Cooperation Strategies for the Amazon Marketplace

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List of Abbreviations

AMDI	Amazon Market Dominance Index
APLO	Amazon Product Listing Optimization
AWS	Amazon Web Services
B2B	Business-to-business
B2C	Business-to-consumer
CEO	Chief Executive Officer
DIY	Do it yourself
e.g.	Exempli gratia
ed.	Editor
eds.	Editors
Eh.m.	Einzelhandel mit
et al.	Et alii
etc.	Et cetera
FBA	Fulfillment by Amazon
GMV	Gross merchandise volume
GWB	Gesetz gegen Wettbewerbsbeschränkungen
HHI	Herfindahl–Hirschman Index
HY1	Half-year 1
HY2	Half-year 2
http	Hypertext transfer protocol
IT	Information technology
NPS	Net-promoter score
OECD	Organisation for Economic Co-operation and Development
p.	Page
Ph.D.	Doctor of Philosophy
pp.	Pages
Q1	First quarter
ROI	Return on investment
RQ	Research question
SD	Standard deviation
TV	Television
USA	United States of America
UK	United Kingdom
WTA	Winner-takes-it-all

List of Symbols

@	At
#	Number
€	Euro
$	US dollar
%	Percent
N	Number of observations

Executive Summary (English)

Online platforms play an important role in digital commerce by connecting buyers and sellers. However, the growing popularity of digital marketplaces also leads to conflicts: on the one hand, through increasingly intense competition between sellers, and, on the other hand, through conflicts of interest between sellers and platform owners. Dynamic and uncertain platform markets pose various challenges for sellers and lead to uncertain sales performance. This dissertation applies different theories and methods to show how sellers can respond to these dynamic markets to increase product success.

The first article in this dissertation identifies three challenging platform dynamics that sellers commonly face and that complicate the predictability of product success. We argue that online product legitimacy can counteract these dynamics and serve as a mechanism for steering product success in uncertain environments.

The second article aims to increase transparency regarding Amazon's market position. Amazon Marketplace is one of the largest and most revenue-generating e-commerce platforms worldwide. However, it is generally unknown as to how this revenue is distributed among different product categories. In order for merchants to better understand and use Amazon's market position, we have developed the Amazon Market Dominance Index (ADMI), which shows Amazon's market power in each product category.

Based on the results of the first two studies, we developed an intervention tool in the form of an online application. The Amazon Product Listing Optimization (APLO) tool helps companies to optimize the quality of their product pages on Amazon in order to achieve a higher conversion rate and, thus, product success. The last study evaluates the effectiveness of the APLO tool in supporting the implementation of product-page optimizations. We also investigate the impact of these product-page optimizations on sales performance at Amazon.

The results of this dissertation show how sellers can reduce uncertainties and better establish themselves in digital marketplaces. The results and application projects allow for more substantiated, evidence-based decisions for Marketplace sellers and thus increase success in this dynamic environment.

Executive Summary (Deutsch)

Onlineplattformen spielen im digitalen Handel eine wichtige Rolle, da sie Käufer und Verkäufer zusammenbringen. Die zunehmende Popularität von digitalen Marktplätzen führt aber auch zu Konflikten, die einerseits durch intensiveren Wettbewerb zwischen Händlern, andererseits durch Interessenskonflikte zwischen Händlern und Plattformbetreibern begründet sind. Dynamische und von Unsicherheit geprägte Plattform-Märkte stellen verschiedene Herausforderungen an Händler und führen zu ungewissem Verkaufserfolg. Diese Dissertation wendet unterschiedliche Theorien und Methoden an, um aufzuzeigen, wie Händler diesen dynamischen Märkten begegnen und somit den Produkterfolg erhöhen können.

Der erste Artikel dieser Dissertation identifiziert drei herausfordernde Plattform-Dynamiken, denen Seller häufig gegenüberstehen und welche die Berechenbarkeit des Produkterfolgs erschweren. Wir argumentieren, dass Onlinelegitimität von Produkten diesen Dynamiken entgegenwirken kann und als Mechanismus zur Steuerung des Produkterfolgs in unsicheren Umgebungen dient.

Der zweite Artikel beabsichtigt, die Transparenz bezüglich der Marktposition von Amazon zu erhöhen. Der Amazon Marketplace ist einer der größten und umsatzstärksten E-Commerce-Plattformen weltweit. Wie sich der Umsatz auf die unterschiedlichen Produktkategorien verteilt ist aber völlig unbekannt. Damit Händler die Marktposition von Amazon besser verstehen und nutzen können, haben wir den Amazon Market Dominance Index (ADMI) entwickelt, der auf Basis des Marktanteils die Marktdominanz von Amazon in den einzelnen Produktkategorien aufzeigt.

Auf Basis der Ergebnisse der ersten beiden Studien wurde ein Interventions-Tool in Form einer Online-Anwendung entwickelt. Das Amazon Product Listing Optimization (APLO) Tool hilft Unternehmen, die Qualität der Produktdetailseiten auf Amazon zu optimieren, um eine höhere Konversionsrate und damit auch einen höheren Produkterfolg zu erzielen. In der letzten Studie wird die Wirksamkeit des APLO-Tools bei der Unterstützung der Implementierung von Produktseitenoptimierungen evaluiert. Zudem untersuchen wir, welchen Einfluss die Produktseitenverbesserung auf den Verkaufserfolg bei Amazon hat.

Die Ergebnisse dieser Dissertation zeigen auf, wie Händler auf digitalen Marktplätzen Unsicherheiten reduzieren und sich im Markt besser etablieren können. Die Ergebnisse und Anwendungsprojekte ermöglichen fundiertere, evidenz-basierte Entscheidungen für Marktplatzhändler und erhöhen somit den Erfolg in diesem dynamischen Umfeld.

Part I - Research Summary

1 Introduction

Online platforms are successfully used today in various industries to mediate between two or more parties. Moreover, online platforms play an important role in retail. In many markets around the world, online retail platforms generate about half of all online sales (Erich, 2019). Existing research on online platforms has helped us understand their characteristics (Armstrong, 2006; Evans & Schmalensee, 2008), the competition in platform markets (Cennamo & Santalo, 2013; Lee, 2014; Zhu & Liu, 2018), and the pricing and product structures (Hagiu, 2009; Mizuno, Nirei, & Watanabe, 2010). However, one important question—namely, how sellers effectively launch and succeed with products on online platforms—has been left almost unexplored (Jin & Hurd, 2018). Challenging platform dynamics and an increasingly competitive environment make it difficult to achieve and predict product success. New product entry failure is a common and costly problem (Castellion & Markham, 2013). Previous research has identified legitimacy-enhancing factors such as the timing of new product entry (Langerak, Hultink, & Griffin, 2008; Lilien & Yoon, 1990), characteristics of the new product (Aldrich, H., & Auster, E. R., 1986), product reviews (Li & Hitt, 2008), and recently, social media (Gruner, Vomberg, Homburg, & Lukas, 2019), which attribute to new product success. However, while the launch of products on platforms such as the Amazon Marketplace promises fast and easy access to large customer groups, the number of participating market players within the same platform (Redmond, 2013) and powerful platform owners (Zhu & Liu, 2018) make it very difficult to obtain product visibility and legitimacy. Given the importance of online platforms as sales channels for successful product distribution, this dissertation focuses on investigating cooperation strategies and employs a data-driven product-page factor analysis to help sellers increase their cooperation and product success.

To sell products successfully through digital marketplaces, not only the product-page quality is crucial but also knowledge of the market structures in order to better evaluate one's own market position and that of one's competitors and partners (Edeling & Himme, 2018). The market share is an important indicator of market power, and a comparison with market participants in the same industry is essential (Nissan, 2003; Rhoades, 1985). However, Amazon operates in many different segments and does not publish data on the market shares of individual product categories. By creating the Amazon Market Dominance Index (AMDI), we enable sellers to better determine their own market position by showing Amazon's market share and dominance in the individual product categories.

Beyond that, we have developed an online intervention tool for Amazon sellers to make our findings from the first two studies accessible and easier to apply. With the Amazon Product Listing Optimization (APLO) tool, we enable Amazon sellers to identify product-specific evidence-based optimization potentials for their Amazon product pages.

2 Study Background

2.1 Phenomena

Online retail has recorded considerable growth rates in the last few years. From 2017 to 2019, global e-commerce turnover increased from $2.3 trillion to $3.5 trillion. Forecasts predict global online retail revenue of $6.5 trillion by 2023 (Lipsman, 2019). Two different business models have developed in e-commerce (Fan, Yin, & Liu, 2020): the wholesale and the platform model. In the classic wholesale model, manufacturers sell goods to an online retailer, and the latter bears the inventory risk and usually has a high capital commitment. Walmart.com, Zalando, or JD.com are examples that mainly use the wholesale scheme. The second scheme is the platform model, where a manufacturer lists products on a platform and directly sells the products to the consumer. In this case, manufacturers bear the storage risk. Amazon Marketplace, eBay, and Alibaba are examples of this model. Here, the manufacturer pays a sales commission to the platform owner for the mediation between buyer and seller (Tan & Carrillo, 2017). However, Amazon applies a special hybrid form, as they operate both in the form of the wholesale and platform model (Tian, Vakharia, Tan, & Xu, 2018). This requires special considerations, as new conflicts can result from this setting (Ryan, Sun, & Zhao, 2012). Since Amazon is not only a platform owner but also a retailer itself, conflicts of interest with third-party sellers can occur. Due to the extensive data that Amazon generates with every click, it has deep insights into customer preferences and behavior. Amazon can "cherry-pick" products with high sales potential and can have less attractive, long-tail products sold by third-party sellers (Jiang, Jerath, & Srinivasan, 2011). This hybrid model enables Amazon to offer its customers a wide range of different products without having to offer all of the products itself. With higher activity and sales on the platform, the digital systems generate more and more data, and thus, Amazon can make superior decisions (Mattioli, 2020). This situation can become dangerous for third-party sellers, especially for smaller ones who do not have a diversified product portfolio. If Amazon itself offers a product that was previously sold by a seller, this can severely affect the sales performance of the seller's product and can even drive the product out of the market (Zhu & Liu, 2018).

However, this dominant market position may have further consequences. Once a platform owner has achieved a dominant position, access to it can be monetized (Parker & van Alstyne, 2005). Amazon does not exploit its market power vis-à-vis consumers, but vis-à-vis third-party sellers and suppliers. These have to pay a monthly fee to gain access to the platform, a commission on every sale, and additionally, they provide Amazon with valuable data. Amazon not only monetizes the seller, but it pursues a "divide-and-conquer" strategy where one side subsidizes the other. The consumers get very competitive prices, which leads to strong customer and sales growth. This makes the platform a valuable sales channel for sellers. Amazon has already used its market power to control the pricing of independent third-party sellers (*Bundeskartellamt v. Amazon*, 2013). After anti-trust investigations, Amazon has removed this clause from its terms and conditions. In the Netherlands, the dominance of the real estate platform *Funda* and its abuse vis-à-vis its complementary partners have already been legally discussed (*VBO Makelaar v. Funda B.V.*, 2018; Mandrescu, 2018). The accusation made against the platform was that it charged different prices for the same services from different groups of complementary partners and also placed these groups in search results with different levels of visibility. The characteristics of the two-sided structure and the use of personal data and free access already show "that the application of competition law may require some adjustments" (Mandrescu, 2018, p. 148). In addition, more and more politicians and authorities in Europe and the USA are demanding restrictions on or even the break-up of Amazon (Ladd, 2018).

With the hybrid platform model, Amazon has considerably increased its market dominance in e-commerce over recent years. Forty percent of all online sales in Germany are made through Amazon sales channels (digital kompakt, 2020), while 34% of consumers directly use Amazon for their product searches in German-speaking countries (ibi research, 2017). Right now, Amazon is growing by $200 million in sales per day (Bezos, 2019). Advertising services are one of the fastest-growing business units for Amazon, and it is currently the third-largest digital ads platform in the USA behind Google and Facebook (Perrin, 2018). The Amazon Marketplace is an e-commerce platform where independent third-party sellers can offer their products alongside Amazon's regular offerings. This leads to an improved customer experience, which in turn leads to higher traffic. This makes the platform even more interesting for sellers because they benefit from a larger customer base. Amazon calls this mechanism the

"Virtuous Circle" (Cuofano, 2020). Through growth, Amazon can achieve lower cost structures through economies of scale. This allows Amazon to offer its products at even lower prices and thus increase their attractiveness to customers. The necessity for brands and retailers to adopt marketing and distribution strategies tailored explicitly to Amazon increases due to the unique infrastructure and Marketplace system (Atchison, 2017). The increasing number of sellers and products on the platform also heightens the competitive intensity. More and more sellers are entering the Marketplace and fighting for the visibility of their products. On the one hand, it is therefore important that sellers optimize their product presentations on Amazon in order to successfully launch products and be competitive on the platform, and, on the other hand, it is important that sellers select product areas where the risk of being squeezed out by Amazon is limited.

2.2 Dissertation Objectives

2.2.1 Research Gaps

The literature analysis has revealed several interesting gaps in the research. The overarching topic of this dissertation is to elaborate on cooperation strategies with online platforms and to understand how sellers can successfully operate in dynamic and challenging online platform markets to increase product success. We also investigate Amazon's market share and dominance in individual product categories in order to create more transparency for all market participants. The following section provides an overview of the research gaps addressed by the three studies in this dissertation project.

First gap. The prediction of product success is an important topic for both theory and practice (Decker & Gnibba-Yukawa, 2010; Karniouchina, 2011). However, it is not easy to predict product success, especially for new products. In the last decade, the sales channels for products have changed, and digital marketplaces like Amazon or Alibaba play an increasingly important role (Hakala, Niemi, & Kohtamäki, 2017). However, such online platforms lead to a dynamic and competitive environment, which makes it even more difficult to predict product success. Marketplace sellers face three common uncertainties: first, the success of new product introductions lacking trust-building elements, second, the success of incumbent products that could be easily imitated by competitors with low entry barriers, and third, the degree of platform integration, which can lead to different dynamics. Although researchers have already investigated the influence of distribution approaches (Di Benedetto, 1999) and sales activities (Hultink & Atuahene-Gima, 2000) on product success, a platform-specific perspective is missing.

Additionally, research has so far only insufficiently investigated how sellers could counteract these challenging platform dynamics. We argue that online product legitimacy could be an essential component to predict product success in uncertain environments.

Second gap. The market share of a company is an important indicator of its performance (Edeling & Himme, 2018; Feeny & Rogers, 2000) and market power (Nissan, 2003; Rhoades, 1985). In most cases, the market share is determined at the company level, whereas a product-category specific approach would be more appropriate (Connolly, Hirsch, & Hirschey, 1986; Edeling & Himme, 2018). In order to make a correct comparison between companies in the same industry, the market share must be calculated at the product-category level. Transparency about category-specific market shares is essential in order to better assess the competition and one's own market position as well as the attractiveness of the platform for one's own product segment. In the case of large and complex companies that offer products from different segments, determining the market share can be difficult. Amazon is one of the largest e-commerce retailers and platform owners worldwide. Although Amazon publishes sales figures in its annual reports, these reports do not further break down sales into individual product categories, which makes it difficult to analyze the dominance in individual segments more precisely. To date, it is unclear how dominant Amazon actually is and how Amazon's dominance in individual segments affects platform-specific cooperation strategies.

Third gap. The large sales volume of the Amazon Marketplace also attracts more and more sellers to the platform, who fight for visibility and customers. An ever-growing product range on the platform makes it increasingly difficult for individual retailers to gain visibility for their own products. Third-party sellers have limited opportunities to increase the visibility of their products on the platform. Amazon's rigid system makes it difficult for sellers to differentiate their products from other products. Nevertheless, some product-page factors can be adjusted by sellers to present their products in the best possible way. Factors such as reviews and ratings, visual presentation, product information, and shipping have an impact on sales performance on the Amazon Marketplace (Amazon, 2019b). However, retailers often lack access to reliable, evidence-based data about relevant product-page factors and how they relate to a higher conversion rate and sales performance (ShopDoc, 2019). Knowledge transfer from science to practice is a common problem (Rynes, Bartunek, & Daft, 2017). Studies show that tools or applications help companies to obtain relevant information at the right time to implement and achieve business goals (Carlsson, 2018; Lozano, 2020). With the APLO tool, we have developed an application that helps sellers to identify product-specific optimization potentials for Amazon product pages. However, it remains to be evaluated as to how well this tool helps sellers to implement these recommendations and what effect the improvements have on the sales performance of the product on Amazon.

2.2.2 Research Questions

Based on these gaps, this dissertation intends to answer the following research question (RQ):

Overall research question:

RQ: How can Marketplace sellers counteract dynamic and uncertain online platform markets to increase product success?

This dissertation approaches the primary RQ by formulating more specific RQs that are addressed in each article:

Article 1:

RQ1a: How does online product legitimacy contribute to predicting the success of new products on online platforms?
RQ1b: How does online product legitimacy contribute to predicting the success of products with high competition on online platforms?
RQ1c: How does online product legitimacy contribute to predicting the success of products with low platform integration?

Article 2:

RQ2: How dominant is Amazon in individual product categories, and how does this affect cooperation strategies?

Article 3:

RQ3a: How effective is the Amazon Product Listing Optimization (APLO) tool in supporting the optimization of Amazon product-page factors?
RQ3b: How does overall product-page quality affect the sales performance on Amazon?
RQ3c: How satisfied are users with the current version of the Amazon Product Listing Optimization (APLO) tool, and what is their willingness to pay?

3 Main Theoretical Perspectives

With this paper, we relate to several streams of literature.

3.1 Platform-Based Markets

Platforms play an increasingly important role in online markets (Kapoor & Agarwal, 2017; Moore, 1996; Piezunka, Katila, & Eisenhardt, 2016). Platforms mediate between different groups of users. The model is already successfully established in several industries. Some examples are smartphone operation systems (app developers and users), video consoles (game developers and users), social networking sites (advertisers and consumers), and retail (sellers and buyers). In most cases, the platforms are multi-sided in which the platform owner brings several groups together. The decisive factor for the success of platforms is that a critical mass of users can be gained as quickly as possible (Parker & van Alstyne, 2005; Rochet & Tirole, 2003). Network effects play a significant role, usually resulting in only a few large players being able to exist in a segment (Katz & Shapiro, 1994; Zhu & Iansiti, 2012).

Research on platform-based markets is critical for this dissertation. We focus primarily on the interaction and interdependencies between the platform owner and complementors (Panico & Cennamo, 2015; Yoffie & Kwak, 2006). On the one hand, prior literature shows positive outcomes when companies cooperate with a platform owner, mainly because complementors get access to the platform's infrastructure and installed bases such as customers (Claussen, Kretschmer, & Mayrhofer, 2013; Venkatraman & Lee, 2004; Zhang & Li, 2010). On the other hand, some studies show threats and dependencies that could arise through cooperating with a platform owner (Huang, Ceccagnoli, Forman, & Wu, 2013; Zhu & Liu, 2018). On Amazon, sellers compete not only with other third-party sellers but also with Amazon itself, which also acts as a retailer. Researchers already gained first insights into the fact that Amazon uses data from its Marketplace sellers to identify attractive product segments (Zhu & Liu, 2018). In a second step, Amazon itself enters this segment and displaces the smaller retailers through the prominent placement of its own products. This illustrates the plurality of risks sellers face on online platforms.

3.2 Platform Dynamics and Legitimacy

Retailers face three common challenging dynamics and uncertainties in platform markets. First, the success of new products is uncertain due to the lack of trust-building elements and a lack of product history (Bunduchi, 2017; Schoonhoven, 2015). This poses challenges for sellers at market launch on online platforms. Second, products on digital marketplaces are continually facing new competition (Geroski, 1995). Easy and fast access to online platforms enable retailers to launch new products quickly and on a global scale (Jin & Hurd, 2018). Existing products have to continuously face this challenge and counteract possible threats from new, competing products (Lee, Smith, Grimm, & Schomburg, 2000; Redmond, 2013). Third, sellers have to decide how closely they want to cooperate with a platform owner. Deeper integration into the platform can be beneficial but also puts the seller in a dependent position (Ahuja, 2000; Katila, Rosenberger, & Eisenhardt, 2008; You, Shu, & Luo, 2018). A lower level of integration allows sellers to retain more control over individual steps in the value chain, but it also increases uncertainty about the success of the product, as platform-specific advantages can disappear (Venkatraman & Lee, 2004).

Legitimacy, which is actually an institutional concept, helps companies to achieve greater acceptance and growth (Zimmermann & Zeitz, 2002). By building legitimacy, companies can secure access to important resources, especially in the early years. Legitimacy factors can help to build trust with customers and thus to enhance product success (Suchman, 1995). In the online world, however, there are new possibilities and approaches to building legitimacy (Hakala et al., 2017; Li & Hitt, 2008). For this reason, researchers have recently been increasingly exploring the concept of online legitimacy (Antretter, Blohm, Grichnik, & Wincent, 2019; Gallagher & Savage, 2015). In the context of digital marketplaces, there are two main reasons for a new perspective on the concept of legitimacy: the creation and publication of digital product information (Häubl & Trifts, 2000) and the ability of customers to unobstructedly share their opinions online (Chen & Xie, 2008; Li & Hitt, 2008). Based on previous research and on our results, we propose that online product legitimacy, a concept building on an institutional perspective of the liability of newness and legitimacy, could counteract challenging platform dynamics and serve as a mechanism for steering product success in uncertain environments.

3.3 Interorganizational Relationships and Coopetition

This dissertation is also connected to interorganizational relationships (IORs) and the coopetition literature. The connections to a network with other companies are often highly relevant to the success of a company (Oliver, 1990). Entrepreneurial companies that proactively build alliances benefit from better firm performance (Eisenhardt & Schoonhoven, 1996; Sarkar, Echambadi, & Harrison, 2001). Both companies that establish cooperation can benefit from this. One party gets access to, for example, an infrastructure and customer base, and the other party (the platform owner) could increase the attractiveness of the platform. This phenomenon is rooted in the resource dependency theory that identifies interdependence as the key motivator to tie formation (Ozcan & Eisenhardt, 2009). However, IORs could also expose firms to dangers such as misappropriation (Hallen, Katila, & Rosenberger, 2014), often referred to as the "swimming with sharks" dilemma. Entrepreneurs cooperate with larger but risky partners where they have a high potential for misappropriation when they need resources that established firms uniquely provide (Kapoor, 2013; Katila et al., 2008). In most cases, companies must disclose valuable knowledge during cooperation and thus expose themselves to the risk of appropriation and cannot protect themselves from a more skilled and well-resourced so-called cooperative partner. (Diestre & Rajagopalan, 2012).

