describing their past transactions. Depending on the feedback profile (negative and positive feedback), consumers are convinced to buy or not to buy. Moreover, higher transaction values (financial risk) and more complex high involvement products (product risk) are risk drivers, which require an enhanced need for detailed feedback (Bei et al., 2004; Huang et al., 2009; Dai et al., 2014). At the same time, customers who purchased something of higher value and with a higher intrinsic risk of loss should something go wrong, are more prone to reward the good performance by leaving positive feedback. And when something goes wrong, consumers want to show their dissatisfaction by leaving feedback (Dellarocas and Wood, 2008). Participating in the feedback profile helps shape the reputation of the store and establishes a trust mechanism between potential and past customers. Since reputation promotes customer trust and influences sales, vendors need to monitor and react to negative feedback in order to boost their reputation and transform dissatisfied customers into satisfied customers.

2.8.1 Product complexity

Many studies of e-commerce tend to focus on a single product or group of similar products when investigating issues related to the acceptance of online transactions. As a result, with the exception of Chu and Li (2008), Huang et al. (2009) and Dai et al. (2014), the effects of different product categories have been relatively neglected.
Most existing research focuses on product level rather than on category level. Ba and Pavlou (2002) primarily used electronics-related products to determine the effect of trust on prices, and Resnick et al. (2002) collected data on hundreds of products to analyse feedback patterns. MacInnes et al. (2005) analysed vacation packages (to represent services), in addition to camcorders, musical keyboards and heavy-duty welders. Cabral and Hortacsu’s (2010) analysis found that negative feedback leads to a lower sales rate (in a study based on four products). Huang et al. (2009), who examined consumer behaviour on search and experience goods, differentiated between product categories, as will be done in this study.

This study analyses three different product categories, which are classified into simple low involvement products, moderately complex products with higher involvement, and highly complex, high involvement products. According to Nelson’s product classification, one product category belongs to search products and the other two product categories are devoted to experience products. The product categories differ in their level of complexity and shape the nature of the relationships between the variables in the research model. The hypotheses presented in the following section, will be tested for each product category.

2.8.2 Hypothesis 1: Average transaction value and feedback profile access
According to McKnight et al. (2002), it is important for vendors to engender sufficient trust in first time visitors at an early stage in order to overcome consumers’ perceptions of risk. Customers visiting an online store for the first time rely heavily on website cues and vendor reputation to form their initial trust beliefs (McKnight et al., 2002).

As described above in the chapter on risk (see section 2.4.3), the risk perception of a consumer is greatest when the product is technologically complex or has a high price. Bhatnagar et al. (2000), in a study in which they analysed a combination of experience and search products (software, hardware, food, beverages, travel, clothing, concerts and so on), found that
products with high transaction values such as hardware or travel are perceived as risky to buy online. This risk is linked to the consumers’ belief as to whether the product will function according to their expectations. The risk is greatest when the product is, for example, technologically complex (product risk). They showed that the value of the transaction is an important driver for users’ perception of risk, which means the higher the price (financial risk), the greater the perception of risk and the consequent need to assess that risk (Bhatnagar et al., 2000; Jøsang et al., 2007). Risk can be evaluated by checking the feedback profile. On the basis of this, the following hypothesis has been formulated:

\[ H1 \text{ (Risk evaluation): The average transaction value will have an influence on feedback profile access (checking feedback).} \]

2.8.3 Hypothesis 2: Feedback profile access and conversion rate
In fact, Jarvenpaa et al. (1999) suggested that reducing the risk (i.e. checking feedback) associated with buying online would increase the probability of a consumer purchasing from the online vendor. Risk has been shown to negatively influence transaction intentions with online vendors (Jarvenpaa et al., 1999; Pavlou, 2001; Van der Heijden et al., 2003; Kim et al., 2008). Resnick et al. (2002) found that the impact of feedback profiles on the probability of selling a product is relatively higher for riskier transactions and more expensive products. Offering customer feedback increases the likelihood that consumers will purchase, which is true to a greater extent for experience products (dominated by experience attributes) than for search products (easily evaluated before purchase) (Huang et al., 2009). In this study, the author will inquire into and seek to define the importance of reputation in B2C online transactions across a variety of product categories (reputation effect). As a point of departure, the following hypothesis has been formulated:

\[ H2 \text{ (Reputation effect): The feedback profile access (checking feedback) will have an influence on the conversion rate.} \]
2.8.4 Hypothesis 3: Positive feedback profile and conversion rate

The chapter covering online feedback systems (see section 2.6) stated that consumer feedback reflects the history of transactions related to the products and their acceptance or rejection by previous buyers. The availability of feedback is the basis for building trust, which, in turn, influences sales (Resnick and Zeckhauser, 2002; Ba and Pavlou, 2002; Houser and Wooders, 2006; Chevalier and Mayzlin, 2006; Brown and Morgan, 2006; Bolton et al., 2008; Hu et al., 2008; Cabral and Hortacsu, 2010). Most studies have focused on the online auction marketplace eBay. Chevalier and Mayzlin (2006) found that online consumer ratings significantly influence product sales in the book market. Potential consumers trust those customers who are similar to themselves and who have bought from the same store (Doney and Cannon, 1997; Lim et al., 2006). Thus, customer feedback assists in making purchase decisions by reducing risk and developing trust (Yao et al., 2009). In this study, the author will attempt to determine the importance of the aspect of trust in B2C online transactions for various product categories. To this end, the following hypothesis is proposed:

\[ H3 \text{ (Trust effect / trust transference): The positive feedback profile will have an influence on the conversion rate.} \]

2.8.5 Hypothesis 4: Positive feedback profile and arbitrations

There is a substantial body of research on reputation mechanisms, but it does not analyse the relationship of such mechanisms to arbitrations. As was described in the chapter on feedback problems (see section 2.7.5), unfair and untruthful customer feedback serves to unjustly punish a vendor by diminishing the vendor’s reputation. Especially for vendors with complex products a positive reputation is important to reduce risk and enhance trust towards the potential customers (Wetsch and Cunningham, 1999; Jarvenpaa et al., 2000; Girard et al., 2002). Many vendors on eBay made use of revoking feedback to maintain a positive reputation (Ye et al., 2014). In this study the author tries to find out if vendors in the B2C environment make use of arbitration to maintain trust in the form of high positive feedback levels.
In this regard, this study will test the following hypothesis:

**H4 (Reputation maintenance): A positive feedback profile will increase the likelihood of arbitrations.**

### 2.8.6 Hypothesis 5: Positive feedback profile and feedback submission

A feedback system works on the basis of the active participation of the customer (Bauer et al., 2007). The submission of feedback transfers the experienced trust (see section 2.5.4) of the recent buyer to the next potential customer (building trust transference see section 2.6.4) planning to purchase in an online store (Decker, 2007). Such satisfied customers tend to leave feedback to help other customers in the way that they may have been helped, or wished to have been helped by the feedback of others before their purchase. Dellarocas and Wood (2008) analysed the effect of the reputation profile on participation in the bilateral eBay marketplace. Their calculations show that the higher the reputation scores (consisting almost entirely of positive feedback) of customers and vendors are, the higher the participation in feedback submission will be. When the purchase is made, customers experience certain levels of satisfaction or dissatisfaction and tend to express their opinions in form of feedback to others (Taylor, 1991). In this way, they support the reputation building of the online store and help to transfer trust to potential customers. According to Dellarocas and Wood (2008), the participation on eBay’s reputation mechanism can be explained in part through the concept of altruism. In contrast to Dellarocas and Woods’ eBay study, this research does not examine a bilateral feedback system. Here, customers are the only ones in the position to post feedback. Nevertheless, it would be interesting if there was a relationship between a positive feedback profile and feedback submission. Therefore, the following hypothesis is proposed:

**H5 (Building trust transference): A positive feedback profile will have an influence on feedback submission.**
2.8.7 Hypothesis 6: Average transaction value and conversion rate
Purchases with high transaction values are purchases that are very important for the consumer. Due to the high price, these purchases may entail a financial risk for the consumer (see section 2.4.2). Customers experience a more complex decision-making process in a situation where they have to make a high involvement purchase (see section 2.3.2.2) (Meffert, 1992; Assael, 1995). In these instances consumers typically go through a longer buying process, which may influence the conversion rate. This leads to the following hypothesis:

\[ H6 \text{(Risk perception)}: \text{Higher average transaction value should have lower conversion rates.} \]

2.8.8 Research model
The research model (figure 2.6) is based on the hypotheses mentioned in sections 2.8.2 to 2.8.7 above. The model is partly based on the literature. Several marketing and IS papers have tested the relationship between trust, risk, reputation and purchase intention (Jarvenpaa et al., 1999; Resnick et al., 2000; Ba and Pavlou, 2002; Chevalier and Mayzlin, 2006; Brown and Morgan, 2006; Bolton et al., 2008; Kim et al., 2008; Huang et al., 2009; Cabral and Hortacsu, 2010). The model of Kim et al. (2008) has played an important role in the present study. On the basis of a questionnaire Kim et al. (2008) tested the degree to which consumer trust and risk influence online purchase intentions. They also integrated positive reputation (transaction history of a vendor) into the model, showing that it affected trust positively and risk perception negatively, and thus leads to a higher purchase intention. However, Kim et al. (2008) did not consider different product categories. The present study classifies product categories into search and experience products, which is for the most part consistent with Huang et al. (2009). These researchers also tested the presence of consumer reviews and their effect on purchase likelihood. In seeing online risk as a multidimensional factor (financial, product, time and physical risk) this study follows the lead of Zheng et al. (2012) and Dai et al. (2014).
In contrast to other models in the literature, this conceptual model analyses the decision and purchase behaviour based on an online feedback system. This
study uses factual data to further the understanding of online customer risk, online customer trust and online vendor reputation:

- How users’ actual interactions with an online feedback system during a decision and purchase process simultaneously reduce risk and develop trust.
- How vendors respond to feedback mechanisms in order to increase trust and reduce risk.

Vendor reputation and vendor trustworthiness (trust in the vendor) are measured by the vendor’s feedback history. In the model, transaction value (financial risk), feedback profile access (vendor reputation to evaluate the risk to purchase) and positive feedback profile (vendor trustworthiness) act as independent variables and impact the conversion rate (purchases). In addition, the model tests the impact of the positive feedback profile on arbitrations and feedback submissions. On the whole, the model attempts to identify and confirm a moderating effect of product category on the relationships among the variables.

Only the relationship (H6) between the average transaction value (price in EUR) of a product and the conversion rate is not based on feedback data. This hypothesis is supposed to bring more results on risk perception, which means the higher the price, the greater the risk to purchase in the online store.

Dellarocas et al. (2004) have conducted an in-depth study of the motives behind trader participation in eBay’s reputation system. They could not find any evidence that the transaction value (price of a product) influences the feedback submission. There will be some details on this relationship regarding the B2C e-commerce in section 5.3.5.

The first hypothesis (H1) measures the customer’s behaviour regarding the evaluation of risk prior to the purchase decision. In several studies, customers were asked about their risk perception and if they want to check if the vendor is risky to transact with before purchasing a product from them. In this study, the author uses data on the actual click behaviour of the customer. As soon as a
customer enters the feedback profile page with the whole transaction history of the vendor, this process is tracked in the database (see later section 3.4.6.2). This means that this analysis provides a more in-depth view into the actual process of interaction between a user and an online feedback system. In addition, different product categories and prices are taken into consideration in order to determine a pattern for the consequent need to assess the perceived risk.

**Figure 2.6: Research Model**

![Research Model Diagram]

Source: Julia Bartels
2.9 Summary of the literature review

The literature review discussed a number of areas of inquiry covered by current and past research. These included B2C e-commerce, the buying behaviour of Internet users, online risk, online trust, online feedback systems and online reputation. The literature review aimed to link the important factors of risk, trust and reputation in online transactions. It emphasised the consideration of different product categories, using Nelson’s distinction between search products and experience products. The literature review also established a link between experience products and the importance of trust-building strategies such as online feedback as it relates to vendor reputation and thereby leads to increased purchase intention. Then the literature review introduced the conceptual framework and the proposed research model, and posited hypotheses to test how an online feedback system enhances vendor reputation, mitigates product complexity and facilitates online purchase decision-making. The hypotheses aim to provide more insight into users’ actual interactions with an online feedback system during a decision-making and purchase process, as well as into how vendors respond to feedback mechanisms in order to increase trust and reduce risk. The effects of different product categories with different levels of product complexity will be taken into consideration.
3 Methodology
This chapter describes the methodology used in this empirical study. First, an overview of the different research paradigms and methods is presented, followed by the introduction of the research method and the research design of this study. Second, eKomi, the company which provides actual transaction-based online feedback data from their own database, is introduced. Third, the data collection process and the description of variables is described. The chapter closes with the time horizon, unit of analysis and the limitations and validation of the research design.

3.1 Research paradigms
When planning a research project the researcher has to answer the questions How is knowledge generated?, What is the nature of the produced knowledge? and What is the value and status of this knowledge? In order to answer these questions the researcher can turn to the major paradigms that represent the main epistemological streams in organisational science (Thiétart, 2001).

The term ‘paradigm’, in the sense it will be used here, was introduced in 1962 by Thomas Kuhn. According to Kuhn, different theoretical schools can be distinguished by their paradigms. He defines the meaning of paradigm as follows: Paradigms are large systems of philosophical and theoretical frameworks that emerge out of the overall form and bring together members of a scientific school in which laws, methods, science and problems are defined and consistently implemented. On the one hand, paradigms constitute a common perspective by providing ways to interpret empirical phenomena in their subject area, and on the other hand, they create a strong network of commitments, which are congruent in their theoretical, methodological and instrumental nature. Over a certain period of time, a discipline became controlled by a specific paradigm. Thus, the chosen paradigm took on a distinct form, never questioned by the social scientific community, and allowed for the background knowledge for the researcher and their research projects to be taken as self-understood and unproblematic (Kuhn, 1996).
Social science is characterised by two main epistemological positions: positivism and phenomenology. These paradigms guide researchers in a certain direction and enable them to generate and evaluate the knowledge relating to their research questions (Thiétart, 2001).

Positivism is a dominant paradigm in the social sciences, including organisational science, and sees the researcher as an objective, independent interpreter of an observable social reality (Remenyi et al., 2005). The paradigm’s aim is to explain reality, to find a universal law and to reveal objective truth. The positivist paradigm assumes a single and precise observable reality, a dualism of observer and observed and an aspiration for regularities that are independent of time and context, which allow for the pursuit of value-free research (Kelle, 2008). The reductionist approach is one of the key tenets of positivism and helps to explore the relationships among the variables being studied and to control the investigation. Pure positivism is based on using quantitative data to test hypotheses and emphasises quantifiable observations that lend themselves to statistical analysis (Remenyi et al., 2005).

Unlike positivism, phenomenology does not consider reality as objective, but instead focuses on the influence of the subject or researcher on the research object (Remenyi et al., 1998). Each situation is seen as unique and its meaning is a function of the individual involved. Therefore, subject and object are dependent on each other. The degree of dependence differs between two main schools of phenomenology: interpretivism and constructivism.

Interpretivism views the universe as composed of more than just a single reality. The position is somewhat similar to parallelism, but in this case there is a total distinction between the existing versions of reality. The world must be discovered holistically through interpretations and the external knowledge objective does not influence the research process. Hence, the research process consists of the development of an understanding of the reality of the subjects studied. This understanding grows through the experience of the relationship between the research subjects and the objects (Thiétart, 2001). Both the interaction and the development of the understanding lead to the research
problem. The validity criteria for interpretivism are related to trustworthiness, and include (1) approved credibility, (2) transferability to other contexts, (3) dependability on factors of instability and on factors of design-induced change, and (4) conformability of the data.

The aim of constructivism is to construct reality. It does not accept that reality has an independent existence. For constructivists the process of understanding consists of contributing to or constructing that reality. In this way the paradigm tries to contribute to improvements for the social world (Thiétart, 2001).

The following table summarises the assumptions underlying the nature of the knowledge produced by applying the different paradigms mentioned above:

### Table 3.1: Overview paradigms

<table>
<thead>
<tr>
<th></th>
<th>Nature of knowledge produced</th>
<th>Nature of reality</th>
<th>Nature of subject-object relationship</th>
<th>Vision of social world</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Positivism</strong></td>
<td>A-contextual, objective</td>
<td>Ontological hypothesis</td>
<td>Independence</td>
<td>Determined</td>
</tr>
<tr>
<td><strong>Interpretivism</strong></td>
<td>Subjective, Contextual</td>
<td>Phenomenological propositions</td>
<td>Interdependence</td>
<td>Intentional</td>
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<tr>
<td><strong>Constructivism</strong></td>
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<td></td>
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<td></td>
</tr>
</tbody>
</table>

Source: Thiétart (2001)

These elements, i.e. (1) nature of knowledge produced, (2) nature of reality, (3) nature of subject-object relationship and (4) vision of social world, help researchers to choose the appropriate epistemological position for their research.

### 3.2 Research methods

The design of the research project determines whether to use the deductive or inductive approach. It is useful to link these research approaches with the different research philosophies that correspond to them. Whereas induction owes more to interpretivism, deduction is attached to positivism (Saunders et al., 2009). Deductive research involves the development of a theory and hypotheses and a strategy to test the hypotheses. The inductive approach
refers to the collection of data and the development of a theory that results from
the data analysis (Saunders et al., 2009). The inductive approach is chosen
when little on the subject is published in the literature (Kelle, 2008).

A study like this relies on the available literature, and in this case the materials
considered for examination include literature that discusses such topics as the
risks associated with e-commerce, online trust, online feedback and online
reputation. An attempt has been made to look for confirmation of the following
propositions (different product categories have been considered): (1)
transaction value influences decision-making behaviour (potential customers
perceive more risk when planning to buy a product with a higher transaction
value. Thus they develop a higher need to evaluate this risk); (2) when potential
customers perceive any risk, they will be influenced by the vendor’s reputation
based on online feedback from previous customers (reputation effect); (3)
customers automatically have more trust in purchasing from online stores with a
positive feedback profile (trust effect/trust transference (a potential customer
trusts former customers)); (4) vendors of high involvement products care more
about their reputation profile than vendors of low involvement products. Vendors
need to carry out arbitration procedures on the feedbacks given by the visiting
consumers (reputation maintenance); (5) a positive reputation profile influences
feedback submission. Customers were helped with online feedback in the
buying decision process and therefore submit feedback to help potential
customers (building trust transference); (6) transaction value has an influence
on the conversion rate. Higher product prices involves a higher financial risk,
which keeps some potential customers away from purchasing online. Lower
transaction values facilitate the customer’s decision to purchase (risk
perception).

By using the deductive approach, the researcher is in the position to test the
above body of hypotheses established in this field. Researchers choosing the
deductive approach, often use large scale samples in order to generalise
conclusions and are more likely to work with quantitative data.
The following chapter explains important research methods and discusses the advantages and disadvantages of each approach. It also describes the reasons for selecting the research method for this study.

3.2.1 Qualitative research
Originating in Europe, qualitative methods have become increasingly popular as a mode of inquiry in the social sciences (Travers, 2009). According to Erickson (1986), the most distinctive feature of qualitative investigation is its emphasis on interpretation – not simply that of the researcher, but more importantly that of the individuals who are studied (Thiétart, 2001). Furthermore, the qualitative approach is holistic and allows for investigation into more complex phenomena. Due to the small sample sizes in qualitative research, qualitative data is based on meanings expressed through words and not derived from numbers, as is the case with large scale samples in quantitative research (Dey, cited in Saunders et al., 2009). The data collection process is flexible and structured in such a way that while staying in close contact with the respondent, the researcher develops an understanding of the respondent’s social reality (Kromrey, 1986).

The disadvantage of the qualitative approach is that it is less structured, and researchers often have the feeling of data overload as a result of the huge volume of rich data (Cassell and Symon, 2004). Nevertheless, data are gathered with a limited number of cases and so the investigated structures only possess a narrow scope of validity. This leads to a limited validity of generalisations (Remenyi et al., 2005).

3.2.2 Quantitative research
This research method aims at independence in observation, objectivity in data collection and data evaluation, and the statistical generalisation of results that is at the same time theoretically informed (Kelle, 2008). Whereas detailed knowledge will be gained in the qualitative approach described above, generality and evidence collection will be achieved with quantitative techniques (Remenyi et al., 2005).
Patton (2002) points out that the advantage of a quantitative approach is the possibility of measuring many people on the basis of a limited set of questions, thus facilitating comparison and statistical aggregation of the data. This allows researchers to create a more broad and generalisable set of findings. This simplification can, however, lead to the result that complicated, and thus important, factors are omitted (Remenyi et al., 2005).

Remenyi et al. (2005) describe four basic steps in quantitative research: (1) literature review, (2) assessment of established theoretical frameworks, (3) development of theoretical conjecture and (4) generalised formulation of hypotheses. Quantitative analysis techniques help to explore, present, describe and examine relationships and trends within the collected data. The techniques named above are very helpful for techniques of data representation, such as tables and diagrams indicating frequencies, and for using statistical techniques, such as indices, to enable comparisons based on statistical relationships between variables (Saunders et al., 2009). Statistical analysis leads to results that can be reproduced, and hence are testable.

3.3 Research in Information Systems (IS)
The field of Information Systems (IS) has developed during the last three decades. One of the key contributions came from Hirschheim et al. (1987), who researched the nature, purpose and practise of IS development. Quantitative analysis is the primary methodology used in IS, although qualitative methods are on the rise (Chen and Hirschheim, 2004). According to Orlikowski and Baroudi (1991), positivist researchers are advocates of the hypothetic-deductive testability of theories. According to this position, scientific theories should allow for verification or falsification and seek generalisable results through the use of statistical analyses. The researcher uses numerical outputs to derive meaning from the observations of an objective reality (Straub et al., 2004). The primary objective of this thesis is to evaluate how customers and vendors correspond to different factors of e-commerce. Thus, the research design of this study will be based on the positivist model of measuring variables and testing pre-specified hypotheses (Kauber, 1986; Straub et al., 2004).
3.4 Research strategy and design

3.4.1 Research strategy

Studies on online risk and online trust, as well as the positive influence of online feedback and online reputation on purchasing behaviour, can be found in marketing and IS literature (Jarvenpaa et al., 1999; Resnick et al., 2000; Ba and Pavlou, 2002; Chevalier and Mayzlin, 2006; Brown and Morgan, 2006; Bolton et al., 2008; Kim et al., 2008; Huang et al., 2009). These studies are dominated by a positivist philosophical underpinning. Many studies on online risk, online trust, online feedback and online reputation make use of statistical analysis, experiments and surveys. Surveys have traditionally been the most popular method to measure risk, trust and reputation, largely because individuals can be asked directly about their communication habits. This method, however, has been challenged due to the fact that the self-reporting of behaviour can lead to possible bias as far as the measurements are concerned, and therefore represents a very likely source of opinion inflation (Dellarocas and Narayan, 2006).

Turner and Martin (1984) warn that people’s self-reported preferences hardly ever match their behaviour in the real world. The advantage of topics involving the Internet is that certain data, such as the actual click behaviour of consumers on websites, can be easily recorded. Therefore, studies can look at the saved data from online transaction systems and analyse actual user behaviour online. Researchers (Resnick and Zeckhauser, 2002; Ba and Pavlou, 2002; Houser and Wooders, 2006; Bolton et al., 2008) who have investigated the well-known eBay feedback system have made use of data recorded on the eBay platform. Other researchers have identified the risk reducing mechanism of online customer feedback by means of questionnaires or a combination of an experiment (respondents had to visit a given online store or a simulated store) and a final questionnaire (Lee and Lee, 2006).

The results adopted in this research have been obtained from the database of a feedback company under study, and therefore the data collection is not able to be influenced by the researcher. The researcher neither affects, nor is affected by the subject of research. A personal interview, in contrast, can involve the
feelings of the researcher when framing the questions and interpreting the respondent’s answers. The emphasis in this study is on quantifiable observations that lend themselves to statistical analysis. Following this positivist approach and looking at an objective reality through the use of quantitative methods seems to be the most appropriate paradigm for this research study. Crucial aspects of positivist research are presented in: (1) the formulation of hypotheses, models, or causal relationships among constructs (existing theory of risk, trust and reputation are used to develop hypotheses); (2) the use of quantitative methods that test or verify theories or hypotheses; and (3) the researchers’ objective, value-free interpretation (support or discard a formulated hypothesis) (Chen and Hirschheim, 2004), which is rationalised, explicit and formal. Supported hypotheses can then be used for predictions.

Table 3.2: Characteristics of positivist research in this thesis

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Assumption</td>
<td>The research assumes that the observer is independent and working with an observable social reality with quantifiable observations</td>
<td>Creswell (2009) Thietart (2001)</td>
</tr>
<tr>
<td>Objective</td>
<td>The research focuses on the discovery of facts and the generation and/or testing of hypotheses</td>
<td>Remenyi et al. (2005)</td>
</tr>
<tr>
<td>Method</td>
<td>Entailing the collection of numerical data and exhibiting a view to the relationship between theory and research through the frequent use of large-scale and quantitative methods</td>
<td>Bryman and Bell (2007)</td>
</tr>
</tbody>
</table>

Source: Julia Bartels
3.4.2 Research design and research process

An appropriate research design is an essential component of any empirical research project. The quality of the research design is dependent on the logic of the chosen research strategy, as well as on the coherence of the various components (Thiétart, 2001). It is used to structure the research, to highlight the central parts of the research project (i.e. samples or groups, measures, methods, approaches, etc.) and to address the essential research objectives. It contains clear objectives, specifies the sources from which the researcher intends to collect data and considers further mitigating factors, such as access to data, time, location and money. Yin (1994) defines research design as a ‘logical plan for getting from here to there, where here may be defined as the initial set of questions to be answered, and there is some set of conclusions (answers) about the questions’. Furthermore, Yin (1994) states five components that should be covered in the research design: (1) the research questions, (2) its propositions (if any), (3) the unit(s) of analysis, (4) the logical links between the obtained data and its corresponding propositions, and (5) the criteria for interpreting the findings. This study uses hypothesis testing. Such studies usually explain the nature of certain relationships or establish the differences between groups (Sekaran, 2003).
Figure 3.1: Research process

- The research aims to find out how a feedback system supports vendor reputation, mitigates product complexity and facilitates online purchase decision-making.

- Definition of risk types, trust, feedback and reputation in e-commerce
- Definition of theoretical frameworks (trust and risks in online stores, impact of customer feedback and perceived reputation in purchase behaviour)
- Research gaps

- Definition of the research aim and objective
- Definition of the research problem
- Theoretical framework is based upon models derived from academic literature

- Data collection
- Methods of analysis

- Linking concepts and data
- Conclusions, implications and limitations

Source: Julia Bartels in accordance with Thiétart (2001)
3.4.3 Research model

The conceptual framework was already presented at the end of the literature review (figure 2.6). Product categories with different levels of product complexity and classified into experience and search products, influence the following relationships: (1) average transaction value and feedback profile access (2) feedback profile access and conversion rate, (3) positive feedback profile and conversion rate, (4) positive feedback profile and arbitrations (5) positive feedback profile and feedback submission, and (6) average transaction value and conversion rate. The model assumes that the customer–vendor relationship is voluntary.
3.4.4 Development of e-commerce in Germany
The overall number of Internet users shows continuous growth. In the industrial countries, the Internet has reached the status of a mass phenomenon, and website design is, accordingly, more sophisticated. The study’s scope is limited to German online stores. According to the recent study by A.T. Kearney, Germany has shown the most growth in Western Europe (A.T. Kearney, 2013). Figure 3.3 below illustrates that the percentage of German online shoppers has doubled, from 54.1% in 2002 to 96% in 2012 (BVDW, 2014).

![Figure 3.3: Online shopper growth between 2002 and 2012 in Germany](source: BVDW (2014))

The talk of ubiquitous access to the Internet is increasingly becoming a reality. It is possible through the use of an ever larger variety of devices to access the Internet from any location. The transmitter-receiver relationship is changing. It has become cheaper to publish texts, images and videos on the Internet. More and more people use social software like blogs and wikis to obtain information, cultivate social networks, or publish their own opinion on the Internet (Gehrke, 2007). ECC published a study in 2012(b) on trust building mechanisms in German e-commerce, in which an online experiment involving 11,914 Internet users demonstrated the impact of trust building mechanisms on the conversion
rate. The figure below shows that customer feedback systems lead to a 25% increase in the conversion rate.