This dilemma can often be observed in companies that are in a coopetition relationship. Coopetition is a situation where companies simultaneously pursue cooperation and competition with another company (Bengtsson & Raza-Ullah, 2016; Nalebuff & Brandenburger, 1997). This concept is increasingly important for firms when they want to survive and prosper in today's highly competitive environment (Luo, Rindfleisch, & Tse, 2007). Amazon is an excellent example of a coopetition-based business model. With the Marketplace, it allows third-party sellers to distribute their products over the Amazon website. This increases the product offering and, thereby, the attractiveness of the platform for the customers. However, Amazon itself is a retailer of many products and is, therefore, in direct competition with third-party sellers from the Marketplace.

This can be explained by the fact that Amazon pursues a clear customer-centricity strategy. Through the coopetiton approach, Amazon creates even more customer value than would otherwise be possible (Ritala, Golnam, & Wegmann, 2014). Therefore Amazon sees third-party sellers as collaborative partners that help it to achieve its goals (Ritala et al., 2014). Studies show that companies who apply a coopetition strategy have negative as well as positive implications in terms of innovation and market performance (Lado, Boyd, & Hanlon, 1997; Luo, Slotegraaf, & Pan, 2006; Ritala, 2012). Some studies show that coopetition could be financially beneficial because alliances lead to “expanded pie” effects, but firms have to carefully consider to what extent and in what area they will cooperate with other companies (Luo et al., 2007, p. 81). Bengtsson and Kock (2000) argue that coopetition is complex but could also be a very profitable relationship for competitors. Through the open Marketplace and Amazon’s coopetiton-based business model, Amazon itself, but also third-party sellers, achieve market growth and resource efficiency (Ritala et al., 2014). Besides positive effects on market performance, innovation capacity could also benefit from coopetition (Quintana-García & Benavides-Velasco, 2004). However, other researchers show that coopetition could also be a risky approach that often ends up in failure (Kim & Parkhe, 2009; Park & Russo, 1996).

4 Overview of Paper Series

4.1 Structure of the Dissertation

The recently described phenomena, research gaps, and theoretical streams built the foundation for this dissertation. Moreover, to complete this foundation, this chapter contains a summary of the three conducted research projects. The first part of the dissertation (research summary) closes with the conclusion. The purpose of the first part is to provide the conceptual background on online platforms against which we can reflect on the individual articles in this dissertation. The second part of this dissertation consists of three research articles. Article 1 is co-authored by Knape, Hess, Blohm, Wincent, and Grichnik. Article 2 is co-authored by Knape, Hess, and Grichnik. Article 3 is a single-authorship paper. Knape is the lead author in all the articles and has had the primary responsibility for data collection, analysis, writing, and managing the respective relationships with the research partners.

In addition to the three research papers, two application projects were also developed within the scope of this dissertation. Based on the research results from the first two articles, the APLO tool was developed, which supports Amazon sellers in identifying and implementing product-page optimizations. Besides that, and in the context of the second article, the E-Commerce Germany Report was developed, which makes the results of the study accessible to a practice-oriented readership.

4.2 Summary of Research Projects

A summary of all three articles, including the main RQs and the main findings, is depicted in Table 1.

Table 1: Summary of Articles, RQs, and Main Findings

Authors	**Main research questions**	**Main findings**
Article 1: *Product innovation and entry failure on online platforms: A machine-learning approach*		
Dominic Knape Manuel Hess Ivo Blohm Joakim Wincent Dietmar Grichnik	• How does online product legitimacy contribute to predicting the success of products on online platforms?	• We developed a measurement for online product legitimacy and show how product-page factors attribute to predicting product success on online platforms. • Using this measure, we can enhance the predictability of product success for three common and uncertain platform dynamics. • We could show how online product legitimacy could be used to counteract the uncertainty in digital marketplaces. • We demonstrate the potential of machine-learning approaches in testing product legitimacy constructs.
Article 2: *Amazon's market power decoded by the Amazon Market Dominance Index*		
Dominic Knape Manuel Hess Dietmar Grichnik	• How dominant is Amazon in individual product categories, and how does this affect cooperation strategies?	• Market share is the core element for determining the market power of a company. • With the Amazon Market Dominance Index (AMDI), we show Amazon's market dominance on the product-category level. • Amazon has a particularly high market share in the categories Electronics & Computers (24%) and Toys & Baby, Sports & Leisure (17.87%), whereas Apparel (2.65%) and Groceries & Beverages (0.18%) only achieved small market shares. • Amazon could "cherry-pick" profitable product areas through big data analysis. Sellers need to select product areas where the risk of being squeezed out by Amazon is limited.
Article 3*: Evaluation of the effectiveness of the Amazon Product Listing Optimization tool*		
Dominic Knape	• How effective is the Amazon Product Listing Optimization (APLO) tool in supporting the optimization of Amazon product-page factors?	• The APLO tool helps Amazon sellers with evidence-based optimization suggestions to enhance product-page quality. • Product pages of sellers using the APLO tool significantly increased product-page quality compared to sellers who did not use the tool. • By improving the overall score of the product page by one percentage point, the Amazon sales rank improves by 0.996 percentage points. • An online survey among tool users confirms a high level of satisfaction with the tool and shows that the majority of users are also willing to pay for it.

5 Conclusion

Online platforms play an increasingly important role in digital commerce. In many regions worldwide, digital marketplaces account for about half of all online sales (Erich, 2019). Although research has already examined online platforms in some areas, the process and factors for successful product launches on online platforms have barely been examined (Jin & Hurd, 2018). This dissertation aims to contribute to our knowledge about platform-based markets and how Marketplace sellers could counteract dynamic and uncertain online platform markets to increase their product success.

For individual retailers to successfully use platforms as a distribution channel, they need to understand the market dynamics and how they can address them for a successful product launch and long-term success on digital marketplaces. We identified three common platform dynamics and showed how retailers could use online product legitimacy as a mechanism for steering product success. Compared to other studies that investigate success factors individually, our study provides a comprehensive and inclusive view of predictors for product success in digital marketplaces. While our research focuses on Amazon as an empirical setting, our findings have implications for sellers in many different platform-based markets by showing how product success can be predicted with the help of machine-learning techniques and online legitimacy measures.

Knowledge of one's own market position and that of the platform is also crucial for successful cooperation with digital marketplaces. Amazon is a key player in e-commerce, but we know relatively little about the market position and sales shares of the individual product categories. We build the Amazon Market Dominance Index (AMDI) that forms the first basis for a more detailed understanding of Amazon's market position. The AMDI provides insights into Amazon's actual market dominance, segmented by individual categories, and thus reveals data that was previously unavailable. We demonstrate how IORs emerge in the context of online platforms like the Amazon Marketplace and how they affect third-party sellers.

The APLO tool aims to make the research results of our previous studies more accessible. The tool allows Amazon sellers to easily determine the optimization potential of a product listed on the platform. Through specific and evidence-based recommendations, we help retailers to improve their product-page quality on Amazon and thus to increase their sales performance. Obtaining this clarity on the optimization potentials for products listed on online platforms is critical to identify leverages to increase product success. With an evaluation study, we assess the effectiveness of the tool and find that Amazon sellers who use the APLO tool can significantly improve their product pages. Additionally, we could show that these improvements result in a higher sales performance on Amazon.

In conclusion, this dissertation provides evidence that product-page quality and the resulting online product legitimacy are crucial to counteract dynamic platform markets and to increase product success. With the AMDI, we create more transparency regarding Amazon's market dominance in individual product categories. Finally, we strive to encourage sellers to analyze their market position in more detail and to develop a comprehensive platform strategy that will enable long-term success.

Part II - Papers of the Dissertation

First Dissertation Article

Predicting Success of Product Introductions with Online Legitimacy on Digital Marketplaces: A Machine Learning Approach

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6 Predicting Success of Product Introductions with Online Legitimacy on Digital Marketplaces: A Machine Learning Approach

Abstract

Digital marketplaces such as Amazon or eBay enable rapid product launches on a global scale with the promise of accessing numerous potential customers. However, few studies have considered how products become successful on these digital marketplaces, which have developed into highly competitive environments where most new products fail to gain buyers' attention. We analyzed product data from 3,879 products listed on Amazon and sold by Marketplace sellers to investigate the effects on predicting product success. Our investigation covered new product introductions, products subject to new product imitations by new entrants, and new and incumbent products where firms engage in deeper platform collaboration. We used context-specific machine learning approaches such as artificial neural networks and gradient boosted decision trees. Based on our results, we developed the concept of online product legitimacy, building on the institutional perspective of the liability of newness and legitimacy. Online product legitimacy offers potential to counteract challenging platform dynamics and serve as a mechanism for steering product success—for new product introductions in particular. Our results indicate the predictability of a product's future success in dynamic platform markets with an average error of only 27.2%. Thus, this study contributes to the literature on new product success and the literature examining digital marketplaces and platforms, demonstrating the potential of machine learning approaches in testing product legitimacy constructs.

Keywords: online legitimacy, digital marketplace, online platform, product introduction, platform dynamics

6.1 Introduction

Practitioners and researchers alike have shown keen interest in predicting the success of products in general and new product introductions in particular (Decker & Gnibba-Yukawa, 2010; Karniouchina, 2011). Within the last decade, market channels for reaching consumers with new products have changed dramatically, moving to digital marketplaces such as Amazon or Alibaba that are now serving 39% of consumers worldwide (Activate, 2019; Hakala et al., 2017). Powerful platform owners enable firms to reach these large markets through a standardized platform integration process, inviting many retailers to sell their products (Xu, 2018). While previous research has shown benefits as well as uncertainties for the firms that use these online channels (Gallagher & Savage, 2015; Gruner et al., 2019), engaging in such platform ecosystems can lead to fierce competitive and dynamic conditions fostered by platform owners to serve consumers with a wide product range (Kwark, Chen, & Raghunathan, 2017; Mantin, Krishnan, & Dhar, 2014; Tian et al., 2018).

Three primary online platform dynamics are commonly challenging product success and firm performance. First, introducing new products on digital platforms can be difficult. New products lack trust-building elements such as online reviews and recommendations (Schoonhoven, 2015) or target early adopters open to technological innovations. As a result, consumers often consider new products illegitimate compared to incumbent products on the platform (Bunduchi, 2017). Second, competitors can easily observe the products offered on the platform, fostering product imitation and entry in the same product category (Lee et al., 2000; Porter, 2001; Wen & Zhu, 2019). Since market entry barriers are low, competing products may easily affect focal product demand, which suggests that product success is highly uncertain and unpredictable. Third, powerful platform owners offer different methods of platform integration for firms, affecting how products are displayed as well as how firms reach their consumers (Ryan et al., 2012). Knowledge of how deeper platform integration serves product success is uncertain; integration may provide a legitimate signal to consumers while at the same time creating dependencies between the seller and platform owner (Zhu & Liu, 2018).

Investigating the peculiarities of such platform dynamics is relevant to understanding what constitutes product acceptance and how factors indicating product acceptance can be used to predict its relationship to product and, ultimately, firm performance. The broader and better-known literature on product acceptance suggests that factors related to one general mechanism—legitimacy—are of importance (Bunduchi, 2017; Wang, Song, & Zhao, 2014; Zimmermann & Zeitz, 2002, p. 414). Previous research has acknowledged how digital channels have changed consumers' shopping habits and how products are presented, developing the concept of online legitimacy (Antretter et al., 2019; Gallagher & Savage, 2015; Yu, Tao, Chen, Zhang, & Xu, 2019). Although earlier research has advanced understanding of how products can compete on online platforms (e.g., Jiang et al., 2011; Piezunka et al., 2016; Zhu & Liu, 2018), scholars have not addressed how online legitimacy, i.e., a given set of factors proprietary to digital marketplaces, can contribute to predicting product success on such channels.

We created a unique data set containing 3,879 products listed on Amazon that were offered by 136 sellers. We applied artificial neural networks (Chollet, 2018) and gradient boosted decision trees (Chen & Guestrin, 2016; Friedman, 2001) to investigate legitimacy-enhancing product page characteristics and their ability to predict the future success of products. As part of the process, we closely examined the conversion rate, a crucial indicator in e-commerce that indicates the attractiveness of a product and its presentation (Fox, 2017). We also combined several product page factors common to digital marketplaces into one online product legitimacy measure and investigated its impact on the predictability of a product's success. This approach allowed us to formulate statements on the overall quality of product presentation and its effects, in contrast to most of the previous studies that have focused on single factors such as product reviews and ratings (Cezar & Ögüt, 2016), visual presentation (Song & Kim, 2012), or social media communication (Gruner et al., 2019). Prior research has not yet offered an integrative investigation of product page factors and how they can help predict the success of new product listings on online platforms (Di Fatta, Patton, & Viglia, 2018).

This study makes three contributions to the product innovation management literature. First, in our research, we have drawn upon the concept of online legitimacy to predict new product success on online platforms (Gallagher & Savage, 2015; Stinchcombe, 1965; Yu et al., 2019; Zimmermann & Zeitz, 2002). Using a comprehensive set of product page factors provided on digital marketplaces, we have been able to build an online product legitimacy measure that successfully enhances the predictability of product success under challenging platform settings. This valuable contribution to product success literature shows how to better predict product success and reduces uncertainties for new product introductions as well as incumbent products facing new competition (Di Benedetto, 1999; Henard & Szymanski, 2001).

Second, we have also contributed to the discussion of market dynamics on online platforms (Belleflamme & Peitz, 2010; Chen & Tse, 2008; Li, X., Ren, X., & Zheng, X., 2015). A new product's liability of newness, high competition, and a low degree of cooperation with the platform provider are three common challenges that firms face on online platforms (Evans, 2016; Ritala et al., 2014; Stinchcombe, 1965). We have shown that in these challenging platform situations, online product legitimacy can serve as a valid strategy to increase the predictability of a product's future success, mitigating the deteriorating effects of dynamic platform environments for firms. By creating online product legitimacy, marketplace sellers can counteract uncertainties in digital marketplaces, which represent increasingly important sales channels.

Third, we have shown that machine learning is an important technique for analyzing and predicting new product success. The machine learning approaches of artificial neural networks and gradient boosted decision trees have allowed us to predict the future conversion rate of a product with an average error of 27.2%. We have built predictive models using product-specific data from online platform product listings. Additionally, we have provided an account of how to use machine learning techniques for generating and testing new constructs in product innovation research (Shmueli, 2010). Consequently, our research shows that machine learning can be used to operationalize novel theoretical constructs such as legitimacy using fine-grained real-world data. Furthermore, this novel measure improves the predictive accuracy of our machine learning models across all three investigated platform dynamics. Thus, a machine learning-based prediction approach facilitates assessing the value and applicability of our novel theoretical construct, mastering the reality test of practice.

This paper proceeds as follows: First, we discuss the theoretical background, deriving three hypotheses. Next, we present our data set and the study context and then introduce the predictive approach and the machine learning techniques used. After describing the measures used, we provide the results of our calculations. The article concludes with a comprehensive discussion and conclusion.

6.2 Theoretical Background and Hypotheses

Digital marketplaces such as Amazon, Alibaba, or eBay allow retailers and manufacturers to launch products rapidly on a global scale and to gain access to a large number of potential customers. However, products that are launched on online platforms face additional requirements and challenges. First, new products have a lower level of trust from potential buyers than established products (Schoonhoven, 2015). Since new products usually cannot rely on product reviews or recommendations from existing customers, they lack trust-building elements that would otherwise signal certain qualities to customers. Additionally, new innovative products are often accompanied by a high level of uncertainty and sometimes also involve a change in the customer's way of thinking, which often results in consumers considering these products illegitimate (Bunduchi, 2017). The literature refers to this circumstance as the liability of newness (Stinchcombe, 1965). New products also have lower visibility on online platforms than incumbent products, making a market launch even more difficult. Second, the ability to quickly launch new products via open online marketplaces also results in a high number of competing products, which can rapidly increase the intensity of competition. New competitive entries can harm the success of one's own product by giving customers more choice and diverting attention (Piezunka et al., 2016). Third, sellers can choose integration into the platform's services and infrastructure to varying degrees. A low degree of integration into the platform can cause additional challenges for products. In contrast, products that are more deeply integrated into the platform will often enjoy higher visibility or other benefits. Therefore, investigating how the level of integration affects a product's success is vital.

To address these challenges, the legitimacy of products can play a crucial role. Legitimacy can be defined as "a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions" (Suchman, 1995, p. 574). Building legitimacy helps new products to increase their social acceptance and appropriateness to overcome the liability of newness. In other words, legitimacy can mitigate the problem of new products—lacking trust and depending on many external skills to overcome the limited internal resources in the innovation process—being unable to compete effectively against established products (Shepherd & Zacharakis, 2003; Stinchcombe, 1965). Because of the importance of this factor, scholars have suggested that firms consider steps to improve legitimacy even during the new product development process. Screening and assessing markets, players, and structures can contribute to a better understanding of the target markets and more clearly define the distribution strategy (Cooper, 1979). The sum of the activities carried out throughout the development and marketing process ultimately leads to success for new, innovative products (Cooper & Kleinschmidt, 1986). Delmar and Shane (2004) stressed that, especially in the case of new companies and products, the creation of legitimacy should be a priority, as legitimacy is a precondition for many other activities and connections. Just as processes of legitimization take place at the organizational level, we assume that similar mechanisms also occur at the product level (Deephouse & Suchman, 2008; Meyer & Rowan, 1977). However, the legitimacy-building process in the online world differs from a traditional perspective. The literature proposes two main reasons for this: the creation and publication of digital product information (Häubl & Trifts, 2000) and the ability of customers to share their opinions online without obstruction (Chen & Xie, 2008; Li & Hitt, 2008).

First, the role of digital product information and presentation is crucial because increased product understanding from the customer's perspective leads to higher acceptability and intention to buy (Chen & Xie, 2008; Kim & Lennon, 2008; McDowell, Wilson, & Kile, 2016). Shepherd and Zacharakis (2003) emphasized that the communication of product characteristics to customers should be the highest priority for a new product. Especially for new products, customers need much information to form a comprehensive picture of product characteristics and features (Shepherd & Zacharakis, 2003). Building on this argument, scholars have stressed that the amount of information a company provides through online platforms is positively associated with product sales and success in the marketplace (Clark & Melancon, 2013; Reuber & Fischer, 2011). Previous studies have found that missing product images and outdated information lead to a perception of lower website quality (e.g., Everard & Galletta, 2005), influencing users' trust as well as their buying intentions. Another study supported this idea by showing that a higher number of images, equivalent to providing a more complete visual representation of the product, has a positive effect on legitimacy (Di, Sundaresan, Piramuthu, & Bhardwaj, 2014). A video can also visually benefit the practical understanding and legitimacy of a product (Mollick, 2014). In other words, videos can enhance the presentation and clarification of emotional and interactive elements. Not only are visual elements usually the components that provide the first impression of a product, but visitors typically look at the images of a product first before reading further elements such as descriptions. If a product's visual presentation is not convincing, the other elements may not play any role at all when the potential customer can move to another page with a simple click (Wu et al., 2016). Elements such as videos or interactive visual presentations, more difficult to achieve in physical retail stores, especially distinguish the legitimacy-building process in the online world. On the one hand, website visitors cannot touch and experience products before purchase. On the other hand, online retailers have vastly more possibilities and space to comprehensively describe a product and its characteristics in an interactive way (Häubl & Trifts, 2000). Additionally, customers can obtain information about a product online on different websites and are not dependent on information from a single retailer. Social networks and video platforms also play an essential role in this process (Zhang, Luo, & Boncella, 2020).

Besides visual information, product descriptions contribute to the legitimacy-building process. When aspects of the product description meet customer expectations and show a pattern reminiscent of similar products, the customer's understanding and acceptance will increase (Lee, 2002). Product reviews can also serve as another important source of information, validating product characteristics and presenting them from the perspective of existing customers (Chen & Xie, 2008). In summary, transparency and less information asymmetry are crucial factors in establishing online legitimacy for a new product, especially in online retail.

Second, customer reviews and evaluations are a rich source for additional information and legitimation of a product (Chevalier & Mayzlin, 2006; Ludwig et al., 2013; Zhu & Zhang, 2010). Legitimacy results from reviews or by customers showing satisfaction with the product (e.g., Chen & Xie, 2008; Whelan, Moon, & Grant, 2013). Online platforms allow the public to provide direct unfiltered feedback about new products. While traditional newspapers and opinion pages offer limited possibilities for expressing personal judgment (Lee & Carroll, 2011), online platforms such as Amazon Marketplace have created public arenas where consumers continuously discuss and evaluate products (Etter, Colleoni, Illia, Meggiorin, & D'Eugenio, 2018; Whelan et al., 2013). Unlike offline retail, product reviews are easy to access in online business. As a result, bad products may be more easily recognized online compared to the offline world. This high level of transparency helps potential customers to gain a more comprehensive picture of product characteristics. Such evaluations can consequently have significant impacts on product performance (Chevalier & Mayzlin, 2006; George, Haas, & Pentland, 2014). Online consumer product reviews are increasingly important for consumers' purchase decisions (Chen & Xie, 2008). The perspective of other independent customers can help interested consumers better assess whether a product fits their own usage situation. Online shoppers have a 12 times higher trust in peers' opinions than in marketer-initiated sources (Ludwig et al., 2013). Cezar and Ögüt (2016), analyzing the impact of review ratings on the conversion rate in online hotel bookings, found that a high number of recommendations can have a significant positive impact on conversion rates. As another example, an improvement in the overall review rating led to an increase in sales in the category of books on Amazon (Chevalier & Mayzlin, 2006).

In the following, we investigate and compare the importance of online legitimacy factors in three different platform-specific dynamics: (1) new products vs. incumbent products, (2) low vs. high competition, and (3) low vs. high integration depth into the platform.