**Figure 3.4: Impact of trust building mechanisms on conversion rate**

![Bar chart showing increase in conversion rate](source: ECC (2012b))

### 3.4.5. Research setting

#### 3.4.5.1 The feedback company eKomi

eKomi Ltd. (subsequently eKomi) is a fast growing international e-commerce company founded in 2008. eKomi has entered the market with an online feedback system at a time when online shopping has become increasingly popular (BVDW, 2009). eKomi has grown rapidly and has established a presence in the Spanish, Dutch, Swiss, Austrian, French, English, South African, Australian, US, Canadian and the eastern European markets. eKomi is a part of the Medici Holding, which consists of three divisions, Medici, Yields and eKomi. Medici is an international digital marketing agency, with its main focus on online marketing. The second division is Yields, which offers professional telemarketing and telesales services (eKomi, 2011(a)).

eKomi developed feedback systems for three different sectors: (1) e-commerce, (2) hotel and (3) medical surgery. The main criteria in choosing online shops with an eKomi feedback system for this study were: (1) the companies are part of the German market and (2) they do not operate in the hotel industry or in the field of medical surgery. The last two sectors are still under development, and
eKomi’s main focus lies on e-commerce. Therefore, German online shops from this sector have been chosen to enable a better basis for comparison.

In table 3.3 below, we provide information on the five main competitors of eKomi. In the following paragraph, the prime focus will be on the main competitors in and for the German market.

**Table 3.3: Main competitors of eKomi on the online feedback market**

<table>
<thead>
<tr>
<th>Feedback company</th>
<th>Countries</th>
<th>Feedback submission</th>
<th>Editorial control of feedback</th>
<th>Widget on website</th>
<th>Comment function</th>
<th>Arbitration function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bazaarvoice</td>
<td>8</td>
<td>Buyer only</td>
<td>By Bazaarvoice</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Trusted Shops</td>
<td>13</td>
<td>Buyer only</td>
<td>By Trusted Shops</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Trustpilot</td>
<td>26</td>
<td>Buyer only</td>
<td>By online store</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>UIfOB</td>
<td>1</td>
<td>Buyer only</td>
<td>By UIfOB</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Ausgezeichnet.org</td>
<td>1</td>
<td>Buyer only</td>
<td>By Ausgezeichnet.org</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>eKomi</td>
<td>8</td>
<td>Buyer only</td>
<td>By eKomi</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

Bazaarvoice is a company which mainly focuses on product feedback (evaluations of single products), rather than online store feedback (evaluations of the whole shop including products and service/delivery), with a primary clientele of bigger customers as their price of an online feedback system starts at about 1,600 US dollars. This means that they only target key accounts. The availability of product feedback, when clicking on a certain product, is a recent development of eKomi. Therefore, Bazaarvoice is, or will become, one of the main competitors in the feedback market. The only central difference between eKomi and Bazaarvoice are the prices and the visibility of the widget on the website. Bazaarvoice does not offer guidance to a complete feedback profile.
Potential customers can only read feedback about the product they have clicked on (Bazaarvoice, 2015).

Trusted Shops is the biggest competitor in the German market. Both Trusted Shops and eKomi started their business in Germany in 2008. Both companies have shown parallels in their development, prices and strategies. Trusted Shops also currently provides their service to 13 countries. The main difference is that eKomi offers additional product feedback, whereas Trusted Shops only concentrates on shop feedback. Trusted Shops, which was also a possible candidate for this research project, does not, however, maintain a detailed database as eKomi does, which makes cooperation difficult (Trusted Shops, 2015).

Another main competitor for eKomi is Trustpilot, as their prices are similar to eKomi’s. The main difference is that Trustpilot does not offer a real arbitration process. Trustpilot does not control the content of any submitted feedback. However, the vendor is able to inform Trustpilot if he or she is of the opinion that the submitted review does not correspond to the guidelines of Trustpilot. In such a scenario, employees of Trustpilot will have a look at the content of the review. But Trustpilot adopts a neutral position in cases of disagreements about delivery and service because they are of the opinion that it is hard to discern whether the vendor or the customer is in the right (Trustpilot, 2015).

The feedback companies UIfOB (Unabhängiges Institut für Online Bewertungen) and Ausgezeichnet.net.org entered the German feedback market in 2012. Their concepts are quite similar to eKomi and Trusted Shops, and UIfOB tries to stand out with their layout (UIfOB, 2015), while Ausgezeichnet.net.org does so by offering a new service such as an industry test. This means that Ausgezeichnet.net.org analyses online shops with respect to website usability, service, support, usage of the feedback system, prices and offers. They then evaluate and determine the best online shops for each branch, and post the ranking on their website (Ausgezeichnet.net.org, 2015). Although these two companies are newcomers in the market relative to eKomi, they try to focus on the German market with new services and functionality.
3.4.5.2 Business optimisation for online stores

Business optimisation refers to ensuring that the online store is visited by as many consumers as possible. A business is said to have been maximised if the store’s frequent visitors are easily converted into active buyers. The main aim of eKomi is to provide a less risky and more transparent Internet environment. The main reason consumers buy products over the Internet is that it is a quick and efficient option compared with shopping offline. eKomi, with its transaction-based customer feedback system, supports online stores. Examples of important eKomi customers who have implemented the feedback system on their website include:

- Alternate (Feedback: last 12 months: 22,317 and total: 61,097) (eKomi, 2015a)
- Sparhandy.de (Feedback: last 12 months: 13,822 and total: 69,770) (eKomi, 2015b)
- buerostuhl24 (Feedback: last 12 months: 3,090 and total: 24,286) (eKomi, 2015c)
- posterXXL (Feedback: last 12 months: 47,852 and total: 218,273) (eKomi, 2015d)
- medipolis (Feedback: last 12 months: 6,365 and total: 38,243) (eKomi, 2015e)

Increased trust and decreased risk

For online stores it is important to increase their visitors’ trust and decrease the purchasing risk. Within the e-commerce branch, it is very important to establish trust as this is one of the most important issues for potential buyers. When visitors do not trust the online store, or perceive buying from it as risky, they are likely to leave and buy from a competitor. The eKomi feedback system increases trust by posting the feedback of recent customers, thereby enabling potential customers to see whether or not past customers have been satisfied (eKomi, 2011b).
Conversion rate optimisation
Online stores can optimise their conversion rate through increased trust and decreased risk (Kim et al., 2008). Because of the eKomi feedback system, potential customers who visit a site trust the online shop more as they can see actual feedback from recent customers. An increased conversion rate means increased sales relative to the amount of visitors (eKomi, 2011b).

Positive reputation development and arbitration
The eKomi feedback system also helps online stores to protect their established positive reputation against negative opinions spread over the Internet. Customers leave feedback onsite and not offsite. Furthermore, most negative reviews are actually caused by a lack of communication or a misunderstanding. eKomi encourages communication between the customer and vendor through a private arbitration process through which most issues can be resolved amicably. This works as a kind of complaint management system and enables the online vendor to appease their unsatisfied customers (eKomi 2010).

Google ranking
For online vendors it is very important to be visible on the Internet. This can be achieved by search engine optimisation (SEO), which makes it easier for customers to find the online store. SEO means that the online shop improves the volume or quality of its traffic. For an online shop it is advantageous to be ranked as highly as possible in the Google search results. Working in partnership with Google, eKomi’s independent reviews are integrated within Google Product Listings. Using eKomi’s social commerce technology, reviews are not only collected, but are used to increase traffic and add customers (eKomi, 2011b).
3.4.5.3 Transparency for online customers

The virtual environment of the e-commerce situation carries a higher degree of uncertainty than the traditional settings for economic transactions. The literature review (see 2.3.2.3) has shown the importance of information searches by online consumers. The need for word-of-mouth communication is especially high for complex products (Ha, 2002). Many online consumers regularly read customer feedback before making a purchase (see 2.6.4). New customers then transfer their trust of the satisfied customers to the online store. Potential consumers trust those customers who are similar to them (have bought in the same store) (Lim et al., 2006). Thus, customer feedback is a part of the critical “social information” that potential customers can rely on to reduce risk and assist in making decisions. The published feedback creates transparency, and thus trust between the customer and the online vendor.

Furthermore, customers prefer feedback systems operated by a third party. In cases of dispute there are qualified eKomi mediators present to find the appropriate solution for both the online vendor and the online customer. This means that when the customer is in the right, with regard to consumer rights, he or she is supported by eKomi in the discussion with the online vendor, and vice versa.

3.4.5.4 Participation in the online transaction process

eKomi offers eye-catching links (eKomi widget = component of a graphic window system), which directly lead the visitors to the feedback profile of the online vendor. The widget enables interaction with the visitors. On the feedback profile page visitors can read all positive, negative and neutral comments. Furthermore, they can see how many arbitrations have been solved between past customers and the online vendor. By consulting this information, the potential customer learns about the reputation of the online store that he or she is considering buying from and can judge how risky it may be to buy at the store. If the information available regarding the reputation of the store is good, trust can increase between visitor and vendor. When the potential customer decides to buy, the eKomi online feedback system represents an effective
platform for the customer to evaluate an online store. Each purchase is followed by a feedback form that is sent by email to the customer. In this way, the customer has the possibility to evaluate both the online store and the purchase. As they were helped during the purchase decision by the feedback of recent customers, the new customer has the opportunity to help other potential customers by submitting feedback.

The magnitude of the trust that exists between the customers visiting a website and the vendors depends on the prevailing information that describes the vendor’s reputation. The effective evaluation of the vendor’s online store, as far as eKomi online feedback system is concerned, is a function that determines the customers’ decision-making regarding whether or not to purchase from the store in question. Upon the purchase of products, the customers are mailed feedback forms which they are expected to complete and submit to the company for statistical evaluation and analysis. The feedback forms are intended for the purpose of product evaluation by the customer and enable the consumer to evaluate the vendor’s store, as well as the transaction itself. It is a well known fact that consumers who end up engaging in business transactions, or those who simply get persuaded to purchase products from a particular store, do so after being persuaded by feedback from prior visitors or consumers. In return, the feedback that they leave behind is also very useful to the potential customers who are expected to visit the online store in the future. Figure 3.5 illustrates all the steps that are monitored by eKomi. It begins with visiting an online store, and continues through clicking on the widget to study the reputation profile of the vendor, the purchase itself, the feedback submission and finally an initiated arbitration in the event a vendor feels unfairly rated.
Figure 3.5: eKomi participation in online transaction process

Figure 3.6 shows that a feedback system has the ability to transform potential customers into satisfied customers. This feedback cycle again reflects the mechanism of trust. A customer buys a product and submits feedback about the product and purchase experience. The eKomi team releases and publishes the feedback, so it can be reviewed by potential customers. Customers who were satisfied with the purchase and communicate this in the form of feedback to potential customers thereby transfer their satisfaction to them and communicate that this vendor can be trusted.

Figure 3.6: eKomi feedback cycle

Source: eKomi (2011b)
3.4.6 Data collection method and description of variables

3.4.6.1 Data collection method

In this study, the focus lies on system-collected data based on factual occurrences. Such raw data, which is collected by most organisations to support their operations, represents actual buying processes that have taken place. Raw data is available only from the company that produces it (Saunders et al., 2009). For many research projects, the main advantage of using data from a database is the enormous time, money and effort it saves. Thus, more time can be used to analyse and interpret the data that is already collected. The data used for this study have been collected daily by the company for internal statistics. For this research project, in particular, selected data was drawn from the eKomi database. The author made calculations with the data sets and collected the average transaction value and the unique store visitors independently. Therefore, it can be said that the study is based on primary data.

The literature from Internet market research suggests a classification into reactive and non-reactive methods. According to Batinic et al. (1997), online questionnaires, online experiments and online interviews are reactive methods, whereas server evaluations and observations (browsing behaviour via log file analysis) belong to non-reactive methods. The essential difference between the two is that reactive methods ensure that study participants are aware of being analysed, while non-reactive methods, such as those used in this study, are used to analyse participants who are unaware of being observed.

eKomi employees from customer care and customer feedback management (gatekeeper) extracted a sample of data covering 400 randomly selected online stores from their system. The data included information on the transactions and browsing behaviour of online users over a six month period from 1st October 2011 to 31st March 2012. The raw data was provided to the researcher in a Microsoft Excel file. Variables in the dataset include transaction numbers, feedback profiles (positive, neutral, negative), vendor experience with the feedback system, rating numbers, widget-clicks and the number of arbitrations that have occurred for each store (total transactions, total feedback (positive, negative, neutral) total widget-clicks and total arbitrations). The data was filtered
so that it would only consider new customers. As previously mentioned in the literature review, trust and reputation are more important for new customers than for repeat business from existing customers (Kim et al., 2004). Furthermore, the online stores have been drawn by product category. Company databases have the advantage that large amounts of real data related to consumer behaviour can be saved, structured and later analysed (Saunders et al., 2009).

This study uses data of factual events from a company database to measure aspects of risk perception, trust mechanism and reputation of online purchases. The numbers in the dataset reflect actual consumer behaviour, i.e. the number of transactions over a period of six months that has been recorded in the eKomi database. The eKomi feedback system is implemented in B2C online stores in the environment of the product or the product purchase. In this study, only new customers are considered who have completed their first purchase before leaving feedback. eKomi uses a web-based Social Commerce SaaS Technology to obtain customer feedback and to provide online stores with data. This technology combines social networking and e-commerce to form a social commerce web application (eKomi, 2012). The author has a contract with eKomi that grants her access to this data in return for supplying a report of the findings of this study.

Data for the conversion rate, which shows how many visitors become customers, is measured by the proportion of the number of transactions (purchases) and unique visitors during the period investigated. The number of transactions per day for each store is taken from the eKomi database. The number of unique visitors for each online store and the average transaction value were gathered by contacting each store by phone and email. Each store was asked for (1) the average transaction value in EUR of all transactions made by the company during the period investigated, and (2) for unique visitors in the period investigated.
3.4.6.2 Variable description and linkage to presented constructs

Average transaction value

The data collection was carried out by phone and email to ask for the average transaction value in EUR of all sold products during the period investigated. Table 3.4 shows an extract of how the transaction values have been collected. The stores had to be anonymised in this table.

Table 3.4: Data collection of average transaction value (extract)

<table>
<thead>
<tr>
<th>Online store</th>
<th>Average transaction value in EUR (October 2011 to March 2012)</th>
<th>Data received</th>
</tr>
</thead>
<tbody>
<tr>
<td>Online store A</td>
<td>79.00</td>
<td>09 October 2012</td>
</tr>
<tr>
<td>Online store B</td>
<td>1023.00</td>
<td>10 October 2012</td>
</tr>
<tr>
<td>Online store C</td>
<td>102.00</td>
<td>06 November 2012</td>
</tr>
<tr>
<td>Online store D</td>
<td>180.00</td>
<td>10 October 2012</td>
</tr>
<tr>
<td>Online store E</td>
<td>44.00</td>
<td>07 November 2012</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

The given average transaction value can be used to investigate the impact of expensive, and therefore riskier, products on the eKomi feedback system (as Cabral and Hortacsu (2010) did in examining the importance of eBay's reputation mechanism). A higher-priced item entails greater risk (financial risk) for the buyer, as the higher the price, the greater the loss will be if the other party fails to fulfil the terms of the agreement (MacInnes et al., 2005).

Several case studies focusing on transaction value were conducted on the eBay marketplace. The entire dataset describing the transaction values for eBay has been made available to the public as an Internet publication. Cabral and Hortacsu (2010) collected the transaction level information of four products from eBay. From the published selling prices they calculated the average transaction value for each of the four products. Other researchers such as Chen et al. (2004) developed a data acquisition program to gather prices from the Amazon.com website. However, this study only considers online stores with
their own website, and hence online marketplaces such as eBay or Amazon are beyond its scope.

**Feedback profile access**
The eKomi database makes it possible to measure the click behaviour of website visitors. The variable “feedback profile access” is used to measure how many potential customers want to evaluate the risk of buying in the online store. Such customers access the feedback profile of the online shop to check the reputation of the vendor.

The aforementioned database records the number of website visitors to all 400 online stores who have accessed the eKomi feedback profile of the respective online vendor before making a purchase. In order to review feedback, visitors have to click on the eKomi widget (see figure 3.7 and 3.8). The widget is usually located on the homepage/product page of the store or in the purchasing area. In order to make this variable comparable between vendors (all investigated online stores) it is transformed as follows: a proportion is calculated between feedback readers and unique store visitors in the period investigated. The number of unique store visitors for the stated period was collected by calling each store. In order to verify the number of unique visitors by a second source, the websites have been additionally analysed by free statistical tools, such as sitefile and WebStats. Feedback profile access for the period investigated was calculated as follows:

\[
\frac{\text{Widgetclicks (visitors, who read feedback)}}{\text{Unique store visitors}}
\]

The equation produces a number that indicates the store in which more visitors read feedback and wanted to assess the risk before committing to buy. Clicking on the widget (to access the feedback profile) means that the potential customers perceive risk. With the help of feedback from past customers (= reputation of the vendor), they seek to assess the risk before making a purchase. When potential customers click on the widget (see figure 3.7) they
are able to see the reviews on the certificate page (reputation/feedback profile) given by former customers.

**Figure 3.7: eKomi widget**

![eKomi widget](image)

Source: BabySecurity (2011)

**Figure 3.8: eKomi widget implemented on the website “BabySecurity”**

![eKomi widget on BabySecurity website](image)

Source: BabySecurity (2011)

eKomi conducted a small experiment on the impact of the eKomi widget on the conversion rate. They wanted to compare the conversion rate when the eKomi widget is implemented on the website and the conversion rate when the eKomi
widget is removed from the site. Four online stores participated in this trial: (1) GamePointsNow, (2) IT-Budget Hardware, (3) Goldankauf123 and (4) Rucksack Center. Through this test it can be seen if on average, the conversion rate for online shops increased while using the eKomi widget. The eKomi IT-Team removed the eKomi widget from the website for seven days and then afterwards replaced it for seven days. The four online stores noticed a 10% to 12% increase in their conversion rate when the widget was displayed on their website (eKomi, 2010b). This test is illustrated by figure 3.9 below.

**Figure 3.9: Visitors to buy process**

Process one shows the number of people visiting the website and the number of visitors who click on the widget. As soon as a visitor enters the website, he or she will get a unique identity number (cookie). Process two shows the number of customers who submit feedback, as all the people visiting were allotted a personal identity. The cookie file sees immediately when a person who clicked on the widget gives an evaluation. Through this cookie file system, online stores are able to see how many customers clicked and/or submitted feedback and how many customers did not click and/or did not submit feedback. By using this system the online vendor can assess the impact of the widget on the development of sales.
As previously mentioned in the literature review, an e-commerce setting, as it exists in a virtual environment, is more uncertain than the traditional settings for economic transactions. Online customers have limited information about the vendor’s reliability or the product quality (product risk) during the transaction. As a result, customers in the online setting are faced with a higher degree of risk in their purchasing decisions (Kim et al., 2008). Looking for feedback from other customers represents a subjective evaluation of a possible loss or sacrifice in conducting transactions with an online vendor. Based on factual data, this study attempts to quantify the number of potential customers who make actual use of a feedback profile. This means that consumers perceive a certain risk and want to evaluate this risk based on the reputation.

Generally researchers who make use of data from online marketplaces have only been in a position to measure reputation (is it risky to transact with the vendor or not) on the basis of published feedback (Resnick et al., 2002; Gregg and Walczak, 2009; Ye et al., 2014; Moreno and Terwiesch, 2014), but have not been in a position to measure risk evaluation (the actual reputation check).

Positive feedback profile
Each online store investigated in this thesis has its own eKomi feedback profile page (see figure 3.10). The trustworthiness of each store is measured by the degree of positive feedback measured in percentages (e.g. 99% positive feedback) that the store had achieved up to the point at which the investigation started. This means that at the time when the investigation started each of the 400 stores had a feedback score. This feedback score, in turn, was based on the quantity of positive feedback left by customers for the online vendors, following each customer’s completed purchase, in proportion to the total collected feedback. This feedback collection started with the implementation of the feedback system.

A positive reputation profile confirms that the vendor has met his obligations toward other customers in the past. In the case of a positive reputation, the potential customer believes that the vendor fulfills his obligations to the
satisfaction of the customer. Therefore, he can be seen as a trustworthy vendor. Focussing on positive reputation should show if the produced trust leads to economic advantages (Ba and Pavlou, 2002), in this case expressed as a higher conversion rate.

Reviews are published in chronological order on the eKomi feedback profile page of the online store. A rating scale from 1 to 5 stars is available for each item of feedback submitted. When reviewing customer feedback, positive, neutral and negative comments will be differentiated. Customer reviews rated with three stars are considered as negative reviews. Reviews rated with four or five stars are considered as positive reviews.

The eKomi feedback profile below is integrated on the website, and shown here on babysecurity.co.uk. This feedback system follows the type of feedback that is applied on eBay.

**Figure 3.10: Example of an eKomi feedback profile**

![Example of an eKomi feedback profile](source)
In many of the studies of the eBay feedback system, reputation in terms of positive feedback against total feedback (positive and negative) is a common measured variable (Standifird, 2001; McDonald and Slawson, 2002; Bolton et al., 2004; MacInnes et al., 2005; Ye et al., 2014). As already mentioned, this study aims to present the degree of positivity in the eKomi feedback profile for each store.

Feedback submission
The eKomi feedback system, similar to the eBay feedback system, is a buyer-driven reputation system that accumulates and disseminates information about the online vendor’s past trading behaviour. This IT system provides information about the reputation of online vendors by allowing customers to post their experiences with the online store.

The variable feedback submission shows how many customers have submitted feedback over the six month period extracted for this study. The number of submitted feedback results is set in relation to the transactions made in each store for the period investigated.

\[
\frac{\text{Number of submitted feedback}}{\text{Number of transactions}}
\]

Thus, it is a measure of how many of the purchasing customers ended up leaving feedback. For the purposes of this study, submitted feedback is considered as a trust evaluation criterion. Whether or not a buyer trusts an online vendor is based on the online vendor's feedback profile (Ba and Pavlou, 2002). The potential buyer checks feedback, and positive feedback serves as a proxy for the lack of a personal relationship and establishes the trust necessary to make the transaction happen. For a given buyer, other buyers are trusted third parties because they have nothing to gain by providing inaccurate feedback on sellers (Pavlou and Gefen, 2004). Any customer who gets assistance from the prevailing feedback (trusted the feedback of others), would prefer to pass this advantage on to a fellow customer, and can do so through feedback submission.
The eKomi feedback process progresses through different stages. After a successful transaction, the eKomi Web service interacts directly with the company database and dispatches an email to the customer within a given number of days. The company determines the time when the email with the evaluation link is sent to the customer. After successfully reviewing the feedback, the reviews are released every day by the eKomi customer care center. The submitted feedback is then displayed in the public feedback profile (see figure 3.11).

**Figure 3.11: Feedback process of eKomi**

1. Customer makes a purchase and receives an email from the online store. This email will be dispatched by the eKomi software and contains an evaluation link.
2. The customer submits feedback.
3. eKomi Customer Care Centre eKomi Team reviews customer feedback.
4. Reviewed customer feedback is now available for the online store in the password-protected company account.
5. Customer feedback waits for further processing in the company account.
6. Customer feedback is published on the website of the online store.

Source: eKomi (2009)

This measure of the variable feedback submission is in complete agreement with the past studies conducted by scholars such as Pavlou and Gefen (2004) and Dellarocas et al. (2004). Post-purchase feedback ratings left by buyers for online vendors were examined on the eBay auction marketplace and include buyers’ feedback ratings for sellers they transacted with. In contrast to eBay, eKomi is not a marketplace, but rather a feedback system implemented in B2C
online stores. Feedback data is saved independently in their own company databases and is not publicly available as it is on eBay.

According to Dellarocas and Wood (2008), feedback is mostly posted when customers are either very satisfied or very dissatisfied. Based on this statement, the researcher assumes that customers who purchased something of higher value with a higher intrinsic risk of loss should something go wrong, would also be more prone to reward good performance or punish bad performance by leaving feedback.

Arbitrations
There is a substantial body of research on feedback mechanisms, but it does not analyse their relationship to arbitrations.

This study seeks to test if there is a relationship between a positive reputation profile and arbitrations. In this study, the variable "arbitration" means that online vendors know the importance of a good reputation profile and that they try hard to maintain this positive reputation. To do this, they make use of arbitrations, which means they initiate arbitration processes as a way of trying to delete received negative feedback. The number of closed arbitration processes is set in relation to the transactions made in each store for the period investigated:

\[
\frac{\text{Number of closed arbitrations}}{\text{Number of transactions}}
\]

In the eKomi database, each arbitration between customers and the 400 chosen online stores has been saved for the period investigated. The eKomi arbitration process between a dissatisfied customer and the online vendor proceeds as follows: when negative feedback is submitted, the eKomi customer care centre verifies if the feedback fits the eKomi guidelines. Customer feedback managers pay attention to insulting, xenophobic or other criminal content. After the examination by the eKomi Team has taken place, the review is sent to the online store. The online store then has five working days to reply
to the complaint in order to still satisfy the customer. An arbitration process can be opened as a reaction to neutral or negative customer feedback. If an arbitration process is opened, the customer feedback remains unpublished for the duration of the arbitration process. During this time, it is only visible to the online store and the customer concerned. When both parties find a solution, the review is deleted. One eKomi customer, the company “Click und Flieg”, valued their online reputation for use as a reference for trustworthiness. They appreciate the arbitration process because it represents a possibility to take up position. They can apologise and explain why certain things happened (e.g. late delivery) (eKomi, 2013a). Another company using the eKomi feedback system, AvivaMed, has introduced a new service due to customer feedback: Shopping by brands. Customer complaints helped them to discover that customers want to find all the products of their favourite brands very easily and quickly. Within one year their sales have increased by 15% (eKomi, 2013b).

**Figure 3.12: Arbitration process from a customer's point of view**

![Comments](image)

A successfully closed arbitration process is not published. The online store is not in the position to close such an arbitration process. Only the customer can withdraw their negative feedback (see figure 3.12 above), once a satisfactory solution is found with the Internet vendor or the customer feels that they submitted unfair feedback. In the event that the customer fails to comment on the arbitration process within 14 days, the procedure is stopped and the negative customer feedback remains unpublished. If the online store does not take part in the arbitration process, the procedure is stopped and the negative customer feedback is published. If both parties fail to find a solution, an eKomi manager is required to make a decision. If the problem was caused by the
online store, the feedback will be published. However, if eKomi judges the submitted review to be an unfair complaint on the part of the customer, the feedback will be deleted. The online store is not in the position to remove or edit negative and neutral feedback (eKomi, 2010a). In essence, an eKomi arbitration process shows that past customers wanted to express their dissatisfaction in the form of negative feedback, but that instead an arbitration process was initiated.

In order to set a standard for appropriate feedback (McDonald and Slawson, 2002), eKomi has developed this arbitration process between customers and online vendors. It is worth pointing out that eBay encourages buyers to negotiate and to try to work out their problems before simply leaving negative comments. Until 2008, eBay also employed “revoking” - the possibility to withdraw negative feedback once buyer and seller came to an agreement. The aim of revoking was to reduce the actual number and impact of negative ratings from the online auctions (Resnick and Zeckhauser, 2002; Ba and Pavlou, 2002; McDonald and Slawson, 2002; Ye et al., 2014). Ye et al. (2014) studied the effect of revoking on eBay and collected revoked feedback. This revoked feedback can be equated with arbitrations, since both involve feedback that has been withdrawn.

Conversion rate

The research model of this study tries to discover a relationship between average transaction value and conversion rate, as well as between feedback profile access and conversion rate and positive feedback profile and conversion rate.

The conversion rate, which shows how many visitors become customers, is measured in this study by the proportion of unique visitors to an online store who went through with online transactions in the period investigated:

\[
\frac{\text{Number of transactions}}{\text{Number of unique visitors}}
\]
The number of unique visitors for the said period was collected by calling each store. In order to verify the number of unique visitors with a second source, the websites have been further analysed by free statistical tools, such as sitefile and WebStats. They provide detailed traffic reports.

The measurement of the variable conversion rate is consistent with the study of Salam et al. (2003). The only difference is that Salam et al. (2003) captured the number of past buyer transactions objectively from each marketplace website that reported the number of each buyer’s transactions. In this study, the number of past buyer transactions was taken from the eKomi database.

Existing literature on the subject shows that the consumer’s perception of the risk associated with a higher transaction value will tend to strongly affect his or her decision to engage in a transaction (Salam et al., 2003). Research data from the eBay marketplace indicates that negative ratings and complaints carry a much stronger effect than positive ones on a buyers’ trust level and sales rate (Ba and Pavlou, 2002; Weinberg and Davis, 2005; Cabral and Hortascu, 2010).

In order to measure the variable conversion rate, the number of transactions (real purchases) is essential. Many studies on trust, risk and reputation measure purchase intention instead of real purchases. Theory of reasoned action based studies (TRA: looking to predict the behavioural intention of users) have confirmed a strong correlation between behavioural intentions and actual behaviour (Sheppard et al., 1988; Venkatesh and Davis, 2000), which means that researchers assumed that the intention to use technology to carry out online purchases equates to the actual purchase. Lim et al. (2006) believe that the relationship between purchase intention and actual buying behaviour is neither trivial nor evident, especially in the online shopping context. Market research firms have reported that many people abandon their shopping carts when they reach the checkout process. This suggests that, in the online context, intention to buy might not necessarily lead to actual buying behaviour. In order to avoid such bias it is important to test the mechanism of actual consumer buying behaviour.
3.4.7 Unit of analysis

The unit of analysis is the major entity analysed in a study. The research question determines the unit of analysis. For example, a unit of analysis can be people (individuals or groups), animals, artifacts (i.e. books, journals, etc.), geographical units (countries, states, cities, etc.) or social interactions (e.g. arrests, divorces, weddings, etc.) The research question of this study refers to German online stores that have implemented the eKomi feedback system (eKomi customers) for at least one year and up to no more than 3. Therefore, the units of analysis for this research project are German online vendors who have implemented an eKomi feedback system in their online stores.

Sampling techniques fall into broad categories, namely those for non-probability samples, which are the domain of the phenomenologist, and those for probability samples, which are used by the positivist researcher (Remenyi et al., 2005). In this thesis, the author has used a stratified random sampling approach. The population (all online vendors who have implemented an eKomi feedback system in their online stores) has been divided into meaningful segments (product category with a different level of complexity). Therefore, the unit of analyses is at a group level (Sekaran, 2003). The key criterion for using this approach is that it is an effective method for obtaining differentiated information regarding various strata within the population. In the literature, many studies make use of comparing products, since the type of product affects the browsing and purchasing behaviour.

This thesis does not aim to study a single product category (e.g. electronics, automotive, jewelry etc.), but rather seeks to identify differences in decision-making and the behaviour associated with feedback across different product categories. This study draws on Nelson’s (1970) product classification, and juxtaposes search and experience products. Three different product categories have been filtered in the eKomi database by setting the filter “category”: electronics, health/wellness and office/school supplies. According to Nelson’s product classification, office/school supplies belong to search products (low involvement and low complex products) and electronics and health/wellness are
experience products (medium to high involvement and higher complex products).

Office/school supplies involve products such as paper, pencils, writing books or ink cartridges. These products are standardised. Customers do not expect qualitative differences when buying HB pencils or HP ink cartridges. On the whole, these are simple products devoid of complex technology.

The category of health/wellness involves both beauty products, such as shampoo and lotions, and health products, such as vitamin pills. This category involves moderately complex products. On the one hand, these products are subject to regulations concerning mixture and ingredients. On the other hand, people use these products for their bodies and for their own health, and so the products automatically demand more attention (medium to higher product involvement).

Electronics mostly involve digital cameras and computers. These products are of high complexity. Generally speaking, electronic products are sensitive machines that can sometimes be defective at the time of purchase, or shortly thereafter. Furthermore, electronic products function as status symbols for many people, and it is important that the new, and frequently expensive, product works.

The choice of experience products is consistent with the study of Huang et al. (2009), with the difference being that their choice was on a single product level, as opposed to the category level analysis of this work. While this study considers electronics (involving cameras, computers, etc), Huang et al. focussed solely on cameras. Moreover, Huang et al. (2009) chose “health and beauty” as another experience product. This is very similar to the investigated category “health/wellness”.

With the category of electronic products, this study considers a product category which involves all the central characteristics of complex products, such as high personal relevance, the importance of product quality, numerous
technical features and high prices. The second category, health/wellness, is very interesting to analyse, because these products are rather complex (used for the consumer’s own health and beauty) but are bought at lower prices. The third category of office/school supplies displays all the characteristics of search products, such as low complexity and lower prices, meaning that the quality of the products can be easily assessed prior to purchase. As in the study of Johnson et al. (2004), another reason for choosing these categories was that these product categories were relatively frequently purchased online during the period of data collection.

The research model will be applied to each of the three product categories in order to see the extent to which the product category will shape the other variables that describe the transaction. If consumers have a different search behaviour for information regarding search and experience products, this perspective implies that online purchase behaviour may be different for these three product categories as well (Huang et al., 2009). Trust-building mechanisms (McKnight et al., 2002) such as an online feedback system might increase purchases to a greater extent for experience products than it will for search products.

### Table 3.5: Analysed product categories

<table>
<thead>
<tr>
<th>Product categories</th>
<th>Product complexity</th>
<th>Nelson’s classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Office/School Supplies</td>
<td>Relatively simple</td>
<td>Search products</td>
</tr>
<tr>
<td>Health /Wellness</td>
<td>Relatively medium complex</td>
<td>Experience products</td>
</tr>
<tr>
<td>Electronics</td>
<td>Relatively high complex</td>
<td>Experience products</td>
</tr>
</tbody>
</table>

Source: Julia Bartels in accordance with Nelson (1970)

### 3.4.8 Time horizon

A cross-sectional approach is advantageous when the timeframe of research does not allow the investigator to conduct research over a period of many years. Cross-sectional research answers the research question by taking a snap-shot of the situation in time. Data are gathered over a period of some
months or even weeks. On the whole, a cross-sectional study saves both time and money, problems which researchers commonly have to face (Sekaran, 2003).

With regard to this study, the author is interested in the impact of online feedback systems on customers and for which product category a system is of more advantage. Since there was insufficient time to conduct a longitudinal study, the results of the primary data will be evaluated. Data was collected during the period from October 2011 to March 2012. A limited time frame and a sample of the target group may be sufficient to identify important relationships and mechanics in the domain of online transactions.

3.4.9 Limitations of the research design

According to Patton (2002), design strategies and trade-offs must always be discussed, due to the fact ‘that there are no perfect research designs’ (Patton, 2002, p. 223). Several limitations of the research design must be noted.

Although the sample of 400 online stores is quite high, these firms differ in their type of business, and thus the sample size of each branch is relatively low. Furthermore, the research is limited to a selection of branches and limited to the effects in Germany. This may inhibit the generalisability of this research to international contexts and alternative settings. It is possible that if the research would have investigated a higher number of firms per branch and taken samples from other countries the magnitude and the correlations would be different.

The use of primary data as the sole method of data collection has the drawback of becoming obsolete and not meeting the specific needs of the particular situation or setting (Sekaran, 2003). Cross-sectional research does not enable the researcher to determine causality, whereas a longitudinal analysis would.

Another limitation is the source of the primary data. The author of this study received most of the data from the feedback company eKomi. Since the author
has not collected the data herself there was no real control over the data quality.

The advantage of using data from a database is that it allows inferences to be drawn from observations of actual behaviour, and thus avoids the self-reporting and non-response bias concerns that often plague survey methods (Anderson, 1998). A limitation of the data set is that there is no information concerning why a customer has decided not to submit feedback (Dellarocas et al., 2010).

3.4.10 Validity and reliability
Validity means the degree to which what is measured complies with the purported measured results (Remenyi et al., 2005). Objectivity and reliability are of no avail when the test is not valid. Content validity, for example, ensures that the measure adequately measures the concept (Sekaran, 2003). Due to the high number of participants, the content validity is quite high. While carrying out the application of quantitative methods in the form of primary data, it is important to consider and include the key components belonging to the investigated subject. It is important to prove if the primary data collected enables the researcher to answer the research question and meet the objectives.

The other important criterion is coverage. A researcher needs to be sure that the data cover the population in question for the allotted time period and contain data variables that will enable the study to answer the research question and meet its objectives (Saunders et al., 2009).

The reliability and validity of data is further linked to the method of collecting the data and its source. Dochartaigh refers to this in Saunders et al. (2009) as assessing the authority or reputation of the source. The collection of the customer data has been well thought through by the company eKomi. Web-based technology enables eKomi customer care employees to directly obtain data from the feedback system (click behaviour, transactions, feedback submission and arbitrations) for each eKomi customer (online store). Assessing
the validity and reliability in detail is possible by finding out what method was used to collect the data and who was responsible for the data collection or recording. It can happen that commercial providers of reliable and high-quality datasets may be unwilling to reveal how data was collected. A good methodology can be a competitive advantage (Saunders et al., 2009).

As already mentioned in section 3.4.5.1, there are only a few companies on the market that have introduced an online feedback system for online stores. The company eKomi is among the largest and most experienced customer feedback companies in Germany. In terms of external validity, although the study may only look at one online feedback system, the eKomi feedback system is among the most used feedback systems for all kinds of online stores in B2C e-commerce. The results obtained from the 400 online stores can potentially be extended to make predictions about the entire population.

The validity and reliability of survey data is easier to assess than data from company databases. Due to the fact that such system-generated data was not collected by the researchers themselves, the understanding of this data is not complete and might affect the analysis. When the data is already compiled, as in a report, the researcher has to pay careful attention to how this data was analysed and the results reported. The further the researcher is removed from the original data, the more difficult it will be to judge its quality (Saunders et al., 2009).

Measurement bias occurs when data is recorded inaccurately on purpose. Some managers fail to record minor errors, or play down negative numbers or comments, in order to improve reports and satisfy their target audience. The researcher needs to triangulate the findings with other independent data sources in the hope of arriving at similar conclusions (Saunders et al., 2009).

Reliability refers to stability and accuracy and indicates to what extent the same results are achieved when a measurement is repeated under the same conditions (Yin, 1994). The reliability of research can be enhanced by standardising the data collection techniques. Protocols, as well as always
documenting the time, day and place of observations, are of great importance (Silverman and Marvasti, 2008).

3.5 Summary of the methodology
This chapter outlined the methodology of the study, which consists of a positivist quantitative approach and deductive strategies and procedures to address the research objective. For this research project, in particular, a sample of 400 German online stores was drawn randomly from the eKomi database, and the sample includes information on the transactions and feedback usage of online users and vendors over a six month period. Data concerning unique visitors and the average transaction value of the sold products was collected by contacting the online store directly. Statistical techniques shall be used to determine patterns and numerical information across the different product categories. Furthermore, these techniques allow generalising to a broader population and determining relations between variables.
4 Descriptive statistics and hypothesis testing
This chapter describes the data analysis of this empirical study. It provides
descriptive statistics of the data drawn from the eKomi database. The data have
been split into three different product categories. Since the data does not follow
a normal distribution, the recommended practice of logarithmic transformation
has been applied. The hypotheses, which have been formulated in the literature
review have been tested with linear regression and partial correlation. The
chapter considers the validation and generalisation of the data. The histograms,
box plots, test of normality and the regression output are attached as
Appendices B, C, D, E and F.

4.1 Access to eKomi database
eKomi was selected because it belongs to the largest companies developing
and operating feedback systems in Germany. Furthermore, eKomi is one of the
few companies in Germany that maintains a database with daily statistics about
transaction-based customer feedback and ratings.

The first contact person at eKomi in Berlin was K. G., the team leader of
Customer Feedback Management. He passed the research proposal on to M.
A., the CEO of eKomi (gatekeeper). eKomi is known for their interest in data
analyses and have already published a couple of case studies. Hence, the
company drafted an agreement which swears the researcher to secrecy in
dealing with the data. Further correspondence by phone and email and the data
delivery were made with S. D., Head of Customer Care. He maintains the
eKomi database and extracted the data which eKomi provided for this research
project.

As already mentioned in the methodology chapter (see 3.4.7), the three product
categories have been chosen because they induce different levels of risk
perception. When conducting the data analysis this may lead to the discovery of
patterns in risk-reducing activities (checking the vendor reputation), feedback
profile acceptance as a trust-building mechanism, feedback submission,
initiation of arbitrations and influences on the conversion rate.
4.2 Assessing the regression model: Descriptive statistics and normality

Regression analysis (as part of variance based parametric analysis) creates estimates on the relationship between variables. The purpose of simple regression analysis is to evaluate the relative impact of a predictor variable on a particular outcome variable. A linear regression assumes that the examined variables are quantitative, which means that the variables measure or count something (Urban and Mayerl, 2011).

Descriptive statistics are used to describe the basic features of the data in this study. Through the distribution of data they provide a simple summary of the characteristics of the sample and the measures used to study it.

4.2.1 Sample size

It is important to collect enough data to ensure normality of distribution and fulfil the preconditions for parametric statistics and variance methods. The literature suggests several rules of thumb. According to Field (2005), it is common to have 10 to 15 cases per predictor in the model, and hence with 5 predictors there should be 50 to 75 cases. Overall the required sample size depends on the effect size that is being evaluated when trying to determine the statistical power required to detect such effects. The correlation coefficient $r$ helps to quantify the strength of the linear relationship between two numerical variables. This coefficient can lie between -1 and +1. A value of +1 represents a perfect positive correlation, which means that two variables are related on the highest level (as values of one variable increase, values of the other variable increase). A value of -1 means that the variables point out a perfect negative correlation (as values of one variable increase, values of the other variable decrease). While correlation coefficients ($r$) between -1 and +1 show positive and negative correlations, a value of 0 means the variables are perfectly independent (Saunders et al., 2009).

Within business research it is extremely unusual to obtain perfect correlations (Saunders et al., 2009), as will also be seen later in chapter 4.5 with respect to the regression results of this study. The estimate of $r$ getting from regression is
dependent on the number of predictors (k) and the sample size (N). So $r$ for random data is $k/(N-1)$. With a small sample size of 30 cases, $r$ can show a low effect size according to Cohen (1992) (Example: $6/(30-1)=0.2$). However, for random data $r$ is expected to be near 0. When increasing the cases from 30 to 100, $r$ changes to a value of 0.06. The present study containing 5 predictors and a sample size of 400 cases results in an acceptable $r=0.01$. Miles and Shevlin, as cited in Field (2005), produced a graph (see figure 4.1) that illustrates the sample size needed to achieve different levels of power depending on the number of predictors and the size of the expected effect as the number of predictors varies. The figure below shows some examples of a small, medium and large effect (Field, 2005).

**Figure 4.1: Sample size in regression and expected effect**

![Graph showing sample size in regression and expected effect](source: Miles and Shevlin (2001), cited in Field (2005, p.173))

For the present study, 400 valid online stores can be identified, of which 35% are online stores selling electronic products, 36.5% belong to the health/wellness category and 28.5% are online stores for office/school supplies. For purposes of better comparability, it was decided to include a similar number of online stores in each category.
4.2.2 Testing for normality of the independent and dependent variables

4.2.2.1 Distribution of variables

At the start of the data analysis it is of great importance to test for normality, i.e. whether the distribution of the variables corresponds approximately to a theoretical ideal. The normal (or Gaussian) distribution is a very commonly occurring continuous probability distribution (continuous variables such as age, income or weight can have an infinite number of possible values). Testing the normal distribution can be done by graphic or statistical methods (Pallant, 2007).

The following variables, which are valid and complete for all 400 cases, will be analysed for each product category (electronics, health/wellness and office/school supplies):

- Average Transaction Value (price in EUR)
- Feedback Profile Access
- Positive Feedback Profile (degree of positivity)
- Feedback Submission
- Arbitration
- Conversion Rate

Table 4.1 shows the basic descriptive statistics (minimum, maximum, mean, median and standard deviation) of the variables and indicates values with quite high spreads. With regard to the first variable “transaction value”, the lowest
value is 3.00. This means that there is an online vendor in the sample who calculated 3.00 EUR as the average price of all products sold during the period of investigation. The next column shows the highest average price (4,870.00 EUR) of all products sold in one store during the period of investigation. This value was given by an online vendor with very expensive products. The mean value in the third column shows that when all the average prices provided by the vendors are added up and are divided by 400 (sample size), then the average value of the transaction value is 263.57 EUR. However, the median in the next column shows a lower value of 68.00 EUR. The deviation between the mean value and the median reveals a skewed distribution. Looking at the other means and medians in this table, most variables are skewed to the left, which means that the variables are abnormally distributed. Extreme values can distort the regression estimation to a significant extent (Urban and Mayerl, 2011).

Table 4.1: Descriptive statistics of the sample

<table>
<thead>
<tr>
<th></th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. Transaction Value in EUR</td>
<td>3.00</td>
<td>4870</td>
<td>263.57</td>
<td>68.00</td>
<td>590.124</td>
</tr>
<tr>
<td>Feedback Profile Access in %</td>
<td>.10</td>
<td>100.00</td>
<td>3.68</td>
<td>1.26</td>
<td>7.136</td>
</tr>
<tr>
<td>Positive Feedback Profile in %</td>
<td>.00</td>
<td>100.00</td>
<td>96.39</td>
<td>99.97</td>
<td>16.282</td>
</tr>
<tr>
<td>Feedback Submission in %</td>
<td>.00</td>
<td>100.00</td>
<td>30.34</td>
<td>28.93</td>
<td>28.624</td>
</tr>
<tr>
<td>Arbitrations in absolute value</td>
<td>.00</td>
<td>1140.00</td>
<td>27.03</td>
<td>15.00</td>
<td>86.098</td>
</tr>
<tr>
<td>Conversion Rate in %</td>
<td>.10</td>
<td>58.17</td>
<td>3.82</td>
<td>1.91</td>
<td>5.223</td>
</tr>
</tbody>
</table>

Source: Julia Bartels
A Q–Q plot ("Q" stands for quantile) is a probability plot and one of several graphical methods for comparing an actual observation with a theoretical distribution (e.g. normal distribution). If the two distributions being compared are similar, the points in the Q–Q plot will lie on the 45° line, or very close to it. Q–Q plots are used to compare a data set to a theoretical model. They are generally a more precise way to test the normality than the common technique of comparing histograms. Q–Q plots are often arced, or “S” shaped, which indicates that one distribution is more skewed than the other, or that one of the distributions has heavier tails than the other (Cohen et al., 2003).

The following Q-Q plots (see table 4.2 – 4.4) show the distribution of the variables divided by the product category electronics, health/wellness and office/school supplies. The arced and “S” shaped Q-Q-plots clearly show that in this case there is no normal distribution present for all six variables analysed.
Table 4.2: Q-Q plots of tested variables by product category (Part 1)

<table>
<thead>
<tr>
<th>Electronics</th>
<th>Health/Wellness</th>
<th>Office/School Supplies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transaction Value</td>
<td>Transaction Value</td>
<td>Transaction Value</td>
</tr>
<tr>
<td>Feedback Profile Access</td>
<td>Feedback Profile Access</td>
<td>Feedback Profile Access</td>
</tr>
</tbody>
</table>

Source: Julia Bartels
Table 4.3: Q-Q plots of tested variables by product category (Part 2)

<table>
<thead>
<tr>
<th>Electronics</th>
<th>Health/Wellness</th>
<th>Office/School Supplies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive Feedback Profile</td>
<td>Positive Feedback Profile</td>
<td>Positive Feedback Profile</td>
</tr>
</tbody>
</table>

Source: Julia Bartels
Table 4.4: Q-Q plots of tested variables by product category (Part 3)

<table>
<thead>
<tr>
<th>Electronics</th>
<th>Health/Wellness</th>
<th>Office/School Supplies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arbitration</td>
<td>Arbitration</td>
<td>Arbitration</td>
</tr>
</tbody>
</table>

Source: Julia Bartels
P-P plots and histograms are other widely used procedures to test the distribution:

The P-P plot (Probability-Probability) follows a similar principle to that of the Q-Q plots and compares the accumulated portion of the observed variables or residuals with the accumulated portion of a theoretical distribution (i.e., normal distribution). P-P plot is especially expressive for deviations of the distribution in the middle, but not so for those at the parameters of the distribution. The Q-Q plot is especially useful for expressing deviations in the edges of the distribution (Gerson, 1975).

The histogram is the easiest graphic method to use to test a variable for its normal distribution. Histograms represent the frequencies, shown as adjacent bars, erected over discrete intervals (bins) with an area equal to the frequency of the observations in the interval. The height of a bar is equal to the frequency density of the interval, i.e. the frequency divided by the width of the interval. A normal distribution curve can be superimposed so that any divergences from a normal distribution become visible (Bellgardt, 2004).

4.2.2.2 Logarithmic transformation

In situations where the variables are naturally constrained due to the type of factual events that are being observed (from 0 to infinity), the measures carrying the data of these occurrences will not have a normal distribution. In situations when the data are left skewed, Hair (2010) recommends using the accepted practice of applying a logarithmic transformation. The logarithmic transformation transforms factually observed abnormally constrained variables into a normally distributed variable that complies with the assumptions of variance-based parametric analysis.

The improvement of the distribution of data when applying logarithm transformation will be illustrated below by two of the six variables.
Two examples of such variables in the dataset are:

- Average Transaction Value
- Arbitration

They are constrained by a large number space. Transaction value varies between 3 and 4,870, and arbitrations vary between 0 and 1,140, but here, in relation to the number of transactions (arbitration/transactions * 100), they vary between 0.02% and 61.22%. These variables were transformed using the natural logs (LN) and achieved an improved distribution with log values for transaction value between 1.10 and 8.49, and log values for arbitrations between -3.91 and 4.11. The logarithmic transformation applied in this study significantly improves the data, as seen in table 4.5 below to a log-normal distribution.

**Table 4.5: Q-Q plots with log-normal distribution**

<table>
<thead>
<tr>
<th></th>
<th>Electronics</th>
<th>Health/Wellness</th>
<th>Office/School Supplies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transaction Value</td>
<td><img src="1" alt="Image" />&lt;br&gt;<img src="2" alt="Image" />&lt;br&gt;<img src="3" alt="Image" /></td>
<td><img src="4" alt="Image" />&lt;br&gt;<img src="5" alt="Image" />&lt;br&gt;<img src="6" alt="Image" /></td>
<td><img src="7" alt="Image" />&lt;br&gt;<img src="8" alt="Image" />&lt;br&gt;<img src="9" alt="Image" /></td>
</tr>
<tr>
<td>Arbitration</td>
<td><img src="10" alt="Image" />&lt;br&gt;<img src="11" alt="Image" />&lt;br&gt;<img src="12" alt="Image" /></td>
<td><img src="13" alt="Image" />&lt;br&gt;<img src="14" alt="Image" />&lt;br&gt;<img src="15" alt="Image" /></td>
<td><img src="16" alt="Image" />&lt;br&gt;<img src="17" alt="Image" />&lt;br&gt;<img src="18" alt="Image" /></td>
</tr>
</tbody>
</table>

Source: Julia Bartels

The two examples above illustrate how this logarithm transformation was conducted for each variable to achieve an improved distribution. The final Q-Q
plots and histograms of all log transformed variables can be found in Appendices B and C.

If the dependent and the independent variable are log transformed, it can be referred to as a log-log model. An essential reason for the popularity of logarithmic models derives from the fact that the inherent variance of log transformed variables corresponds closely with the relative variance of the original variables. In the case of logarithm transformation, the gradient coefficients are not dependent on the chosen measure, and are therefore simplistic in their interpretation. As the distribution is 'compressed' by logarithmic transformation, logarithmic functions are often less susceptible to outliers (Stocker, 2011).

This study works with a log-log model. As already mentioned, the natural distribution of these factual variables requires their transformation to a logarithmic scale. Reviewing the IS literature with a focus on online feedback, many studies work with log transformed data to normalise their distribution (e.g. Resnick and Zeckhauser, 2002; Miller et al., 2002; Ba and Pavlou, 2002; Chen et al., 2004; Khopkar et al., 2005; MacInnes et al., 2005; Dimoka et al., 2012; Diekmann et al., 2014).

It is important to note that log transformation can only be applied to variables with positive values. If there are values that are negative or zero, then one accepted procedure is to add a miniscule constant number to each value in the data before transforming the data, small enough to not substantially alter the overall variance of the variable. The literature suggests adding 1 to avoid the possibility of taking the log of 0 (Mosteller and Tukey, 1977; Resnick and Zeckhauser, 2002; Ba and Pavlou, 2002). This adjustment is important to keep the cases: an analysis with a log of 0 would lead to a loss of many cases, and this, in turn, would lead to a distortion of the results. This study cannot afford to lose any data because such a loss would result in the statistical power (standard errors) becoming too high.
This method was applied to the following two variables and affected a total of 18 cases: (1) feedback submission and (2) arbitrations. Concerning the variable "positive feedback profile" there is one case with a value of 0. This very new store with no feedback has not been taken into consideration and has been deleted.

Table 4.6: Cases with added value of 1

<table>
<thead>
<tr>
<th>Product category</th>
<th>Feedback submission</th>
<th>Arbitrations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronics</td>
<td>3 cases</td>
<td>3 cases</td>
</tr>
<tr>
<td>Health/Wellness</td>
<td>4 cases</td>
<td>4 cases</td>
</tr>
<tr>
<td>Office/School Supplies</td>
<td>1 cases</td>
<td>3 cases</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

4.2.2.3 Outliers

It is essential to look for outliers when testing normal distribution, since they can cause the model tests to be biased due to their influence on the values of the estimated regression coefficients. An outlier can be described as a case that differs considerably from the main trend of the data (Field, 2005), thus skewing the resulting outputs of analyses.

The applied logarithmic transformation in this research is used to avoid extreme values or strong divergences by arithmetic means. Extreme values may distort the estimation of regression in a significant way. The logarithmic values were examined to assess the extent to which they still contain outliers and whether or not these ideally fit a normal distribution. The validation takes place for each product category, since regressions for all categories will be estimated separately.

When looking at the Q-Q plots, it is evident that some outliers are not on the regression line. Therefore, the sample was tested for outliers.
In descriptive statistics, a box plot, or boxplot, is a graphic method, which identifies outliers. The spacing between the different parts of the box indicates the degree of dispersion (spread) and skew in the data. Data, which deviates more than the 1.5-fold of the box height are displayed as outliers, values which deviate more than the 3-fold are extreme values (Bellgardt 2004).

According to the box plots, the following variables contain outliers:

- 1 outlier in LN Feedback Profile Access in electronics
- 1 outlier in LN Feedback Profile Access in office/school supplies
- 5 outliers in LN Positive Feedback Profile in electronics
- 4 outliers in LN Positive Feedback Profile in health/wellness
- 2 outliers in LN Positive Feedback Profile in office/school supplies
- 1 outlier in LN Feedback Submission in health/wellness
- 1 outlier in LN Arbitration in office/school supplies
- 1 outlier in LN Arbitration in health/wellness
- 1 outlier in LN Conversionrate in health/wellness

The outliers listed above, with the exception of the variable “LN Positive Feedback Profile” (see Appendix D), were removed. Most of the outliers found for the variable “LN Positive Feedback Profile” were kept because values with a feedback profile of 96% are already calculated as outliers. The box plots for this variable show no extreme values, and all outliers will be tested for their influence on regression. If a case-wise diagnostic and Cook’s distance in chapter 4.3 does not detect influential outliers, then they will be kept for this study.