How Online Legitimacy Affects the Success of New Products on Online Platforms

New product developments and launches are costly and time-consuming for companies, yet they often fail to lead to the intended success. While previous research has shown that the failure rates for new products comprise up to 40% of all product launches (Barczak, Griffin, & Kahn, 2009; Castellion & Markham, 2013; Markovitch, Steckel, Michaut, Philip, & Tracy, 2015), products launched on online platforms face additional requirements and challenges. New product entries, defined as the introduction of an innovative new product that has not previously been active on the online platform, can expect challenges in establishing online legitimacy. Based on the previous literature, we reasoned that legitimacy is especially problematic for pioneers and those new products that are innovative on an online platform. Legitimacy is critical, especially in the early phase of a new product launch; when legitimacy is absent, early customers do not trust a product, become hesitant, and subsequently avoid buying the product (Delmar & Shane, 2004; Wang, Song et al., 2014). As such, lacking legitimacy makes it hard for a new product to communicate its true value and functionality. Many researchers investigate product success at the micro-level—i.e., product development or the product itself. However, the macro-level can also play an essential role in the success of a product (Redmond, 1995). Although studying legitimacy for new products (Crespin-Mazet & Dontenwill, 2012; Wang, Zhou, Mou, & Zhao, 2014) is useful for understanding new product launches on online platforms, the characteristics of online platforms challenge methods for examining a new product's online legitimacy. Primarily, online selling through online platforms exposes companies to a new product innovation launch on a rapid global scale, which allows them to reach customers in an immediate way (Kozinets, Valck, Wojnicki, & Wilner, 2010). On online retail platforms such as Amazon Marketplace or Alibaba, sellers directly share information about new products to the global community. Additionally, and in contrast to traditional offline entries or independent online shops, marketplace-imposed restrictions only allow the possibility of optimizing a pre-determined list of individual product page factors. Thus, to build online legitimacy, sellers need to implement their products in a way that corresponds to the norms and standards of the platform owner while meeting the expectations and assumptions of customers. Especially in the online world, where the customer cannot touch or experience a product, limited legitimacy is a problem for a product's success. Especially in markets offering many similar products, where all niches are already occupied, the chances for product success are limited. In online marketplaces, such situations can quickly arise, making it difficult for manufacturers to differentiate their products from others. However, sellers have the possibility to influence and design certain product page factors in the marketplace, building online product legitimacy and increasing customers' trust in a new product. As new products face the challenges described above, a legitimate product presentation will counteract these obstacles to reduce uncertainty. The sale of a new product could accordingly be subject to fewer uncertainties and fluctuations in demand. In addition to potential customers with strong demand actually buying the product, other interested shoppers, previously deterred from buying by poor product presentation, will make a purchase decision. Legitimacy factors such as more comprehensive product information or customer reviews help better communicate product characteristics to potential buyers to increase their willingness to buy. In our view, online legitimacy is an antidote for a new product's liability of newness (Stinchcombe, 1965) and a critical issue for new products. We assume that website visitors will make more frequent and more reliable purchases when product legitimacy is high. Therefore, sales of a new product are more dependably predictable using a legitimate product presentation as the conversion rate is less subject to fluctuations. For established products that have been listed longer on the platform, legitimacy factors play a less important role as the product already enjoys a certain degree of trust among potential customers. Here, the conversion rate from the previous month (baseline variable) is probably the best predictor. Therefore, we assume that online product legitimacy factors are necessary to increase the predictability of new product success in digital marketplaces.

H1: Online legitimacy is more important for predicting product success for new products than for incumbents.

How Competitive Entries Affect Success on Online Platforms

New competition can affect the sales performance of one's own products. Successful products are at risk of imitation by other marketplace participants (Lee et al., 2000; Porter, 2001). Therefore, being first in the market as a pioneer with a new, innovative product can offer both advantages and disadvantages (Lilien & Yoon, 1990; Porter, 1985). On the one hand, a pioneer can shape the market and build a reputation early on, which usually also helps toward benefiting from a higher willingness to pay (Robinson

& Fornell, 1985; Schmalensee, 1982). On the other hand, the pioneer bears a higher risk in entering the new market and developing product innovation, while any advantages may be easily lost to competition (Dobrev & Gotsopoulos, 2010; Mansfield, Schwartz, & Wagner, 1981).

Reasonably, this downside from competitors is particularly prominent in digital marketplaces since online platforms greatly reduce entry barriers such as access to distribution (Jin & Hurd, 2018). Open platforms such as Amazon Marketplace allow manufacturers and retailers to offer their products on the platform through a self-registration process (Xu, 2018). Amazon imposes few restrictions as the company wants to provide its customers with the widest possible range of products. Greater competition gives consumers a wider range of products that can better meet customer needs and wishes. The large selection and additional access to international sellers and products lead to increasingly intense competition, meaning that sellers and products have no protection in the form of an entry barrier for access to distribution as platforms are usually accessible to a wide range of companies without major hurdles. Therefore, sellers must protect themselves from new entries in other ways to establish themselves on the platform and ensure product success.

The literature has already identified different protective entry responses of incumbent firms, such as pricing responses (Simon, 2005), entry deterrence strategies (Smiley, 1988), and technology barriers (Lieberman, 1989). However, little research has investigated how online legitimacy in the case of new competitive entries can make it easier to accurately predict product success. In addition to a high level of legitimacy for the product itself and its degree of innovation, product presentation and marketing play a particularly vital role in long-term product success (Eisend, Evanschitzky, & Calantone, 2016). However, platforms usually offer a rigid framework for presenting product features. To prevail and stand out against competitors on a platform, it is essential to design these platform-specific product page factors optimally (Gudigantala, Bicen, & Eom, 2016; Kim, Ferrin, & Rao, 2008). All these factors form online product legitimacy; therefore, we assume that this perception of legitimacy plays a decisive role in ensuring product success, even in a highly competitive environment where new competing products are launched frequently. Comparing products that face new competition to products that have no new competition, online legitimacy helps, in particular, to better predict product success. A high level of online product legitimacy allows a product to maintain demand and, thus, a relatively stable conversion rate even under high competitive pressure. Therefore, we assume that the legitimacy factors are more important for predicting product success for products exposed to new competition than for products without new competition.

H2: Online legitimacy is more important for predicting product success for products that face new competition.

How Deeper Collaboration with the Platform Owner Affects Success on Online Platforms

Ahuja (2000) stated that one reason why firms build alliances and cooperations is the insufficiency of their resources. This phenomenon is rooted in the resource dependency theory that identifies interdependence as the key motivator for forming ties (Ozcan & Eisenhardt, 2009; Pfeffer & Salancik, 1978). In product development and new product entry, firms try to achieve a competitive advantage by collaborating with other firms. Often, companies seek to surpass their closest competitors by also building alliances with prior competitors. Different types of needed assets are a core driver for cooperation. Some assets cannot be purchased in the free market or need time to develop and thus are most efficiently acquired by cooperations. Hagedoorn and Schakenraad (1990) name the following motives why firms seek to achieve a better position: (1) faster access to new markets, (2) lack of financial resources, and (3) the technological competence of a partner. Online platform owners provide the technical infrastructure that complementors can benefit from simply by offering their products on the platform. Complementors have no need to care about the technical setup of the website or payment processing, allowing a faster market entry compared to the development of an own online distribution channel and reducing financial expenses and risks. Thus, by building company linkages, companies are also trying to keep up with the competition (Ahuja, 2000; Garcia-Pont & Nohria, 2002). This is especially the case for smaller companies that often do not have the means and possibilities to compete in the technological arena. One way to compensate for this disadvantage is to cooperate with partners who offer technological competence. The greater the need for additional competencies and the greater the deficit in one's own company, the more likely companies are to form cooperations or alliances (Ahuja, 2000, p. 319). In addition, access to the already existing customer base of an online platform is an important asset that motivates companies to cooperate (Zhu & Liu, 2018).

The types and depth of cooperations between platform providers and complementors can have different effects on their outcome (Hagedoorn & Schakenraad, 1990). Previous research has shown that stronger connections or alliances can lead to better firm performance (Sarkar et al., 2001). Access to platforms' infrastructure and installed bases such as customers are the most common reasons for a positive outcome for complementors (Claussen et al., 2013; Venkatraman & Lee, 2004; Zhang & Li, 2010). Further studies have reported positive outcomes for collaborating firms (Eisenhardt & Schoonhoven, 1996; Gulati & Higgins, 2003). Both sides can benefit from cooperation. For example, one party gets access to an infrastructure and customer base, while the other party (the platform owner) can increase the attractiveness of the platform. Moreover, You et al. (2018) found that more intense competition in online retail markets leads to a higher degree of cooperation, and such cooperations increase firm performance.

In traditional vertical retail-manufacture relationships, manufacturers sell their products to a retailer who is then responsible for listing and selling the product (Fan et al., 2020). However, online retail platforms have a different scheme in this case. Manufacturers can list their products on a platform themselves and act as sellers on it. In the classic model, the manufacturer also ships the goods himself. The online platform merely serves as a virtual intermediary between seller and buyer. Some platforms offer additional services in addition to the technical infrastructure. For example, Amazon offers logistical services to marketplace sellers so that they can have their products shipped by Amazon. Thus, platform complementors can form different levels of depth of collaboration with a platform provider. Companies that have closer cooperation with a platform provider can profit from additional benefits. For instance, sellers that use Amazon's logistic services receive the "Prime" label on the online platform. Consequently, companies that have deeper cooperations with platform providers should already enjoy higher trust from platform users, in turn increasing the conversion rate of these products as customers favor free and reliable shipping (Xu, Bai, & Wan, 2017). Due to the benefits that products with a high degree of cooperation receive on a platform, we assume that online product legitimacy factors are more important for predicting product success when products have a low degree of cooperation with the platform. Building legitimacy allows products from sellers with a low degree of cooperation to compensate for the additional trust that highly integrated products receive from customers, potentially decreasing demand uncertainties and fluctuations, which increases predictability.

H3: Online legitimacy is more important for predicting product success for products that have a low degree of platform cooperation.

6.3 Methods

6.3.1 Study Context and Dataset

Consistent with our hypotheses, we tested our claims in the context of an online retail platform. Such platforms have gained popularity worldwide over the last few years (Gao, Chan, Chi, & Deng, 2016). In the platform model, a large number of retailers and manufacturers offer their products via one channel (Abhishek, Jerath, & Zhang, 2016), providing customers a large, diverse range of products without the need to go to different stores to shop.

To empirically study the predictive power of product information on online platforms, we used data from Amazon Marketplace. Already one of the largest online retailers worldwide, Amazon is still growing significantly. From 2018 to 2019, Amazon's global sales increased by 20%. Amazon operates a hybrid platform on which they sell their own products or resell products from other brands (first-party sales) and let other sellers offer their products via the Marketplace (third-party sales). For all first-party sales, Amazon is responsible for the service and shipping of the products. For third-party business, the seller himself typically takes care of the product presentation on the website as well as shipping and service. Since the Marketplace business was launched in 1999, it has grown by an average of 52% per year. In comparison, first-party sales have grown by only 25% per year. The revenue of the Marketplace business (third-party sales) overtook Amazon's first-party sales in 2015, and in 2018, third-party sellers were responsible for over 58% of all sales on Amazon.

We obtained Amazon product listing and transaction data from a data agency in Germany specializing in Amazon. The strength of our dataset lay in the detailed combined information for product listing and transaction data. The dataset included all main attributes of Amazon's product listings (e.g., description length, number of bullet points, number of reviews, average review rating, number of images, number of videos, etc.). In addition to the product listing characteristics, each data item also included monthly transaction data (e.g., conversion rate, number of transactions, etc.). The unique dataset was compiled using Amazon Marketing Services from December 2018 to March 2020 and was gathered on a monthly basis. We included all products for which we had at least seven months of consecutive data—all other products were discarded when the available data was not sufficient for our prediction approach. We analyzed over 3,879 products listed on Amazon and sold by 136 marketplace sellers. In total, the entire data set comprised 51,278 product-seller-month combinations. The products from our set were launched on Amazon between 2001 and 2020. The average age of product was 4.9 years (SD 3.8 years). The average number of orders per month was 96, with an average conversion rate of 11.7%. The analyzed products belonged to various product categories, with most products belonging to "home and living" (37%), "toys and baby" (19%), and "grocery, drug stores, and pets" (13%).

Although the data provided a unique, fine-grained empirical account regarding product success on digital platforms, individual time series for products were highly aggregated, extremely short, and of varying length. Thus, standard autoregressive forecasting approaches (e.g., ARIMA models) were not easily applicable to this highly challenging prediction task; for that reason, we opted for developing a prediction approach involving state-of-the-art machine learning approaches.

6.3.2 Prediction Approach

We predicted each product's success—that is, its conversion rate—at time $t+1$ given the available predictor variables PV at time t. Thus, we assumed that we could predict a product's conversion rate in the next month, given the available data in the current month. Applying a prediction function f to the predictor variables PV at time t, we assumed that CR_{T+1} could be decomposed into the predicted conversion rate $\widehat{CR}_{T+1}$ as well as an unpredictable part r:

$$CR_{t+1} = \widehat{CR}_{t+1} + \mathrm{r}$$

$$\widehat{CR}_{t+1} = f(PV_t)$$

The predictor variables included past conversion rates, legitimacy-enhancing factors, and a series of time-invariant factors such as product numbers. We defined past conversion rates for each product and seller. Assuming lagged conversion rates for 1 month, M products and N sellers, past conversion rates could be defined as $[CR_{1,1,t}, CR_{1,1,t-1}, \ldots, CR_{M,N,t}, CR_{M,N,t-1}]$, where $CR_{M,N,t}$ describes the conversion rate of product M from seller N at time t. We used two different state-of-the-art machine learning approaches (artificial neural networks and gradient boosted decision trees) to construct the prediction functions f. The following sections provide details for these algorithms as well as the predictor variables and their measurement.

To test our hypotheses, we combined our prediction approach with bootstrapping. This technique relies on the logic of resampling from a dataset to approximate the actual distribution of parameters and has proved to produce highly accurate and robust results

(Efron & Tibshirani, 1993). In each bootstrap resample, we followed a four-step approach. First, we separated the available raw data into two separate groups for each hypothesis. For instance, when referring to H1, we formed a group of incumbent products and a group of new product entries. Then, as a second step, we drew 1'000 randomly selected products with replacement out of each group. Third, we applied our prediction approach and estimated $\widehat{CR}_{t+1}$ for each of the two groups. Lastly, we evaluated the predictive accuracy of the obtained models and determined the gain in predictive performance that was grounded in the legitimacy-enhancing factors. We repeated this procedure for each hypothesis and 100 bootstrap samples. [1] Following this approach, our goal was not to build the most accurate model in terms of predictive accuracy given the available data. Instead, we focused on creating a robust setting for investigating the predictive ability of legitimacy-enhancing factors that was free of potential sampling biases and that was grounded in our specific data set.

Evaluating the accuracy of our predictions, we built the models with one part (i.e., training data) and evaluated their predictive accuracy by applying it to an unused part of the data (i.e., testing data). In greater detail, we used each product's last three months of data as testing data and all previous months as training data. In order to further increase the robustness of our results, we applied a walk-forward validation approach (Stein, 2007). Thus, we trained our prediction functions on all available training data. Then, we took the last two months of data from the training set to predict the products' conversion rates in the first month of the testing data. Next, we moved one month ahead and used the last month of the training data and the first month's data from the testing set to predict the products' conversion rates in the training set's second month. Similarly, we used the testing set's first two months of data to predict the conversion rates in the third month. In each step, we calculated predictive accuracy using the Root Mean Squared Error (RMSE) and the Volume-weighted Mean Percentage Error (VMAPE)—two common measures in the forecasting literature (Herrin, 2007; Sivillo & Reilly, 2004). We reported averages for the two measures across all three time steps.

For determining the contribution of the legitimacy-enhancing factors to the accuracy of our predictions, we followed Molnar (2020) and Fisher, Rudin, and Dominici (2019) to calculate permutation importance scores. Permutation importance is conceptually related to effect sizes. They measure the increase of a model's prediction error after

[1] This number of bootstrap iterations is in line with similar applications that rely on computationally highly intensive models (e.g., Dai, Dietvorst, Tuckfield, Milkman, & Schweitzer, 2018).

permuting its variables' values, that is, randomly changing the order of a variable's values to break its association with the dependent variable. In greater detail, permutation importance values are obtained by calculating the prediction error e of a model for the original data set. Then, one variable or a bundle of variables in the data set are permuted, obtaining the resulting prediction error e_{perm}. Based on these error measures, permutation importance values are calculated by dividing e by e_{perm}. Repeating this procedure for each variable or bundle of variables in the data set, permutation importance values allow for showing the relative importance of the variables for the model's ability to make accurate predictions. To test our hypotheses and make scores comparable across algorithms, we scaled permutation importance scores such that they added up to 1.

6.3.3 Machine Learning Algorithms

The term machine learning broadly refers to algorithms that optimize performance criteria, e.g., certain error measures, by evaluating predicted outputs against observed (or "true") data points. [2] Typically, machine learning algorithms have the capacity to uncover non-obvious patterns in data and facilitate reliable and accurate predictions about future events. Compared to classical regression approaches that seek to explain the variance in a given dataset and focus on causality, machine learning algorithms aim to predict future outcomes. As such, machine learning algorithms may accept a lower explanatory power in exchange for the ability to perform more accurate predictions that can be generalized to new data.

In order to obtain robust results, we applied artificial neural networks and gradient boosted decision trees (Chen & Guestrin, 2016; Friedman, 2001; Hastie, Tibshirani, & Friedman, 2009).

(1) Artificial neural networks have been recently applied to various areas that are highly relevant to this paper (Chong, Ch'ng, Liu, & Li, 2017; Sharma, Chakraborti, & Jha, 2019; Zhao et al., 2020). Artificial neural networks reflect a large set of differently interconnected computational units—neurons— each of which performs a specific calculation (Chollet, 2018; Zhang, Keil, Rai, & Mann, 2003). These neurons are organized in layers: artificial neural networks usually consist of one input layer, one or more hidden layers, and one output layer. The number of nodes in the input layer refers to the number of predictor variables and the output layer's number of nodes to the

[2] This notion refers to supervised machine learning James, Witten, Hastie, and Tibshirani (2013), which we use in our study.

dependent variable. In contrast, the number of hidden layers and the number of nodes within these layers are questions of network architecture (Chollet, 2018). Neurons in one layer are not connected to each other, but they are connected to the neurons of the previous and the subsequent layer. In the case of a feed forward network, information flows from the input layer via the hidden layer(s) to the output layer. In so doing, each neuron receives inputs from the nodes of its previous layer and sums up these inputs into a weighted output. Then, as a second step, it applies an activation function to that output to account for non-linearities in the data and passes the transformed output to all connected neurons in the subsequent layer. The weights for all inputs across all neurons and layers are optimized using a backpropagation algorithm, i.e., a defined error measure between the predicted and actual values of the outcome are minimized (Hastie et al., 2009). In this study, we created a multi-level perceptron—in other words, a feed forward network with several hidden layers—to estimate a product's future conversion rate using a "Keras" interface to "TensorFlow" (Chollet, 2017), a state-of-the-art library for training neural networks. We describe the details of our network architecture in Appendix 1.

(2) Gradient boosted decision trees have recently been applied to predict new venture survival (Antretter et al., 2019), bank failure (Carmona, Climent, & Momparler, 2019; Climent, Momparler, & Carmona, 2019), credit risk assessments (Chang, Chang, & Wu, 2018), and cryptocurrency fluctuations (Li, Chamrajnagar, Fong, Rizik, & Fu, 2019). The approach is based on the idea of creating multiple decision trees, with each tree segmenting data into groups by following a series of decision rules (James et al., 2013). In order to make a prediction for a given observation, each tree makes a decision on which group the observation belongs to and then uses the group's average to make a prediction. The general idea of boosting is to combine the predictions of many "weak" decision trees to produce a powerful "ensemble" that provides more accurate predictions (Hastie et al., 2009). In this approach, each new decision tree is trained to improve the existing ensemble of decision trees by learning from their past prediction errors (Chen & Guestrin, 2016). In other words, newly trained decision trees are fitted to the residuals from the combined ensemble of trees and not the outcome itself. Thus, new decision trees, which can consist of simple individual models, are integrated into the ensemble so that they update the residuals until a certain minimum is reached (James et al., 2013). In our study, we used Chen and Guestrin's (2016) "eXtreme Gradient Boosted Trees" (XGBoost), currently one of the most advanced implementations of this technique. Again, we describe implementation details in the Appendix 1.

6.3.4 Measures

The following section describes how we operationalized and measured the variables underlying our study. (1) The dependent variable and prediction goal refers to product success measured as conversion rates. For predicting future product success, we employed a series of (2) baseline variables that are commonly used in forecasting tasks as well as (3) a novel measure for capturing online legitimacy. (4) We also describe our grouping variables, such as a product's level of incumbency that we employed to test our hypothesis within the bootstrapping approach. Table 2 offers an overview of all variables used in our model, their measurement, and their descriptive statistics.

Most of our measures had a time-series character, i.e., a collection of values over time (Chatfield, 2000). As described in the prediction approach section, this was most important for conversion rates as our product success measure. We incorporated the time-series character by including past values—lagged variables—of our predictor variable as well as our outcome variable whenever possible. Only variables that were time-invariant in nature, e.g., the marketplace country in which a product was listed, were not included as lagged versions into the prediction.

Table 2: Description of Variables

Variable	Measurement	Mean	SD	Min	Max
Product success (dependent variable)					
Conversion rate $_{t+1}$	Conversion Rate measures the ratio of product page visits to sales (t+1 = Conversion Rate in the next month)	0.12	0.1	0	0.97
Baseline variables					
Conversion rate $_{t}$	Conversion Rate measures the ratio of product page visits to sales (t = Conversion Rate in this month)	0.12	0.1	0	0.95
Conversion rate $_{t-1}$	Conversion Rate measures the ratio of product page visits to sales (t-1 = Conversion Rate in the last month)	0.12	0.1	0	0.95
Country	Marketplace country where the product is listed	Categorical variable			
Product category	Product category where the product is listed	Categorical variable			
Product number	Number/ID of the product	Categorical variable			
Seller number	Number/ID of the seller	Categorical variable			

Quarter	Quarter of the year (Q1, Q2, Q3, or Q4)	Categorical variable			
Online legitimacy variables					
Marketing budget					
Marketing budget $_{t+1}$	Marketing budget on Amazon, which is planned for the next month	152.66	588.1	0.02	29579.26
Marketing budget $_{t}$	Marketing budget on Amazon, in the current month	156.41	600.38	0.02	29579.26
Marketing budget $_{t-1}$	Marketing budget on Amazon, in the previous month	156.84	596.74	0.02	29579.26
Product information					
Video	Dummy variable indicating if the product page has a video	0.24	0.42	0	1
Images	Number of images of a product page	5.03	1.99	1	8
Bullet points length	Number of characters in all bullet points of a product page	584.03	383.04	0	2258
Description length	Number of characters in all product descriptions of a product page	1057.92	840.69	4	6381
APlus content	Dummy variable indication if the product page contains Amazon APlus Content, which allows a more comprehensive product description with visual elements	0.6	0.49	0	1
Product reviews					
Number of reviews $_{t}$	Number of reviews in current month	118.43	343.97	0	14678
Number of reviews $_{t-1}$	Number of reviews in the previous month	118.89	348.02	0	14678
Average rating $_{t}$	Average product review rating in current month	4.23	0.59	1	5
Average rating $_{t-1}$	Average product review rating in the previous month	4.23	0.59	1	5
Grouping variables					
Level of incumbency	Dummy variable indicating level of incumbency: 0 = new entrant, listed for less than one year; 1 = incumbent, listed for more than one year	0.03	0.17	0	1
Level of competition	Dummy variable indicating level of competition: 0 = low competition, 0 new entrants or competitors leaving the market; 1 = high competition, 1 or more new entrants	0.37	0.48	0	1
Level of platform cooperation	Dummy variable indicating level of cooperation: 0 = low cooperation (no FBA); 1 = high cooperation (FBA)	0.84	0.37	0	1

Product Success

We determined product success by means of conversion rates. The *conversion rate* is one of the most important metrics in online business and especially in e-commerce (Fox, 2017), as it indicates the percentage of visitors who made a purchase. (Di Fatta et al., 2018). On an online store basis, the conversion rate shows how attractive the website and products are overall. However, looking at the conversion rate on an individual product basis makes it easier to determine more precisely how convincing an individual product and its presentation may be. Therefore, the conversion rate can speak volumes about the success of a product. A product that succeeds in attracting customers will achieve a similar or better conversion rate compared to other products in the online store. However, if a product is not successful, it has a below-average conversion rate that often decreases even further over time. The conversion rate is, therefore, an essential indicator for determining the success of a product on digital platforms.

Online Legitimacy Variables

To predict a product's future success, we considered three dimensions of legitimacy: (1) product information, (2) product reviews, and (3) marketing spend. All these factors contribute to building online legitimacy. We assume that in launching new products on online platforms, creating online legitimacy plays an important role. Using the following three categories, we propose a measurement framework for online product legitimacy.

Product information. First, the information about a product is crucial for building legitimacy. Assuming that companies also use online platforms to create online legitimacy for their new products, the effort they show in providing more information should thus reflect their legitimacy (Kuppuswamy & Bayus, 2017). Visual information such as images shows the optical nature of products and can easily convey a wide range of product characteristics. To investigate these factors in our model, we measured the number of *images* and *videos*.

The scope of the textual product description is another important factor in the creation of legitimacy. A description can put product characteristics in context and emphasize features even more clearly. At Amazon, bullet points, descriptions, and APlus Content all contribute to this factor. Bullet points are displayed in the upper part of the website, next to the images. Here, the seller can concisely present the most important features. In addition, a seller can either implement a pure text description or create more comprehensive APlus Content. The latter option offers the seller more extensive layout possibilities (Amazon, 2020a). To examine the factors in our model, we measured the *bullet points length*, *description length*, and whether a product page included *APlus Content*.

Product reviews. Second, customer reviews are an important part of a product page. Amazon provides the *number of reviews* and the *average rating* for each product. We included these two factors in our online product legitimacy measure to consider the impact of product evaluations on the legitimacy of a product. We also included the *number of reviews*$_{t-1}$ and the *average rating*$_{t-1}$ from the previous month in our model as the change or growth of these values is an essential indicator for a change in legitimacy.

Marketing budget. Third, the *marketing budget* determines visibility in the Marketplace. Visibility is an important factor that is difficult to achieve on online platforms for both new and incumbent products. Products must be recognizable by the appropriate target group to have the chance of a successful market launch and long-term product success. Advertisements and the resulting visibility also contribute to creating legitimacy. The more often a potential customer sees and perceives a product, the more awareness and legitimacy the latter receives (Ayanwale, Alimi, & Ayanbimipe, 2005). We have integrated the marketing budget of the previous, current, and next month. A change in the marketing budget is an indicator of the change in the visibility of a product on the platform. The budget for the next month is a forecast that shows the marketing budget a seller has planned for the next month. The allocated marketing budget for Amazon advertisements is another element in our online product legitimacy measure.

Baseline Variables

Besides these legitimacy-enhancing factors, we included a series of "baseline" variables into our prediction models that are commonly used in time-series forecasting. First, this included conversion rates from the current and the previous month. Second, products were identified with a unique *product number*. In addition, each product was assigned to a seller that had a unique *seller number*. On Amazon, each product is related to a specific product category. This categorization is expressed in the *product category* variable. The *country* variable indicates on which international Amazon Marketplace the product is listed. The products in our data set were listed in one of the five European marketplaces (DE, UK, IT, ES, FR).

Grouping Variables

Level of incumbency. To investigate the first hypothesis, we analyzed the product release date on the platform. We classified products that had been listed on the platform for more than one year as incumbent products. Products that had been listed on the platform for less than one year were classified as new products.

Level of competition. For the investigation of the second hypothesis, we analyzed the scope of products from competitors to which a product was exposed on an online platform. The number of similar products played a particularly important role in this case. We could thus identify how many similar products the examined item was exposed to on the platform.

Level of platform cooperation. Sellers can have a high or low level of cooperation with the platform provider. Each of these models is associated with a different level of integration into Ama-zon's operations and services. In the simplest model, sellers offer their products via the platform while taking care of shipping, service, and returns themselves, a model reflecting cooperation with a low level of integration. However, sellers can also choose a highly integrated model where they make use of additional services from Amazon. Participation in the Fulfillment by Amazon (FBA) program allows sellers to have Amazon handle shipping, service, and returns. In this case, a seller is more deeply integrated into the infrastructure of the platform provider. To as-sess the depth of cooperation with the platform, we measured whether a seller used Amazon's FBA service.

6.4 Results

Before testing our hypotheses, we reported important overarching statistics. Using the full data set to make predictions, we reached an overarching VMAPE of 27.2% with the gradient boosted decision trees and 31.4% with the artificial neural network. Table 3 reports the averaged prediction errors of the two machine learning models across the different conditions in the bootstrapping approach. Interestingly, we see that prediction errors in the platform dynamics, which are less challenging and uncertain (incumbent products [H1], low number of competitive entries [H2], and high integration depth with the platform [H3]), are more or less on the same accuracy level when being compared with the overall models. In contrast, the predictability of future product success is lower in almost all high-dynamic platform situations across both error measures and both algorithms, as indicated by consistently higher prediction errors. For instance, the prediction error of future conversion rates is 31.2% for new products, while averaging 28.2% for incumbent products.

Table 3: Predictive Accuracy

Hypotheses	**Group**	**Gradient boosted decision trees**		**Artificial neural network**	
		RMSE	**VMAPE**	**RMSE**	**VMAPE**
H1: Level of incumbency	New products	5.6% [5.3%; 5.9%]	31.2% [28.0%; 35.4%]	5.5% [5.0%; 7.0%]	33.9% [28.2%; 45.4%]
	Incumbent products	5.3% [5.0%; 5.6%]	28.2% [24.9%; 31.8%]	5.5% [5.0%; 7.8%]	32.7% [26.5%; 52.7%]
H2: Level of competition	High competition	5.3% [5.0%; 5.6%]	27.6% [24.3%; 31.9%]	5.6% [5.0%; 7.5%]	33.4% [27.4%; 51.1%]
	Low competition	5.4% [5.0%; 5.7%]	27.4% [24.4%; 32.0%]	5.3% [5.0%; 5.7%]	30.4% [26.4%; 33.7%]
H3: Level of integration depth	Low integration depth	4.9% [4.6%; 5.2%]	33.3% [25.7%; 40.7%]	5.4% [4.8%; 6.2%]	40.7% [31.9%; 54.8%]
	High integration depth	5.4% [5.1%; 5.7%]	27.0% [23.6%; 31.8%]	5.4% [5.0%; 7.0%]	31.1% [26.8%; 44.9%]

Note: 95% Confidence intervals in square brackets

To test our hypotheses, we compared permutation importance scores between groups for both algorithms. Results between algorithms were highly consistent; therefore, we focused on reporting results for the gradient boosted decision trees.

In testing Hypothesis 1, we found that legitimacy-enhancing factors had higher permutation importance scores in the new product group than in the incumbent group for both algorithms. When referring to gradient boosted decision trees, average importance scores were 0.145 (10.6% increase in prediction accuracy) for new products, while average importance scores for incumbent products were 0.144 (10.3% increase in prediction accuracy). Although the differences seemed marginal, they were significant, with $p < 0.001$. We found support for Hypothesis 1.

In testing Hypothesis 2, we again found that across both algorithms, permutation importance of the legitimacy-enhancing factors was higher for the high-competition group than for the low-competition group. When referring to gradient boosted decision trees, permutation importance scores for the high-competition group were 0.147, in comparison to 0.141 in the low-competition group. This resulted in a 12.5% vs. 9.5% increase in predictive performance, significant at the $p < 0.001$ level. Thus, we found support for Hypothesis 2.

Finally, for Hypothesis 3, we again found permutation importance scores to be more important for products that showed a low integration depth with the platform than for products having a high integration depth. Using gradient boosted decision trees, we found permutation importance scores of 0.171 for products in the low-integration group. In comparison, the permutation importance scores in the high-integration group were, on average, 0.141. These differences resulted in a 29.7% performance gain in the low-integration group, while the performance gain in the high-integration group equaled 9.8%. Differences were significant ($p < 0.001$), offering compelling support for Hypothesis 3.

Table 4: Permutation Importance Values for Legitimacy-Enhancing Factors

Hypotheses	**Group**	**Gradient boosted decision trees**		**Artificial neural network**	
		Importance	**P**	**Importance**	**P**
H1: Level of incumbency	New products	0.145	< 0.001	0.134	< 0.001
	Incumbent products	0.144		0.132	
H2: Level of competition	High competition	0.147	< 0.001	0.132	< 0.001
	Low competition	0.141		0.130	
H3: Level integration depth	Low integration depth	0.171	< 0.001	0.134	< 0.001
	High integration depth	0.141		0.130	

6.5 Discussion and Conclusion

This paper's objective was to investigate how legitimacy factors enhance the predictive power of a product's future success on online platforms. In the digital world, every interaction generates an enormous amount of data (Bajari, Chernozhukov, Hortaçsu, & Suzuki, 2019). We took advantage of our unique access to data from a globally operating retail platform and studied whether online product legitimacy could be used to enhance the predictability of product success on digital marketplaces. Our results showed that using online platforms' product information facilitated predicting product success in dynamic platform markets with an error of 27.2%.

We tested the impact of online product legitimacy in three typical situations that sellers face on dynamic online platforms. First, we investigated how online legitimacy affects the predictability of new products compared to an established product's success. As potential customers tend to trust new products less than incumbent products due to a lack of trust-signaling elements such as a high number of existing product reviews (Sharma et al., 2019), we assumed that legitimacy factors are more important for predicting product success for new products. Indeed, our results showed that online product legitimacy factors are more important for new products when predicting product success. Legitimacy-building strategies can counteract the liability of newness and help to predict product success more accurately, successfully compensating for reduced trust due to newness (Zimmermann & Zeitz, 2002). Therefore, new products should ensure that legitimacy factors are already optimally arranged at the time of product launch to reduce uncertainty and increase predictability on online platforms.

Second, new competitive entries can influence the performance of products on online platforms (Seamans, 2013). A greater supply in the same product category shifts visibility away from one's own product and increases competition on the platform. Sellers can overcome new competition through high legitimacy and a comprehensive product presentation. Our results show that legitimacy factors are more crucial for success predictions for products that face new competition than for products that do not face new competition.

Third, we investigated how online legitimacy could help predict product success, depending on the degree of cooperation with the platform provider. Because products that are more deeply integrated into the platform obtain additional benefits and trust-signaling elements on the platform (Li, H., Fang, Y., Wang, Y., Lim, K. H., & Liang, L., 2015), we assumed that legitimacy-enhancing factors are more important for products having a low degree of cooperation with the platform provider. The results show this is the case—online legitimacy factors increase the predictability of product success when the cooperation degree for a product is low.

6.5.1 Theoretical Implications

Our study contributes in several ways to the literature on product success and platform markets. For example, this investigation adds to the recent discussion of the role of online platforms in retail (Armstrong, 2006; Xu, 2018) by proposing an integrated measure of online product legitimacy and testing its validity for product success prediction (Garber, Goldenberg, Libai, & Muller, 2004). To date, the research has neglected the factors for successful competition within online platforms, even though growing competition is increasingly forcing sellers to counteract platform dynamics (Zhu & Liu, 2018). Our contribution to the rising stream of online platform literature involves showing how to increase the predictability of future product success under various challenging platform dynamics through legitimate product presentation (Bajari et al., 2019; Sharma et al., 2019). This approach can reduce uncertainty for sellers, which also supports planning reliability. Creating online legitimacy plays a vital role here, especially for new market players and new products. We have proposed a measure for online product legitimacy that includes all essential online platform product page factors. We are thus also offering additional knowledge to the current online legitimacy literature stream and enabling a comprehensive assessment of product pages on online platforms (Antretter et al., 2019; Yu et al., 2019).

We have shown that product success on online platforms can be better predicted if products have a higher online legitimacy. This valuable addition to product success and failure literature illustrates how to make product success more predictable and reduce uncertainties in highly dynamic environments (Di Benedetto, 1999; Henard & Szymanski, 2001). In doing so, we are particularly contributing to the literature streams of the three examined platform dynamics. First, we have shown how online legitimacy can help reduce uncertainty and increase predictability for new products to counteract the liability of newness and enable a more predictable market launch (Bunduchi, 2017; Stinchcombe, 1965). Second, we are contributing to the new entry literature by offering a new response option for existing companies to react to new competitive entries or to protect their own product a priori (Geroski, 1995; Seamans, 2013). Third, we are adding to the cooperation and alliance literature (Ahuja, 2000; Eisenhardt & Schoonhoven, 1996) by displaying how the degree of cooperation and integration into a platform can be balanced by other legitimacy mechanisms, reducing uncertainty and allowing product success to be reliably predicted.

We have highlighted the potential for large data samples generated on online platforms and machine learning in predicting future outcomes, using two different state-of-the-art machine learning approaches—artificial neural networks and gradient boosted decision trees—to predict future product success. However, this particular contribution is not that our study is among the first to apply these methods in the innovation management domain. Instead, our study may serve as a primer for innovation management researchers in exemplifying how these predictive approaches can be applied to *generate and test theoretical constructs*. We propose a novel measure of online legitimacy that goes beyond classical survey-based operationalizations of constructs by exploiting a large-scale empirical account of highly granular real-world data. Since developing new measures is frequently at the core of developing new theories, machine learning may open new data vaults that have thus far remained unused for theory generation in the innovation management literature. Using two different machine learning approaches, we have been able to further show that our novel measure of legitimacy improves the predictability of future product success across a wide variety of different conditions. Thus, our measure withstands the litmus test of reality, pinpointing its relevance and value. This outcome would not have been possible with standard explanatory regression approaches (Shmueli, 2010). By demonstrating how well machine learning can be applied to large data sets extracted from existing online infrastructures, we want to encourage other innovation management researchers to include machine learning in their toolbox to generate, test, and compare theory.

6.5.2 Practical Implications

Companies may use our insights to shape their strategic decisions regarding how to build legitimacy in a digital environment for new product listings. Entrepreneurs can deliberately choose the amount and type of content they share via online platforms to increase new products' chances of success. In the three situations we selected to represent issues that online marketplace sellers frequently face, we have shown how legitimacy factors enhance the predictability of product success in dynamic platform markets. The product launch precedes every activity on an online platform (Frattini, Bianchi, Massis, & Sikimic, 2014). However, new products are at a disadvantage compared to already established products because they lack some trust-building elements that existing products have built up over time (Evanschitzky, Eisend, Calantone, & Jiang, 2012). Nevertheless, our results show that a legitimate product presentation can better predict the success of a new product and thus reduce uncertainty in this dynamic environment. Therefore, sellers should pay attention to enhancing the trustworthiness of their product presentation with legitimacy factors, especially in the case of new products. Once the product launch has been completed successfully, a product on a global platform such as Amazon Marketplace will always face new competition from similar products (Lee et al., 2000; Ryan et al., 2012). In particular, the rapidly growing marketplace business (Bezos, 2019) is attracting more and more customers and sellers, intensifying competition on the platform (Mantin et al., 2014; Tian et al., 2018). But even these challenging situations can be countered by legitimate product presentations. Legitimacy factors increase the predictability of products facing new competition compared to products without new competitors. Thus, sellers should not stop optimizing product presentation after product launch. To be successful with a product in a dynamic platform market in the long term, legitimacy must always be maintained or increased. Companies can use the relevant legitimacy factors identified to gain an advantage over competitors on online platforms. Moreover, sellers must ask themselves how much they want to cooperate with the platform owner to determine to what extent they and their products are integrated into the platform. Cooperation can compensate for the lack of own resources but also leads to higher dependency (Ahuja, 2000; Ritala et al., 2014). Alternatively, since sellers usually receive certain advantages if they are more deeply integrated into the platform, it is even more important for sellers who have a low level of integration into the platform to have a legitimate product presentation. Our results reveal that legitimacy factors increase the predictability of future product success for products that are less integrated into the platform compared to highly integrated products.

In summary, our results illustrate that online product legitimacy improves the predictability of future product success in uncertain, challenging, and dynamic platform markets. We only needed two months of past data to predict future product success with an error of 27.2%. This result means that sellers who have only recently entered the market can make reliable predictions about future product success, making it easier to plan for future product quantities. As a result, fewer resources are tied up, and warehousing is more efficient, allowing more efficient use of capital. Better forecasting can also have a positive effect on sales as product availability is always guaranteed, which also contributes to higher customer satisfaction.

6.5.3 Limitations and Future Research

Our study is not without limitations. First, future studies should explore additional methods and online channels where new product information can be communicated, such as online shops, eBay, or social media channels. Such platforms could help in assessing the external validity of our results. Customers inform themselves about a product using different channels and via various types of media such as images, video, and text (Häubl & Trifts, 2000; Zhang et al., 2020).

Second, further research could enhance our measure of online legitimacy on online platforms by adding more factors. Text analysis of product descriptions could provide further insights into the quality of product presentation on online platforms. Sentiment analysis of customer ratings could also provide a more comprehensive picture of the satisfaction of previous buyers, which has a strong effect on the conversion rate (Yuan, Xu, Li, & Lau, 2018).

Third, in future studies, the product category should be considered in failure analysis. For example, Redmond (1995) assumed that failure rates differ according to product category. The researcher investigated new product failures on a macro level and found that new food products have higher failure rates than new industrial products. Currently, no evidence is available to show whether new product developers in different industries enjoy better or worse results than others. Therefore, an investigation of product-category-specific factors and failure rates could be interesting.

Fourth, the perception of online product legitimacy can differ depending on the target group (Smith, 2011). Many products are designed for specific target groups and consequently require explicit marketing. Thus, legitimacy-enhancing factors may vary or have a different weighting for individual target groups. For example, younger customers might attach more importance to a product video than older consumers who want a detailed product description. A target group-specific analysis could yield further information about how to present a product on an online platform to avoid possible product failure.

Additionally, our data collection period covered 15 months. Although this time span allowed us to reflect seasonal factors, it can often take longer to determine whether new products can establish themselves on the market. A period of at least two years could improve the results. Our data was at a monthly level. Alternatively, disaggregated data (weekly or daily) could deliver more granular results (Palacios Fenech & Tellis, 2016).

This study is the first to use Amazon Marketplace to build an integrated measure of online product legitimacy and test its predictive power in product innovation research, a novel approach that opens new avenues for future research to investigate whether online legitimacy can be used to predict other company outcomes (e.g., brand awareness or exit probabilities). It is likely that the results of this study can also be transferred to other channels. Our measure of online legitimacy could behave similarly in other online media as it does in online platforms and marketplaces. Manufacturers and brands can also use our legitimacy factors to improve product presentation in their own online shops, on social media, and on other digital channels. Interaction effects of the individual legitimacy variables could play an important role in predictions (Sharma et al., 2019). Further studies should take note. In conclusion, all the mentioned points promise fruitful avenues for future research.

Second Dissertation Article

Amazon's Market Power Decoded by the Amazon Market Dominance Index

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7 Amazon's Market Power Decoded by the Amazon Market Dominance Index

Abstract

Amazon is one of the largest online retailers worldwide. Amazon had an annual turnover of over $280 billion in 2019 but is very reluctant to publish figures and data on the distribution of sales across individual product categories. However, from the retailer's point of view, these data would be particularly critical to determine the relevance of the sales channel and to understand the competition within specific product categories better. The objective of this study is to build a measure that illustrates Amazon's market share and dominance in individual product categories to enhance market understanding and to enable retailers to make more informed decisions. By combining various high-quality data sources, we were able to create the Amazon Market Dominance Index (AMDI), which reflects Amazon's market dominance compared to the entire German retail sector. The AMDI is calculated on a category-specific basis for Amazon's ten main product categories. The semi-annual calculation of all AMDI values allows for growth-rate comparisons and the identification of seasonal effects. With the AMDI, we increase market transparency and provide data on Amazon's market position that was previously unavailable. We help retailers with relevant and evidence-based insights that enable the identification of opportunities and risks in individual product categories.