The revised sample used for this study amounts to 392 cases. The following tables 4.7 and 4.8 describe the new allocation:
Table 4.7: Frequency of product categories (outliers removed)

<table>
<thead>
<tr>
<th>Category</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronics</td>
<td>131</td>
<td>33.4</td>
</tr>
<tr>
<td>Health/Wellness</td>
<td>138</td>
<td>35.2</td>
</tr>
<tr>
<td>Office/School Supplies</td>
<td>123</td>
<td>31.4</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>392</strong></td>
<td><strong>100.0</strong></td>
</tr>
</tbody>
</table>

Source: Julia Bartels

Table 4.8: Descriptive statistics of the log transformed sample

<table>
<thead>
<tr>
<th></th>
<th>N= 392</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>LN_Transaction_Value</td>
<td>1.10</td>
<td>8.49</td>
<td>4.29</td>
<td>1.553</td>
<td></td>
</tr>
<tr>
<td>LN_Feedback_Profile_Access</td>
<td>-3.00</td>
<td>4.04</td>
<td>.25</td>
<td>1.478</td>
<td></td>
</tr>
<tr>
<td>LN_Positive_Feedback_Profile</td>
<td>4.57</td>
<td>4.61</td>
<td>4.59</td>
<td>.008</td>
<td></td>
</tr>
<tr>
<td>LN_Feedback_Submission</td>
<td>-1.13</td>
<td>4.61</td>
<td>3.11</td>
<td>1.162</td>
<td></td>
</tr>
<tr>
<td>LN_Arbitration</td>
<td>-3.91</td>
<td>4.11</td>
<td>.13</td>
<td>1.608</td>
<td></td>
</tr>
<tr>
<td>LN_Conversion_Rate</td>
<td>-3.51</td>
<td>4.05</td>
<td>.64</td>
<td>1.364</td>
<td></td>
</tr>
</tbody>
</table>

Source: Julia Bartels

4.3 Assessing the regression model: Diagnostic statistics

4.3.1 Residuals

The differences in the sample between the predicted values of the outcome and the observed values of the outcome are defined as residuals. “These residuals effectively represent the error present in the model” (Field, 2005, p. 163). If a model fits the data sample, then all residuals will be quite minimal. If a model is a poor fit with the sample data, then the residuals will be rather large. In order to evaluate if a deviation is small or large, standardised residuals were calculated. Generally speaking, standardised residuals are used in data analysis because they are divided by an estimate of their standard deviation (Field, 2005). Standardised residuals are normally distributed with a mean of 0 and a standard deviation of 1. Values larger than 2 or smaller than -2 (standard deviation of more than 2) are detected as outliers (Bühl, 2008).

When running a first regression of the hypotheses to analyse the residuals statistics, the mean of the standardised residuals is 0, but sometimes with a minimum and maximum value larger than 2 and smaller than -2. Using a
casewise diagnostic, eight cases have been identified for which the absolute value of the standardised residual is 3 or more (see table 4.9).

**Table 4.9: Identified cases with too large standardised residuals**

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Product category</th>
<th>Case number</th>
<th>Std. Residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>Electronics</td>
<td>18</td>
<td>3.131</td>
</tr>
<tr>
<td></td>
<td></td>
<td>63</td>
<td>-3.746</td>
</tr>
<tr>
<td></td>
<td></td>
<td>85</td>
<td>-3.104</td>
</tr>
<tr>
<td>H1</td>
<td>Health/Wellness</td>
<td>138</td>
<td>-3.123</td>
</tr>
<tr>
<td>H4</td>
<td>Electronics</td>
<td>110</td>
<td>3.039</td>
</tr>
<tr>
<td></td>
<td></td>
<td>148</td>
<td>-3.052</td>
</tr>
<tr>
<td>H4</td>
<td>Health/Wellness</td>
<td>199</td>
<td>-3.052</td>
</tr>
<tr>
<td></td>
<td></td>
<td>208</td>
<td>-3.052</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

These may be detected as outliers. However, this does not mean that these cases really influence the regression results. Therefore, the influence of each case on the model is measured with Cook's distance in the next chapter.

### 4.3.2 Influential cases

In addition to testing for outliers in 4.2.2.3, it is also important to examine whether certain cases exert undue influence over the parameter of the model. In a linear model, not all data points have the same influence on the regression results. Testing for influential cases helps “to determine whether the regression model is stable across the sample, or whether it is biased by a few influential cases. Again this process will unveil outliers” (Field, 2005 p. 164).

There is one statistic that does consider the influence of a single case on the whole model. Cook’s distance is a measure of the overall effect of a case on the model. Cook and Weisberg (1982) have suggested that values that are greater than 1 are to be considered as a cause for concern (Field, 2005).

As already mentioned in the previous chapter, it is necessary to test how greatly the detected eight cases influence the regression results. To do so, a scatter
plot has been created for each regression with Cook's distance (y-axis) and the dependent variable (x-axis). The scatter plots have identified five of the eight cases with Cook's distance greater than 1 (see figure 4.3 – 4.5). These five cases have been deleted and as a check of their influence, the two regressions (Hypothesis 1 and Hypothesis 4) have been rerun without the cases. For both regressions, there was an improvement of $r^2$. In the first regression (Hypothesis 1) $r^2$ increased from 0.56 to 0.67 for electronics, and from 0.53 to 0.56 for health/wellness. A second regression (Hypothesis 4) showed an improvement of $r^2$ from 0.28 to 0.30 for electronics. When looking at the dataset in more detail it becomes evident that, with regard to hypothesis 1, online stores with moderately high prices show very low feedback access from their visitors (see figure 4.3 and 4.4):

- Case 18: Approximately 1.7% of visitors reviewed the feedback profile page although the store showed average prices of 536 EUR.
- Case: 63: Approximately 0.3% of visitors reviewed the feedback profile page although the store showed average prices of 498 EUR.
- Case 85: Approximately 0.1% of visitors reviewed the feedback profile page although the store showed average prices of 340 EUR.
- Case 138: Approximately 0.4% of visitors reviewed the feedback profile page although the store showed average prices of 298 EUR.

With regard to hypothesis 4, this online store (case 110, see figure 4.5) points out a high number of arbitrations. The online store conducted 411 arbitrations, which accounts for 6.05% of all made transactions in the store in the period of investigation.

The regression analysis in chapter 4.5 will be conducted with a sample of 387 cases (5 deleted cases in electronics and health/wellness, see figure 4.3, 4.4 and 4.5 with circles).
Figure 4.3: Identified influential outlier in H1 (electronics)

Source: Julia Bartels

Figure 4.4: Identified influential outlier in H1 (health/wellness)

Source: Julia Bartels
4.4 Validity, reliability and generalisation

“Three key concepts in quantitative research are validity, reliability and generalisation” (Muijs, 2011, p. 56). When conducting quantitative research, the researcher always aims to measure something (Muijs, 2011). Therefore, it is important to ensure that a correct measurement is taken. That is where (1) validity (internal and external) and (2) reliability come into play.

Internal validity refers to the systematic accuracy of the data analysis. Systematic errors can arise from unforeseen disruptions during the data collection (Homburg and Krohmer, 2009). This study works with system-generated data, which minimises measurement errors. There are no influences, such as interview situations or an interviewer, that may distort the results of the study. However, with web-based research methods there is always the possibility that programs or cables may contribute to an increased error variance.

Figure 4.5: Identified influential outlier in H4 (electronics)

Source: Julia Bartels
Another procedure to increase internal validity is the random assignment of participants. This study considers three populations: (1) online stores belonging to the category of electronics, (2) online stores belonging to the category of health/wellness and (3) online stores belonging to the category of office/school supplies. From each population a random sample was drawn.

For purposes of internal validity, the following principal assumptions are necessary in order to ascertain reliable parameters of the regression estimation, such as standard errors, t-value, regression coefficient and confidence interval (Janssen and Laatz, 2007):

1. Variable Types: All variables (predictor and outcome) must be quantitative
2. Non-Zero Variance: The predictors should have some variation in value (no variances of 0)
3. Linearity: The dependence of the variables must be given by a straight line.
4. Homoscedasticity of errors $e_i$ or residuals, which means that the variance of the distribution of the residuals is the same for each observation of the predictors.
5. Normality of the error distribution $e_i$: The distribution of the errors is normally distributed for each given observation.
6. Covariance of errors $e_i$ is i and j equal to 0 for different observations, i.e. the distribution of errors for i and j are independent. No autocorrelation of the errors is present.

In regard to 6: The Durbin-Watson statistics carried out for each regression were based on the null hypothesis (no autocorrelation exits) in order to test the autocorrelation of the residuals (Greene, 2002).
It is true for each calculated value “d” of the Durbin-Watson statistic (Greene, 2002):

If d< d<sub>L</sub>: Null hypothesis rejected: a positive autocorrelation is present.
If d between d<sub>L</sub> and d<sub>U</sub>: No decision possible.
If d between d<sub>U</sub> and (4- d<sub>U</sub>): Null hypothesis cannot be rejected.
If d between (4- d<sub>U</sub>) and (4- d<sub>L</sub>): No decision possible.
If d> (4- d<sub>L</sub>) Null hypothesis rejected: a negative autocorrelation is present.

The value d<sub>L</sub> describes the lower critical border of d and the value d<sub>U</sub> the upper critical border of d as a function of the number of predictors and the sample size. With a predictor and a sample size of at least N= 200, the low border of d amounts to 1.66 and the upper border of d amounts to 1.69 (Greene, 2002).

External validity, meanwhile, relates to whether or not research findings can be generalised beyond the immediate study sample and setting. According to Welker et al. (2005), web experiments, in comparison to traditional experiments, have a higher external validity concerning the setting situation. During an online experiment, people are situated in individual settings, thus improving the ability to generalise. This study works with actual browsing behaviour, meaning that people neither suspect that they are being analysed nor are they in a research setting. Furthermore, the more representative the sample, the more confident the researcher can be in generalising from the sample to the population.

When a regression analysis is conducted, it is usually interesting to generalise from the findings, which indicates whether or not it can be assumed that the conclusions drawn are true for a wider population. In order to make a regression model suitable for generalisation, the method of cross-validation is applied. Even if the model may not represent the entire population, cross-validation is an approach that can assess how well the model can predict the outcome in a different sample. Cross-validation in general is the partition of the data into two sets: the calibration (or training) set and the validation set. This is also called data splitting (Field, 2005). The company eKomi first sent a sample with 200 cases. This was used as the calibration set (sample with N= 200) to calibrate the model. Then eKomi sent another sample of 200 cases, which functioned as
the validation set. The calibrated model produced a set of predicted values to be compared with the validation set (N= 200). The similar trend of the results of predicted values and the validation set improves the credibility of the model (Morrison et al., 2011).

Reliability refers to stability and accuracy, and indicates to what extent the same results can be achieved when a measurement is repeated under the same conditions (Yin, 1994). The reliability of research can be enhanced by standardising the data collection techniques. The variables within the categories electronics, health/wellness and office/school supplies have been drawn from the raw data that has been automatically recorded by the feedback systems and then stored in the company’s database. Each case can be identified by an ID number. If there is an inherent bias, then this bias is on a systemic level as executed by the company’s technology, not on a case-by-case level (i.e., given a repeat of the data, the operationalisation of the study can be repeated with the same results).

4.5 Regression analysis
Simple linear regressions were used for testing the hypotheses and generating the estimated coefficients for each product category. The logarithmic values of the variables were used for this analysis. The hypotheses presented in table 4.10 were tested.

The extent to which the respective independent variable influences the dependent variable is tested through the linear regression analysis. This is carried out for each hypothesis. The objective of the regression analysis is to describe the relationship between the variables in terms of the strength of fit of a straight line. To estimate the linear relationship, the regression coefficient, which in unstandardised form is the B coefficient, is determined. In standardised form, the coefficient beta (β) describes the strength of the relationship. Furthermore, for each linear regression the coefficient of determination $r^2$ is determined. In principle, this should indicate just how well the predictors used can explain the variance of the dependent variable.
Table 4.10: Hypotheses tested with linear regression

<table>
<thead>
<tr>
<th>No</th>
<th>Variables</th>
<th>Formulated hypothesis</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>Transaction Value &gt; Feedback Profile Access</td>
<td>The average transaction value will be an influence on feedback profile access (checking feedback).</td>
</tr>
<tr>
<td>H2</td>
<td>Feedback Profile Access &gt; Conversion Rate</td>
<td>The feedback profiles access/checking will have an influence on the conversion rate.</td>
</tr>
<tr>
<td>H3</td>
<td>Positive Feedback Profile &gt; Conversion Rate</td>
<td>The positive feedback profile will have an influence on the conversion rate.</td>
</tr>
<tr>
<td>H4</td>
<td>Positive Feedback Profile &gt; Arbitrations</td>
<td>The positive feedback profile will increase the likelihood of arbitrations.</td>
</tr>
<tr>
<td>H5</td>
<td>Positive Feedback Profile &gt; Feedback Submission</td>
<td>The positive feedback profile will have an influence on feedback submission.</td>
</tr>
<tr>
<td>H6</td>
<td>Transaction Value &gt; Conversion Rate</td>
<td>Higher average transaction value should have lower conversion rates.</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

4.5.1 Impact of average transaction value on feedback profile access

For testing Hypothesis 1, three separate regressions, divided into the groups electronics, health/wellness, office/school supplies, were analysed with “average transaction value” as the predictor and “feedback profile access” as the dependent variable.

Table 4.11 lists the most important results of the regression analyses. According to these analyses, all three regression models show three significant regression coefficients of the predictor with p < 0.05. The unstandardised regression of coefficients B are documented, which indicates how the independent variable affects the dependent variable (Field, 2005). The group of electronics exhibits a strong positive influence with a coefficient of 0.813, indicating that feedback profile access is expected to increase for 0.813, if transaction value increases for 1 measuring unit. Regarding health/wellness the coefficient even amounts to 0.885. Thus, both coefficients indicate strong
influencing variables. The coefficient of office/school supplies amounts to $B = 0.467$, which is a correlation of moderate strength.

Accordingly, the coefficients of determination for the two categories, electronics and health/wellness are higher, with $r^2$ at a value of 0.671 and 0.563. In both categories, more than half of the variability of “feedback profile access” is explained by the predictor “average transaction value”. Looking at office/school supplies, the $r^2$ in this category amounts to 0.230. In this group the predictor “average transaction value” can only explain 23% of the variability of “feedback profile access”.

Considering the reliability of the regression estimation, it can be pointed out that the residuals are distributed normally based on the results of Kolmogorov-Smirnov test, with $p > 0.05$ (see Appendix E). Furthermore the residual analysis shows no leverage effects. Sometimes a visual test (scatter plot) is difficult to evaluate. Therefore, the statistical Levene’s test will be applied for the sake of thoroughness, that is, to confirm which residuals show heterogeneous or homogenous variances. The test determines how significantly the variances differ within the single groups. When the Levene’s test fails to show any significance ($p > 0.05$), one can presume homogeneity of variance. For all three groups the test shows results that are not significant (see Appendix F).

Overall, Hypothesis 1 can be confirmed for all sub-samples of the data.

Table 4.11: Hypothesis 1 - results of the regression analyses

<table>
<thead>
<tr>
<th>Product Category</th>
<th>$r^2$</th>
<th>Unstandardised Coefficients B</th>
<th>Std. Error</th>
<th>Sig. ** p &lt; 0.01</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronics</td>
<td>.671</td>
<td>.813</td>
<td>.051</td>
<td>.000**</td>
</tr>
<tr>
<td>Health/Wellness</td>
<td>.563</td>
<td>.885</td>
<td>.067</td>
<td>.000**</td>
</tr>
<tr>
<td>Office/School Supplies</td>
<td>.230</td>
<td>.467</td>
<td>.078</td>
<td>.000**</td>
</tr>
</tbody>
</table>

Source: Julia Bartels
4.5.2 Impact of feedback profile access on conversion rate

For testing Hypothesis 2 three separate regressions, divided into the groups electronics, health/wellness, office/school supplies, were analysed with “feedback profile access” as the predictor and “conversion rate” as the dependent variable.

The regression analyses confirm, with $p<0.05$, significant regression coefficients for all three groups (see table 4.12). The strongest influence of the predictor “feedback profile access”, with $B=0.380$, can be found in electronics. With regard to the other two groups, $B$ amounts to 0.330 for the category health/wellness and 0.353 for office/school supplies. Altogether, these coefficients identify moderate influence strengths of the predictor. The coefficients of determination show a similar ordering of the categories. The $r^2$ amounts to 0.221 for electronics. In this group the predictor “feedback profile access” can only explain 22.1% of the variability of the “conversion rate”. The $r^2$ are smaller for the groups health/wellness and office/school supplies. With $r^2=0.103$ for health/wellness, only 10.3% of the variability of “conversion rate” is explained by the predictor “feedback profile access”. Finally office/school supplies follows with $r^2=0.081$, which means that only 8.1% of the variability of “conversion rate” is explained by the predictor “feedback profile access”.

Regarding the reliability of the regression estimation, it must first be pointed out that the residuals are normally distributed according to the results of the Kolmogorov-Smirnov test, with $p>0.05$ (see Appendix E). Furthermore, the residuals show no leverage effects. The test confirms homogeneity of variance for all three groups (see Appendix F).

Overall, Hypothesis 2 can be confirmed for all sub-samples of the data.
Table 4.12: Hypothesis 2 - results of the regression analyses

<table>
<thead>
<tr>
<th>Product Category</th>
<th>$r^2$</th>
<th>Unstandardised Coefficients B</th>
<th>Std. Error</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronics</td>
<td>.221</td>
<td>.380</td>
<td>.064</td>
<td>.000**</td>
</tr>
<tr>
<td>Health/Wellness</td>
<td>.103</td>
<td>.330</td>
<td>.084</td>
<td>.000**</td>
</tr>
<tr>
<td>Office/School Supplies</td>
<td>.081</td>
<td>.353</td>
<td>.108</td>
<td>.001**</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

4.5.3 Impact of positive feedback profile on conversion rate

For testing Hypothesis 3, three separate regressions, divided into the product categories (electronics, health/wellness, office/school supplies), were analysed for each product type looking at the relationship of “positive feedback profile” as the predictor and “conversion rate” as the dependent variable.

The regression analyses only confirm significant results ($p<0.05$) for electronics (see table 4.13). In this group, the strength of positive influence of “positive feedback profile” on “conversion rate” amounts to $B=0.253$. The coefficient of determination in this group amounts to $r^2=0.145$, which means that 14.5% of the variability of “conversion rate” is explained by the predictor “positive feedback profile”.

Considering the reliability of the regression estimation, it can be pointed out that the residuals are normally distributed according to the results of Kolmogorov-Smirnov test, with $p>0.05$ (see Appendix E). Furthermore, the residual analysis shows no leverage effects. However, there are some heterogeneous variances of the residuals observable for health/wellness. In this case, where the distribution of the variable feedback profile is very skewed, a visual test is difficult to evaluate. The Levene’s test confirms the homogeneity for electronics and office/school supplies, and heterogeneity for health/wellness (see Appendix F).
Overall, the Hypothesis 3 can be confirmed for the group electronics.

Table 4.13: Hypothesis 3 - results of the regression analyses

<table>
<thead>
<tr>
<th>Product Category</th>
<th>( r^2 )</th>
<th>Unstandardised Coefficients B</th>
<th>Std. Error</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronics</td>
<td>.145</td>
<td>.253</td>
<td>.053</td>
<td>.000**</td>
</tr>
<tr>
<td>Health/Wellness</td>
<td>.014</td>
<td>.201</td>
<td>.151</td>
<td>.161 not sig.</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

4.5.4 Impact of positive feedback profile on arbitrations

For testing Hypothesis 4 three separate regressions, divided into the groups electronics, health/wellness, office/school supplies, were analysed with “positive feedback profile” as the predictor and “arbitration” as the dependent variable.

The regression analysis confirms significant regression coefficients (p < 0.05) for electronics and health/wellness (see table 4.14). The degree of positive influence of the “positive feedback profile” on “arbitration” is \( B = 1.675 \) for electronics. The coefficient of determination in this group amounts to \( r^2 = 0.309 \). Thus, 30.9% of the variability of “arbitration” is explained by the predictor “positive feedback profile”. The influence in the group health/wellness is quite different. Here the value \( B \) shows 1.199, and the coefficient of determination \( r^2 \) is 0.068. Altogether, this marks a positive influence and an explained variance portion of variance of only 6.8%.

When considering the reliability of the regression estimation, it can be first pointed out that the residuals of all categories are normally distributed according to the Kolmogorov-Smirnov test, with p > 0.05 (see Appendix E). The residual statistics show no leverage effects. With regard to the homogeneity of residuals,
the Levene's test will again be applied, as visually it is difficult to say if heterogeneity exits for all three groups. The test confirms homogeneity for all three groups (electronics, health/wellness and office/school supplies) (see Appendix F).

Nevertheless, Hypothesis 4 can be confirmed for electronics and health/wellness.

Table 4.14: Hypothesis 4 - results of the regression analyses

<table>
<thead>
<tr>
<th>Product Category</th>
<th>$r^2$</th>
<th>Unstandardised Coefficients B</th>
<th>Std. Error</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>** p&lt; 0.01</td>
</tr>
<tr>
<td>Electronics</td>
<td>.309</td>
<td>1.675</td>
<td>.224</td>
<td>.000**</td>
</tr>
<tr>
<td>Health/Wellness</td>
<td>.068</td>
<td>1.199</td>
<td>.383</td>
<td>.002**</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

4.5.5 Impact of positive feedback profile on feedback submission

For testing Hypothesis 5, three separate regressions, divided into the groups electronics, health/wellness, office/school supplies, were analysed with “positive feedback profile” as the predictor and “feedback submission” as the dependent variable.

The regression analysis shows statistically significant regression coefficients, with $p< 0.05$, for all groups (see Table 4.15). For the electronics and health/wellness groups there are positive regression coefficients present: Electronics, with $B= 0.263$, and health/wellness, with $B= 0.275$, which constitute moderate influences between the variables. The variance portion explained by the predictor amounts to 9.9% ($r^2= 0.099$) for electronics, and 4.2% ($r^2= 0.042$) for health/wellness. These are generally regarded as minor variance portions.

When looking at office/school supplies, with $B= - 4.523$, there is a statistically
A significant negative regression coefficient present, which points to a negative relationship. The variance, at 4.6% \((r^2 = 0.046)\), is likewise small.

Considering the reliability of the regression estimation, it can be pointed out that the residuals of the category health/wellness and office/school supplies are normally distributed based on the results of Kolmogorov-Smirnov test, with \(p > 0.05\) (see Appendix E). Furthermore, the residual analysis shows no leverage effects.

The Levene’s test shows homogeneity for health/wellness and electronics, but heterogeneity for office/school supplies (see Appendix F).

A reliable confirmation of Hypothesis 5 is given for health/wellness.

**Table 4.15: Hypothesis 5 - results of the regression analyses**

<table>
<thead>
<tr>
<th>Product Category</th>
<th>(r^2)</th>
<th>Unstandardised Coefficients B</th>
<th>Std. Error</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronics</td>
<td>.099</td>
<td>.263</td>
<td>.071</td>
<td>.000**</td>
</tr>
<tr>
<td>Health/Wellness</td>
<td>.042</td>
<td>.275</td>
<td>.113</td>
<td>.016*</td>
</tr>
<tr>
<td>Office/School Supplies</td>
<td>.046</td>
<td>-4.523</td>
<td>1.875</td>
<td>.017*</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

Since there is no normal distribution for electronics, a nonparametric Spearman’s Correlation analysis was applied to evaluate the relationship between a positive feedback profile and feedback submission for electronics.

The correlation table (see table 4.16) shows (1) the correlation coefficient and (2) the significance for each variable. In this analysis, only metric variables, which are not distributed in a normal way, are calculated. Therefore, the Spearman Rank Order Correlation is used. The value for the Spearman
A coefficient can range from -1 to +1. Values close to -1 signify a strong negative relationship, values close to +1 indicate that there is a strong positive relationship between the variables and values close to zero indicate that there is no relationship at all between the variables (Pallant, 2007).

In this analysis, there is a positive correlation for electronics and health/wellness, and a negative correlation for office/school supplies. When looking at the categories of electronic products and office/school supplies, it is evident that with a Spearman coefficient of 0.254 for electronics and -0.266 for office/school supplies, the correlation is weak to moderate. The health/wellness products show a very weak coefficient of 0.067. The negative coefficient for the category office/school supplies means that when the value of one variable increases, the value of the related variable decreases.

With regard to the value of significance, there is no correlation between variables when the significance level exceeds 0.05 (i.e. the null hypothesis will be accepted). If the value of significance is lower than the significance level, i.e. less than 0.05, there is a correlation between variables (and the null hypothesis will be rejected) (Field, 2005). In this case, only the electronic products (p= 0.004) and office/school supplies (p= 0.003) indicate a significance value lower than the significance level.

A positive correlation of Hypothesis 5 is given for electronics and a negative correlation is given for office/school supplies.

| Product Category         | Spearman’s rho Coefficients (rs) | Sig. \\
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>** p &lt; 0.01</td>
</tr>
<tr>
<td>Electronics</td>
<td>0.254</td>
<td>0.004**</td>
</tr>
<tr>
<td>Health/Wellness</td>
<td>0.067</td>
<td>0.440 not sig.</td>
</tr>
<tr>
<td>Office/School Supplies</td>
<td>-0.266</td>
<td>0.003**</td>
</tr>
</tbody>
</table>

Source: Julia Bartels
4.5.6 Impact of average transaction value on conversion rate

For testing Hypothesis 6, three separate regressions, divided into the groups electronics, health/wellness, office/school supplies, were analysed with “average transaction value” as the predictor and “conversion rate” as the dependent variable.

The regression analysis gives significant results for the electronics and health/wellness groups, with p< 0.05 (see table 4.17). The two groups show positive regression coefficients: B= 0.260 for electronics, and B= 0.235 for health/wellness. However, with the plus sign, this hypothesis is contrary. This means the hypothesis should be formulated: “Higher average transaction value does not lower the conversion rate”. The values in both categories characterise moderate to minor relationships. The percentage of variance explained by the predictor amounts to 10.3% (r^2 = 0.103) for electronics and 3.8% (r^2 = 0.038) for health/wellness. These percentages of variance are quite small.

According to the Kolmogorov-Smirnov test, the residuals in all three groups follow a normal distribution, with p> 0.05 (see Appendix E). Furthermore, the residual analysis shows no leverage effects.

The scatter plots, on the other hand, display no conspicuously heterogeneous variances of the residuals for any of the three groups, which is also proved by the Levene’s test (see Appendix F). However, the results of the Durbin-Watson test lie between 1.5 and 1.66, which means d< dl. Thus, although the literature says that with a Durbin-Watson value of 1.5, the data are still independent (Zakerian and Subramaniam, 2009; Khodaverdi et al., 2014), the results of these regression analyses are nevertheless regarded with caution.

Hypothesis 6 can be confirmed for electronics and health/wellness.
Table 4.17: Hypothesis 6 - results of the regression analyses

<table>
<thead>
<tr>
<th>Product Category</th>
<th>$r^2$</th>
<th>Unstandardised Coefficients B</th>
<th>Std. Error</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electronics</td>
<td>.103</td>
<td>.260</td>
<td>.069</td>
<td>.000**</td>
</tr>
<tr>
<td>Health/Wellness</td>
<td>.038</td>
<td>.235</td>
<td>.102</td>
<td>.023*</td>
</tr>
<tr>
<td>Office/School Supplies</td>
<td>.018</td>
<td>.160</td>
<td>.108</td>
<td>.142 not sig.</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

It was originally assumed that the “average transaction value” lowers the “conversion rate”. But in fact, Hypothesis 6 shows contrary results, which means that the two variables show a positive relationship. In order to examine this relationship in more detail, a partial correlation is carried out in the next section to describe the relationship between the two variables and illustrate the influence of a third variable, which is yet to be partialled out. This means checking for a third variable. This third variable is also called a control, or confounding, variable (Pallant, 2007).

4.6 Partial correlation

As already mentioned above, a partial correlation is applied in order to examine if the feedback system could exercise an influence on the positive relationship between “average transaction value” and “conversion rate” (H6). Therefore, a partial correlation is carried out with “feedback profile access” as the control variable. This means that the influence of the variable “feedback profile access” needs to be investigated. This variable has been chosen, because it shows the need of potential customers to learn more about the reputation of the vendor.