Keywords: Amazon, market share, market dominance, market power, online platform, e-commerce

7.1 Introduction

Amazon.com is one of the most important online retail platforms worldwide. With global sales of over \$280 billion and a compound annual growth rate of 21% from 2015 to 2019, Amazon is causing both excitement and anxiety in the retail industry (Amazon, 2020f). A shift in the market can lead to both new entrepreneurial opportunities and risks for vendors and Marketplace sellers. On the one hand, Amazon enables new business opportunities and sales channels, while on the other hand, there is a risk of market-power abuse. With its platform model, Amazon operates in a two-sided market that is strongly characterized by indirect network effects (Armstrong, 2006; Cennamo & Santalo, 2013). This often leads to “winner-takes-it-all” (WTA) structures in which companies focus on rapid growth to position themselves as market leaders (van der Aalst, Hinz, & Weinhardt, 2019). Once achieved, a company could benefit from this position with higher profitability and market power. The special characteristic of Amazon’s model is that it operates a hybrid platform, which can lead to interesting market dynamics and risks for complementors. Amazon is not only a platform provider and thus an intermediary between sellers and buyers, but it also acts as a retailer on its own platform.

The literature shows that the market share of a company has a strong effect on firm performance and market dominance (Edeling & Himme, 2018; Nissan, 2003). Strictly speaking, a market share analysis should always be conducted in a product category-related manner, so that the real share in a market with companies in the same category can be determined (Connolly et al., 1986). However, Amazon does not publish any figures with regard to its category-specific sales distribution. Retailers and brands neither know how much revenue Amazon generates in the individual product categories nor the market share that comes with it. This makes a strategic assessment of possible cooperation difficult. Even regulatory authorities cannot make any meaningful analyses without a category-specific, market-share perspective.

For a better understanding of Amazon’s market position, we have developed the Amazon Market Dominance Index (AMDI). This Index illustrates the market share of Amazon compared to the overall (online and offline) retail market in Germany. We not only analyze the market share on a company level but also for all main product categories. In short, the AMDI has the goal of making the dominance of Amazon more transparent. Based on the product catalog of Amazon, ten main categories were built: (1) *Electronics & Computers*, (2) *Kitchen, Household, & Living*, (3) *Toys & Baby, Sports & Leisure*, (4) *Beauty & Drug Store*, (5) *Apparel*, (6) *DIY*, (7) *Books & Office Supplies*, (8) *Garden*, (9) *Groceries & Beverages*, and (10) *Pet Supplies*.

Combining data from Amazon’s annual and quarterly financial reports, an Amazon data specialist agency, and other market data, we could, for the first time, calculate Amazon’s revenues per product category in the German market. Comparing the Amazon sales with the total German retail market sales per category enables us to calculate Amazon’s market share in Germany. The figures from the Federal Statistical Office serve as the data basis for the calculation of the overall retail sales in Germany.

The AMDI ranges from 1 (low dominance) to 10 (high dominance). The higher the market share, the higher the dominance, and thus the Index value. An exemplary market share of 9% results in dominance level 5. From a market share of 40%, a company is considered dominant according to the German Act Against Restraints of Competition (§ 18 Abs. 4 GWB). As soon as Amazon reaches the 40% market share threshold in a segment, the maximum dominance value of 10 is reached. Based on the latest market figures (HY2 2019), Amazon has the highest market shares in the *Electronics & Computers* category at 24% and the *Toys & Baby, Sports & Leisure* category at 17.87% of the market share. This results in an AMDI value of 8 and 6 in these categories. Among the two weakest categories is *Apparel* with a market share of 2.65% (AMDI = 3), and by far, the category with the lowest market share is *Groceries & Beverages* at 0.18% (ADMI = 1). Besides the sales breakdown into individual product categories, we show the vendor/seller share in every category, the average product price per category, the share of Prime availability, and the visibility of the top brands in every segment.

The increasing dominance of Amazon leads to interesting implications for both practice and science. In dominant product categories where Amazon has a high market share, it tends to sell products itself (a high Buy Box share of vendors), whereas, in less dominant categories, the Buy Box share of third-party sellers is higher. We assume that Amazon leaves the less dominant product categories where profitability is also lower to third-party sellers and focuses itself on the profitable product areas. Amazon’s access to a comprehensive set of data, which enables in-depth insights into customer behavior and demand, allows Amazon to precisely select attractive products. Unattractive product areas are left to the third-party sellers. This enables Amazon to offer its customers a broad range of products without having to sell all of the products itself.

7.2 Study Background

7.2.1 Phenomena

Jeff Bezos founded Amazon in 1994 as an online bookstore and launched its online store just one year after foundation (Palumbo, 2019). In May 1997, the company went public (Kawamoto, 1997). Every year since 1997, Bezos shares his thoughts about Amazon and the market in the letter to the shareholders. Amazon's philosophy and many principles described in this letter are still deeply rooted in Amazon's culture today. In the section "It's All About the Long Term," Jeff Bezos describes how Amazon focuses on growth and prioritizes this over short-term profitability (Bezos, 1998). Even today, Amazon is still pursuing this strategy, which can be seen in the growth rates and low profitability in the retail business. The focus on the customer is also a core part of Amazon's philosophy. In the 1999 shareholders' letter, Bezos stated: "Our vision is to use this platform to build Earth's most customer-centric company" (Bezos, 2000). By 1997, Amazon was already storing around 200,000 books in large logistics centers and was thus able to offer its customers a selection that would never be possible in a physical store. This led to a sales growth of 838% in 1997 compared to the previous year (Bezos, 1998). Then, as now, Bezos emphasizes that it is day one of the Internet and, therefore, day one for Amazon. Although Amazon is already a large company today, Bezos wants to express, with the "Day One" metaphor, how much potential still lies ahead in the e-commerce market. In 1999 Bezos spoke of a "multi-trillion dollar global market" (Bezos, 2000). Also, a culture of failure and learning becomes clear through the writings of Bezos: "But we still have so much to learn" (Bezos, 1998). In order to constantly evolve in a dynamic technical environment and to maintain its leadership, Amazon is steadily developing innovations. While some innovations are very successful, this innovative culture can, of course, also lead to failures like, for example, the Fire Phone. In the 2018 letter to its shareholders, Bezos affirms that, as a company grows, the number of failed experiments must also increase, otherwise it does not move fast enough or it carries out too few ambitious projects: "Failure needs to scale too" (Bezos, 2019).

Gradually, Amazon began to sell other products on its online platform such as music, video games, and electronics. In October 1998, Amazon launched its online store in Germany and the UK (Gurãu, Ranchhod, & Hackney, 2001). France, Italy, Spain, and the Netherlands followed later. Amazon operates online stores worldwide in Asia, Australia, Europe, North America, and Brazil. So, Amazon's German online store (amazon.de), together with the store in the UK (amazon.co.uk), were the first to have an online presence outside the home market in the USA. In 1999, Amazon launched the

Marketplace in the USA that enables third-party sellers to directly sell products over the platform (DePillis & Sherman, 2019). Here Amazon solely functions as a platform that brings sellers and customers together, without owning or selling products itself but gaining a sales commission. Moreover, this allows Amazon to further expand its product offerings and therefore gain advantages for its customers. In return, the Amazon Marketplace gives retailers and manufacturers access to Amazon's customer base and infrastructure. In recent years, Amazon's growth has primarily been driven by the third-party Marketplace business. Beyond that, the Marketplace business is not only growing faster than first-party sales but has already overtaken them. In 2018, 58% of physical gross merchandise volume (GMV) sold on Amazon was generated by independent third-party sellers (Bezos, 2019). From 1999 to 2018, third-party sales grew from $0.1 billion to $160 billion—a compound annual growth rate of 52% (Bezos, 2019). In contrast, Amazon's first-party sales grew 25% annually from $1.6 billion to $117 billion in the same period.

Offering the widest possible selection of products requires sophisticated logistics. In 2008, the retail giant operated around 800 in-house logistics sites worldwide (Thieuleux, 2020). Over the years, Amazon has greatly expanded its portfolio of supply chain services. In its warehouses, Amazon not only stores its own products but also provides third-party sellers with the opportunity to have their products stored and shipped by Amazon. This service is called Fulfilment by Amazon (FBA). The increasing volume of orders also creates more and more demand for logistical capacities. The introduction and offering of faster delivery times (Same-Day Delivery or Prime Now) cost Amazon a lot of money. The transportation costs as a percentage of net sales have risen steadily in recent years (Thieuleux, 2020).

To counteract these rising costs, Amazon is investing more and more in the development of its own logistics services. Through vertical integration, Amazon hopes to have more influence on costs and to reduce them in the long term. As early as 2012, Amazon took over the robot manufacturer "Kiva," which is to be used to automate processes within logistics centers (Leblanc, 2019). With Amazon Prime Air, the online retailer is building up its own fleet of aircraft, which will transport goods over longer distances between logistics centers faster and more cost-effectively (Buchman, 2018). The purchase of its own air hub in Kentucky underlines this plan. Last but not least, the so-called last mile in particular, meaning the transportation of products from the logistics center to the final destination, results in high costs (Altenried, 2019). Up to now, Amazon has mostly relied on service providers such as DHL. However, with the project "Amazon Flex," Amazon is also trying to improve service and save costs in the last mile (Amazon, 2020c). With Flex, independent contractors can deliver Amazon parcels with their own vehicles. Amazon uses crowdsourcing or the so-called gig economy approach to find delivery drivers for the increasing volume of parcels and to meet the increased expectations of fast or same-day delivery (Lierow, Janssen, & D'Incà, 2016).

All these processes in trade and logistics generate a huge amount of data. Amazon began early on to use and evaluate this data in order to better understand customers and to optimize its processes. In 2006, Amazon had consolidated its expertise in data analysis and cloud computing into an independent subsidiary (Amazon Web Services or AWS) and also made it available to external companies. According to Wright, Smith, Bala, and Gill (2019), AWS is one of the leading cloud computing providers worldwide and contributes to a significant part of the company's profits (Ladd, 2018).

Today Amazon is one of the largest Internet companies in terms of sales and is one of the highest-valued companies worldwide. However, the rapid rise of Amazon does not please all market participants. In particular, smaller offline retailers are struggling with declining sales. Amazon's supremacy in online retailing is also attracting political critics from around the world. Some players even call for Amazon to be split up, arguing that the multinational conglomerate technology company already has too much market power (Wells, Weinstock, Ellsworth, & Danskin, 2015). Ladd (2018), for example, suggests breaking up Amazon into "five different companies": Amazon Web Services, Amazon Logistics, Amazon Retail, Amazon Entertainment, and Amazon Health and Life Sciences.

The EU competition authorities are also investigating suspicions of illegal business activities at Amazon. The retailer may have been involved in illegal business practices when dealing with sellers on its platform (DW, 2019). Besides, Amazon is under criticism for misusing its market power in negotiations or by directing pricing strategies (Eugene, 2017). As Amazon acts as a retailer as well as a platform owner, it is a horizontal competitor to its Marketplace sellers. This leads to further conflicts and risks for Marketplace participants (*Bundeskartellamt v. Amazon*, 2013). A platform owner itself can become the most significant competitor by competing directly with complementors on the platform (Farrell & Katz, 2000; Jiang et al., 2011). Platform owners have a comprehensive insight into all activities on the platform. This enables them to analyze supply and demand accurately and thus enter attractive market segments. Amazon already has a broad selection of private label brands, which it sells on its own platform as a retailer. It has the power to present them prominently on the platform. In this case, third-party sellers can lose visibility and sales very quickly. "Platform owners can exert considerable influence over complementors' welfare" (Zhu & Liu, 2018, p. 2619).

In many digital markets, we see the WTA phenomenon (van der Aalst et al., 2019). Amazon accounts for about 50% of all online sales in the USA and about 40% in Germany (digital kompakt, 2020). It already has a pretty dominant market position. Network and lock-in effects play a crucial role here (Kuchinke & Vidal, 2016). So will e-commerce end in oligopoly, duopoly, or even monopoly markets? In other digital areas like the search engine market, we already see monopoly situations around the world. The market share of a company is crucial in determining its power over a certain market (Nissan, 2003; Rhoades, 1985). However, Amazon offers many different services and products, which makes it difficult to calculate market shares. Therefore, a deeper analysis of Amazon's market and product structure is necessary to gain a better understanding of the market conditions in the respective submarkets and their implications for corporation strategies with Amazon.

7.2.2 Related Literature

Platform economics

Platforms play a central role in many industries and markets today (Abhishek et al., 2016; Armstrong, 2006). They mediate between different user groups. Some examples are personal computers (application developers and users), video consoles (game developers and users), smartphone operation systems (app developers and users), and e-commerce platforms (sellers and buyers). Besides the increasingly popular online platforms, classical offline concepts can also be understood as a form of platform. For example, a shopping mall operator must attract both retailers and consumers for the concept to work (Hagiu, 2009). What is closely connected to platforms is the literature on two-sided markets. A platform is a two-sided market where the platform owner is the intermediary between two parties (Armstrong, 2006; Rochet & Tirole, 2003). Both parties, therefore, need access to the same platform in order to make a transaction possible. Various conditions contribute to the success of a platform. There should be different customer groups that benefit when their interaction is coordinated. The intermediary should coordinate the relationship more efficiently than two parties could do via a bi-directional exchange (Evans, 2003). The literature also speaks of multi-sided markets because more than two parties could be involved (Caillaud & Jullien, 2003;

Cennamo & Santalo, 2013). The platform economy entails a new business logic and leads to new competitive dynamics. Technological aspects, as well as strategic aspects, play an essential role in Internet-based platforms (Bettis & Hitt, 1995). Platform owners striving for market dominance must coordinate the various parties involved and manage strategic conflicts (Yoffie & Kwak, 2006). Evans (2003) points out that the platform model is of increasing importance, especially for Internet-based commerce businesses. Today's mall in the digital world appears in the form of online retail platforms such as the Amazon Marketplace. The mechanism is the same. Amazon tries to bring as many merchants as possible to the platform in order to unite the most extensive product range in one online store. This attracts many customers and increases the attractiveness of the platform for merchants as well.

Network effects. Network effects play an important role in platform markets. A distinction is made between direct (horizontal) and indirect (vertical) network effects. In the case of direct network effects, a user benefits from a good because a large number of other users use this good. A classic example is the telephone. If only a small number of people had a telephone, the benefit for each individual would be limited. However, the more people own a telephone, the greater the benefit for each participant in this network (Cennamo & Santalo, 2013; Evans, 2003). With indirect network effects, one party in the network benefits with the increase in complementary goods (Katz & Shapiro, 1985; Liebowitz & Margolis, 1994). If both sides of a platform benefit from a higher number of participants, mutual indirect network effects prevail. Evans and Schmalensee (2008) describe platforms as businesses in which indirect network effects significantly influence business activities and strategy. A shopping mall attracts more consumers if it has a large selection of products and merchants, and at the same time, the mall is more attractive for businesses if more consumers visit it. This can lead to the so-called chicken-and-egg problem when introducing a new platform because if neither side has a minimum number of participants, it is difficult to attract new participants (Caillaud & Jullien, 2003). However, once a platform has reached a critical mass and can secure market leadership, markets with strong network effects, especially in the digital sector, often lead to WTA outcomes where one platform dominates an entire market (Besen & Farrell, 1994; Katz & Shapiro, 1994; van der Aalst et al., 2019). In many cases, this then leads to exponential growth. An important task of platform providers is the coordination between consumers and complementary goods. Gawer (2009) points out that it can be more important for platforms to focus on the increase in complementary goods than on the consumer. By focusing on complementary goods, the attractiveness of the platform increases through a diverse range of products and a large selection, resulting in consumer growth. Another strategy for platforms can be to offer goods exclusively. In this way, it is easier to differentiate oneself from competitors (Cennamo & Santalo, 2013). At Amazon, this can be observed through the increasing number of exclusive private labels.

Implications of network effects. Network effects have important strategic implications. To dominate in a market with platform dynamics, companies often choose very aggressive approaches. One example is the get-big-fast approach (Eocman, Jeho, & Jongseok, 2006), in which companies attract users to their platforms as quickly as possible, keep them there with lock-in effects, and try to prevent their competitors from behaving similarly. The strategy is often supported by extremely low product prices, where companies make losses for a long time. Bezos repeatedly emphasized that he puts growth before profitability (Bezos, 1998). Given the platform dynamics and network effects, this is a reasonable approach. In the first several years, Amazon made high losses with its retail business. Through aggressive pricing strategies and high investments in infrastructure and marketing, Amazon tried to get as many users as possible on its platform to increase its attractiveness and deter competitors from entering the market. By winning new complementors (third-party sellers) for a platform, not only the product range but also the competition among complementors increases (Parker & van Alstyne, 2005). This can lead to an aggressive price war and, ultimately, to lower prices. This increases the attractiveness of the platform from the consumer's point of view. A positive upward spiral is set in motion, which helps the platform to gain even more participants and to achieve a higher market share (Chen, Doraszelski, & Harrington, Jr., J.E., 2009). Hagiu (2009) presents yet another effect of low prices. By offering lower prices than competitors, customers are drawn away from other platforms to one's own. This, in turn, makes other platforms less attractive for complementors and also drives some of them away, again leading to fewer consumers using the competing platform. It results in a negative spiral. Venkatraman and Lee (2004) support this by arguing that complementors choose a platform for its relative market position. A dominant platform attracts more complementors because it has better access to relevant target groups. High legitimacy and the stability of platforms also play a role in the selection. However, WTA approaches could be costly because providers have to win a critical user base quickly. Cennamo and Santalo (2013) argue that platforms can establish and position themselves well in the market even without the WTA approach if they manage to differentiate themselves from the competition.

Possible outcomes of dominant players. Once achieved, a dominant platform owner with a large customer base can use its market power and monetize access to it. In many cases, the consumers are not asked to pay, but the producers are (Parker & van Alstyne, 2005). For companies, platforms are valuable distribution channels for which they are even willing to pay. Consumers, on the other hand, often have low switching costs and can change to other retailers and platforms more easily. Parker and van Alstyne (2005) argue that a "widely observed solution is to discount one market in order to grow both" (Parker & van Alstyne, 2005, p. 1496). This pricing strategy is also called "divide-and-conquer," where one side subsidizes the other (Caillaud & Jullien, 2003). Caillaud and Jullien (2003) examine the equilibrium market structure in markets with indirect network effects and intermediation providers. They conclude that the efficient market structure often leads to a duopoly or monopoly. However, this concentration does not necessarily lead to inefficiencies. The authors show that a user's surplus could be higher and better protected in more concentrated markets as long as there is enough contestability (Caillaud & Jullien, 2003). They emphasize that Internet-based markets, in particular, have some specificities and that transaction costs play an important role in pricing and business strategy. Eisenmann, Parker, and van Alstyne (2011) show that a platform provider can tap into another platform market through platform envelopment by leveraging its user base. By achieving a strong market position, a provider can use this to develop further platform businesses more easily. Gawer (2014) proposes an integrative framework to bridge the economic and technology perspective on platforms. She describes platforms as "evolving organisations" that coordinate, utilize economies of scope, and that "entail a modular technological architecture" (Gawer, 2014, p. 1239). She concludes that platform architecture is associated with special governance guidelines and challenges. Platform providers have a difficult task of managing different stakeholders so that the platform can thrive.

Abhishek et al. (2016) examine when and under what conditions an online retailer should choose the platform model instead of the conventional reselling (wholesale) model. Given that Amazon follows both models in a hybrid setting, this is a fascinating study. After a comprehensive analysis, the researchers conclude that the platform model (agency selling) is the more efficient option. However, this is not always the case, and several factors need to be considered. First, the choice of model depends on whether there are negative or positive spillover effects on traditional offline retailing. If an increase in e-commerce sales leads to a decrease in offline sales, the platform model is usually the better choice for an online merchant. However, the platform model also implies that online merchants leave pricing to the manufacturers. If sales in the online channel have a strong, positive effect on offline sales, then manufacturers have an incentive to reduce prices in the online channel. This, in turn, harms the platform owner, who receives lower commissions. In this case, the reselling model is the better choice from an online retailer's perspective. Second, the researchers' model predicts that increasing competition in e-commerce will favor the platform model. Platforms are also more advantageous as more revenue shifts from offline to online retail. The strong e-commerce growth in recent years has led to the creation of platforms rather than reselling models. This can also be observed in the German market. Otto (Otto, 2020) and Zalando (Zalando, 2020), two online retailers who started with the reselling model, are increasingly turning to platforms. Abhishek et al. (2016) also found that if a merchant can benefit from positive externalities by selling a product, he has an incentive to reduce the prices to increase sales. In this scenario, a reselling model is more attractive because it is the only way for the online retailer to have a direct influence on prices. The interaction between the sale of e-books and the e-book reader Kindle from Amazon is an example of this scenario. To drive the business forward, Amazon can reduce one of the two sides to grow the overall market. However, this is only possible under the reselling model. This could explain why Amazon has chosen a hybrid retail scheme. Amazon sells strategically-relevant products with positive externalities by itself and leaves other products that are less relevant for Amazon to third-party sellers (Abhishek et al., 2016). With a game-theoretic model, Jiang et al. (2011) investigate how Amazon chooses the products it sells itself and how Amazon can learn from the activities of the sellers. They show that platform providers monitor the demand for products sold by sellers. Amazon can then "cherry-pick" high-demand products and it leaves the sale of less-frequented, long-tail products to sellers. In the short term, the entry of the platform owner can reduce the customer surplus, whereas, in the long term, it is usually increased. The authors conclude that platforms can be a win–win for everyone as long as the platform owner does not crowd out his own third-party sellers. Also, other authors highlight the role of big data for online platforms (Bourreau, Streel, & Graef, 2017; Lerner, 2014). Nuccio and Guerzoni (2019) stress that it is not the data per se but the extraction of knowledge that creates business value. "Yet data, by itself, are often of low value" (Rubinfeld & Gal, 2017).