The partial correlation is carried out for each product category, beginning with electronics (table 4.18), followed by health/wellness (table 4.19) and finally office/school supplies (table 4.20).
The first table, 4.18, shows three zero-order (Pearson) correlations on the left, without the control variable. The right side contains the partial correlation, which means that the control variable “feedback profile access” is subtracted out. The left side of the table shows that feedback profile access exhibits moderate to strong correlations (0.819 and 0.470), which are highly significant (p= .000***). Further the variables of “average transaction value” and “conversion rate” show significant results. However, the results change significantly when using the partial correlation. Now the relationship between “average transaction value” and “conversion rate” is negative (-0.118) and no longer significant (p= 0.187). For electronics, it can be concluded that the bivariate correlation (zero-order) between “average transaction value” and “conversion rate” is a spurious correlation. The control variable “feedback profile access” has a decisive influence on this relationship.

Table 4.18: Partial correlation with control variable feedback profile access (electronics)

<table>
<thead>
<tr>
<th></th>
<th>With Control Variable &quot;Feedback Profile Access&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Transaction Value &lt;&gt; Feedback Profile Access</td>
</tr>
<tr>
<td></td>
<td>Conversion Rate</td>
</tr>
<tr>
<td>Correlation</td>
<td>.321</td>
</tr>
<tr>
<td>Significance (2-tailed)</td>
<td>.000</td>
</tr>
<tr>
<td>df</td>
<td>125</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

The category health/wellness delivers similarly strong and significant zero-order (Pearson) correlations (0.751, 0.320, p=.000) to those of electronics. When applying the partial correlation, however, the relationship between “average transaction value” and “conversion rate” becomes negative and shows no significance at all. In addition, it can be observed regarding the category health/wellness that the bivariate correlation (zero-order) between “average transaction value” and “conversion rate” is a spurious correlation. The control
variable “feedback profile access” has an important influence on this relationship.

Table 4.19: Partial correlation with control variable feedback profile access (health/wellness)

<table>
<thead>
<tr>
<th></th>
<th>Transaction Value &lt;&gt; Conversion Rate</th>
<th>Transaction Value &lt;&gt; Feedback Profile Access</th>
<th>Conversion Rate &lt;&gt; Feedback Profile Access</th>
<th>Transaction Value &lt;&gt; Conversion Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation</td>
<td>.194</td>
<td>.751</td>
<td>.320</td>
<td>Correlation</td>
</tr>
<tr>
<td>Significance (2-tailed)</td>
<td>.023</td>
<td>.000</td>
<td>.000</td>
<td>Significance (2-tailed)</td>
</tr>
<tr>
<td>df</td>
<td>135</td>
<td>135</td>
<td>135</td>
<td>df</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

Unlike electronics and health/wellness, the category involving office/school supplies does not show a significant relationship between “average transaction value” and “conversion rate” (Hypothesis 6 was not accepted). However, the other two correlations are highly significant. The results of the partial correlation are similar to the results found for electronics and health/wellness, except for the fact that the negative correlation coefficient is lower (-0.005) and the p-value is quite close to 1.000. There is no relationship at all between the two variables “average transaction value” and “conversion rate”.

Table 4.20: Partial correlation with control variable feedback profile access (office/school)

<table>
<thead>
<tr>
<th></th>
<th>Transaction Value &lt;&gt; Conversion Rate</th>
<th>Transaction Value &lt;&gt; Feedback Profile Access</th>
<th>Conversion Rate &lt;&gt; Feedback Profile Access</th>
<th>Transaction Value &lt;&gt; Conversion Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation</td>
<td>.133</td>
<td>.480</td>
<td>.285</td>
<td>Correlation</td>
</tr>
<tr>
<td>Significance (2-tailed)</td>
<td>.142</td>
<td>.000</td>
<td>.001</td>
<td>Significance (2-tailed)</td>
</tr>
<tr>
<td>df</td>
<td>121</td>
<td>121</td>
<td>121</td>
<td>df</td>
</tr>
</tbody>
</table>

Source: Julia Bartels
The effect of a spurious correlation between “average transaction value” and “conversion rate” has been tested using a second partial correlation. This time the “rating number” has been chosen as the control variable. The rating number is displayed on the eKomi widget and on the feedback profile page, and is calculated as follows: A feedback submission consists of a comment and a star rating from 1 to 5 stars, 5 stars being the best. The rating number is based on the number of star ratings submitted over the last 12 months. The total number of stars relating to the past 12 months are divided by the number of reviews (Example: 100 customer reviews, each with 4 stars resulting in a rating number of 4.0). The “rating number” is also a variable representing the reputation of the online vendor.

The results of the partial correlation for the category electronics shows significant results for zero-oder (Pearson) correlations. A correlation between “conversion rate” and “rating number” can be seen, which would support the view that good reputation and higher sales are related. The coefficient of the correlation “average transaction value and the conversion rate” has a value of 0.321. This value decreases to 0.309, when the “rating number” is used as the control variable. This means that the “rating number” supports a higher correlation between “average transaction value” and “conversion rate”.

Table 4.21: Partial correlation with control variable rating number (electronics)

<table>
<thead>
<tr>
<th></th>
<th>Transaction Value &lt;-&gt; Conversion Rate</th>
<th>Transaction Value &lt;-&gt; Rating Number</th>
<th>Conversion Rate &lt;-&gt; Rating Number</th>
<th>Transaction Value &lt;-&gt; Conversion Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation</td>
<td>.321</td>
<td>-.184</td>
<td>.381</td>
<td>.309</td>
</tr>
<tr>
<td>Significance (2-tailed)</td>
<td>.000</td>
<td>.038</td>
<td>.005</td>
<td>.000</td>
</tr>
<tr>
<td>df</td>
<td>125</td>
<td>125</td>
<td>125</td>
<td>124</td>
</tr>
</tbody>
</table>

Source: Julia Bartels
A partial correlation with the “rating number” as the control variable has been carried out for health/wellness products as well. No correlations with the “rating number” show significant results. Only the relationship between “average transaction value” and “conversion rate” is significant (p= 0.023). Although the correlations, including rating number, are not significant, this variable has a very minor influence on the relationship between “average transaction value” and “conversion rate”. The correlation coefficient decreases from 0.194 to 0.189.

Table 4.22: Partial correlation with control variable rating number (health/wellness)

<table>
<thead>
<tr>
<th></th>
<th>Transaction Value &lt;-&gt; Conversion Rate</th>
<th>Transaction Value &lt;-&gt; Rating Number</th>
<th>Conversion Rate &lt;-&gt; Rating Number</th>
<th>With Control Variable “Rating Number”</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation</td>
<td>.194</td>
<td>-.054</td>
<td>-.130</td>
<td>.189</td>
</tr>
<tr>
<td>Significance (2-tailed)</td>
<td>.023</td>
<td>.529</td>
<td>.130</td>
<td>.027</td>
</tr>
<tr>
<td>df</td>
<td>135</td>
<td>135</td>
<td>135</td>
<td>134</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

A second partial correlation for office/school supplies with the “rating number” as the control variable has been neglected. The reason for this is that Hypothesis 6 was not accepted and the correlations are not significant (see table 4.17). Therefore, it is not important to take a closer look at the relationship between “average transaction value” and “conversion rate” for this category.

4.7 Summary of the results

The regression results show a clear pattern regarding how a feedback system is used across the different product categories and how product complexity affects the purchase decision-making. Differences between risk perception, trust and reputation building become evident. In the following, the research model is shown for each category (see figure 4.6 – 4.8) with the $r^2$ results and the p-value of each hypothesis. All p-values below 0.05 testify to the fact that such results
are significant. The red arrows represent the hypotheses about the risk perception and risk evaluation of the customer in an online transaction, the blue arrows represent the hypotheses about the feedback system as a trust-building mechanism, which means customers trust the feedback from others (positive reputation profile) and decide to purchase. They then submit feedback to transfer their trust to future customers. The green arrows represent the hypotheses about reputation based on feedback, which means checking the vendor reputation and maintaining that reputation through the use of arbitrations. In order to evaluate the effect sizes of the \( r \) and \( r^2 \), Cohen (1992) proposes the following classification of effect sizes:

- \( r^2 = .01 - .19 \) (\( r = .10 - .29 \)) means low effect size
- \( r^2 = .19 - .26 \) (\( r = .30 - .49 \)) means middle effect size
- \( r^2 = .26 \) and higher (\( r = .50 \) and higher) means high effect size

**Figure 4.6: \( r^2 \) and significance for electronic products**

\* \( p< 0.05 \), ** \( p< 0.01 \), (NS) \( p> 0.05 \)

Source: Julia Bartels
Of the three categories, the regression analysis for electronics exhibits the highest values for $r^2$ and the most significant results. The very high result of $r^2 = 0.671^{**}$ reveals that risk perception exists and that potential customers want to first reduce the risk by checking the feedback profile (risk evaluation). With regard to the hypotheses about reputation, these are the highest results for Hypotheses 2 and 4. This means that checking the feedback profile first leads to an increased conversion rate. The result of Hypothesis 4 shows that vendors with complex products know the importance of a positive reputation, and thus pay attention to their feedback profiles and properly conduct their management of complaints. The vendors induce arbitrations to avoid negative feedback, and maintain a positive reputation, and thus trust, for potential customers. The two hypotheses presenting trust (Hypothesis 3 and Hypothesis 5) show lower, but significant results. This means that a positive reputation profile leads to an increased conversion rate, and that there is a correlation between the positive feedback profile and submitted feedback.

When looking at Hypothesis 6, the results show that a higher transaction value does not lead to a lower conversion rate. Considering Hypothesis 1, it could be said that most visitors check feedback in the category of electronics. Therefore, a partial correlation was carried out, which stresses the assumption that the feedback profile (reputation check) gives people enough security, and that they trust the vendor. The high transaction value fades into the background. Therefore, higher transaction values do not lead to lower conversion rates, when vendor reputation is present.
The regression results for health/wellness are not as high as those for electronics. Although the average transaction values in the category health/wellness are lower than those for electronic products, the risk perception is clearly evident, with a value of $r^2 = 0.563^{**}$ for Hypothesis 1. Further still, the relationship between feedback profile access (i.e. checking the feedback profile for reputation) and conversion rate, is significant, even if the value of $r^2 = 0.103^{**}$ is relatively low. The result of Hypothesis 4, which analyses the use of arbitrations, is likewise low. Hypothesis 5, which examines whether or not customers leave feedback as a result of being helped with customer feedback before a transaction, is significant. For this category, the partial correlation also indicates that accessing the reputation of the vendor influences the relationship between average transaction value and conversion rate.
When reviewing the results for the category office/school supplies, the values of $r^2$ are very low, and most regressions are not significant. As already observed in reference to the other two categories, here too, Hypothesis 1 presents the highest $r^2$ with 0.230**. Yet compared to the other two product categories, the result is quite low due to cheaper product prices and a low product complexity. With respect to Hypothesis 5, there is a negative correlation, which means that if the value for the positive feedback profile increases, then the value for feedback submission decreases, and vice versa.

It is, however, important to note that $r^2$ is not the ideal aspect of quantifying the results, since the most defining factors are the p-values and the standardised regression coefficient Beta ($\beta$). As already mentioned in 4.5, the p-value makes the results significant, and $\beta$ shows how strong the relationship between the variables is. Table 4.23 gives an integrated summary of the $\beta$-values (the
standardised regression coefficient) for the different product categories for Hypotheses 1 to 6 (for Hypothesis 5 the correlation coefficient is mentioned as well). The standardised regression coefficient “β” has been calculated in order to make the different variables comparable with respect to their measuring units. The β-value shows the strength of the relationship between the given variables. For example, β = 0.819 depicts a strong relationship as compared to β = 0.480, which is considered to be of moderate strength.

Based on the explanations provided, the relationship between the variables of hypotheses Hypothesis 1 and Hypothesis 2 are seen to be strongest for electronics and health/wellness products. This can be attributed to the fact that the value of the transaction and functional/technical complexity are hugely important determinants of the customers’ involvement in electronic commerce transactions (Bhatnagar et al., 2000; Jøsang et al., 2007; Huang et al., 2009). This result shows that the availability of feedback is an important factor in the customer’s decision to purchase online. The relationship, however, is of less strength when it comes to school/office products, because such products are usually cheap and less complex. The cost differences are thus not as significant to the consumers, and this helps to make the decision to purchase online easier.

Hypothesis 3 and Hypothesis 4 exhibit a moderately strong correlation for electronic products (β = 0.381 and β = 0.556), while health/wellness displays low results (β = 0.115 and β = 0.260). Positive feedback will play an important role in conversion rates, while feedback from highly complex products will be subject to arbitration procedures should there be any feedback submitted that is seen to be unfair and to the disadvantage of the vendor. This is due to the fact that customers of such products are very sensitive to the nature of the feedback left by former buyers (this explains the observations made on Hypothesis 3 and Hypothesis 4) (Resnick and Zeckhauser, 2002; Girard et al., 2002). It can also be noticed that the β-values corresponding to office/school products, as displayed in hypotheses 3 and 4, have negative values (β = -0.096 and β = -0.047) The negative sign means that the results corresponding to these hypotheses have inverse relationships. The negative sign in Hypothesis 3 and
Hypothesis 4 implies that positive reputation does not play a very important role, because office/school products are less complex and less expensive, and therefore customers perceive less risk. The technological makeup of these products are also simple and are usually associated with less costly risks, if any. A consumer will therefore see no need to inquire about the reputation of the vendor before making up his or her mind as to whether to purchase such a product. From the perspective of the vendor, vendors of office/school products seem to pay little attention to incoming feedback, especially negative feedback.

All the results for Hypothesis 5 show weak to moderate relationships for experience products and search products. The positive results for electronics reflect the relationship between a positive vendor feedback profile and feedback submission in the post-purchase phase (Dellarocas and Wood, 2004; Decker, 2007; AlGhamdi et al., 2013). Hypothesis 5 implies that for office/school products there is an inverse relationship between positive feedback and feedback submission. Here there is a negative correlation coefficient for office/school supplies.

When looking at the β-values of Hypothesis 6, it can be seen that the relationships for all three categories are quite low, which means that the transaction value is not a main driving factor for making online purchases. However, the fact that there are three different classes of products with different transaction values and technological/functional complexities is responsible for the lateral decrease in the figures as one moves along the different product categories.
### Table 4.23: Overview of relationship strength

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Coefficient β</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronics</td>
<td>Health/Wellness</td>
</tr>
<tr>
<td>H1</td>
<td>.819</td>
</tr>
<tr>
<td>H2</td>
<td>.470</td>
</tr>
<tr>
<td>H3</td>
<td>.381</td>
</tr>
<tr>
<td>H4</td>
<td>.556</td>
</tr>
<tr>
<td>H5</td>
<td>.315</td>
</tr>
<tr>
<td>H6</td>
<td>.321</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Spearman rho Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>H5</td>
<td>.254</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

The following table, 4.24, gives an overview of all confirmed hypotheses for each category. The hypotheses are associated with what they actually measure, namely, risk, trust and reputation. It is evident that with a decline in product complexity the number of confirmed hypotheses decreases.

### Table 4.24: Confirmed hypotheses for different product categories

<table>
<thead>
<tr>
<th>Product Category</th>
<th>Risk</th>
<th>Trust</th>
<th>Reputation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronics</td>
<td>H1, H6</td>
<td>H3</td>
<td>H2, H4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>H5 (only correlation)</td>
<td></td>
</tr>
<tr>
<td>Health/Wellness</td>
<td>H1, H6</td>
<td>H5</td>
<td>H2, H4</td>
</tr>
<tr>
<td>Office/School Supplies</td>
<td>H1</td>
<td>H5 (only correlation)</td>
<td>H2</td>
</tr>
</tbody>
</table>

Source: Julia Bartels
4.8 Summary of descriptive statistics and hypothesis testing

In this chapter, data analysis methods and study results have been presented. Concerning the distribution of the values, the skewed distributions required a transformation in logarithmic values to avoid extreme values or strong deviations. The regression analyses and, in part, the correlation analyses, were used to test the hypotheses. The results show a clear pattern in the way a feedback system is used across the different product categories and how reputation and trust affect the purchase decision-making. Some findings from this study have been found to be consistent with the findings of several related studies on online risk, online trust and online reputation. The results for electronics show the most significant and highest results compared with the other two categories. However, the findings for health/wellness, as a moderately complex product category in a lower price bracket than electronics, also showed that the presence of vendor reputation is important for decreasing risk perception. The results for office/school supplies are quite low due to cheaper product prices and a low product complexity.
5 Discussion of the study findings
In this chapter, the main findings from testing the six hypotheses are summarised and general conclusions based on the findings of the studies presented in this thesis are described. Additionally the contribution this thesis makes to theories of risk, trust and reputation is stated.

5.1 Comparison with literature
With the aid of browsing and purchasing data from 387 B2C online stores, this study furthers our understanding of customer’s online risk and trust, and vendor’s online reputation. System-generated data from the feedback company eKomi (a total of 445,135 feedback entries from 1,517,374 transactions were considered) enabled an analysis of the customers’ actual interactions with a feedback system during a purchase process, as well as of how vendors make use of a feedback system. Three product categories (electronics, health/wellness and office/school supplies) with different levels of complexity (high, moderate and low) were analysed to explore how a feedback system enhances vendor reputation, mitigates product complexity and thereby facilitates online purchase decision-making.

As has already been described in the literature review, the study is based on research about risk, trust and reputation in the online environment, as well as online feedback systems and purchase decision-making regarding both search and experience products in an online store. A preliminary research model and conceptual framework were developed (see figure 2.6). Hypotheses were tested in order to explore the degree to which users seek to assess the recognised risk relative to the amount of the transaction value and functional complexity (product complexity), how far users trust the feedback profile, the influence of reputation on their purchase decisions, the influence of a positive feedback profile on feedback submission and how seriously online vendors care about their reputation profile and respond to negative feedback. For all hypotheses, three different product categories were taken into consideration.
When comparing the main findings of this research with those already documented by other scholars, it is evident that some findings confirm their results and others grant new insights into risk, trust and reputation in an online setting.

Risk, which is considered as one of the inhibiting factors of customer conversion, is found to increase with the level of product complexity. This result is perfectly in line with existing literature, as evident from publications such as Bhatnagar et al. (2000). Thus, complexity is found to have an inevitable influence on online purchase decision-making. Results from the data analysis of the present study show that feedback is an influential factor in a purchase process and mitigates product complexity.

Trust is acquired through good reputation, and a good reputation is fostered by positive feedback. In contrast to the literature (Ba and Pavlou, 2002; Houser and Wooders, 2006; Chevalier and Mayzlin, 2006; Brown and Morgan, 2006; Bolton et al., 2008; Cabral and Hortacsu, 2010), it is evident that for highly complex products, the aspect of trust is more important than for products of moderate and low complexity. Building trust and influencing purchases has the most significant impact on consumers of highly complex products. Furthermore, the same effect of positive reputation on feedback submission found in the study of Dellarocas and Wood (2008) is recognised in this study. Without a differentiation in product complexity, Dellarocas and Wood’s findings on eBay (C2C) show that the higher the positive reputation scores of vendors the greater the participation in feedback submission. This study confirms the relationship between positive reputation and feedback submission with an emphasis on complex products.

A reputation based on positive feedback, as found during the study, will help the vendor to achieve a higher conversion rate. Literature that supports the findings here include Ba and Pavlou (2002), Houser and Wooders (2006), Chevalier and Mayzlin (2006), Brown and Morgan (2006), Bolton et al. (2008), Cabral and Hortacsu (2010). Positive reputation is found to have the greatest effect on the number of arbitration procedures conducted regarding the feedback for highly
complex products. Thus, evidence is provided that vendors of high complex products are well aware of the importance of developing and sustaining their good reputation. This finding confirms the importance of a positive reputation for complex products and agrees with the existing literature, confirmed by Girard et al. (2002). The reputation helps the vendor to show competence and integrity, which fosters trust in potential customers (see section 2.7.2).

5.2 Relevance of product classification
The relevance of the classification between search and experience products is illustrated on the next page (see figure 5.1). The pie charts show the percentage of widget clicks (in %), the percentage of transactions (in %) and the percentage of submitted feedback (in %) for each product category of all 387 stores in the period investigated. It becomes evident that reviewing feedback (based on widget clicks) is especially more frequent for experience products (electronics, health/wellness) than it is for search products (office/school supplies). Also, more feedback is submitted for experience products than for search products (health/wellness shows the highest percentage of feedback submission due to the highest sample size). When looking at the pie chart for office/school supplies, it is evident that a feedback system (reviewing feedback) does not have the same impact as it does on the other two product categories.
Figure 5.1: Feedback and transaction data of different product categories

(Database of all 387 online stores analysed in the period investigated:
Electronics = 127 stores, Health/Wellness = 137 stores, Office/School = 123 stores)
Source: Julia Bartels
Table 5.1 illustrates the differences in the acceptance of a feedback system between experience and search products based on the medians of widget clicks, submitted feedback (positive and negative) and the average transaction value. The number of widget clicks reflects that potential customers of experience products see the need to review the feedback of past customers. With a median of 1,799 widget clicks, it is evident that potential customers of electronic products have a higher feedback access rate than potential customers of health/wellness products (875 widget clicks) and potential customers of office/school supplies (461 widget clicks). Thus, feedback availability is important for complex products.

The next column of table 5.1 shows the submitted feedback of the different product categories. Here there is no percentage of submitted feedback, but submitted negative and positive feedback is shown in absolute numbers. These numbers confirm the findings of the thesis. Electronics show a higher median for positive feedback than the other two categories. This shows that vendors of this highly complex product category know about the importance of a positive reputation and, if necessary, make use of arbitrations to maintain it. The quite low value of negative feedback (mean = 3.97) for this category suggests that the vendors make use of arbitration processes.

The health/wellness category has a lower median for positive feedback and a greater mean for negative feedback than the category of electronics. This confirms the finding that positive reputation does not play as important a role fostering trust and thereby facilitating purchase decisions. The findings could be interpreted as meaning, on the one hand, that the feedback access is important, but, on the other, that vendors of health/wellness products do not make such an extensive use of arbitrations.

The feedback medians for office/school supplies show quite a high value for positive feedback and a low value for negative feedback. The low level of complexity for this category may not lead to many complaints. The widget clicks show that less visitors read customer feedback than is the case for the other
two categories. This fact may emphasise that reputation does not play a great role for this low complex product category.

Table 5.1: Medians (means) for different product categories

<table>
<thead>
<tr>
<th>Product category</th>
<th>Number of widget clicks</th>
<th>Number of submitted feedback</th>
<th>Average transaction value (EUR)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Positive feedback</td>
<td>Negative feedback</td>
</tr>
<tr>
<td>Electronics</td>
<td>1799</td>
<td>260</td>
<td>0 (3.97)*</td>
</tr>
<tr>
<td>Health/Wellness</td>
<td>875</td>
<td>121</td>
<td>0 (11.06)*</td>
</tr>
<tr>
<td>Office/School</td>
<td>461</td>
<td>229</td>
<td>0 (1.85)*</td>
</tr>
</tbody>
</table>

*Means are given to show a trend / medians show always a value of 0
(Database of all 387 online stores analysed in the period investigated)

Source: Julia Bartels

5.3 Analysis of findings

5.3.1 Impact of average transaction value on feedback profile access

Hypothesis 1 shows the strongest results of all the hypotheses, as justified by the significant p-values = 0.000** for electronics, health/wellness products and office/school supplies. The standard regression coefficient Beta (β) shows 0.819 for electronics, 0.751 for health/wellness and 0.480 for school/office.

Hypothesis 1 implies that whenever the cost of the product in question is high, there is a high tendency for consumers to try to inquire about more feedback information about the vendor to evaluate the risk, before actually deciding on whether or not to complete a purchase. It can clearly be seen that the rate of risk perception increases as product complexity increases from low to high. This implies that the complexity of the consumers’ decision-making process increases from the most straightforward decisions involving office/school products, to those involving health/wellness products, to those involving electronic equipment, which is characterised by the most complexity. This finding confirms what can be found in the literature, i.e., that the value of the transaction is an important driver for users’ ‘perception of risk’. Or, in short, that
the higher the price of a product, the greater the perception of risk, and the need for the online user to evaluate that risk, will be (Bhatnagar et al., 2000; Jøsang et al., 2007).

As described in the literature (Bhatnagar et al., 2000), risk perception is greatest when the product is technologically complex, which mostly also involves high prices. The results of this study show that the impact of the average transaction value on risk perception is highest for electronic products. These products were classified as highly complex products, and, according to Nelson’s (1970) classification, as experience products (the ones with the most difficulty to evaluate the product quality before purchase). Figure 5.2 shows the median of the average transaction value (average price in EUR) for all analysed online stores, divided into the three product categories. The category of electronics shows the highest median (average transaction value = 297 EUR), followed, at a large distance, by health/wellness. Office/school supplies show the lowest median (average transaction value = 34 EUR), but are also very close to health/wellness. This figure confirms that the more complex the products, the higher the average transaction value. This leads, as already mentioned, to a higher need for risk evaluation.

Figure 5.2: Average transaction value (median) for different product categories

![Figure 5.2: Average transaction value (median) for different product categories](image)
Figure 5.3 below shows the median of the percentage of all visitors who reviewed the feedback profile (by clicking on the widget) before a purchase was taken into consideration for each analysed online store. The user’s click actions to access the feedback profile in the sample was greatest for the category with electronic products (median = 3.1%).

**Figure 5.3: Reputation check (median) for different product categories**

![Bar chart showing feedback profile access in different categories]

When comparing the two diagrams, it is evident that stores with high transaction values are high in feedback profile access. This reflects the degree of financial risk, which will be mentioned later in this chapter.

A similar impact of transaction value on feedback profile access was also found for the category of health/wellness. These products are likewise classified as experience goods, albeit with a relatively moderate complexity. The results calculated for electronics and health/wellness comply with the literature (Bei et al., 2004; Huang et al., 2009) showing that online information sources from other consumers tend to be more frequently used by consumers of experience products. Whereas Chu and Li (2008) found in their study that the level of perceived risk is the same for search and experience products in the online environment, this study found differences in checking the reputation of the vendor between search and experience products.
A lower result regarding impact of transaction value on feedback profile access was obtained from the analysis of the category office/school supplies. Nevertheless, there is an influence of a similar type for office/school supplies, though to a weaker extent than for the other categories. The lower result can be explained by the product classification. Office/school products are rather simple goods with a lower transaction value. They are classified as search products whose product attributes and overall quality can be assessed prior to purchase, and they therefore appear to be less risky in the eyes of purchasing users.

This research result, and the literature on the subject, confirms that the level of product complexity and the transaction value influences the online consumer’s search for information and information processing (Bhatnagar et al., 2000; Lin and Chen, 2006). Whereas experience products require more information and social influence, low involvement products, such as search products, require only a limited decision-making process.

When reviewing figures 5.2 and 5.3 above, it becomes evident that product complexity plays a very significant role for Hypothesis 1. Figure 5.2 on transaction value shows that the price of health/wellness and office/school supplies does not differ in that dimension, as it can be recognised for electronics and health/wellness. Although beauty products such as shampoo are not so expensive, but since they are directly used on the consumers’ bodies, the overall risk perception (feedback profile access) for health/wellness (see figure 5.3) is higher than for office/school supplies.

Considering the different risk types, electronic products carry the highest financial risk of the three product categories (see figure 5.2). This is because of all products available on the Internet, electronic equipment usually has the highest prices, given the technological nature and the expenses incurred during their manufacturing and transportation. A customer who is interested in purchasing electronic equipment usually has many questions to ask about the product that have to be answered for the amount of money spent on such items to seem justified. If a loss occurs from purchasing a product of such nature, it would, of course, be a significant loss. For obvious reasons, an online customer
would rather lose a less expensive item than an expensive one. There are many similarly obvious reasons why health/wellness products are second to electronic products in terms of risk perception and risk evaluation. First, these products are relatively more expensive than office/school related goods, which make them more valuable than the latter. Hence, customers will ask more questions regarding these items than regarding office/school products. Office and school products, in turn, are usually characterised by the smallest number of inquiries, since they are simple, cheap and have specific uses. The buyers, therefore, have lower fears of being cheated concerning these items, and, even if any risks are considered, they are expected to be less costly to the customers than items from the above-mentioned categories. This is probably the reason behind the less complex decision-making processes, as illustrated by the low click behaviour shown in figure 5.3.