Competition in platform markets. Zhu and Liu (2018) examine the competition between the platform owner and complementors in the context of amazon.com. Since Amazon is not only a platform owner but also a retailer (hybrid model), Amazon can become a direct competitor to its complementors (third-party sellers). The researchers find that Amazon specifically identifies successful products and sells them itself. This may result in a product of a complementor being forced out of the market. “Platform owners can exert considerable influence over their complementors’ welfare” (Zhu & Liu, 2018, p. 2619). To mitigate this risk, complementors can specialize in niches or focus on products that require a high level of platform-specific investment. The probability that Amazon will enter such an area is rather low. The continuous identification of new innovative products can also help to break the dependency of existing top sellers who are in danger of being copied by Amazon. The researchers conclude that platform markets do not work like other markets and, therefore, should not be treated as such. Amazon uses large amounts of data on all platform activities to identify attractive market segments and products. In an interview with employees from Amazon, this approach was confirmed (Stone, 2013). High competition for a specific product or segment does not deter Amazon from becoming active there too. The researchers note that Amazon often lists itself as a standard seller, even though the product is offered at a lower price by third-party sellers (Zhu & Liu, 2018). Complementors can, however, use certain product characteristics to predict which segments Amazon is likely to enter and thus prepare for this.

Sellers try to offer their products in a marketplace that gives them the best possible access to a large number of potential customers (Piezunka et al., 2016). However, this is usually related to the fact that a large number of sellers are active on this platform, all of whom want access to these potential customers. This increases the competition between the sellers on the platform (Redmond, 2013). Piezunka et al. (2016) call this the “big fish v. big pond” dilemma. A seller wants to have both a large customer base (big pond) and a high relevance (big fish) within this platform. It is usually difficult to have both at the same time. The researchers found that a seller tends to be a “big fish” if he or she is highly dependent on the resources of the platform and competition between peers is high. Sellers are more likely to choose a “big pond” platform if they need few resources and the competition between peers is low. The choice of the right platform is driven by the tension between cooperation and competition.

Market share

The market share of a company is calculated as a “monetary-based” or “volume-based” share of the total market (absolute market share). If a company compares its market size only with that of the largest competitor or a group of competitors, this is called relative market share (Edeling & Himme, 2018). In most cases, the market share is determined at the company level, whereas a product-category specific approach would be more appropriate (Connolly et al., 1986; Edeling & Himme, 2018). Only a category-specific perspective allows market shares to be properly compared. Many retailers only operate in one or a few similar product categories. Here, a calculation of the market share with the existing company figures is easily possible. In the case of large and complex companies that offer products from different categories, market shares must be calculated separately for the different segments in order to enable a comparison with companies in the same product market. Since Amazon is an extensive online retail store that offers products from a wide variety of categories, a category-specific view of the market share is essential (Evans, 2019).

The influence of the market share on firm performance is a widely researched topic (e.g., Edeling & Himme, 2018). The market share of a company is often used as a performance indicator. However, what influence does the market share have on the profitability and market power of a company? Buzzell, Gale, and Sultan (1975) investigated the relationship between the market share and the return on investment (ROI) and found that there is a positive relationship. The researchers primarily attribute this to positive economies of scale and increased market power. They further argue that a higher market share reduces marketing costs as a percentage of sales and that higher-priced products can achieve higher profit margins. These advantages pay off, especially when fragmented customer groups buy products infrequently (Buzzell et al., 1975). In contrast to this, small companies with a low market share but frequently-purchased products can also achieve good results. Which goal a company should pursue in terms of gaining market share depends on various factors such as its competitors' strength and the available resources. The researchers divide possible market-share strategies into three categories: (1) building strategies, (2) holding strategies, and (3) harvesting strategies. They conclude that companies should carefully analyze their own market position to be able to choose the right strategy. In order for companies to analyze their own position, they must also know the positions of their competitors and other market participants. Therefore, for the retail industry, it is important to have a better understanding of Amazon's market share for individual product categories, as Amazon is one of the most important retailers in the market.

In line with the previous results, Gale and Branch (1982) also showed a relationship between the market share and profitability. They examined whether concentration or the market share had a greater effect on performance. A high market share mainly leads to economies of scale, whereas market concentration leads to oligopolistic profits.

However, they note that "scale economies are far more powerful than oligopoly power in determining profit levels" (Gale & Branch, 1982, p. 83). Also, Szymanski, Bharadwaj, and Varadarajan (1993) show the positive correlation between the market share and business profits but add that moderating factors influence this relationship. Jacobson and Aaker (1985) also emphasize the importance of third factors and argue that management quality influences marketing and product quality, which in turn leads to high market shares. Good management can also lead to productivity improvements and better cost control, which in turn leads to a higher ROI. Prescott, Kohli, and Venkatraman (1986) show that the connection between the market share and business profitability is context-specific and that the strength depends on the environment of a business. Feeny and Rogers (2000) state that the relationship between the market share and profitability is complex and demonstrate a U-shaped relationship. They show that the profitability of a company starts to increase from a market share of 30%. Edeling and Himme (2018) use a comprehensive meta-analysis to examine how a strong market share affects firm performance. They conclude that the correlation exists but is weaker than many early studies assumed. In addition, the strength of the correlation must be considered context-specific, as there are significant differences. For example, the effect for business-to-business (B2B) firms is smaller than for business-to-consumer (B2C) firms (Edeling & Himme, 2018). Furthermore, Gale (1972) stresses the importance of interaction effects in the analysis of market shares on company performance. Generally, he also found that a high market share leads to high rates of return.

For this study, the effect of the market share on market power is of particular importance as we build a dominance measure for Amazon. Rhoades (1985) particularly emphasizes the direct link between the market share and market power. Although market concentration is an important element in determining the market structure and competition, his results show that the market share in itself can be a "source of market power regardless of the concentration level" in a market (Rhoades, 1985, p. 359). Also, Shepherd (1972) draws attention to the importance of the market share as the "main element" in the analysis of market power and profitability. He found that, among other factors examined such as entry barriers and oligopolistic structures, the market share is a decisive factor for market power. This is also supported by Gale and Branch (1982), who find that it is mainly the market share and not market concentration that is responsible for higher profitability. The economies of scale generated by a higher market share have a stronger effect than the oligopolistic power of profit maximization. Nissan (2003) shows that even markets with a low concentration have market-power problems.

He thus underlines the findings of Rhoades and argues that the market share is the crucial factor in determining market power, not concentration. Therefore, concentration measures are not suitable for determining possible monopolistic powers. In many cases, only the strongest player in a market must be considered in order to identify market-power problems (Shin, 2002). In summary, we therefore conclude that the market share is fundamentally important in determining market power.

This leads to important implications for anti-trust policies (Rhoades, 1985; Utton, 2003). In today's anti-trust investigations, market concentration is often used as a measure to determine possible market abuse and to approve mergers and acquisitions. However, the results imply that the market share of a single company can already lead to market power and should, therefore, be taken into account in anti-trust investigations. In German law against restraints of competition, the market share is an essential criterion for assessing the market position of a company (§ 18 Abs. 4 GWB). A company is considered to be dominant if it has a market share of at least 40%.

7.2.3 Project Objectives

Amazon remains very reluctant to publish figures and data showing its business development or market shares. In addition to the legally-binding transparency requirements in the annual and quarterly reports, more detailed figures, for example, for the German market, are not published at all. Also, figures for individual product categories are generally not available. However, especially from a retailer's point of view, such figures seem elementary to enable a better understanding of the relevance of the sales channel for its own products. Choosing the right distribution channel can play an essential role for a company in terms of customer satisfaction and performance (Nie & Zhang, 2017; Shipley, Egan, & Edgett, 1991). A good data basis is one of the most crucial factors in the selection process (Khouja, Park, & Cai, 2010). Companies should have a comprehensive overview of all relevant key figures in order to understand the advantages and disadvantages and make the best possible decisions. In order to create more transparency and to enable retailers and manufacturers to make evidence-based decisions, we want to develop an Index that illustrates Amazon's market dominance in the individual product categories. By doing so, they will gain a better understanding of the current market situation and the category-specific factors at Amazon, which serves as a basis for their decisions. This leads us to the following RQ: How dominant is Amazon in individual product categories, and how does this affect cooperation strategies?

7.3 Data and Method

7.3.1 Research Design

In the first step, it was important to define on which level we want to investigate Amazon's dominance. Amazon is an online retailer with an extensive range of products. However, manufacturers and brands usually operate in a specific category. Therefore, it is not only interesting for them regarding how dominant Amazon is compared to the overall market, but especially how dominant Amazon is in the specific product categories. Based on the main categories of the Amazon product catalog, we have identified ten categories for which we analyze Amazon's market dominance in more detail.

In the next step, we have defined how to determine market dominance. In common practice and in the German legislation, the market share is generally determined by revenue. To illustrate Amazon's market share more clearly, we have created the AMDI. The AMDI translates Amazon's market share into a single number that indicates how dominant Amazon is in a specific product category. For this purpose, Amazon's revenue was compared with the revenue of the total German retail market for each of the ten product categories.

To make these calculations possible, two partners were especially important. On the one hand, for the market side, we used the data from the Federal Statistical Office of Germany. On the other hand, for the Amazon data, we worked together with a company specialized in Amazon data analysis. We chose Germany as our country of investigation because Amazon has been active in Germany since 1998 (Fischer & Habel, 2020) and the German e-commerce market is growing rapidly. Besides that, Amazon has a powerful market position in Germany (Handelsverband Deutschland [HDE], 2018b), which makes the study of a category-specific market-share analysis particularly interesting. Lastly, Germany was chosen because of the researcher's in-depth knowledge of the German e-commerce market, its most important players, culture, and context.

7.3.2 Data Description

The following section describes the research partners and datasets used for the calculation of the AMDI.

Dataset 1. The Federal Statistical Office of Germany provided the first dataset. It contains most of the market data from Germany for the calculation of the market sizes of the individual product categories. The basis for the calculation of market sizes is the "annual statistics in retail" from the year 2015, which covers all companies based in Germany that are exclusively or predominantly active in retail. In contrast to the monthly "Konjunkturerhebung," the annual survey is also referred to as the "Strukturerhebung." As shown in the Quality Report of the Federal Statistical Office, the data are collected via written surveys from companies (Statistisches Bundesamt, 2017b). The companies are drawn for selection by a stratified random-selection procedure. The annual survey in retail is conducted among 48,000 companies, the so-called reporting population. This represents about 7.9% of all companies. The owners or managers of the selected companies are obliged to provide the requested information.

The breakdown of the revenue of all companies is based on the type of economic activity (Statistisches Bundesamt, 2017b). *The Classification of Economic Activities, Edition 2008* (WZ 2008), serves to record the economic activities of enterprises, establishments, and other statistical units in a uniform manner in all official statistics (Statistisches Bundesamt, 2008). For our analysis of the retail market, we exclusively consider the category WZ08-47 (retail sector) and its subcategories. This division includes the resale of new and second-hand goods mainly to households for private use or consumption, in sales outlets, including department stores, at market stands, by distance-order, via street trade, and by door-to-door sales. Services (travel, tickets, etc.), streaming, and online rental services are not included in the data.

If the retailing of a company mainly takes place outside of stationary salesrooms, these volumes are assigned to the sector WZ08-4791 (Versand- und Internet-Einzelhandel). In order to break down this aggregate sector and thus assign sales to the individual industries, we have used the data from bevh (2018). For the category *DIY*, additional data from IfH Cologne, and for the category *Drugstore*, data from Statista were used (digital kompakt, 2019).

The annual revenue per industry is the most important information in the annual survey for our study. With additional data from the monthly statistics, we could calculate monthly sales volumes. The absolute monthly values can only be calculated approximately. Due to the methodological differences between the annual and monthly surveys (Konjunktur- zur Strukturerhebung), which are combined here, the values are only estimates. Further details regarding the limitations of this study can be found in section 7.6.3.

The breakdown of data by (1) economic sectors and (2) monthly time intervals was particularly important for our study. On the one hand, we wanted to analyze Amazon's dominance in the individual economic sectors in order to determine whether Amazon's market share is unequally distributed across the categories. On the other hand, we want to update the Index throughout the year, as market shares in the dynamic online world change rapidly, and a monthly analysis can also reveal seasonal effects. The data from the Federal Statistical Office met both of these requirements. Various quality assurance measures ensure a reliable database. For these reasons, we decided to use data from the Federal Statistical Office to determine the total retail volume in Germany (Statistisches Bundesamt, 2017b).

Dataset 2. The second dataset was built with the official Amazon financial reports. The annual report is the basis for Amazon's revenue in Germany. In 2019, Amazon made \$22.23 billion in Germany compared to \$193.63 billion in the USA. The worldwide revenue was \$280.52 billion in 2019. The German share of worldwide turnover is, therefore, around 7.9%. However, this turnover includes all Amazon products and services. Amazon breaks down its sales in the annual report into the following divisions: (1) Online Stores, (2) Physical Stores, (3) Third-party Seller Services, (4) Subscription Services, (5) AWS, (6) Other. However, for this study, only online sales in the retail business are relevant. This turnover is reported under the division "Online Stores" and totaled \$141.25 billion worldwide in 2019. The share of online store sales in terms of total sales is thus 50.3%.

Finally, we would like to determine how much revenue was generated in total via the Amazon Online Store. Amazon distinguishes between two sources of revenue: (1) first-party sales and (2) third-party sales. Both revenue streams together result in the GMV. First-party sales are those sales where Amazon itself acts as the retailer. We also call this revenue "vendor sales," as Amazon buys products from suppliers (known at Amazon as "vendors"), and then resells them to customers through the online store. Therefore, this is Amazon's classic retail business. Amazon reports these sales in its financial reports under the section "Online Store" sales. Third-party sales are generated by Marketplace sellers. Amazon is not legally the seller here, but merely offers the platform for mediation between seller and buyer. Amazon receives a commission for this service. The commission is reported by Amazon under the section "Third-party Seller Services" in the annual report. Amazon does not report the actual revenue from these sales, but only the commission it has received in return. Since Amazon receives different commissions per category, and this section also includes other income from fulfillment and shipping services, we need further data sources to calculate the value of third-party sales correctly. For this, we used data from an Amazon data specialist company (see dataset 3). Therefore, the GMV cannot be calculated with the official figures from Amazon alone.

The quarterly reports are used to track sales growth during the year. This allows us to update the AMDI on a half-yearly basis. However, the quarterly reports do not include figures for sales in Germany. Therefore, we assume that sales growth in Germany is the same as it is worldwide. The annual report, in which Amazon provides data for Germany, allows this assumption to be reviewed at the end of each year. All figures in our study are quoted in euros. We have used the official exchange rates of the Federal Ministry of Finance in Germany to convert from dollars to euros (Bundesministerium der Finanzen, 2019).

Dataset 3. An Amazon data specialist company contributed the third dataset. It provided us with the necessary data that was missing, in addition to the already listed Amazon data from the official financial reports, to enable us to calculate the GMV per category. Furthermore, the data from this partner is better structured, which allowed us to take a category-specific view. This enables us to break down sales by category in order to compare them with the overall market data in Germany. The data partner was, therefore, able to provide us with the distribution of Amazon's sales in Germany across all of Amazon's main product categories. In addition, the dataset also contains additional information on the distribution by sales source (First-party Sales/Third-party Sales) for each category. This enables us, in connection with the data from the Amazon financial reports, to determine the revenue per category and source of revenue. For example, 33.95% of Amazon's sales in Germany in the second half of 2019 came from the *Electronics & Computers* category. In this category, 44% of sales were generated by vendors and 56% by sellers.

7.3.3 Data Consolidation

The following section describes how we consolidated and analyzed all data and numbers from our three datasets. In the first step, we defined ten product categories based on the main categories of the Amazon catalog: (1) *Electronics & Computers*, (2) *Kitchen, Household, & Living*, (3) *Toys & Baby, Sports & Leisure*, (4) *Beauty & Drug Store*, (5) *Apparel*, (6) *DIY*, (7) *Books & Office Supplies*, (8) *Garden*, (9) *Groceries & Beverages*, and (10) *Pet Supplies*. All products that could not be assigned to one of these categories are summarized in the category *Other*. The Federal Statistical Office of Germany lists over 60 different product categories and sub-categories in the retail sector (WZ08-47). Amazon, on the other hand, lists about 40 categories. In the next step, it was important to combine the Amazon and the Federal Statistical Office categories in a way in which to form congruent categories with regard to the products contained therein. In Table 5, we show the exact allocation of the economic sectors of the Federal Statistical Office to our AMDI categories.

Table 5: Assignment of the Economic Sectors by the Federal Statistical Office to the Corresponding AMDI Categories.

AMDI category	**Economic sectors**	
Electronics & Computers	WZ08-474: WZ08-47782:	Eh.m. Kommunik.- und Info.technik (in Verkaufsr.) Eh.m. Foto- und opt. Erzeugn. (ohne Augenoptiker)
Kitchen, Household, & Living	WZ08-4751: WZ08-4753 (50%): WZ08-4754: WZ08-47591: WZ08-47592: WZ08-47599:	Einzelhandel mit Textilien Eh.m. Vorhängen,Teppichen u. Bodenbelägen, Tapeten Einzelhandel mit elektrischen Haushaltsgeräten Einzelhandel mit Wohnmöbeln Eh.m. keramischen Erzeugnissen und Glaswaren Eh.m. Haushaltsgegenständen a.n.g.
Toys & Baby, Sports & Leisure	WZ08-4764: WZ08-4765:	Eh.m. Fahrrädern, Sport- und Campingartikeln Einzelhandel mit Spielwaren
Beauty & Drugstore	WZ08-4774: WZ08-4775:	Eh.m. medizinischen und orthopädischen Artikeln Eh.m. kosmet. Erzeugnissen und Körperpflegemitteln
Apparel	WZ08-4771: WZ08-4782: WZ08-4772: WZ08-4777:	Einzelhandel mit Bekleidung Eh.m. Textilien usw an Verkaufsständen u.Ä. Einzelhandel mit Schuhen und Lederwaren Einzelhandel mit Uhren und Schmuck
DIY	WZ08-4752: WZ08-4753 (50%):	Eh.m. Metallw., Anstrich.u.Bau-u.Heimwerkerbedarf Eh.m. Vorhängen,Teppichen u. Bodenbelägen, Tapeten
Books & Office Supplies	WZ08-4761: WZ08-4762:	Einzelhandel mit Büchern Eh.m. Zeitungen, Zeitschr. u.Schreibw., Bürobedarf
Garden	WZ08-47761:	Eh.m. Blumen, Pflanzen, Sämereien u. Düngemitteln
Groceries & Beverages	WZ08-4711: WZ08-472: WZ08-4781:	Eh.m. Waren versch. Art, Hauptr. Nahrungsm. usw Eh.m. Nahrungsmitteln usw (in Verkaufsräumen) Eh.m. Nahrungsmitteln usw an Verkaufsständen u.Ä.
Pet Supplies	WZ08-47762:	Eh.m. zoologischem Bedarf und lebenden Tieren

The basis for the calculation of the total offline retail volume in Germany is the structural survey by the Federal Statistical Office of Germany from the year 2015. We extracted the revenues for each product category from this dataset. Using the annual rates of change, we were then able to extrapolate the sales for the years 2016 to 2018. In the next step, we calculated the sales for the individual months, using the monthly economic data from the Federal Statistical Office. Once this basis was established, the monthly growth rates could be used to determine the current monthly revenue for the following periods. In the next step, all revenues of the economic sectors per AMDI category for the respective reporting period were aggregated. For example, for the category *Beauty & Drugstore*, we summed the revenue of the two product categories WZ08-4774 and WZ08-4775. This gives us the federal offline revenue per AMDI category. To calculate the online revenue per category, we used the collective category *Versand- und Internet-Einzelhandel* (WZ08-4791) and divided it into the AMDI categories using the e-commerce data from the e-commerce association bevh (2018). In the last step, we then added the offline and online revenues per category to get the total retail volume per category.

In the following section, we describe our approach for the calculation of the Amazon revenue per category. Using Amazon's annual report, we extracted the overall sales for Germany. Amazon only provides an aggregated figure for the German market. This figure includes sales from the retail business as well as all other sales from other services (e.g., AWS, Prime fees, etc.). In order to determine the pure retail sales, we assumed that the sales in Germany were distributed among the individual segments in the same way as on a global basis. For the global sales, Amazon breaks down the sales into (1) Online Stores, (2) Physical Stores, (3) Third-party Seller Services, (4) Subscription Services, (5) AWS, and (6) Other. On a global basis, Amazon generates almost 50% of its total sales with its first-party retail business. However, there are currently no physical Amazon stores in Germany, so we subtracted them from total global sales when calculating the distribution of sales by segment. For 2019, we thus arrived at a 53.64% share of sales from the first-party retail business. We then applied this percentage to total sales in Germany to obtain online store sales (first-party) for Germany. Since Amazon does not provide any information on Germany in its quarterly report, we applied the German online store sales share from the last annual report to the current global quarterly results. This allowed us to approximate the German online store sales for each quarter. We then converted the quarterly sales from US dollars to euros using data from the German Federal Ministry of Finance (Bundesministerium der Finanzen, 2019). Thus, we determined the first-party retail sales per quarter for Germany. Using the vendor/seller share from dataset 3, we were also able to determine the third-party sales per category. The sum of first-party and third-party sales finally resulted in the GMV per category that is sold on Amazon.

Now that we have the sales for the total market and Amazon, we can put these two numbers into relation to determine Amazon's market share. In the second half of 2019, Amazon's GMV in Germany amounted to €15.60 billion. The total German retail volume (online and offline) amounted to €244.78 billion in the analyzed categories. Hence, Amazon had an overall market share of 6.37%. Breaking down the revenues by individual product categories, we can also determine the market share for each category. For example, Amazon generated €5.30 billion in revenue in the category *Electronics & Computers* in the second half of 2019. The retail market volume for the same period was €22.06 billion. This resulted in a market share of 24%. A comprehensive insight into all data and figures is provided in section 7.5 (Results).