The aspect of product (performance) risk is associated with the value of the transaction and might have a significant effect on the strength of the relationship between transaction value and accessing the feedback profile of an online store. Electronic products again take the lead here for reasons that relate to their technical nature. This sort of equipment is usually accompanied by the manufacturer instructions and manuals. However, it is not always guaranteed that users purchase the product that actually matches their tastes and preferences, nor is it assured that the quality standard of the goods being purchased by the consumers will meet expectations. The functionality, as described in the user manuals, is never guaranteed to be in accordance with the advertised performance claims of the products. For this reason, consumers are always quite sceptical about the effectiveness of these products and will have to ask many questions before making any transactional decisions. The fear of buying a defective product still revolves around the product being characterised by high transactional value, which is the driving factor in increasing the customer’s risk perception. The decision-making involved in the purchase of electronic products from an online store becomes even more complex when this aspect is taken into consideration.
The other product category that conforms to this rule, according to Hypothesis 1, is health/wellness products. These are products have direct influence on the health and wellbeing of the customer/user, which means that any failure to adhere to the manufacturers’ directions could result in adverse effects. Most of these products usually include drugs, drinks and other forms of edible substances that will directly affect consumers’ physiological systems. A consumer willing to buy pills intended for weight loss, for instance, will have many queries about the pills. Such concerns may include how to consume them, the period during which they should be consumed, any negative incidents that may occur during consumption (and the corresponding remedy) and, most importantly, any side effects associated with the product. These worries concerning the product category health/wellness are reflected in figure 5.3, which shows a quite high access to feedback information relative to the lower transaction value illustrated by figure 5.2. In this context, it is important to mention the physical risk, as defined in the literature review. This could be an explanation for the high feedback access. For this product category, users may perceive a mix of product risk and physical risk. It is important that all products perform as expected, but in contrast to electronics, the health/wellness products directly affect the consumer’s health and body.

Office and school-related products are usually simple, both in terms of their material composition as well as their application; and, most importantly, they are cheap. Customers are well acquainted with the functionality of most such products, and even though they would not want to buy a defective product, the extent to which they would worry about the losses associated with purchasing defective items of this kind is significantly lower than it would be for the two types of products discussed above. If a customer purchases an item such as a stapler that is defective, he or she can very easily replace and/or throw away that item at minimal cost. This is not the case, e.g., with a refrigerator. This offers support for Hypothesis 1 and explains why the standardised regression coefficient Beta (β) indicates lower values in these types of commoditised products.
Another trend prevailing in the findings of the first hypothesis is that it shows the strongest relationships (see Table 4.23 in the previous chapter) as compared to the rest of the hypotheses. These trends were recorded as highest in all types of products. The argument of Bhatnagar and Ghose (2004) and Lu et al. (2005) can be used to improvise an explanation for this trend. They argued that the most important aspects of risk, and the types of risks that affect online shopping the most, are financial risks and product risks. These two can be seen to have a direct link with the value of the transaction and product complexity. And physical risks, too, seem to play a role in online transactions.

In general, Hypothesis 1 indicates that the combination of the value of the transaction and functional/technical complexity generally determines the risk perception of online customers and the need to evaluate this risk. The technological sophistication and relative price of the products is the first factor that plays a significant role in the complexity of the decision-making process of online shoppers. As a result, the entire behaviour of online customers is heavily dependent on financial and product (performance) risks.

5.3.2 Impact of feedback profile access on conversion rate
Hypothesis 2 reviewed the influence of the ability to access the feedback profiles (reputation check) on the conversion rate (i.e., enabling a transaction to take place). Although the results are not as strong as for Hypothesis 1, all values are significant (p= 0.000** for electronics and health/wellness and p= 0.001** for office/school supplies) and in line with prevalent view in the literature (Huang et al., 2009) that checking the vendor reputation allows the online customer to re-evaluate the risk associated with buying online from a specific retailer, and would thus increase the probability of a consumer purchasing from that retailer.

Again, the highest and most valid result was found for the category of electronic products. This is based on the results indicated by the standardised coefficient Beta (β) in Hypothesis 2 (standardised β= 0.470), which is highest here. When considering electronic products, the vast majority of online users in the sample
checked the vendor’s feedback profile to learn more about the vendor’s reputation before they actually made a purchase. The category health/wellness shows lower results ($\beta = 0.320$) that are very close to the results for the category office/school supplies ($\beta = 0.285$). Although the values, especially for health/wellness and office/school supplies, are somewhat lower, there is still a recognisable pattern in the results. It can be seen that a risk-reduction mechanism in the form of checking customer feedback is conducive to purchases for more complex products. Whereas the literature only tested the impact of feedback profiles on the probability of sale, this research tested the actual purchase. Aside from the difference between purchase likelihood (Huang et al., 2009) and actual purchase (this study), however, both confirm that offering customers feedback to facilitate the online purchase is more important for experience products than for search products.

The conversion rate with regard to online shopping refers to the fraction of the website’s total visitors that goes on to take the extra step and conduct an actual online purchase as a result of being persuaded by the feedback and advertisements available on the website. The aspect of risk perception has remarkable effects on the rate at which visitors are converted into active paying buyers. Risk perception is a very general term that can be divided into subsections depending on the types of risks under consideration. As the results suggest, financial and product (performance) risks affect the customer conversion rate.

With regard to the financial risk, customers are known to always be in constant need of reassurance that the type of business transaction in which they are taking part is accompanied with very little or no monetary loss. According to the findings collected, it can be seen that for expensive products in the electronic category, the rate of conversion increases as the level of customers’ risk perception decreases, which is evident from checking the customer feedback profile. This implies that when customers visiting an online store find any sort of feedback that convinces them that their cooperation with such a store in any sort of transaction involving monetary exchange is not associated with heavy
monetary losses, then they are more likely to be converted than if the reverse is the case.

When potential customers argue to themselves about the possible risks that may arise in the transportation of the purchased products, as well as the potential risks that may surround the process of online fund transfers, they tend to put more emphasis on experience and expensive products than they do for search products. As a result, they conduct more research and consult more feedback. The scatter plot (see figure 5.4) considers all analysed stores with electronic products. It seems to indicate a positive relationship between the feedback profile access (reputation check) of visitors and the conversion rate. The regression line based on $r^2$ ascends from left to right (positive values) and the more the line is steeply rising the stronger the relationship. The plot shows a medium relationship between the two variables, which confirms that feedback profile access (reputation check) leads to higher conversion rates. The mainly positive values of the log transformed data in the plot illustrate quite high levels of feedback profile access and higher conversion rates for the category of electronics.

**Figure 5.4: Relationship between feedback profile access and conversion rate for electronics**

![Scatter plot showing the relationship between feedback profile access and conversion rate for electronics.](source: Julia Bartels)
The next scatter plot (see figure 5.5) compares the same variables for the health/wellness stores. The plot shows a weak relationship between the feedback profile access (reputation check) of visitors and the conversion rate. Health/wellness products are associated with relatively lower monetary values and hence lower risk perceptions, according to Hypothesis 1. The values for the conversion rate are quite high, but the values for the feedback profile access are lower than those of electronic products. There are not so many dots in the top right corner as there are in figure 5.4. The scatter plot illustrates that reviewing the feedback profile in some cases does not automatically lead to higher conversion rates.

Figure 5.5: Relationship between feedback profile access and conversion rate for health/wellness

The following scatter plot (see figure 5.6) compares the same variables for the stores selling office/school supplies. The plot seems to show a very weak relationship between the feedback profile access (reputation check) of visitors and the conversion rate. The log transformed values for feedback profile access are very low compared to the other two product categories. Office/school related products tend to be cheap, and hence associated with the lowest risk perceptions. Therefore, the dots for feedback profile access and conversion rate do not really illustrate a connection between reviewing the feedback profile to
learn more about the vendor reputation and conversion rates. Online visitors may become involved in transactions involving them because they do not expect to be conned on such items, and even if they are conned, they would not lose so much as a result.

**Figure 5.6: Relationship between feedback profile access and conversion rate for office/school supplies**

The effort required to check the feedback profile can lead to another type of risk. Time risks, as defined by Forsythe and Shi (2003), refer to the time and effort that the potential buyer is likely to waste as a result of engaging in an online shopping activity involving a particular type of product. In this study, time risks can be reduced by checking the feedback profile, or, in other words, by potential customers taking the time to research the vendor’s reputation to avoid a bad purchase. A bad purchase would result in wasted time (waiting for delivery, product usage, returning the product). The results confirm with the literature (Huang et al., 2009) that consumer feedback and experience simulation (e.g., consumer reviews and multimedia) increase the time spent in a domain, but only for customers looking at experience products. Electronic equipment will still take the lead, followed by health and wellness products and then office/school based equipment. Click behaviour would remain high for electronic equipment, as customers would still be willing to put in time to get a
broad understanding of the vendors’ trustworthiness before subjecting themselves to any sort of business cooperation with them. This is because the losses associated with time risks involving these products are much costlier than with the others. The technical nature of electronic products and the sensitivity of health-related products, coupled with their relatively expensive prices, make them record higher results than office/school related products.

In conclusion, the data results presented above concurs with the findings of already existing literature (Girard et al., 2002; Resnick and Zeckhauser, 2002; Lee and Malmendier, 2005; Güth et al., 2006), with the only difference being that the findings documented in this thesis reflect the actual and real-life experiences in the online shopping sector, while the literature surveyed only provides hypothetical expectations and proposals (Kim et al., 2008). The effects of reputation checks on the rate of customer conversion can be tabulated to result in a trend quite similar to that of the first hypothesis, even though these effects are not as intense as those of Hypothesis 1. The process of keeping the customers’ feedback on a close check has a significant influence on the rate at which potential customers become converted into actual customers. This is because the process leads to a substantial reduction in the extent to which such potential customers expect to suffer risks involved in such transactions, and hence increases the probability of their being willing to engage in such transactional practices.

Product complexity involving sophisticated technology and higher prices greatly contributes in shaping the customers’ feelings about wanting to buy certain items. For this reason, potential customers who may be interested in purchasing electronic equipment will have to make exhaustive inquiries into these items before agreeing to subject themselves to any agreements involved in the online purchase. The level of feedback required is higher for health and wellness products than it is for office/school equipment for similar reasons. It can be seen that customers are easily converted in the case of cheap/search products, due to their low prices and the correspondingly low risks involved.
5.3.3 Impact of positive feedback profile on conversion rate

Whereas the hypothesis above has shown the impact of accessing the vendor’s feedback profile (reputation check) on the conversion rate, the following hypothesis tested the impact of trust on the conversion rate. Technically speaking, the rate at which customers are converted is a function of the vendors’ trustworthiness and the extent to which they can win the confidence of the target buyers. This means that potential customers have already had the chance to read past customers’ feedback and learn more about the vendor’s reputation. The regression analysis only confirms very significant results ($p=0.000^{**}$) for electronics, with standardised coefficient $\beta=0.381$. This means that a positive reputation influences the purchase of highly complex products.

Whereas the literature shows that online vendor reputation based on feedback influences sales of different types of products (Resnick and Zeckhauser, 2002; Ba and Pavlou, 2002; Houser and Wooders, 2006; Chevalier and Mayzlin, 2006; Brown and Morgan, 2006; Bolton et al., 2008), this study finds evidence that a positive feedback profile (positive reputation) is especially important for highly complex products. With the help of vendor reputation, the consumer is likely to infer that the vendor will continue its behaviour (as seen in the positive feedback profile) in the present transaction, and therefore concludes that the selling party is trustworthy. Consequently, trust plays an important role in expensive and complex transactions. With respect to health/wellness and office/school products, the values were not significant ($p=0.161$ for health/wellness and $p=0.291$ for office/school supplies). From these results, it can be concluded that vendor reputation, and therefore trust, does not play an important role when purchasing moderately complex and simple products.

The best method vendors can adopt in the attempt to create confidence among their target customers (and hence in their trust and willingness to conduct business cooperation with them) is the employment of positive feedback from customers who have been involved with them in the past. When this is done, the vendors’ reputation receives a heavy boost and most potential customers are more likely to be converted into active buyers who are willing to complete transactions. The most discussed form of reputation in this particular case is
positive reputation, which in the case of online stores is usually dictated by the quantity of positive feedback available on the feedback profile page. It should be taken into consideration that feedback depicting the weaker sides of the business are also displayed to give the customers a broader picture and allow them to see how, on average, the online store’s strengths outweigh its weaknesses. The diagram (see 5.7) below shows the distribution of positive feedback in proportion to total feedback (as well as the negative and neutral feedback involved) (in percentages) for the analysed cases. Most online stores have a feedback profile of 99%–100%, and this is quite similar throughout all product categories. However, the results also show that this positive feedback profile only matters for electronic products.

**Figure 5.7: Distribution of positive feedback in analysed online stores**

![Diagram showing the distribution of positive feedback profiles in different categories of online stores.](image)

Source: Julia Bartels

Vendor trustworthiness is associated with the assurance to customers that there is absolute reliability and competence in the delivery of services. Accordingly, a vendor who is highly reputed for making timely deliveries, delivering products in the expected conditions and properly dealing with customers’ queries is more likely to convert a large population of Internet visitors into active customers. Items that a customer can see in the feedback system have been found in this study to include the quality of the products that their potential vendors are offering, and the way in which their problems and concerns can be handled by the vendors. With all these qualities, it stands to reason that most of the people
who happen to visit the websites of such stores are more likely to change their minds about clicking away or calling on the services of a competitor.

Of all the analysed products, the assurance of product quality would cause a relatively high increase in the conversion rate of customers intending to buy electronic equipment, as well as health/wellness products, while search products would record the least increase.

Again, expensive and technical products such as electronic equipment are more likely to provide high results because fund transfers in transactions involving these products involve large sums of money. The customers will therefore require exhaustive feedback in the attempt to avoid losing large amounts of money. The search products, as usual, will be characterised by few queries for the reason that the customers value their time more than the potential losses that they tend to incur, should the transactions involving such products end up with irregularities.

Overall, given variations among different types of products in most online stores, there is bound to be a corresponding variation in the manner in which customers respond to different feedback related to them. As stated in the literature review (2.5.4) a high level of positive feedback of former customers transfers trust to the potential customers (trust transference). Trust in a vendor significantly increases the willingness of customers to purchase electronic equipment, since it offers a guarantee of protection against the risks that act as barriers to customer conversion. The health/wellness products and the office/school-related products do not show significant relationships. The reason behind this is that these products are cheaper and have fewer technological variables than electronic products. This result was expected for office/school supplies. However, it is more surprising for health/wellness products, since these products affect the consumers’ health and body. This result might be explained by this category’s inclusion of many beauty products from well-known manufacturers. This trust, which is transferred from the manufacturers reputation to the customer (trust transference), is enough to convince the customer, making the actual vendor reputation rather irrelevant. As seen in the
previous hypothesis, customers want to check the feedback profile, but the degree of positivity is less important. The vendor's role is also of limited importance when it comes to the delivery of such products. Due to their smaller scale, most beauty products are fairly easy to pack and post, whereas the delivery of larger, fragile electronic items is far more difficult to manage, and so the positive reputation of the responsible vendor in these transactions is paramount.

5.3.4 Impact of positive feedback profile on arbitrations
This study has showed the importance of reputation for vendors of complex products. As described in 5.3.3, a positive vendor reputation to develop trust is especially important for highly complex products. This study provides some evidence that vendors of complex products are well aware of the importance of developing and keeping their good reputations. Hypothesis 4 is confirmed for electronics (p= 0.000**) and health/wellness (p= 0.002**). This means that vendors in these product categories monitor incoming feedback and try to avoid the publication of any negative feedback. When they notice negative feedback that they feel might be unfair, they initiate an arbitration process, as described in the methodology chapter 3.4.6.2, and conduct a complaint management initiative (arbitration process) to satisfy the customer. As expected, the strongest relationship was found for electronics with a standardised coefficient \( \beta \) of 0.556, which means that the importance of positive reputation is now proven from both the customer side (Hypothesis 3) and vendor side (Hypothesis 4). As the literature states, a positive reputation is important for reducing risk and enhancing trust toward potential customers, especially for vendors with complex products (Girard et al., 2002).

Although the category of health/wellness had a very low standardised coefficient \( \beta \) of 0.260, the relationship is still significant. Therefore, it can be concluded that vendors of complex products really make an effort to engage with the feedback system to establish a good reputation. The initiation of an arbitration process can be seen as a form of complaint management. They can learn from dissatisfied customers ways to improve their processes. With proper
complaint management, vendors can prove or restore their competence, ability and integrity (Lee and Lee, 2006). Since eKomi takes part in the arbitration process, vendors are not in a position to simply delete negative feedback.

The hypothesis cannot be confirmed for office/school supplies. The reputation for vendors of simple products is not seen as being of great import, and therefore these vendors seem less likely to initiate arbitrations. When reviewing the number of transactions and the number of arbitrations, analyses show that for electronics arbitrations increase when a mark of 1,600 transactions is passed. Vendors, dealing with health/wellness products displayed a similar tendency, but with lower numbers. Here, there was no increase in arbitrations relative to the number of transactions. In the category office/school supplies, however, the number of arbitrations increases with the number of years the vendor has been using the system. An increase of arbitrations begins when a mark of 2,000 transactions is passed.

As mentioned in the methodology chapter 3.4.7, the online stores analysed in this thesis have been working with the eKomi feedback system between 1 and 3 years. Both the feedback system experience (1, 2 or 3 years) and product category columns in table 5.2 display the median number of arbitrations conducted by vendors. It is evident that vendors of electronic equipment, regardless of their experience with the system, make extensive use of the arbitration processes. During the period investigated many vendors of electronics conducted between 22 and 30 arbitrations. The other two categories exhibited lower numbers.
Table 5.2: Median of arbitrations and the vendor’s experience with eKomi

<table>
<thead>
<tr>
<th>Product category</th>
<th>Number of cases</th>
<th>Experiences with eKomi feedback system</th>
<th>Median of arbitrations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronics</td>
<td>35</td>
<td>1. Year</td>
<td>22.0</td>
</tr>
<tr>
<td></td>
<td>47</td>
<td>2. Year</td>
<td>30.0</td>
</tr>
<tr>
<td></td>
<td>47</td>
<td>3. Year</td>
<td>30.0</td>
</tr>
<tr>
<td>Health/Wellness</td>
<td>34</td>
<td>1. Year</td>
<td>13.5</td>
</tr>
<tr>
<td></td>
<td>58</td>
<td>2. Year</td>
<td>16.5</td>
</tr>
<tr>
<td></td>
<td>43</td>
<td>3. Year</td>
<td>14.0</td>
</tr>
<tr>
<td>Office/School</td>
<td>39</td>
<td>1. Year</td>
<td>2.0</td>
</tr>
<tr>
<td></td>
<td>41</td>
<td>2. Year</td>
<td>7.0</td>
</tr>
<tr>
<td></td>
<td>38</td>
<td>3. Year</td>
<td>8.5</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

The above-tabulated results confirm that vendors who communicate with their potential customers via online feedback systems are usually well informed about how important it is for them to achieve and sustain a positive reputation. The main method of concluding that the vendors’ reputation for competence and integrity is impressive is looking at the comments and feedback left by previous customers. Positive customer feedback submissions have positive effects on the reputation of a particular vendor, while negative customer feedback negatively affects the reputation of a vendor, and hence reduces the vendor’s chances of converting potential customers into active customers. The sole objective of any online vendor is to attract as many buyers as possible and to prove to those potential customers that they have chosen the right vendor to buy from and need not turn to a competitor. The $\beta$-value of 0.556 shows that vendors of electronic products with inherently high complexity are especially knowledgeable about the need to maintain a positive reputation at all times and are motivated to initiate arbitration processes on the negative feedback they receive. As already mentioned in the method chapter, the arbitration process involves modification of the negative and neutral feedback provided by certain customers to avoid the various effects that their businesses may end up suffering as a result of such feedback submissions. The negative feedback
usually provided to customers includes complaints about the quality of products, mistrust and other negative aspects that characterise a business.

It is self-explanatory that customers will only give negative feedback if they are displeased with certain things about the vendor in question. Vendors whose reputations are positive will tend to maintain this status to prevent the loss of the public’s trust, which could cost them many customers. If such vendors come across any feedback deemed to be a potential barrier to the manner in which they relate to most of their customers, they must attend to it urgently and attempt to make things right. If, for example, a particular customer complains about an incident of poor quality regarding a product purchased from that particular vendor, then the vendor will have the possibility to explain to the customer that they received a defective product by mistake. This can always be followed by apologies and skilful attempts to make the customer alter his or her feelings about the vendor and the products. Therefore, vendor reputation has a significant influence on the arbitrations that the vendors themselves undertake on the feedbacks they receive.

Reviewing the results of Hypothesis 4 (p= 0.000** / \( \beta = 0.556 \) for electronics and \( p= 0.002** / \beta = 0.260 \) for health/wellness) shows that products of high complexity and high prices are more affected by this relationship than search products. This can be justified by the fact that the vendors’ reputations for such products are usually dependent on the systems of feedback they obtain from customers. It is therefore important that the feedback is monitored to ensure that the final forms presented for perusal by new visitors have minimal negatives comments, or none at all. The feedbacks that correspond to such products are therefore characterised by more arbitration procedures than any other form of product.

The impact of a positive reputation on an arbitration process is also confirmed by table 5.3. Here, the feedback profiles of the analysed vendors are compared with the mean number of arbitrations they have conducted. It can be clearly seen that vendors with very positive feedback profiles (99–100%) initiate more arbitrations than vendors with a less positive feedback profile. While table 5.2
shows how the number of arbitrations corresponds to the years of experience the vendor has had with the system, tables 5.3, 5.4 and 5.5 below compare the positive feedback profile (positivity in %) of the vendor with the mean number of arbitrations conducted. It can be seen for electronics, e.g., that the more positive the feedback, the higher the mean number of arbitrations (all vendors considered in this analysis with a feedback profile of 100% conducted about 34 arbitrations (mean value) in the period investigated).

**Table 5.3: Positive feedback profile and arbitrations for electronics**

<table>
<thead>
<tr>
<th>Positive feedback profile</th>
<th>Mean arbitrations</th>
</tr>
</thead>
<tbody>
<tr>
<td>100%</td>
<td>34.0</td>
</tr>
<tr>
<td>99.0–99.9%</td>
<td>32.0</td>
</tr>
<tr>
<td>98.0–98.9%</td>
<td>26.0</td>
</tr>
<tr>
<td>97.0–97.9%</td>
<td>6.5</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

The feedback corresponding to products that fall under the health/wellness category will have fewer arbitration procedures. This is because there is a similar feeling among such vendors as in vendors of electronic equipment, but the number of arbitration procedures is not as important as it is for products of high complexity.

**Table 5.4: Positive feedback profile and arbitrations for health/wellness**

<table>
<thead>
<tr>
<th>Positive feedback profile</th>
<th>Mean arbitrations</th>
</tr>
</thead>
<tbody>
<tr>
<td>100%</td>
<td>16.0</td>
</tr>
<tr>
<td>99.0–99.9%</td>
<td>15.0</td>
</tr>
<tr>
<td>98.0–98.9%</td>
<td>11.0</td>
</tr>
<tr>
<td>97.0–97.9%</td>
<td>16.0</td>
</tr>
</tbody>
</table>

Source: Julia Bartels
Search products, which are here represented by office/school supplies, have the lowest standardised coefficient, which is even negative ($\beta = -0.047$). This corresponds to the lowest number of arbitration procedures conducted on the feedback submissions related to them.

**Table 5.5: Positive feedback profile and arbitrations for office/school supplies**

<table>
<thead>
<tr>
<th>Office/School Supplies</th>
<th>Positive feedback profile</th>
<th>Mean arbitrations</th>
</tr>
</thead>
<tbody>
<tr>
<td>100%</td>
<td>10.0</td>
<td></td>
</tr>
<tr>
<td>99.0–99.9%</td>
<td>12.0</td>
<td></td>
</tr>
<tr>
<td>98.0–98.9%</td>
<td>19.0</td>
<td></td>
</tr>
<tr>
<td>97.0–97.9%</td>
<td>11.0</td>
<td></td>
</tr>
</tbody>
</table>

Source: Julia Bartels

The reason behind this is that the conversion rate, and hence the purchase of such products, is not very dependent on the reputations of the respective vendors. For instance, a customer who wishes to purchase a product that sells for 5 euros will not need to deliberate so much about the vendor’s reputation before making a decision to purchase such an item. Most of the feedback given by the customers will therefore have very little influence on the reputation of the vendor in question. The vendor, for their part, does not see the need for carrying out several modifications of the consumers’ feedback; in fact, most of the time, there is no need to initiate any arbitration procedures at all.

From Hypothesis 4 one learns that the vendors of highly complex products care for their reputation and initiate arbitrations, when negative and unfair feedback is monitored. This might arouse interest to find out if the number of arbitrations will be influenced by the quantity of submitted feedback. Therefore, a regression is carried out with the absolute numbers, using the absolute numbers of total feedback as the predictor and the absolute numbers of arbitrations as the dependent variable. The results are very significant for the highly complex electronic products, with $p = 0.000^{**}$ and $r^2 = 11.7\%$. The regression coefficient $\beta$ shows a moderate correlation of 0.341. These results suggest that there is a
relationship between feedback submission and arbitrations. The insignificant results for health/wellness can be neglected.

A very surprising effect was found for office/school products, because they show an even higher $r^2$ of 16.5% and a $\beta$-value of 0.406. The results with $p = 0.000^{**}$ are also very significant. In the section on Hypothesis 4, one discovers that vendors of these products of low complexity prefer to initiate arbitrations when they have more experience with the feedback system. The higher number of more experienced vendors might explain this result. When running a regression with vendor experience (experience with the feedback system) as the predictor and arbitrations as the dependent variable, the significant results confirm the assumption.

Having looked at the relationships between the number of submitted feedback and arbitrations, it would now be interesting to see how the amount of feedback in an online store has been reduced due to arbitrations conducted between vendor and customer. The following table (table 5.6) shows the extent to which negative feedback has been reduced due to arbitrations. The maximum value is 100% in each product category. The reason for these high results is that the smaller online stores have a lower level of negative feedback (e.g. two negative feedbacks) and only conducted two arbitrations. Moreover there are stores with zero negative feedback and some conducted arbitrations. These two reasons have led to high median values. Surprisingly, the highest minimum value of reduced negative feedback due to arbitrations can be found for office/school supplies. This table gives evidence that when set in relation to negative feedback, the online stores make extensive use of arbitrations. When looking at the median value of all three product categories, over 70% of received negative feedback is converted into arbitrations.
The next table (table 5.7) shows the reduction of total feedback (positive and negative feedback) due to arbitrations. Office/School supplies show the highest maximum value, whereas the highest median is shown for electronics, followed by health/wellness and office/school supplies. This table reflects that the amount of positive feedback is much higher than the amount of negative feedback and conducted arbitrations. With regard to electronics, and the corresponding median value, about 5.90% of the total feedback is reduced due to initiated arbitration processes. The other two categories follow with some lower values.

Table 5.7: Reduced total feedback due to arbitrations in %

<table>
<thead>
<tr>
<th>Product category</th>
<th>Maximum value of reduced total feedback due to arbitrations</th>
<th>Minimum value of reduced total feedback due to arbitrations</th>
<th>Median of reduced total feedback due to arbitrations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronics</td>
<td>43.16%</td>
<td>0.002%</td>
<td>5.90%</td>
</tr>
<tr>
<td>Health/Wellness</td>
<td>49.38%</td>
<td>0.003%</td>
<td>4.31%</td>
</tr>
<tr>
<td>Office/School</td>
<td>50.21%</td>
<td>0.01%</td>
<td>2.79%</td>
</tr>
</tbody>
</table>

Source: Julia Bartels
5.3.5 Relationship between positive feedback profile and feedback submission

The results confirm that the greater number of positive feedback entries forming the reputation, the higher the feedback submission. This finding agrees with the findings of Dellarocas and Wood (2008).