7.3.4 Creation of the Amazon Market Dominance Index

Before we could create our own Index for the market dominance of Amazon, we had to define how to determine market dominance. Since we are considering Amazon's market dominance in the German market, the main point of reference for us is the legal regulation on competition and market dominance in Germany. Section 18 of the German Act Against Restraints of Competition (§ 18 Abs. 1 GWB) explains that a company has a dominant position if it has a superior market position in relation to its competitors. In paragraph 3, the market share is used as a first and essential indicator for assessing the market position of a company in relation to its competitors. In paragraph 4, this is further specified: It is presumed that a company is dominant if it has a market share of at least 40%.

Herfindahl and Hirschman have independently developed an Index to determine market concentration (Hirschman, 1945, 1964; Rhoades, 1993). Today known primarily as the Herfindahl–Hirschmann Index (HHI), it is used by some institutions to measure market concentration, for example, in merger processes of companies. However, the Index is not suitable for the dominance determination of a company. As we have already shown in our literature section, it is primarily the market share that has a direct influence on the market power of a company (Nissan, 2003; Rhoades, 1985). Melnik, Shy, and Stenbacka (2008) also propose a calculation for market dominance, which is mainly based on the market share. For most companies, the market share is quite easy to determine using publicly available data, while other market-power determinants are less important and difficult to quantify and measure. Therefore, we base the calculation of the AMDI on Amazon's market share compared to the total retail market in Germany. Since Amazon is active in many different markets, a product category-specific analysis is of particular importance and interest. Therefore, we determine Amazon's market share for all main product categories. This also corresponds to the market-share measure in the strict definition, where the market share should be considered as product category-related (Connolly et al., 1986; Edeling & Himme, 2018).

We also considered creating a composite indicator for the dominance of Amazon. A composite indicator is compiled with an underlying model using several independent indicators to form a single index (Nardo et al., 2008). However, composite indicators have several disadvantages (Saisana & Tarantola, 2002). First, the selection and weighting of the included factors is difficult to determine and can strongly influence the index value. A composite index can lead to misinterpretations and, ultimately, to wrong conclusions. This is because with a composite index, "a large amount of work in data collection and editing is 'wasted' or 'hidden' behind a single number of dubious significance" (Saisana, Saltelli, & Tarantola, 2005, p. 308). The disclosure of individual key figures can often lead to a more precise picture and provide more in-depth insights. Therefore, we decided to show all factors separately for each product category.

However, in order to illustrate Amazon's dominance more simply and clearly, we have translated Amazon's market share into one index. As already described in previous sections, the market share is the most important factor in determining market dominance, both from a regulatory and a scientific perspective. In our case, an index makes it easier to interpret market dominance compared to raw data. It also enables us to communicate more easily with the general public (e.g., media, citizens, etc.) (Nardo et al., 2008). The 10-point scale of the AMDI also makes it possible to demonstrate and better communicate a change in Amazon's dominance. The comparison with AMDI values from a previous reporting period illustrates in a simple way how Amazon's dominance changes in the respective categories.

The AMDI scale ranges from 1 to 10 (see Table 6). 1 stands for very low dominance by Amazon, whereas 10 stands for the maximum dominance in a category. Above a market share of 40%, the German Act Against Restraints of Competition (§ 18 Abs. 4 GWB) presumes that a company is dominant. Therefore, the AMDI scale gets the maximum value of 10 when Amazon has reached a 40% market share in a category. With an increasing market size and market dominance, it is easier for Amazon to gain one percentage point in market share. If a submarket is only just being developed, it is more difficult to increase the market share by an additional percentage point. Therefore, we have not scaled the AMDI linearly. The lower the market share, the fewer percentage points are needed to fall into a higher index class. The higher the market share, the more percentage points are needed to fall into a higher index class.

Table 6: Amazon Market Dominance Index Scale

Amazon market share	**Amazon Market Dominance Index (AMDI)**
0–0.5%	1
0.5–2%	2
2–4%	3
4–8%	4
8–12%	5
12–18%	6
18–24%	7
24–32%	8
32–40%	9
> 40%	10

7.4 Overview of Report Series

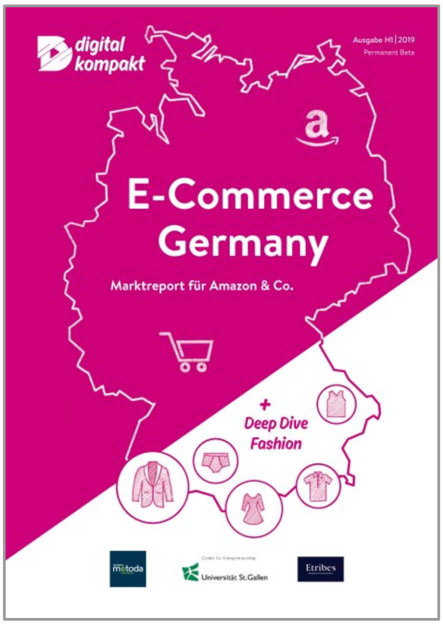
7.4.1 Structure of the Reports

Due to the high practical relevance, we would like to make the results of the AMDI available to companies in a continuously updated report series. Since online retail and the resulting shifts are very dynamic, we want to publish a report that is updated every six months. This will enable companies to continuously monitor the developments and draw conclusions for their own businesses.

Figure 1: Amazon Watch Report Q1 2018

The first report was published in November 2018 and covered the evaluation period of the first quarter of 2018. It is the only report that covers just three months. All of the following reports cover six-month periods. In the first report, the AMDI was presented for the first time, and it was calculated for the eight main categories. Furthermore, the report contains editorials, a market research section, a summary, and a methodology part.

Figure 2: E-Commerce Germany Report HY1 2019



The second report was published in September 2019 and included many innovations and improvements, which were implemented based on readers' feedback. For example, we broke down data into further product categories in order to provide even more detailed insights. We also integrated a so-called Deep Dive section in the report, which focuses on one category in particular and provides a more in-depth analysis. By summarizing the results, we offer readers the most important figures and findings in one overview. For the second report, we could also draw on new data from the Amazon data specialist metoda. This allowed us to include additional key figures in the report such as Prime availability per category. The appendix to the report includes a glossary, the methodology section, and legal texts. The methodology and basic structure were slightly adapted from the first to the second report due to the new data partner. However, in order to be able to compare the figures with previous periods, for example, to determine growth rates, a consistent methodology and data basis is necessary. We do not expect to make any further adjustments from now on to allow for comparisons.

Figure 3: E-Commerce Germany Report HY2 2019

The third report was published in March 2020 with an evaluation period covering the second half of 2019. Due to the consistent methodology compared to the previous report, we could compare the numbers with the previous period. By comparing the first half of the year (HY1) with the second half of the year (HY2), we were able to show how much HY2 had contributed to Amazon's sales. The Christmas business and many sale events such as Prime Day, Black Friday, and Cyber Monday had a significant impact here. Amazon was able to increase its sales by over 35% from HY1 to HY2. Amazon was particularly strong in the Electronics & Computers category. In this category, Amazon generated almost twice as many sales in HY2 as in HY1 (99.45% sales increase). With the help of the export quota, we show for the first time how popular the German Amazon Marketplace is among buyers from abroad. In the Deep Dive "Amazon Business," we show the opportunities and risks that B2B business on Amazon bears for sellers and buyers. We give them a guide for the first steps toward Amazon Business.

7.4.2 Summary of Reports

A summary of all three reports, including the evaluation period, main findings, and the publication date, is depicted in Table 7.

Table 7: Summary of Reports, Main Findings, and Publication Dates

Partner	Evaluation period (edition)	Main findings	Publication date
Report 1: *Amazon Watch: Datenbasierter Analyse-Report für die reale Marktdominanz von Amazon*			
Digital kompakt University of St. Gallen Payback Factor-a Etribes	First quarter of 2018 (Q1 2018)	• The report shows the sales figures, market shares, Marketplace visibility, and the most visible brands for the eight most relevant product categories on Amazon. • First-time creation and publication of the Amazon Market Dominance Index (AMDI), which illustrates Amazon's dominance in each category. • Amazon had the highest dominance in the category *Books* and the lowest dominance in the category *Groceries*.	November 2018
Report 2: *E-Commerce Germany: Marktreport für Amazon & Co. + Deep Dive Fashion*			
Digital kompakt University of St. Gallen Metoda Etribes	First half of 2019 (HY1 2019)	• With total sales of €11.5 billion in the first half of the year, Amazon accounted for around 37% of the German online market. • The core business of Amazon is the category *Electronics & Computers*, with revenues of €2.64 billion and the category *Kitchen, Household, & Living*, with revenues of €2.09 billion.	September 2019
Report 3*: E-Commerce Germany: Marktreport für Amazon & Co. + Deep Dive Amazon Business*			
Digital kompakt University of St. Gallen Metoda Etribes	Second half of 2019 (HY2 2019)	• With growth of over 35%, a comparison of the first half (HY1) with the second half (HY2) of 2019 shows for the first time how much HY2 contributes to Amazon's revenue. • The Christmas business and many sale events such as Prime Day, Black Friday, and Cyber Monday had a significant impact on HY2. • In *Electronics & Computers*, Amazon made almost twice as many sales in HY2 as in HY1 (99.45% sales increase).	March 2020

7.5 Results

In the following section, we present the results of the latest data evaluation, which analyses the period from July 2019 to the end of December 2019 (HY2 2019). In the second half of 2019, €15.6 billion of total sales were generated over Amazon sales channels in Germany. This revenue represents the GMV. The GMV refers to the total turnover of all sales on Amazon, including those by Amazon itself (first-party sales) and those by Marketplace sellers (third-party sales). With this turnover, Amazon achieved a market share of 40% of the German distance-selling market. Amazon has thus already achieved a dominant market position in the field of online commerce. Without a closer look at sales in individual categories, Amazon has already reached the threshold of 40% in the submarket of online commerce, which leads to the suspicion of a dominant market position under anti-trust law in Germany. Amazon's share of the total German retail market (online + offline) was 6.37%. The average price point across all categories for a product sold on Amazon was €28.29. For the calculation of the average price point, about one million products were considered. The Amazon Buy Box is the box at the top right of the product page that contains the "Add to Cart" button. For a given product there is only one product page on Amazon that all sellers who want to sell this product can connect to. Popular products are usually sold by many different sellers and vendors simultaneously. However, there can only be one vendor or seller in the Buy Box at the same time. The seller who owns the Buy Box has a very high probability that the purchase of the product will be completed with him or her and not with another seller offering the same product. On each product page, one seller is already pre-selected in the Buy Box. To determine which seller receives this position, Amazon uses a complex algorithm. Factors such as price, seller rating, Prime availability, and many others play an important role (Lanxner, 2020). The indicator "Buy Box Ownership" shows the percentage of sellers or vendors who owned the Buy Box. Sellers have a Buy Box ownership share of about 57% across all categories. Thus, third-party sellers generate more revenue than Amazon does with its first-party sales. Our calculation is supported by the 2018 letter to the shareholders from Amazon CEO Jeff Bezos. In that letter, he revealed that 58% of the global retail revenue was generated by third-party sellers (Bezos, 2019).

Seventy-six percent of all products sold on Amazon are available through Prime. Amazon Prime is a paid subscription service that provides subscribers with special benefits such as faster shipping. However, fast shipping is not available for all products, as Amazon cannot control or verify the speed of goods shipped by third-party sellers.

Merchants can join the FBA program and have their products shipped through Amazon to qualify their products for fast Prime shipping. The high proportion of "Prime-capable" products shows the importance of fast shipping from the customers' point of view.

Table 8: Amazon Revenue and Market Share per Category (in Billion Euros)

Category	Amazon revenue HY2	Share of sales (in %)	Total retail turnover Germany HY2	Amazon market share	AMDI
Apparel	1.06	6.82%	40.18	2.65%	3
Beauty & Drugstore	1.19	7.62%	17.08	6.96%	4
Books & Office Supplies	0.88	5.64%	5.98	14.71%	6
DIY	1.04	6.64%	15.09	6.87%	4
Electronics & Computers	5.30	33.95%	22.06	24%	8
Garden	0.33	2.12%	3.96	8.36%	5
Groceries & Beverages	0.18	1.16%	102.35	0.18%	1
Kitchen, Household, & Living	3.16	20.25%	27.17	11.63%	5
Pet Supplies	0.14	0.92%	2.21	6.46%	4
Toys & Baby, Sports & Leisure	1.55	9.97%	8.70	17.87%	6
Automotive	0.24	1.55%	--	--	--
Others	0.53	3.37%	--	--	--
SUM	**15.60**	**100%**	**244.78**	**6.37%**	**--**

In the following, we will go into more detail about the results for each individual product category. An overview of all key figures can be found in Table 8, Table 9, and Table 10.

Electronics & Computers. With revenue of €5.30 billion, the category *Electronics & Computers* is the strongest on Amazon in terms of sales. Amazon achieves a market share of 24% in this category compared to the total electronics retail market, which amounted to €22.06 billion in Germany. Thus, Amazon achieved an AMDI score of 8 out of 10. This makes *Electronics & Computers* the category with the highest AMDI value. Compared to the first half of 2019, sales in the second half increased by over 99%, thus almost doubling. In contrast, the total retail volume in Germany grew by 17%.

In 2004, electronic sales surpassed Amazon's book sales for the first time (Channeladvisor, 2018). Amazon initially started as an online bookstore, and until 2004, Amazon had earned a large part of its sales with books. Even though 14.6% of all Amazon orders (in terms of quantity) relate to products from the *Electronics & Computers* category, this category accounts for 33.95% of Amazon's total sales. This is caused by the high average price point of €79.02. It is the highest average price point of all categories. This seems reasonable, as this category includes products such as smartphones, TVs, and speakers, which usually have high product prices. The Prime availability of the products is 77%, which is almost precisely the average across all categories on Amazon. The Buy Box ownership share is 56% for sellers and 44% for vendors and is therefore relatively balanced. Samsung is, by far, the most visible brand in the category. Huawei is in second place, and JBL ranks third.

Kitchen, Household & Living. In the *Kitchen, Household & Living* category, Amazon achieved sales of €3.16 billion in HY2 2019, around 51% more than in the first half of the year. This makes the *Kitchen, Household, & Living* category the third fastest-growing category on Amazon. The category benefits particularly from the Christmas business on Amazon. Especially small kitchen appliances are a popular Christmas gift. The brands Bosch, Philips, and WMF are among the most visible brands in the category. The total retail volume in Germany was €27.17 billion (around 11% growth compared to the first half of the year), resulting in an Amazon market share of 11.63%. Thus, Amazon achieved an AMDI score of 5 out of 10. 16.8% of all Amazon orders (in terms of quantity) related to products from the *Kitchen, Household, & Living* category. In contrast, the category's share of sales was 20.25%, which was due to the above-average price point of €40.87. The Prime availability of 74% is quite close to the average and 58% of Buy Box ownership was with third-party sellers and 42% was with vendors.

Toys & Baby, Sports & Leisure. In the category *Toys & Baby, Sports & Leisure*, Amazon generated sales of €1.55 billion in HY2 2019, around 17% more than in the first half of the year. The total retail volume in Germany grew by almost 4% to €8.7 billion, resulting in an Amazon market share of 17.87%. In the second half of the year, sports articles generated nearly 4% less sales, while toys increased by more than 60%. In light of the Christmas season in the second half of the year, this is quite reasonable. Baby articles also grew by over 27% in sales. Overall, the category *Toys & Baby, Sports & Leisure* achieved an AMDI score of 6 out of 10. 14% of all Amazon orders (in terms of quantity) related to products from the *Toys & Baby, Sports & Leisure* category. In contrast, the category's share of sales was only 9.97%. The average price point was €24.19. The Prime availability was 73%. For 61% of the time, third-party sellers owned the Buy Box in this category. Vendors had a Buy Box ownership share of 39%. Lego took first place among the most visible brands in the category. Playmobil was in second place, followed directly by the sports and leisure brands Adidas and Nike, who shared third place.

Beauty & Drugstore. Amazon had revenues of €1.19 billion in the *Beauty & Drugstore* category in HY2 2019, which was around 21% more than in the first half of the year. The total market turnover was €17.08 billion, around 12% higher than in the first half of the year. With a market share of 6.96%, Amazon achieved an AMDI score of 4 out of 10. The *Beauty & Drugstore* category contributed 7.62% of Amazon's total revenue. The share of all Amazon orders (in terms of quantity) was 11.7%. The average price point was €22.16, which is slightly lower than the average. The Prime availability was above average at 81%. The Buy Box ownership share was 60% for sellers and 40% for vendors. The most visible brands included Philips, Oral-B, and Braun.

Apparel. Amazon had sales of €1.06 billion in HY2 2019 in the *Apparel* category, which was only about 1% more than in the first half of the year. The total apparel market amounted to €40.18 billion in sales, an increase of around 25% compared to the first half of the year. With a market share of 2.65%, Amazon achieved an AMDI score of 3 out of 10. This means that Amazon's market share had declined by almost 19% compared to the first half of the year. This clearly shows that Amazon was weakly positioned in the *Apparel* category and was unable to gain in market share during the Christmas season. *Apparel* accounts for 6.82% of Amazon's total sales. The share of all Amazon orders (in terms of quantity) was 9.9%. The average price point was €23.25, which is slightly lower than the average. The Prime availability was 75% on average. The Buy Box ownership share was 76% for sellers and 24% for vendors. This shows that third-party sellers handled a large proportion of orders on Amazon, and brands rarely worked directly with Amazon as retail partners. The most visible brands included Tommy Hilfiger, ONLY, and Calvin Klein.

DIY. In the *DIY* category, Amazon generated revenues of €1.04 billion in HY2 2019, around 18% more than in the first half of the year. The retail volume in Germany totaled €15.09 billion and remained almost unchanged from the first half of the year. Amazon was thus able to increase its market share by around 18% compared to the first half of the year to 6.87%. Overall, the *DIY* category achieved an AMDI value of 4 out of 10. 5.2% of all Amazon orders (in terms of quantity) related to products in the *DIY* category. The category represented 6.64% of total Amazon revenues. The average price point was €43.66, the second highest of all categories, and 75% of all products in this category were Prime available. Sellers owned 59% of the Buy Box ownership share. Vendors had a Buy Box share of 41%. Makita ranked first among the most visible brands. Bosch Professional was in second place, followed by Bosch Home and Garden.

Books & Office Supplies. The category *Books & Office Supplies* achieved remarkable results in many ways in HY2 2019. This is partly because books were the first products Amazon sold through its online store. In the first Amazon logos until 1997, even the tagline "Earth's biggest bookstore" was used (see Figure 4). With a turnover of €0.88 billion (32% more than in the first half-year), Amazon had a market share of 14.71%. Therefore, with an AMDI of 6 out of 10, this category was one of three categories with the highest AMDI value. 15.1% of all Amazon orders coming from this category, which was the second highest value among all categories. In terms of quantity, Amazon still sells many products in the *Books & Office Supplies* category. However, the share of Amazon's total revenues amounted to only 5.64% in HY2 2019. This is due to the fact that Amazon now offers a comprehensive range of products from different product categories compared to its early years. In addition, the average price point for books and office supplies was only €12.69. It is the lowest of all categories studied. In Germany, the *Books* category is also characterized by a special regulation for fixed book prices (§ 3 BuchPrG). If this regulation did not exist, the average prices would probably be even lower. With 93% Prime availability, products in no other category are delivered faster than in this one. The Buy Box ownership share was also remarkable. At 86%, vendors clearly dominated the Buy Box.

Figure 4: Amazon Logo History

Source: Based on Mali (2019)

Garden. In the *Garden* category, Amazon achieved revenue of €0.33 billion in HY2 2019. This was about 5% less than in the first half of the year. This is hardly surprising, as garden products are seasonal with the spring months being particularly dominant. Nevertheless, Amazon was doing better than the overall market, which was down 10% and had a total turnover of €3.96 billion. This led to an Amazon market share of 8.36%

and an AMDI score of 5 out of 10. *Garden* products contribute only slightly to Amazon's total sales (2.12%) and the number of orders (2.7%). The average price point was €27.06. Prime availability was below average at 58%. A large percentage of the orders was handled by sellers (70%). Vendors had a Buy Box share of 30%. The most visible brands included Intex, Bestway, and Gardena.

Groceries & Beverages. The category *Groceries & Beverages* was by far the weakest Amazon category, with a market share of about 0.18%. Amazon had no dominance in this category and therefore achieved an AMDI score of 1. With a turnover of €0.18 billion in HY2 2019, Amazon could only achieve a relatively low turnover in this category. However, the total market volume for *Groceries & Beverages* was huge. With a turnover of €102.35 billion, it was by far the largest of all the retail categories studied. For this reason, Amazon entered this market in 2007 with AmazonFresh. However, as our figures show, online retail with groceries had not yet been very successful for Amazon. However, compared to the first half of 2019, Amazon did increase sales by 58%. The market, on the other hand, only grew by 5%. Amazon is still trying to occupy a piece of this massive market through new offers and service improvements. In section 7.6.1 of this dissertation, we show the current and future projects, ambitions, and the developments of Amazon in the grocery sector. Only 2.1% of all Amazon orders (in terms of quantity) and 1.16% of Amazon revenues related to products from the *Groceries & Beverages* category. The average price point was €19.08, and Prime availability was 67%. Sellers and vendors shared the Buy Box equally.

Pet Supplies. In the *Pet Supplies* category, Amazon also only achieved revenues of €0.14 billion in HY2 2019. However, the market for pet supplies is much smaller than that for food. With a total market volume of €2.21 billion, Amazon achieved a market share of 6.46%. Amazon thus achieved an AMDI score of 4 out of 10. The share of all Amazon orders was 1.7%, and with 0.92% share of sales, it was Amazon's weakest category in terms of sales. The average price point was €17.95. It is the third-lowest average price point of all categories. Prime availability was also below average at 62%. At 53%, sellers in the *Pet Supplies* category were more often placed in the Buy Box than vendors were (47%). The most visible brand in this category was Trixie. It was followed by Kerbl and Karlie.