As with the other hypotheses, this hypothesis is strongest for electronics, i.e. for experience products characterised by high complexity and price. Most feedback is intended to target products that involve high transactional valuations and higher expectations of risk. Electronic equipment is seen as the class of products with the highest positive correlation coefficient (Spearman), which is here 0.254, as compared to health/wellness with a coefficient of 0.067 and $\beta = 0.206$. Office/school supplies, on the other hand, were the class of products with the highest negative correlation coefficient (Spearman), -0.266. This phenomenon can be supported by explanations similar to those given regarding Hypotheses 1, 2, 3 and 4.

According to Decker (Decker, 2007), trust can be transferred from a customer who already had actual experiences with the vendor to a potential customer who does not know the vendor or the online store. On the basis of the present research results, it can be assumed that customers tend to leave feedback because they once trusted the feedback of others and want to help future potential customers in the way they were helped before. An explanation for this hypothesis regarding experience products might be that customers who purchased something of higher value with a higher intrinsic risk of loss (complex products), should something go wrong, would also be more prone to reward good performance with positive feedback or to punish the vendor for poor performance with negative feedback. As has been seen in the literature review, feedback is mostly posted when customers are very satisfied or very dissatisfied (Dellarocas and Wood, 2008).

The above results can be further confirmed when comparing the different levels of feedback profiles with the mean number of feedback submissions. The fact that positive reputation impacts the feedback submission for electronic products...
can be seen in table 5.8 below. A feedback profile of 99–100% shows a mean number of feedback submissions of over 36%, whereas lower feedback profiles (97–98%) show lower numbers of feedback submissions.

**Table 5.8: Positive feedback profile and feedback submission for electronics**

<table>
<thead>
<tr>
<th>Positive feedback profile</th>
<th>Mean of feedback submission</th>
</tr>
</thead>
<tbody>
<tr>
<td>100%</td>
<td>36.68%</td>
</tr>
<tr>
<td>99.0–99.9%</td>
<td>36.11%</td>
</tr>
<tr>
<td>98.0–98.9%</td>
<td>15.37%</td>
</tr>
<tr>
<td>97.0–97.9%</td>
<td>13.38%</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

When looking at table 5.9, it can be seen that feedback submissions occur no matter how positive the reputation profile. The category still shows a slight trend for more feedback to be submitted for vendors with a more positive reputation.

**Table 5.9: Positive feedback profile and feedback submission for health/wellness**

<table>
<thead>
<tr>
<th>Positive feedback profile</th>
<th>Mean of feedback submission</th>
</tr>
</thead>
<tbody>
<tr>
<td>100%</td>
<td>37.56%</td>
</tr>
<tr>
<td>99.0–99.9%</td>
<td>43.32%</td>
</tr>
<tr>
<td>98.0–98.9%</td>
<td>43.26%</td>
</tr>
<tr>
<td>97.0–97.9%</td>
<td>20.46%</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

The table for office/school supplies even shows higher feedback submissions for feedback profiles lower in positivity.
Table 5.10: Positive feedback profile and feedback submission for office/school

<table>
<thead>
<tr>
<th>Positive feedback profile</th>
<th>Mean of feedback submission</th>
</tr>
</thead>
<tbody>
<tr>
<td>100%</td>
<td>26.55%</td>
</tr>
<tr>
<td>99.0–99.9%</td>
<td>25.82%</td>
</tr>
<tr>
<td>98.0–98.9%</td>
<td>36.55%</td>
</tr>
<tr>
<td>97.0–97.9%</td>
<td>41.38%</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

The relationship between positive reputation and feedback submission was already confirmed by Dellarocas and Wood (2008). The results of this study confirm that this relationship mainly exists for experience products.

Since experience products usually have higher prices a regression was conducted using the average transaction value (price in EUR) as the independent variable and feedback submission as the dependent variable. The results are significant with $p= 0.025$ for electronics and $p= 0.030$ for office/school supplies. The regression shows a weak relationship with $\beta = 0.300$ for electronics and $\beta = 0.217$ for office/school supplies. The fact that the values are quite similar for these categories, which are very different concerning price, (and the fact that the results for health/wellness are not significant) does not really support the hypothesis that transaction value impacts feedback submission. This result is consistent with the findings of Dellarocas et al. (2004), who have analysed selling price and feedback participation in eBay’s reputation system.

5.3.6 Impact of average transaction value on conversion rate

The results of this hypothesis are significant for electronics ($p= 0.000^{**}$) and health/wellness ($p= 0.023^*$). According to the literature (e.g. AlGhamdi et al., 2013), potential online customers experience a more complex decision-making process when they have to make a high involvement purchase. Usually high involvement purchases entail a financial risk, due to higher transaction values.
Users then typically go through a longer buying process, which can influence the conversion rate.

When it comes to the costs that a potential customer is expected to incur by subjecting themselves to certain online business transactions, the decision-making process always varies according to the nature of the product. As indicated by the results, the higher the value of the transaction, the less complex the decision-making of potential customers becomes.

Generally for such products, consumers’ perception of risk is high due to their highly technical features. Consider a case where a consumer is to purchase an electronic product worth 3,000 euros from an online store using online methods of purchasing products. The consumer will be hesitant to buy the item before being assured that there will be no glitches in the transactions involving the purchase. The consumer will also need to ensure that the product is in perfect working condition before making any payments. However, the standardised coefficient $\beta$ shows a positive relationship between transaction value and conversion rate (electronics: $\beta = 0.321$, health/wellness: $\beta = 0.194$ and office/school supplies: $\beta = 0.133$). This means the hypothesis should be formulated: “Higher average transaction value does not significantly lower the conversion rate”. A possible explanation could be that potential online customers feel secure due to the eKomi feedback profile of the vendor, and concentrate less on the higher price. Hence, higher prices do not lead automatically to lower conversion rates. The same result was found for health/wellness products. Although this hypothesis does not investigate the feedback profile, as it only tested the relationship between average transaction value and conversion rate, feedback influences on customer purchasing behaviour cannot be excluded. The partial correlation with the control variables “feedback profile access” and “rating number” indicates a significant influence on the relationship between average transaction value and conversion rate. This means that the presence of vendor reputation lowers the risk and supports a positive correlation between average transaction value and conversion rate.
For office/school supplies, a positive result of H6 was expected due to the fact that they have few if any technical features and are rather cheap. The customers’ concern about losing money during their purchase is not as serious as it is regarding the first two categories.

The results show that a feedback system enhances vendor reputation, mitigates product complexity and facilitates the user’s decision to purchase online.

5.4 Statement of theoretical contribution
This study used data from actual consumers’ browsing behaviours provided by the feedback company, eKomi. Therefore, it was possible to examine online behaviour directly rather than relying on self-reported data from questionnaires or interviews, which tends to carry bias (Kelle, 2008). Research has always led to the inflation of significant estimates. This is due to the fact that it focuses on survey data that is attitude-based and multi-collinear. According to Dellarocas (2000) and McDonald and Slawson (2002), studies based on opinions are characterised by variable inflation from positive opinions. This leads to a scenario where the results of the study suffer distortion as a result of opinion inflation.

A major contribution of this study is the development of a conceptual model which transfers the traditional model of a purchase process to e-commerce with respect to information asymmetry, risk mitigation and trust. The hypotheses demonstrate a clear pattern of the way in which the level of product complexity is mitigated by a feedback system to allow for a beneficial purchase decision. On the basis of feedback and transaction data, the study provides insight into how risk and trust function in the online world and considers the comparison of three different product categories. Although other studies (McKnight et al., 2002; Kimery and McCord, 2002; Gefen and Straub, 2003; Kim et al., 2008; Bolton et al., 2008) have examined the impact of risk and trust on online purchases, they were conducted without taking into account the role of product category. Just as Bhatnagar et al. (2000) the findings of this study point to the continued relevance of the search/experience paradigm for consumer
behaviour. Results from this study have shown that for more complex products (experience products), consumers want to assess vendor reputation in the form of customer feedback to better evaluate the possible risks associated with the transaction (Hypothesis 1). The confirmation of Hypothesis 3 extends the research conducted by Kim et al. (2008) and Hu et al. (2008), showing that trust leads to a higher conversion rate (trust transference from past customers to potential customers in form of positive feedback), strongly favoured highly complex products. The other hypotheses (4,5 and 6) tested in the present study, moreover, have shown significant differences among product categories. Studies (e.g, Kim et al., 2008) that have neglected the consideration of product classification, have stated that the factors trust and risk are crucial for all kinds of products and were not able to differentiate between products.

The study’s conjecture that risk associated with online shopping is multifaceted and that different risk types are linked also constitutes a contribution. The study has identified that product complexity (evoking product risk) might be a more important driver for risk evaluation than a high transaction value (evoking financial risk). This is not clear, when looking at the electronics category, because this category evokes both product risk, due to the high product complexity, and financial risk, due to high prices. However, the health/wellness category characterised by medium complexity and rather lower product prices, showed a high number of visitors who first wanted to check the reputation (risk evaluation) of the vendor before making a purchase. This result confirms the existence of product risk and physical risk. The potential customer wants to learn more about the product quality (reduce product risk), so that he can be sure that the products are not harmful to his health (reduce physical risk). Time risk, meaning that consumers may lose time by researching and making the purchase, or by waiting for the delivery and learning how to use a product, is assumed to increase with increasing product complexity. The higher the product complexity, the greater the time it takes to learn how to use the product and the greater the need to study the vendor reputation. Time risk can be reduced by vendor reputation, which may show that the possibility of receiving a defective product is relatively low, therefore negating worries about having to wait for replacement time. This is especially relevant for electronics because of the
technical features of these products. However, the existence of time risk in this study is more a logical assumption than a verified fact. This study partly confirms and extends the risk types found by Dai et al. (2014), and disagrees with the findings of Chu and Li (2008) that consumers perceive the same level of risk for both search products and experience products.

Another important contribution of the study is the advancement of the existing literature (Ye et al., 2014) about the strategies of vendors to influence or respond to negative customer feedback, as it provides evidence that vendors adopt features of the feedback system to maintain a positive reputation profile. Chen and Xie (2008) showed that vendors should strategically respond to customer reviews based on the type of product. The results of the present study show that vendors of highly complex products make use of arbitration processes to maintain a good reputation and to appear as a trustworthy vendor.

This study also extended Dellarocas and Wood’s (2008) research into the relationship between the feedback profile and feedback participation by adding different product categories and considering the B2C market. Feedback submission is important because feedback builds reputation and trust transference. As already mentioned in the literature review, the trust-building transference process allows potential customers to trust vendors based on information they receive from other customers (Doney and Cannon, 1997). The submission of feedback transfers the experienced trust of the recent buyer to the next potential customer (Stewart 2003). The results confirm the relationship between a positive feedback profile and feedback submission as stated by Dellarocas and Wood (2008), but only for moderately and highly complex products.

The importance of feedback submission, which is needed to build the reputation profile, becomes evident when analysing the positive relationship between average transaction value and conversion rate (H6). Using feedback profile access as a control variable, this research contributes to risk theory in B2C online stores by verifying that the evaluation of risk on the basis of feedback mitigates the risk caused by high transaction value and/or product complexity,
and therefore facilitates a purchase process. This research extends the research of Resnick et al. (2002) who assumed that the impact of eBay feedback profiles on the probability of sale is higher for riskier transactions and experience products. Lee and Huddleston (2006) also claimed that experience products require more risk reduction strategies than search products.

The following three tables show a summarised comparison between the findings and contributions of this research and those already made by various other scholars. Table 5.11 and table 5.12 show the theoretical contribution to risk theory, table 5.13 displays the theoretical contribution to trust theory and table 5.14 describes the theoretical contribution to reputation theory.

**Table 5.11: Theoretical contribution to risk theory (Part 1)**

<table>
<thead>
<tr>
<th>The conclusive findings from the research</th>
<th>The theoretical contribution</th>
<th>The theoretical facts documented in literature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk evaluation (accessing the feedback profile page) increases with increasing product complexity (including transaction value).</td>
<td>The influential aspect of product category regarding risk evaluation. Whereas literature tested risk perception, this study extended the research by measuring risk evaluation.</td>
<td>The transaction value and technological complexity of a product are important drivers for users’ perception of risk (Bhatnagar et al., 2000; Jøsang et al., 2007).</td>
</tr>
<tr>
<td>Product categories including technological complexity, high transaction values and effects on body/health show significant need for risk evaluation by customers.</td>
<td>Risk is multifaceted by having identified the following risk types: Product risk: electronics, health/wellness (complex products) Financial risk: electronics (high transaction value) Physical risk: health/wellness (harmful for body/health) Time risk: electronics, (high product complexity requires time to check the vendor reputation and to learn how to use the product)</td>
<td>Risk is multifaceted (product risk, financial risk, privacy risk) (Dai et al., 2014). Consumers perceive the same level of risk in both search products and experience products (Chu and Li, 2008).</td>
</tr>
</tbody>
</table>

Source: Julia Bartels
Table 5.12: Theoretical contribution to risk theory (Part 2)

<table>
<thead>
<tr>
<th>The conclusive findings from the research</th>
<th>The theoretical contribution</th>
<th>The theoretical facts documented in literature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complex product categories (experience products) show positive correlation between transaction value and conversion rate when online feedback is assessed.</td>
<td>Evidence that a feedback system mitigates risk (useful risk reduction mechanism) of complex products (electronics, health/wellness) and facilitates a purchase process in B2C online stores.</td>
<td>Experience products require more risk reduction strategies than search products (Lee and Huddleston, 2006). Consumers have purchase intentions after finding necessary risk reduction strategies (Chu and Li, 2008). eBay's online feedback system can influence customers' behaviour and future sales (Resnick and Zeckhauser, 2002; Melnick and Alm, 2002; Livingston, 2005; Lee and Malmendier, 2005; Cabral and Hortacsu, 2010). Positive influence between feedback and sales performance in the movie and book industry (Duan et al., 2008).</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

Table 5.13: Theoretical contribution to trust theory

<table>
<thead>
<tr>
<th>The conclusive findings from the research</th>
<th>The theoretical contribution</th>
<th>The theoretical facts documented in literature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trust leads to higher conversion rates only in favour of highly complex products.</td>
<td>This study extended the research by analysing the trust effect on real purchases, taking account of different product categories. Product category matters with regard to the trust transference theory.</td>
<td>Existing literature claims that a positive reputation on eBay boosts conversion rates (Ba and Pavlou, 2002; Houser and Wooders, 2006; Chevalier and Mayzlin, 2006; Brown and Morgan, 2006; Bolton et al., 2008; Cabral and Hortacsu, 2010). A consumer's trust has a strong positive effect on the purchasing intention (Kim et al., 2008). Online reviews have a positive impact on sales (Hu et al., 2008). Customers trust vendors based on feedback they receive from other customers (Doney and Cannon, 1997; Lim et al., 2006).</td>
</tr>
<tr>
<td>Positive vendor reputation influences customer participation in feedback submission and can be confirmed for complex products.</td>
<td>This study extended Dellarocas and Wood's research on the relationship between the feedback profile and feedback participation by adding different product categories and considering the B2C market.</td>
<td>Research on eBay (C2C) shows that the higher the positive reputation scores of vendors the higher the participation in feedback submission (Dellarocas and Wood, 2008).</td>
</tr>
</tbody>
</table>

Source: Julia Bartels
Table 5.14: Theoretical contribution to reputation theory

<table>
<thead>
<tr>
<th>The conclusive findings from the research</th>
<th>The theoretical contribution</th>
<th>The theoretical facts documented in literature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vendors of complex products are well aware of the importance of developing and keeping their good reputation.</td>
<td>Advancement of the existing literature states that vendors of complex products in the B2C environment can strategically influence or respond to negative customer feedback to maintain a good reputation.</td>
<td>The literature states, especially for vendors with complex products, a positive reputation is important to reduce risk and enhance trust toward potential customers (Girard et al., 2002).</td>
</tr>
<tr>
<td>A reputation check on the feedback profile page has a positive influence on the conversion rate. This finding is valid for search and experience products.</td>
<td>This study differentiates between trust and reputation. Whereas trust (positive feedback profile) is important for high complex products, the overall reputation (visiting the feedback profile of the vendor) positively influences the purchase of experience and also search products, but to a lesser extent.</td>
<td>It was only assumed that the impact of feedback profiles on the probability of sale is higher for riskier transactions and experience products (Resnick et al., 2002; Huang et al., 2009).</td>
</tr>
</tbody>
</table>

Source: Julia Bartels

5.5 Implications for researchers
The ideas developed in this thesis have a number of implications for both literature and research at large. The prevailing ideas can be summed up as supportive pillars of e-commerce. The thesis identified the deterministic factors of e-commerce as trust, reputation, risk and the feedback itself. This study contributes to theory by developing a feedback- and transaction-based model that provides new insight into customer and vendor behaviour during an online transaction and across different product categories. Trust, risk and reputation are concepts that have been discussed extensively by previous studies in different contexts (e.g. eBay/C2C transactions). Given the rapid development and application of online feedback systems, this study supplies factual data to aid the understanding of customer risk and trust, and vendor reputation in this research field. With the help of the hypotheses 1 to 6, the thesis managed to demonstrate how a feedback system enhances vendor reputation, mitigates
product complexity and facilitates online purchase decision-making in B2C online stores. The ideas portrayed in this thesis are mainly in line with already existing views in the literature, which makes its integration into academic discussions easy. Hypotheses 1 and 6 are mentioned by Bhatnagar et al. (2000), Lee and Huddleston (2006), Jøsang et al. (2007) and Kim and Gupta (2009), while the concept of Hypothesis 2 is a topic covered by Lee (1998), Resnick et al. (2002) and Miller et al. (2002). The distinction between the publications of the above-mentioned authors and this thesis is the fact that the latter allowed for a little more inclusion of the aspect of product complexity as well as the feedback usage of both the customer and vendor sides, thereby creating a more detailed picture. This study contributes to research that investigates the decision-making process vis-à-vis an online feedback system. Hypotheses 3 and 5 confirm that trust transference theory (Doney and Cannon, 1997; Lim et al., 2006) helps to explain online feedback usage on B2C websites. The analysis of feedback submission sought to support the results of Dellarocas et al. (2004) and Dellarocas and Wood (2008) that feedback participation can be explained through positive vendor reputation. This thesis points to a relationship between positive reputation and feedback submission, with the highest feedback submission being found for the category with the highest prices and highest complexity. This might result from past consumers either wanting to motivate potential customers to buy in this store or to rescue them from buying there, which would then explain the high numbers of arbitration processes.

With regard to arbitrations, this thesis shows that online vendors, especially of complex products, must monitor and react to negative feedback in order to satisfy the customer and thus build up or maintain a good reputation. Whereas Ye et al. (2014) studied revoked feedback on eBay, this study focuses on B2C online stores.
5.6 Summary of the discussion
Overall, this study shows that a good feedback system is capable of changing the consumers’ risk perception concerning more complex products to the benefit of the vendor. By checking the reputation and the assurance of the vendors’ trust, as confirmed by the feedback system displayed on the online store, it is possible to reduce the extent to which consumers perceive a risk associated with such transactions. In this way, the vendor wins the consumers’ trust, and hence a browsing visit is more easily converted into an active purchasing visit. The study findings emphasise the relevance of the search/experience classification in online settings. The distinction that may be witnessed between other academic publications and this thesis is the fact that the present study allowed for a little more inclusion of the aspect of product complexity, as well as the feedback usage of both the customer and vendor on the basis of real online transactions.
6. Conclusions
This study set out to explore how a feedback system enhances vendor reputation, mitigates product complexity and thereby facilitates online purchase decision-making. It emphasises the importance of the factor of product complexity and has identified differences in the usage of a feedback system by the customer and vendor according to product category. This chapter provides a short overview of the research, as well as its theoretical contribution, limitations, implications for managers and further research.

6.1 Overview of research
Although a lot of existing and ongoing research can be found on trust, risk and reputation in e-commerce, only a small amount of it has analysed actual online feedback and online transaction data in B2C online stores. On the one hand, previous research and literature based on interviews or the analysis of online marketplaces, have showed that a positive vendor reputation plays a crucial role in increasing trust and reducing risk with respect to online transactions. On the other hand, many studies have emphasised the need for the inclusion of product categories to account for differences in the consumer’s decision-making processes when making a purchase online. This empirical thesis helped to close this knowledge gap.

The research attempted to identify both the user’s and the vendor’s interaction with an online feedback system on the basis of real browsing behaviour in B2C online stores. In order to find out if a feedback system is able to enhance vendor reputation, mitigate product complexity and facilitate online purchase decision-making, this research aimed to answer the following questions: (1) Do products with higher transaction values and complex functionality evoke greater risk perception, and therefore the need for risk evaluation? (2) How important is the vendor’s reputation in online purchases of low, medium and high product complexity? (3) Does trust (profile of a trustworthy vendor) influence online purchases of low, medium and high product complexity? (4) How do vendors react to negative feedback based on the complexity of the product? (5) Does a vendor’s positive reputation influence the feedback submission of low, medium
and high complexity purchases? The thesis presented a conceptual model that was developed to obtain more insight into (1) the customers’ actual interactions with an online feedback system during a decision and purchase process to reduce risk and to develop trust as well as (2) how vendors respond to the possibilities offered by feedback mechanisms in order to increase trust and reduce risk (positive reputation).

In cooperation with the company eKomi, who develop and operate feedback systems for online vendors, an analysis was carried out on 400 German online stores. About 1,536,403 transactions and 447,201 feedback logs have been drawn from the eKomi database. The data have been split into three different product categories to investigate the impact of transaction value (price in EUR) and product complexity on risk, trust and reputation during an online purchase process. Nelson’s (1970) product classification was used to divide product categories into different levels of product complexity. Two product categories were classified as experience products and one product category was defined as search products.

The study followed a positivist quantitative approach and applied deductive strategies and procedures to address the research objective. The data was collected from primary sources. Selected data were drawn from the eKomi database specifically for this research project, and further data were collected by contacting the online stores directly. The author presented a number of hypotheses and considered three product categories (low, medium and high product complexity), which have been analysed using linear regression and partial correlation: (H1) risk evaluation (impact of average transaction value on feedback profile access), (H2) reputation effect (impact of feedback profile access on conversion rate), (H3) trust effect / trust transference (impact of positive feedback profile on conversion rate), (H4) reputation maintenance (impact of positive feedback profile, or vendor trustworthiness, on arbitrations), (H5) building trust transference (impact of positive feedback profile, or vendor trustworthiness, on feedback submission) and (H6) risk perception (impact of average transaction value on conversion rate).
6.2 Contribution to theory

Based on the findings of the present study, it is clear that product category plays a significant role in explaining the importance of a feedback system for online purchases. As stated in the Information Systems (IS) and marketing literature (Girard et al., 2002; Lee and Huddleston, 2006; Kim et al., 2008; Chu and Li, 2008; Huang et al., 2009) and with a main focus on the eBay marketplace (Ba and Pavlou, 2002; Resnick et al., 2002; Ye et al., 2014), the mechanism of online customer feedback has been identified in the present study as an effective risk reduction strategy, with the emphasis, however, on experience products in B2C online stores. Experience products are products with moderate to high complexity where product characteristics can be ascertained upon consumption. Due to the lack of “product touch” and interaction with the sales representative in the online shopping environment, the experience products in this study (electronics and health/wellness products) are perceived to involve a higher level of risk than the search products. Electronic products such as cameras can only be judged after they have been used; and the effectiveness of health/wellness products can also only be judged after usage. The measured risk evaluation (accessing the feedback profile page) in this study, which increases with increasing product complexity (including transaction value), has a positive influence on the conversion rate. From that it can be concluded that rather experience products (moderate to high product complexity) require a risk reduction strategy in the form of online feedback.

Based on the findings of this research, consumers of highly complex products are willing to trust vendors whose reputations are positive. Although potential customers of both experience and search products check the reputation of the vendor (accessing the feedback profile page), a positive feedback profile only influences the purchase of highly complex products. From this, it can be concluded that product category has an impact on the trust transference theory. In other words, if a potential customer trusts a feedback profile, then it is possible for the potential customer to trust the customers who have submitted the feedback (Doney and Cannon, 1997; Stewart, 2003; Lim et al., 2006), with the understanding that submitted feedback is honest and cheating behaviour of the vendor is communicated in form of negative feedback. Customers of highly
complex products seem to appreciate the trust given to them by past feedback and are willing to reciprocate by likewise submitting feedback to other potential customers. This relationship between a positive reputation and feedback submission is confirmed by Dellarocas and Wood’s (2008) with the difference that they had their focus on eBay (C2C) and did not consider different products or product categories.

Many studies emphasise the need for an online business to cultivate a positive reputation (Ba and Pavlou, 2002; Resnick and Zeckhauser, 2002; Houser and Wooders, 2006; Chevalier and Mayzlin, 2006; Brown and Morgan, 2006; Bolton et al., 2008; Kim et al., 2008; Cabral and Hortacsu, 2010). This study not only looked at the customer side by testing customers’ perceptions of a positive reputation, but also covered how vendors work with the feedback system to establish or maintain a good reputation (such as through the handling of negative feedback). As mentioned in the paragraph above, a positive feedback profile is important for vendors of highly complex products. The higher the complexity, the higher the risk perception and the need to evaluate and reduce the risk. This has led to the conclusion that vendors, especially those of highly complex products, are perfectly aware of the significance of positive reputation. Therefore, they pay attention to negative feedback and react to it in order to reach an agreement with the customer. The findings show that vendors of complex products are especially sensitive to this issue. This study advances the finding of Ye et al. (2014) that vendors of highly complex products in the B2C market are perfectly aware of the importance of building and sustaining positive reputations, given that it is the key to winning the customers’ trust and commitment.

Consumers’ conversion rate is usually limited by the level to which they perceive that risks are involved in taking part in the online purchasing of products. Consumers look for feedback to make them more comfortable with a purchase, or to reduce the perceived risk until it is below their level of acceptable risk. To reduce online customers’ perception of risk and thereby increase the possibility of purchase, it is important to consider the different risk types and keep such risks as low as possible. It is believed that consumers
perceive risk in different dimensions, and the risks of which they are aware range from those that are associated with financial losses (financial risk), to those that can arise when the product they have purchased is in poor working condition (product risk). Previous research (e.g., Forsythe and Shi, 2003; Bhatnagar and Ghose, 2004; Lu et al., 2005) has indicated financial and product risk to be the top concerns with regard to consumer trust in online transactions. The present results have used factual data to confirm the finding of Zheng et al. (2012) that product risk associated with the complexity of a product is a predominant dimension of risk. The aspect of product risk is associated with the transaction value of expensive electronic products (financial risk), as well as with the product quality of health/wellness products (physical risk), and increases the customer's risk perception in an online store.

6.3 Implications for managers in industry
This study was specifically designed with the objective of trying to inform managers about how their online feedback systems can be used to reduce risk and enhance trust, which may lead to higher sales.

A feedback system provided by a third party, as has been seen in this thesis in the case of eKomi, is a very important tool that vendors can use to increase their chances of winning over online shoppers and converting them into active customers. By better understanding the relationships between positive reputation profiles and certain risk types (financial risk, product risk, physical risk, time risk), vendors may be able to take more appropriate actions to make shopping online a less risky experience and motivate purchase behaviour. Vendors must know which risk dimensions are of greatest concern to consumers and how a feedback system may work as a favourable risk-reduction strategy. The class of products that are most significantly reliant on the online feedback systems are highly complex products. This is so because it takes a lot to convince consumers that they should purchase such products from an online store. The products are highly technical and frequently involve high transaction values. As a result, the perception of product risk by online store visitors is very high for these products. Customers want assurances that
products purchased will be delivered on time and in working order. Through the use of feedback systems, consumers can easily evaluate the vendors’ trustworthiness and ability to fulfil buyer-seller agreements. In this way, consumer trust is facilitated and sales of electronics and other products of high complexity are achieved. It can be said that online vendors with informative content and integrated customer feedback on their website benefit more when offering experience products than search products. For products of low complexity, for which positive reputation is not so important, it might be enough to simply have the system implemented in order to provide a sense of transparency by having a trust-building mechanism integrated into the online store.

Since the feedback left by consumers is a direct determinant of the vendors’ reputation, it is important for vendors to ensure that whatever is posted on their websites in the form of feedback is as positive as possible. In the cases where there are unfair comments in the feedback or product reviews, it is recommended that the vendor carry out proper complaint management in the form of arbitration procedures to ensure that such comments do not influence potential new customers. Feedback arbitration is therefore important both for ensuring that vendors do not suffer from unfair comments and that they learn from customer complaints when justified. This thesis shows that vendors of complex products should not regard the feedback system as a sure-fire success. They should take the incoming feedback seriously and work with the feedback system. Of course, arbitration processes also elicit strategic behaviour in vendors. However, to reveal more quality information to customers, eKomi displays the number of arbitration processes on the feedback profile page of each vendor. When potential customers see a high number of conducted arbitrations, they may think either that the vendor wants the best for the customer and takes the complaints seriously or that the vendor is not doing a good job and engages in arbitrations to cover up poor products or services. Vendors need to keep in mind that the number of arbitration processes displayed on the feedback profile page can be advantageous or disadvantageous. The eKomi feedback system offers vendors the possibility to answer negative feedback, and these answers are published on the feedback
profile page. The negative feedback is not deleted, but the vendor can apologise and can give an explanation why something went wrong. This is also a way to come to an agreement with the customer. This is something like a public arbitration, and shows that the vendor understands the problem and has the ability to solve it. Research has shown that an apology satisfies a customer (Abeler et. al, 2010). Vendors should steer a middle course and carefully consider when it is better to induce an arbitration process or simply respond to negative feedback.

This study is useful in helping managers and any other online business practitioners to get a better overview of how different aspects affect electronic commerce, and hence of the kind of measures that can be taken to counteract the problems encountered. To enhance online vendors' reputations, organisations should offer education and awareness programs on the efficiency of working with a feedback system and properly reacting to negative feedback. eKomi recently changed the design of the feedback system regarding the way that customers can submit complaints, and made it so that vendors cannot simply induce arbitration processes at will. These changes make customers more powerful and may force vendors to do a better job.

For vendors who are customers of eKomi, it is especially important to care for their feedback, because eKomi supports the linkage of feedback to social networks such as facebook. This represents a great advertising possibility for vendors seeking new customers. Therefore, it is important for vendors to maintain a reputation with a high quantity of positive feedback, and vendors should undertake actions to receive as much feedback as possible by reminding customers to submit feedback.

6.4 Limitations of this research
Despite the fact that this research achieved its main goals, a few challenges remain. First, the scope of products that were selected for the study was too narrow to give an accurate impression of what actually happens in the actual market. This study chose electronic products, health/wellness products and
office/school supplies to represent different levels of product complexity, and classified them in terms of Nelson’s experience products and search products. It would not be surprising to find out that other commodities within the classes selected show certain relationships that are somewhat, or totally, different from the ones discussed in this thesis. It would be fairer if the study were expanded a little bit to cover a wider range of products before coming up with general deductions about the relationships discussed in this thesis.

Another limitation of this thesis is the fact that some of the results supporting certain hypotheses were adopted despite the fact that they showed noticeable weaknesses. Furthermore, it was not possible to delete all outliers for the variable “Positive Feedback Profile”. It does not make sense to conduct the research solely on the basis of 100% positive feedback. Nevertheless, the outliers have been tested for their influence.

Furthermore, the research is limited to the effects in Germany. This may inhibit the generalisability of this research to international contexts and alternative settings. It is possible that if the research would have investigated a higher number of firms per branch, as well as firms from other countries, then the magnitude and the correlations would be different.

The use of primary data as the sole method of data collection has the drawback of becoming obsolete, and not meeting the specific needs of the particular situation or setting (Sekaran, 2003). Cross-sectional research does not enable the researcher to determine causality, whereas a longitudinal analysis would.

Furthermore, the analysis of quantitative data does not deliver rich information of the kind that can be gained through qualitative research. This thesis delivers knowledge about how people behave during online transactions, but why-questions cannot be answered conclusively.

Another limitation is the source of the primary data. The author of this study received the data sets from the feedback company, eKomi. Since the author has not collected the data herself there is no real control over the data quality.
Finally, a limitation might be that no differentiation has been made between smaller and larger online stores. But a division into smaller and bigger online stores would have led to sample sizes that were too small.

6.5 Further research
This thesis has proposed ideas that only accommodate the level of technology achieved so far. For example, at the moment, the only modes of communication that exists between online users are electronic messages or automatic answering machines, which possess very little human rapidly advancing technology, there may come a time where the interface systems will have a higher level of human characteristics. This thesis hopes to conduct a further development in the future to accommodate these technological changes. This will, of course, lead to a massive expansion as far as the theoretical coverage of the topic is concerned.

The main problem of the thesis were the fact that the scope of products chosen for the study was quite narrow, and this leads to uncertainty, as far as other products are concerned. Since eKomi is situated in other countries, a comparison of the effectiveness and usage of a feedback system in other countries could also be carried out.

eKomi is developing a feedback system for other sectors, such as (1) e-commerce, (2) hotel and (3) medical procedures. As soon as the sample sizes in these sectors are sufficient, further research on risk, trust and reputation in these sectors may yield interesting results.

eKomi recently changed the design of the feedback system to make it possible for customers to submit a complaint. Further research may analyse the amount of complaints submitted by customers in order to find out if customers take advantage of this new powerful tool. The amount of complaints (initiated by the customer) could be set in relation with the number of arbitrations (initiated by the vendor) to get more insight into the strategic handling of customer dissatisfaction and negative feedback in the B2C environment. This would
extend the research of Ye et al. (2014), who compared the powerful position of sellers when revoking was in place to their position when revoking was banned and only buyers are able to submit feedback (asymmetric feedback mechanism).

This study investigated the actual feedback behaviour of new customers (pre-purchase behaviour and post-purchase behaviour). It would be interesting to compare the actual behaviour between new and repeat customers to find any differences.

Future research may also look at the role of written feedback comments. These comments may convey useful knowledge about a vendor’s prior transactions (competence, reliability) that cannot be described by simple positive and negative ratings and arbitrations. The ‘hidden’ content revealed by written feedback comments may play an important role in building customer trust.

The online feedback system that provided the data for this study has introduced a feature that enables vendors to integrate their reviews into their Facebook Fanpage. It would be interesting to find out if this will influence sales, and if vendors will actually make use of it. This could be also analysed on the basis of different product categories.

6.6 Summary of the conclusion
This study is one of a very few recent works to have analysed a research model that is based on actual feedback and transaction data in the B2C environment. On the one hand, users’ actual interactions with a feedback system are analysed, and on the other hand, this study reveals how vendors strategically work with a feedback system. The consideration of three product categories, which differ in their functional complexity and prices, demonstrates how a feedback system enhances vendor reputation, mitigates product complexity and thereby facilitates online purchase decision-making in B2C online stores.
This research has shown that positive vendor reputation in anonymous online transactions is crucial. The results of this research indicate that the aspect of product complexity exercises an inevitable influence on the online buying process. The presence of feedback grows in importance the greater the transaction value (average price) and the complexity of the product are. However, the aspect of trust only influences sales of highly complex products. It is important for vendors of complex products to invest in their reputation and to establish trust on the basis of feedback that is as positive as possible. The study provides suggestions for online vendors concerning how they can use online feedback systems as tools for presenting their competence and trustworthiness.
7. Reflective diary

The DBA programme took me on a journey that significantly broadened my skills in professional research methodology.

It was clear to me from the beginning that I wanted to continue my studies at a British university. I had some very positive experiences during my MA studies in the UK and always felt that the supervision and feedback had been excellent and had consequently raised my academic profile.

The seminar modules in the first year helped me to develop my research skills and also helped me to understand what is required of me in order to successfully write a thesis at doctoral level. The assignments that completed each module were a good opportunity to gain a better understanding of certain aspects relating to my studies. Additionally, I gained direct feedback and advice on how to improve my already completed work.

1. Seminar: Philosophical Underpinning of Research Methods

This seminar introduced the participants to different research methods: quantitative research, qualitative research and triangulation. It quickly showed that the realisation of a thesis would be an extensive endeavour. Up until this point, I had only written down my idea. I knew that I wanted to research the benefit of feedback systems and customer reviews, as I had done extensive work with eBay, and was intrigued by their feedback system. During the seminar, I considered the best way to approach my thesis and decided to focus on quantitative research, as it is more about testing than exploration. I planned to work with a representative sample, as this would enable an analysis of patterns. These patterns would allow the establishment of a hypothesis that could be tested in the research.

During this time, I worked in market research and conducted commissioned studies of miscellaneous product markets. One client requested that the study he ordered should also have incorporated a theoretical part about the
methodology used for the study. The newly gained knowledge about different research methods would prove to be beneficial.

2. Seminar: Quantitative Methods

The seminar provided me with invaluable lessons by reinforcing knowledge about statistics and giving an overview of establishing, using and analysing a questionnaire. It also helped me to familiarise myself with SPSS, a computer tool for statistical analysis, which I wanted to use for my quantitative research. Previously, whenever I had compiled studies in my position as an analyst in a market research company, someone else had carried out the evaluation of the data. Now, I had the chance to compile and evaluate the data myself. The assignment for this seminar helped me to consider practical issues and problems throughout the design phase of my research project.

3. Seminar: Qualitative Methods

At the beginning of my work, I was undecided if I would obtain my data through qualitative interviews. To make my decision, I engaged more with the methods of qualitative research.

Whereas detailed knowledge will be gained through the qualitative approach, evidence of generality will be achieved through quantitative techniques. I understood that qualitative and quantitative methods should be perceived as supplementary and not as contradictory methods.

As for the third assignment, I conducted intensive research for the literature review. Here, it became apparent just how many resources were available, which had the danger of leading to “everything but the dissertation”, meaning one runs the risk of reading/researching to such an extent that one becomes lost in all the new information, ending up with writer’s block and failing to make progress in the work.
4. Seminar: Critical Evaluation

The seminar about critical evaluation of academic articles taught me that a well structured literature review helps to define any research gaps. Additionally, an appropriate research design will allow the reader to follow any argument made and help to understand the derivation of evidence. The coherence of the argumentation is crucial, as it provides the validation and reliability of any research.

5. Seminar: How to Write a Proposal

The writing of the research proposal helped me to conceptualise my research problem and to plan a research project at doctoral level. During my first visit to Guildford, I learnt that my proposal was too broad, as it touched on too many aspects. Hence, it needed to be narrowed down. I also received advice regarding further literature relating to my research. I reviewed the suggested literature and tried to concentrate on only a single topic. Generally speaking, the eBay market was already well researched. However, I had concentrated on a topic that had so far been neglected, but to complicate things, I was entirely dependent on eBay’s internal data to conduct the study.

Unfortunately, eBay had a staff turnover and I lost the support that I had previously been promised. I did not want to change my research topic on feedback systems (user generated content and its influence), as I had already invested much time into it. Through my work with eBay, I had attended many ecommerce fairs and events, which helped me to get in touch with other feedback companies - companies specialising in providing feedback systems similar to the eBay system for B2C online stores. Thus I decided it would be relevant to research what advantage online stores gain when they use these systems. On top of that, I could also compare the C2C feedback system used on eBay’s market place and the systems used by other B2C online stores.
As I wanted to obtain my data through a questionnaire, I created an online survey that I finished for my second visit to Guildford. As there is so much data that can be obtained online, my supervisor encouraged me to instead gain access to the database of the feedback company with which I wanted to work. It was challenging trying to convince the company to allow me access into their database instead of doing online questionnaires with online stores. Through talks with the CEO and staff, I tried to gain interest in my work, which I believed would help me obtain the information that I needed. I wanted to emphasise the win-win situation for everyone. This meant that the company needed to put trust in my capability and permit me access to highly sensitive data. From my side, it needed courage and excellent communication skills, which would highlight my commitment and my professional expertise. I needed to emphasise the benefit the company would gain by providing me with factual data. Compared to data collected through interviews and questionnaires, participants would not know that they are going to be analysed. Therefore, their behaviour would be more natural and very interesting for research.

There was much at stake for me. I only had one chance because other feedback companies had told me that either they did not obtain data or would only save it for a short period of time. The decision made by the company, for which I wanted to work, as to whether or not I could access the data would determine whether I could complete my thesis as intended. I was now completely dependent on the company. It was an advantage for me that the company generally showed interest in research and also conducted case studies of their own. The company was quickly convinced by the benefits of my project and I signed a confidentiality declaration without further delay. Unfortunately, I needed to wait quite some time for the data, as the employee responsible for it was busy with the day-to-day operations of the business.

During another meeting in Guildford, it was decided that I needed to increase my sample size. This led to another delayed data delivery. Additionally, my supervisor was changed twice and both supervisors had provided new input into my research project. Now, I also needed to collect data from the online stores via telephone and email. In my previous work within market research, I had to
conduct telephone interviews, which now proved to be useful. It helped me to build trust and obtain sensitive data.

The entire process showed me that one needs to have a flexible approach toward research, as there can be many unforeseen challenges to overcome.

While browsing and searching through different literature databases, I gained experiences in identifying strengths and weaknesses of research methodologies, as well as contribution and overall style of various published research papers.

The literature review and methods chapter were the most challenging parts of the research; due to the sheer volume of material that I needed to consider, the different ways of approaching the subject led to an interruption of my work and writer’s block. Both problems needed to be overcome. It helped to take a “step-by-step” approach rather than trying to see the overall goal of my thesis. In seminars, instructors would use the image of a street cleaner to elaborate on this thought - a street cleaner only tries to think about the next step rather than the whole street that needs to be cleaned. So sweep after sweep the cleaner would eventually complete the job and would be surprised how quickly it was accomplished.

I noticed that I was often over-complicating my thinking. My supervisors always reminded me to keep my approach simple. I focused on a larger sample size and a few research variables, which meant emphasising a general pattern rather than detailed information (why-questions).

In regard to the methodology chapter, it was difficult to describe how the variables in my dataset linked to the constructs covered by the literature review. Many articles referred to specific questions in questionnaires (e.g., the measurement of risk, trust and reputation). There had not been much work conducted by using the databases of companies to understand more about this topic. Mostly, researchers had used interviews or online data that was freely accessible through the eBay market place. It proved that my work with a
feedback company to gain insight into actual online feedback behaviour was a (then) current research gap.

The challenging part of the data analysis was the normal distribution and data cleansing to perform the regressions at the end. It was necessary to conduct a greater data cleansing in comparison to the evaluation of the questionnaire for the second assignment. This led to the conclusion that people in real life situations act differently than during a survey. This collection of real data was a unique element of my work.

In the beginning, I thought that a positive feedback profile (positive vendor reputation) would automatically lead to an increase in business; however, after evaluation of my obtained data, I concluded that this is not the case in every product category and that some vendors try to strengthen their good reputations by responding to negative feedback.

Kolb (1984, p. 38) stated that “Learning is the process whereby knowledge is created through the transformation of experience”. Kolb's experiential learning style theory is typically represented by a four stage learning cycle in which the learner 'touches all the bases': (1) concrete experience, (2) reflective observation, (3) abstract conceptualisation and (4) active experimentation (testing in new situations).

**Figure 7.1: Kolb’s model**

![Kolb's model diagram](source: Kolb and Fry (1975))
I have learnt that real value and learning take place when one engages in the research process. In conclusion, the work on my research project helped me to improve my academic rigor. It improved my intuitive and critical thinking skills and broadened my understanding of different research paradigms and associated methodologies. I also needed to think on my feet to overcome the various challenges presented whilst conducting my research.

I learnt that time is a finite resource and that it needed to be structured so as to take full advantage of it. It also became apparent that no situation is permanent - information is in flux and thus needs to be constantly reevaluated. The research taught me not to easily accept information, instead I started to question it and discovered the variability of information.

I learnt to read literature critically and to conduct a research project that delivers a valuable contribution to existing research. Whilst reading the newspaper or during discussions with others, critical thinking also increasingly began to be present in my everyday life. I found it especially valuable in my business life, when reading or writing articles or press releases to consider whether or not the content had been built on a solid chain of evidence. In my employed work, I have noticed that my communication skills have improved due to the ongoing meetings with the company that provided me with the data for my research. This has proved useful in the negotiations I have had to conduct with managers.

Furthermore this research project also taught me that nothing is ever perfect. The thesis was intended to produce perfect results and and my primary intentions had been that the results I ended up with would give an accurate impression of what is actually happening in the online market. The thesis was intended to reflect my expectations based on the ideas I had gained from existing literature. However, this was not possible since the entire process of research is never guaranteed to produce the intended outcome to perfection. As a result, this thesis is not to be considered perfect, but rather an approximation of what the study hypotheses have suggested. In fact, some of the results obtained from the study were the exact opposite of those I had hoped for and expected as can be seen in the results corresponding to hypothesis, H6. These
observations are helpful for every day business. One has to accept and work with the results as they come. Ultimately it is of little value to manipulate figures so that a business report appears more optimistic.

Additionally, I learnt that research is not just a fact-finding process, but a study intended to bring new ideas and discoveries into existence. Most of the ideas expected of a study are those that had never existed previously, and as a result of this, results are to be adopted as they are produced. Indiscriminate acceptance of results (irrespective of the researchers’ thoughts, opinions or anticipations) in the thesis can be illustrated using this simple example taken from the findings; it can be seen that transaction value is a boosting factor for feedback access, whereas a positive reputation seems to be only important for highly complex products.

Based on the above arguments, I intended to find a way of obtaining the best and most useful information from my results. I did not intend to debate the accuracy of the results but to use them in identifying useful trends. It is a well known fact that such results are never absolute, rather they possess characteristics that are enough to enable the researcher to identify patterns prevailing in the study.

The most challenging part of the study was when it came to operating with the actual browsing behaviours. My research allowed me to arrive at the conclusion that it is of paramount importance to work with the actual results obtained from a study as this reflects the true situation prevailing in the industry. It is important that managers stop manipulating results from such studies (as some have been known to do) in order to ensure that the counteracting actions taken afterwards are genuine and do not go to waste.

Having learnt that time is a finite resource, I have developed a better time management for business projects. Further still, the thesis has helped me to be succinct, precise and measured in my approach to research. I have learnt how important it is to formulate things in the correct manner and that terms such as risk or trust are not only words but also complex concepts that are required to
be dealt with carefully. Such concepts can have different meanings and thus the formulation plays a prominent role in the research. This care in formulation has taught me to focus, deciding on a specific direction so as to avoid digression in the thesis, as well as in my own business reports.

Overall, the work on my DBA thesis showed me how to scientifically approach business topics at a doctoral level using highly sophisticated research methods.
8. References


9. Appendix

Appendix A

List of search and experience products

<table>
<thead>
<tr>
<th>Electronics</th>
<th>Health/Wellness</th>
<th>Office/School Supplies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Digital cameras</td>
<td>Shampoo</td>
<td>Envelopes</td>
</tr>
<tr>
<td>Camcorder</td>
<td>Lotion</td>
<td>Document case</td>
</tr>
<tr>
<td>Computer</td>
<td>Vitamin pills</td>
<td>Drawing pad</td>
</tr>
<tr>
<td>Printer</td>
<td>Perfume</td>
<td>Coloured pen</td>
</tr>
<tr>
<td>Water supply system</td>
<td></td>
<td>Pencils</td>
</tr>
<tr>
<td>Nutritional supplement</td>
<td></td>
<td>Ink cartridge</td>
</tr>
<tr>
<td>Relax lounger</td>
<td></td>
<td>Ruler</td>
</tr>
<tr>
<td>Aqua fitness</td>
<td></td>
<td>Notepad</td>
</tr>
<tr>
<td>Massage products</td>
<td></td>
<td>Labels</td>
</tr>
<tr>
<td>Massage products</td>
<td></td>
<td>Poster</td>
</tr>
<tr>
<td>Desk chair</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Folder</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Headsets</td>
<td></td>
<td>School bag</td>
</tr>
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</table>

Source: Julia Bartels / eKomi
### Description of variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Measurement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transaction Value</td>
<td>Average transaction value in EUR of all sold products in the online store in the period investigated</td>
</tr>
<tr>
<td>Feedback Profile Access</td>
<td>Proportion of widget clicks in the online store (visitors review feedback of former customers) to total unique visitors in the online store in the period investigated</td>
</tr>
<tr>
<td>Positive Feedback Profile</td>
<td>Feedback score (proportion of positive feedback to total feedback) from implementation of the feedback system to the start of investigation</td>
</tr>
<tr>
<td>Arbitrations</td>
<td>Proportion of arbitrations made after a purchase to total transactions in the period investigated</td>
</tr>
<tr>
<td>Feedback Submission</td>
<td>Proportion of submitted feedback after a purchase to total transactions in the period investigated</td>
</tr>
<tr>
<td>Conversion Rate</td>
<td>Proportion of transactions to total visitors in the period investigated</td>
</tr>
<tr>
<td>Rating Number</td>
<td>The total number of stars relating to the past 12 months divided by the number of feedback comments</td>
</tr>
<tr>
<td>Vendor Experience</td>
<td>The period of time the vendor uses the feedback system</td>
</tr>
</tbody>
</table>

Source: Julia Bartels
Appendix B

Q-Q plots - Logarithmic transformation of variables (Part 1)

Source: Julia Bartels
Q-Q Plots - Logarithmic transformation of variables (Part 2)

Source: Julia Bartels
Q-Q Plots - Logarithmic transformation of variables (Part 3)

Source: Julia Bartels
Appendix C

Histograms - Logarithmic transformation of variables (Part 1)

Source: Julia Bartels
Histograms - Logarithmic transformation of variables (Part 2)

Source: Julia Bartels
Histograms - Logarithmic transformation of variables (Part 3)

Source: Julia Bartels
Appendix D

Box plots of all variables - outliers excluded

As already mentioned in the thesis and as it can be seen above, most outliers found for the variable „LN Positive Feedback Profile“ were kept, because values with a feedback profile of 96% are already calculated as outliers. The box plots for this variable show no extreme values and all outliers were tested on their influence on the regression. The casewise diagnostic and Cook’s distance could not detect them as influential outliers. Therefore they are not excluded from the research.

Source: Julia Bartels
### Appendix E

#### Kolmogorov-Smirnov test

<table>
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<tr>
<th>Product Category</th>
<th>Regression _TransactionV_value_FeedbackProfile_ConversionRate</th>
<th>Regression _FeedbackProfile_ConversionRate</th>
<th>Regression _PositiveFeedbackProfile_ConversionRate</th>
<th>Regression _feedbackProfile_Submission</th>
<th>Regression _TransactionV_value_ConversionRate</th>
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<tr>
<td><strong>electronic</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>127</td>
<td>122</td>
<td>122</td>
<td>122</td>
<td>122</td>
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<td>Mean: 0.047, 0.047, 0.047, 0.047</td>
<td>Std. deviation: 0.047, 0.047, 0.047, 0.047</td>
<td>Mean: 0.0000009, 0.0000009, 0.0000009, 0.0000009</td>
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<tr>
<td>Most extreme Differences</td>
<td>Absolute: 0.055, 0.055, 0.055, 0.055</td>
<td>Positive: 0.055, 0.045, 0.045, 0.045</td>
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<td><strong>health_wellness</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>137</td>
<td>137</td>
<td>137</td>
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</tbody>
</table>

a. Test distribution is normal  
b. Calculated from data  
c. Lilliefors Significance Correction  
d. This is a lower bound of true significance

Source: Julia Bartels
Appendix F

Linear regression output

Linear regression goodness of fit / autocorrelation test – Hypothesis 1

Predictor: LN_Transaction_Value / Dependent Variable: LN_Feedback_Profile_Access

<table>
<thead>
<tr>
<th>Product Category</th>
<th>$r$</th>
<th>$r$ Square</th>
<th>Adjusted $r$ Square</th>
<th>Std. Error of the Estimate</th>
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<tbody>
<tr>
<td>Electronics</td>
<td>.819</td>
<td>.671</td>
<td>.669</td>
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<td>.751</td>
<td>.563</td>
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Source: Julia Bartels

Analysis of variance – Hypothesis 1

<table>
<thead>
<tr>
<th>Product Category</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
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<tr>
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<td></td>
<td>Residual</td>
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<td>.457</td>
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</tr>
<tr>
<td></td>
<td>Total</td>
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<td>126</td>
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<tr>
<td>Health/Wellness</td>
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<td></td>
<td>Total</td>
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Source: Julia Bartels

Linear regression coefficients – Hypothesis 1

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<th>Product Category</th>
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<tr>
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<td>B</td>
<td>Std. Error</td>
<td>Beta</td>
<td></td>
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<td>.467</td>
<td>.078</td>
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</table>

Source: Julia Bartels
Distribution of residuals – Hypothesis 1

![Distribution of residuals](image1)

![Distribution of residuals](image2)

![Distribution of residuals](image3)

Source: Julia Bartels

Test of homogeneity of variances – Hypothesis 1

<table>
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<th>Product Category</th>
<th>Levene Statistic</th>
<th>df1</th>
<th>df2</th>
<th>Sig.</th>
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</thead>
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<td>Office/School</td>
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Source: Julia Bartels
Linear regression goodness of fit / autocorrelation test – Hypothesis 2

Predictor: LN_Feedback_Profile_Access / Dependent Variable: LN_Conversion_Rate

<table>
<thead>
<tr>
<th>Product Category</th>
<th>r</th>
<th>r Square</th>
<th>Adjusted r Square</th>
<th>Std. Error of the Estimate</th>
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<tr>
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Source: Julia Bartels

Analysis of variance – Hypothesis 2

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<th>Mean Square</th>
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<td>.000**</td>
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Source: Julia Bartels

Linear regression coefficients – Hypothesis 2

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<td>Beta</td>
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Source: Julia Bartels
Distribution of residuals – Hypothesis 2

Source: Julia Bartels

Test of homogeneity of variances – Hypothesis 2

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Source: Julia Bartels
Linear regression goodness of fit / autocorrelation test – Hypothesis 3

Predictor: LN_Positive_Feedback_Profile / Dependent Variable: LN_Conversion_Rate

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<td>.014</td>
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Source: Julia Bartels

Analysis of variance – Hypothesis 3

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Source: Julia Bartels

Linear regression coefficients – Hypothesis 3

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<td>Office/School</td>
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Source: Julia Bartels
Distribution of residuals – Hypothesis 3

Test of homogeneity of variances – Hypothesis 3

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<td>Health/Wellness</td>
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<td>134</td>
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<td>Office/School</td>
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<td>119</td>
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Source: Julia Bartels
Linear regression goodness of fit / autocorrelation test – Hypothesis 4

**Predictor:** LN_Positive_Feedback_Profile / **Dependent Variable:** LN_Arbitration

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<th>Adjusted r Square</th>
<th>Std. Error of the Estimate</th>
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<td>.304</td>
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<td>.260</td>
<td>.068</td>
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Source: Julia Bartels

Analysis of variance – Hypothesis 4

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<td>110.450</td>
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Source: Julia Bartels

Table F.16: Linear regression coefficients – H4

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Source: Julia Bartels
Distribution of residuals – Hypothesis 4

Test of homogeneity of variances – Hypothesis 4

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<td>Office/School</td>
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Source: Julia Bartels
## Linear regression goodness of fit / autocorrelation test – Hypothesis 5

**Predictor:** LN_Positive_Feedback_Profile / **Dependent Variable:** LN_Feedback_Submission

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Source: Julia Bartels

## Analysis of variance – Hypothesis 5

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<td>271.341</td>
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<td>244.413</td>
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Source: Julia Bartels

## Linear regression coefficients – Hypothesis 5

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Source: Julia Bartels
Distribution of residuals – Hypothesis 5

Source: Julia Bartels

Test of homogeneity of variances – Hypothesis 5

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Source: Julia Bartels
Linear regression goodness of fit / autocorrelation test – Hypothesis 6

Predictor: LN_Transaction_Value / Dependent Variable: LN_Conversion_Rate

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Source: Julia Bartels

Analysis of variance – Hypothesis 6

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Source: Julia Bartels

Linear regression coefficients – Hypothesis 6

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<td>Beta</td>
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Source: Julia Bartels
Distribution of residuals – Hypothesis 6

Test of homogeneity of variances – Hypothesis 6

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Source: Julia Bartels