Table 9: Amazon Category Key Figures

Category	Share of all Amazon orders	Share of Amazon revenue	Average price	Prime availability	Vendor Buy Box share	Seller Buy Box share
Apparel	9.94%	6.82%	23.25	75.29%	23.60%	76.40%
Beauty & Drugstore	11.66%	7.62%	22.16	80.57%	39.91%	60.09%
Books & Office Supplies	15.05%	5.64%	12.69	92.95%	86.37%	13.63%
DIY	5.16%	6.64%	43.66	75%	41%	59%
Electronics & Computers	14.56%	33.95%	79.02	76.66%	44.48%	55.52%
Garden	2.66%	2.12%	27.06	58%	30%	70%
Groceries & Beverages	2.05%	1.16%	19.08	67%	50%	50%
Kitchen, Household, & Living	16.79%	20.25%	40.87	74.32%	41.84%	58.16%
Pet Supplies	1.73%	0.92%	17.95	62%	47%	53%
Toys & Baby, Sports & Leisure	13.96%	9.97%	24.19	72.88%	38.61%	61.39%

Note: All numbers refer to the period HY2 2019

Seasonal effects

The methodically consistent calculation of all indicators for the first and the second half of 2019 allowed us to investigate seasonal effects. The second half of the year always tends to be stronger than the first half due to the Christmas business. We can also observe this for the market as a whole, which recorded 9.75% higher sales than in the first half of the year (see Table 10). In comparison, however, Amazon was able to benefit much more, achieving a sales increase of 35.08% compared to the first half of the year. Amazon made particularly strong use of the potential of the second half of the year by organizing sales events such as Black Friday and Cyber Monday. Amazon celebrated these Deal Days with a whole discount week (Cyber Week). The online retailer thus took advantage of the increased buying mood of consumers by increasing the purchase rate through many special offers. Besides, Amazon also organized the specially created "Prime Day," which in 2019 took place directly at the start of the second half of the year on July 15 and 16 (Amazon, 2019a). This annual worldwide shopping event is exclusively for members of the Prime subscription service. Amazon tries to boost sales and attract new Prime subscribers during the summer months when sales are rather weak compared to the rest of the year.

The *Electronics & Computers* category benefited particularly strongly in the second half of the year. Amazon almost doubled its sales compared to the first half of the year (99.45% increase). The AMDI score thus rose from 6 to 8. Electronic products are particularly in demand as gifts for Christmas. Amazon also heavily promoted its own electronic devices such as the voice assistant "Echo" or its e-book reader "Kindle." Strong discount campaigns at Amazon sales events generated additional income.

Sales in the *Garden* category fell by 4.91%. Garden products and accessories are increasingly in demand in the spring months, making the results reasonable. However, Amazon was able to maintain its sales better than the overall market did, which fell by 9.89% in the same period. As a result, the AMDI increased from 4 to 5 in the second half of the year. Overall, Amazon was able to increase its market share of the total German retail market from 5.18% to 6.37% in the second half of the year. This represents an increase of 23.08%.

Table 10: Seasonal Change in Amazon and Market Figures (in Billion Euros)

	Amazon revenue			Total retail turnover in Germany			Amazon's market share			AMDI		
Category	**HY1**	**HY2**	**Change in %**	**HY1**	**HY2**	**Change in %**	**HY1**	**HY2**	**Change in %**	**HY1**	**HY2**	**Change in %**
Apparel	1.05	1.06	1.09%	32.26	40.18	24.56%	3.26%	2.65%	−18.84%	3	3	0
Beauty & Drugstore	0.98	1.19	20.99%	15.24	17.08	12.04%	6.45%	6.96%	7.98%	4	4	0
Books & Office Supplies	0.67	0.88	31.99%	4.89	5.98	22.34%	13.63%	14.71%	7.89%	6	6	0
DIY	0.88	1.04	17.79%	15.14	15.09	-0.33%	5.81%	6.87%	18.18%	4	4	0
Electronics & Computers	2.66	5.30	99.45%	18.89	22.06	16.77%	14.05%	24.00%	70.80%	6	8	+2
Garden	0.35	0.33	−4.91%	4.39	3.96	−9.89%	7.92%	8.36%	5.52%	4	5	+1
Groceries & Beverages	0.11	0.18	57.67%	97.32	102.35	5.17%	0.12%	0.18%	49.92%	1	1	0
Kitchen, Household, & Living	2.10	3.16	50.55%	24.54	27.17	10.72%	8.55%	11.63%	35.98%	5	5	0
Pet Supplies	0.10	0.14	42.25%	1.98	2.21	11.53%	5.07%	6.46%	27.54%	4	4	0
Toys & Baby, Sports & Leisure	1.33	1.55	17.20%	8.38	8.70	3.87%	15.84%	17.87%	12.83%	6	6	0
Sum	11.55	15.60	35.08%	223.04	244.78	9.75%	5.18%	6.37%	23.08%			

Export ratio

Amazon.de is one of six Marketplaces that Amazon operates in Europe. The launch of amazon.de was in October 1998, together with the introduction of amazon.co.uk in the UK. Later, France (amazon.fr), Italy (amazon.it), Spain (amazon.es), and the Netherlands (amazon.nl) followed.

However, customers from other countries can also order goods via one of these six Marketplaces. For example, users from Austria and Switzerland also shop at amazon.de. As a result, a portion of the sales generated via amazon.de is attributable to foreign citizens. Similar mechanisms also exist in local retail when a foreign citizen is visiting Germany and makes a purchase there. Amazon itself does not show any distribution of sales from amazon.de to the individual countries. However, using data from SimilarWeb, a web analytics service, we can determine how high the number of hits on the amazon.de website is from different countries worldwide. In Table 11, we show the countries with the highest international traffic (> 1%).

The largest share of foreign visitors comes from Austria, at 7.6%. This is reasonable due to its geographical closeness, its membership in the European Customs Union, and the fact that Austria also has the euro as currency. Switzerland, at 1.7%, is far behind in second place among the countries that make the most visits to amazon.de. Some sellers do not sell their products to Switzerland due to customs regulations. Moreover, Swiss customers are used to Swiss francs but receive euro prices on amazon.de. However, the German Marketplace is not only visited by customers from geographically close countries. China also accounts for 1.6% of the visits to the German Amazon online store.

For the AMDI, we use the total revenue generated via amazon.de. However, with the estimated export quotas listed here, we would like to provide a comprehensive insight and show how many foreign customers visit amazon.de (digital kompakt, 2020).

Table 11: Amazon.de Export Rate

Country	Estimated export rate
Austria	7.6%
Switzerland	1.7%
China	1.6%
Netherlands	1.5%
Belgium	1.0%

7.6 Discussion and Conclusion

7.6.1 Discussion

In the following section, we discuss the results, interpret them, and link them to the literature. To answer our RQ, we calculated Amazon's revenue for individual product categories and compared it with the total German retail volume for these categories. The literature analysis in this study shows that the market share of a company is the crucial measure of market power and dominance (e.g., Nissan, 2003). However, large companies that are active in different segments should determine market shares on a product-category level (Edeling & Himme, 2018). Only by taking a category-specific perspective can market shares be compared with other market participants appropriately. Since Amazon is an extensive online retail store that offers products from a wide variety of categories, a category-specific market-share calculation is essential. In this study, we show for the first time how high Amazon's market share in individual product categories is in relation to the total retail market in Germany. With the AMDI, we have created a measure that illustrates Amazon's market dominance in the individual product categories in a single number.

Before we look at the results for each category, we put Amazon's total retail volume in relation to the entire retail market in Germany. Across all categories, Amazon generated a revenue of €15.6 billion in the second half of 2019. This resulted in a market share of 6.37% of the total German retail market. Our figures and calculations are consistent with the statement from Jeff Bezos when he wrote in the annual letter to the shareholders that Amazon "represent[s] a low single-digit percentage of the retail market" (Bezos, 2019). At first glance, this share may not seem to be very high, but if we look at the individual categories, a different picture may emerge. A report by Ladd (2018) deals with this issue in regards to Amazon. Since the online retailer only has a small share of the total retail market in the USA, from a legal point of view, no breaches of competition law can be found. But a central aspect to the market share and dominance determination is the underlying market definition. By looking at individual product segments, Amazon certainly achieves higher market shares, which have already led to dominant market positions in some categories. Compared to pure online retail, Amazon's market shares would be even higher. Here, Amazon would achieve market shares that already exceed the 40% threshold above which the German Cartel Office initiates further investigations for potential abuse of market power. The determination of the market share and subsequent conclusions on market dominance are significantly influenced by the selection of the underlying market area.

One reason why Amazon only had a small market share compared to the overall retail market is the fact that about 86% of global retail in 2019 was still offline (Lipsman, 2019). This is why Amazon has been increasingly expanding into offline retail in recent years. In 2015, Amazon opened its first bricks and mortar bookstore (Greene, 2015). By the end of 2019, Amazon operated a total of 22 of these stores in the USA (Pymnts, 2020). In its 4-Star Stores, Amazon offers products in local shops that have achieved a rating of at least four stars on the online platform. Amazon chooses the product selection for each local store based on an analysis of its extensive online transaction data on demand in the respective region (Amazon, 2020b). A store in New York can, therefore, offer completely different products than a store in San Francisco if product demand differs in the regions. Amazon Pop Up Stores offer different popular products in physical stores. Amazon regularly updates the product offerings and utilizes these stores to give customers the opportunity to try out new products physically. Most of these shops are located in malls (Amazon, 2020e).

Another reason why Amazon's market share compared to the total retail market was not very high is due to the size of the food market. Amazon has almost no market share here yet (0.18% in Germany). In both Germany and the USA, the total retail volume in the food category is the highest of all categories but is also the one with by far the lowest online share to date (bevh, 2018; Statistisches Bundesamt, 2017a). Already in 2007, Amazon made its first attempts to develop its online food business (McDonald, Christensen, Yang, & Hollingsworth, 2014). With the grocery-delivery service "Amazon Fresh," customers can select food products via the Amazon Online Store and have them sent to their homes, just as they are used to having done with other products. However, to date, this service has not yet become very successful—neither in Germany nor in the USA (Shoup, 2019). The reasons for this could be a monthly subscription fee and insufficient flexibility in delivery time windows. Amazon recently tried to improve both factors in the USA. Amazon has abolished the monthly service fee and introduced more flexible delivery options (Hottovy, 2020). Nevertheless, the retail market for food is currently still mostly offline. That is why Amazon is heavily expanding in this area (Toplin, 2019). It launched "Amazon Go," a bricks and mortar concept without checkout lines. Customers benefit by not having to wait in a checkout line and Amazon can save on personnel costs (Polacco & Backes, 2018). When entering the store, the customer scans a QR code into his or her Amazon smartphone app and is thus identified by the store's intelligent system. A sophisticated camera system using computer vision techniques tracks customers as they shop and registers all the products they pick up from the shelf. The products are virtually stored in a digital shopping cart. As soon as the customer leaves the shop, the products are paid with the payment method stored in the Amazon account (Amazon, 2020d). Amazon plans to open up to 3000 “Go”-Stores by the end of 2021 (Renner & Fedder, 2019). Furthermore, Amazon acquired Whole Foods, an American, organic supermarket chain in 2017 (Wingfield & de la Merced, Michael J., 2017). With the integration of Prime offers in local retail, Amazon tries to connect online and offline channels and to further push its loyalty program. Besides that, Amazon is already planning another grocery store (Rubin, 2019). Compared to Whole Foods, which specializes in organic food, the new store could become a traditional grocery store. The US grocery market accounts for about $800 billion per year, and although Amazon has about 500 Whole Food stores in the US right now, it has a small market share compared to Walmart and Kroger (Rubin, 2019). In summary, Amazon is experimenting with different physical store concepts. Thereby, Amazon is using its technological expertise and knowledge from extensive datasets to create new and better shopping experiences in local retail.

Looking at Amazon’s online business in Germany, we found that Amazon showed particularly strong figures in the *Electronics and Computers* category. Amazon generated over a third (33.95%) of its revenue in Germany in this product category. This led to sales of €5.30 billion in the second half of 2019. Especially the high average price point of €79.02 contributed to the high revenue in this category. Compared to the total retail market in Germany, Amazon had a market share of 24% in *Electronics and Computers*. It is also remarkable that Amazon was able to increase its revenue by 99.45% compared to the first half of the year, whereas the market only grew by 16.77% in the same period. Thus, Amazon achieved an AMDI of 8 in this category in the second half of 2019 (first half of 2019: AMDI = 6). Amazon succeeded in increasing purchase frequency and revenues with sale events such as the Prime Day or Cyber Week and strong special offers. Additionally, Amazon lists its own brands in the *Electronics and Computer* category such as the voice assistant “Echo,” the media-streaming “Fire TV” stick, and the e-book reader “Kindle.” Especially in these product areas, sellers have a disadvantage, as Amazon can place its own products prominently on the platform and has a significant advantage through more visibility. Furthermore, electronic products are usually very homogeneous. Physical testing and inspection are much less important here than in the *Grocery* or *Apparel* categories, for example. Especially standardized products such as HDMI cables can easily be compared online, which leads to a higher willingness to buy on Amazon.

In the *Apparel* category, however, Amazon was much less dominant. With revenue of €1.06 billion, Amazon had a market share of 2.65%. Amazon even lost market share here compared to the first half of 2019 and thus only achieved an AMDI value of 3 out of 10. Compared to the *Electronics and Computer* category, products in the *Apparel* category had a higher offline retail share (Handelsverband Deutschland [HDE], 2018a). However, Amazon also performed poorly compared to online retailers in the fashion segment. Due to the rigid technological infrastructure of Amazon, the relevant product features of fashion items cannot be presented in an appealing way. More focused fashion online retailers like Zalando have adapted their online store much better to the product features of apparel. Furthermore, customers in the fashion sector have different needs, motives, and requirements than in other categories (Kawaf & Tagg, 2012). Inspiration and emotion are crucial elements of fashion shopping (digital kompakt, 2019). Shopping in this category, therefore, goes far beyond the purely functional satisfaction of needs. However, Amazon's system does not offer enough possibilities to present products in the fashion segment in an attractive and inspiring way. This is why Amazon is considered to be of little relevance for fashion shopping by customers (digital kompakt, 2019).

The market-share literature shows that a higher market share is associated with higher profitability and greater market power (Nissan, 2003). Many companies, therefore, have a special focus on market-share growth. This can be observed particularly well at Amazon. The strong focus on growth is not only reflected in Amazon's financial figures but also in the annual letters to its shareholders by CEO Jeff Bezos. In these, Bezos repeatedly emphasizes that Amazon places growth above short-term profitability (Bezos, 1998, 2019). This also illustrates Amazon's long-term perspective. Some researchers note that interaction effects and context play an important role in examining the relationship between the market share and market power (e.g., Feeny & Rogers, 2000). For example, the market share plays a greater role in B2C markets (Edeling & Himme, 2018). Amazon is primarily active in this area with its retail business. Besides, Amazon benefits from the interaction of its different business units. Large server capacities are required to maintain the globally operating Amazon Online Stores. With AWS, Amazon offers cloud computing services for other companies. However, Amazon's own retail business can also benefit from this powerful IT infrastructure and the big data tools, which enable extensive data analyses to evaluate and improve the customer experience in Amazon's online stores. This in turn raises questions regarding the correct determination of Amazon's market share (Day & Soper, 2019). Since

Amazon operates in many different areas (retail, cloud, logistics), market shares must be considered for specific submarkets. However, Amazon also benefits from its cloud business in the retail sector, which could also be used to argue that the individual business areas should not be viewed independently of each other. Furthermore, due to the uniform online retail platform structure, spillover effects could also play an important role at Amazon (Tian et al., 2018; van Alstyne, Parker, & Choudary, 2016). A high market share in one product category means that products in other categories will also benefit. The uniform website structure, design, and checkout process promote cross-category purchasing. Therefore, it is not always easy to define the market appropriately and to find the right level for investigation. Amazon also benefits from a mechanism known in the literature as “platform envelopment” (Eisenmann et al., 2011). By leveraging its existing user base, Amazon could easily tap into another platform market. With its comprehensive online shop and its broad customer base, Amazon was also able to quickly enter the market for e-book readers. With the Amazon Kindle, Amazon not only sells the hardware but also the appropriate content.

Regarding the platform-economics literature, it is understandable that Amazon continues to focus on strong growth since platform markets often lead to WTA structures (Kuchinke & Vidal, 2016; van der Aalst et al., 2019). Amazon must aim to become the largest provider, as network effects and economies of scale mean that often only a few companies can survive in the market. The pricing of the different parties on a platform plays an important role in business success (Evans, 2003). To grow as fast as possible, Amazon uses the “divide-and-conquer” approach, where one side subsidizes the other (Caillaud & Jullien, 2003; Parker & van Alstyne, 2005). On the one hand, Amazon offers customers free access to the platform, with low prices and free shipping. On the other hand, Amazon exploits its market position by charging third-party sellers. Amazon uses a mixed billing model, charging for its service on both a lump-sum and commission basis (Armstrong, 2006). Retailers pay a fixed monthly fee to gain access to the platform and additionally pay a per-transaction fee of 15% on average per product sold.

Due to the increasing number of Marketplace sellers, competition among them is becoming more and more intense. In 2018, more than one million new sellers registered on Amazon (Marketplace Pulse, 2018). The increasing competition leads to lower prices, and it becomes more and more difficult for the individual seller to gain visibility on the platform. Therefore, Amazon introduced ads on the platform. Sellers can use different advertising methods to get more visibility on the Marketplace. It is a rapidly growing and profitable business that generates additional revenue. For Amazon, it does not matter if Seller A or B sells a product, as Amazon always gets a commission. The ad business shows how Amazon cleverly uses its strong market position to squeeze even more out of a seller. Hagiu (2009) argues that in monopoly-platform situations with a high demand for product diversity, platform owners will make more profit by charging third-party sellers than by charging customers. Due to the customers' high demand for different products, which a platform can only achieve with a large third-party seller basis, these sellers are responsible for a larger part of the surplus. Therefore, the platform owner tries to make more profit from the producers instead of the consumers. As a result, Amazon uses its market power not against customers, but against sellers on the platform. Customers are the focus of all efforts at Amazon, and not only because they have lower switching barriers and costs. Amazon's high level of customer orientation ensures long-term customer loyalty and increases platform sales. This, in turn, also increases the attractiveness of the platform for sellers.

A dominant market position situation can also become threatening for independent sellers as soon as Amazon takes advantage of it. Due to the hybrid platform model, Amazon is both seller and platform owner at the same time, which can lead to conflicts (Zhu & Liu, 2018). We identified that Amazon sells goods in dominant product categories more often by itself rather than via third-party sellers. Due to the large amount of data Amazon collects on the platform, it can "cherry-pick" profitable products and leave less attractive ones to third-party sellers (Jiang et al., 2011). As the market share and maturity of a category increases, Amazon can identify very precisely which products are attractive and sells them itself. Due to Amazon's company size and its extensive activity in various business areas and product categories, Amazon does not have to earn any money with its retail business for a long time if it can finance the company through another business division. Low product prices can lead to strong growth and increasing market share. Competitors who are dependent on the retail business are put under pressure by this practice or are completely squeezed out of the market. The importance of low product prices on a platform is underlined by the following policy that Amazon has practiced for many years. Amazon has prescribed to its third-party sellers that they may not offer products via any other channel at a lower price than on Amazon. The German Federal Cartel Office has conducted investigations against Amazon on the basis of this policy (*Bundeskartellamt v. Amazon*, 2013). As a result, the online retailer has removed the obligation of price parity from its terms and conditions. This example shows that Amazon is trying to use its power to support the attractiveness and growth of the platform.

In conclusion, the situation of third-party sellers can often be described with the "swimming with sharks" dilemma (Kapoor, 2013; Katila et al., 2008). Entrepreneurs cooperate with larger but risky partners where they have a high potential for misappropriation when they need resources that established firms uniquely provide. Sellers want to access Amazon's reach and customer base. In return, they pay not only a sales commission, but they also pay with the loss of the direct customer relationship. In addition, only Amazon has complete access to all data generated through customer interaction with the platform, which allows Amazon to precisely analyze customer behavior and use this information for future decisions to increase business success.

7.6.2 Implications

The AMDI provides valuable insights for every retail-oriented company. It is especially interesting for retailers and brands because, through the AMDI, they can better understand the market position of Amazon and the potential threats or opportunities that come with it. The AMDI provides insights into the distribution of Amazon's revenue in Germany and thus provides data that was previously unavailable. The breakdown of sales shows in which product categories Amazon has a high market share and where the market share is particularly small. By calculating the data on a half-yearly basis, we were able to illustrate changes and growth rates per segment. This makes it possible to show dynamics in online retail and, above all, to make interesting comparisons with the total retail market in Germany. For retailers, this results in relevant and evidence-based insights that also show the opportunities and risks in relation to their own industry.

Amazon's strong sales growth in the second half of the year can be seen as an opportunity for sellers. Through sale events such as Prime Day or Cyber Week, Amazon attracts many customers to the platform. Sellers can then also profit from the increased buying frequency. In product areas where Amazon has a lower dominance, sellers have better chances of selling their own products. In dominant categories where Amazon sells many of its private label products, it is hard for sellers to gain visibility with their products. Besides, Amazon has extensive knowledge of purchasing and customer behavior from historical data in these categories that it could use to identify profitable product areas. Therefore, it could be a winning strategy for sellers to focus on product categories with a lower market share where competition from Amazon is less likely. Sellers could also protect their products with a strong brand and unique product features. By doing this, the imitability of other sellers is reduced, and even Amazon cannot easily copy the product.

In the scientific context, the AMDI forms the fundamental basis for a more detailed understanding of Amazon's market position. The AMDI illustrates Amazon's market share for all main product categories in a simple Index measure ranging from 1 to 10. Scholars could use the Index values to conduct further calculations in the area of e-commerce and online platforms. Average price points and vendor/seller shares per category are valuable figures for future scientific studies with which to analyze segment-specific dominance mechanisms. Our data-aggregation approach could also be used to analyze market shares and market dominance for other companies and other industries.

7.6.3 Limitations and Future Research

To determine the AMDI, we have to combine different data sources. Since Amazon only provides a limited amount of data on sales in Germany, we also had to make assumptions that can lead to inaccuracies. Since Amazon does not show figures for the German market in its quarterly reports, we assume that annual sales in Germany are distributed in the same way over the quarters as for worldwide sales. The annual report, in which Amazon provides data for Germany, allows this assumption to be reviewed at the end of each year. The same applies to the distribution of revenues among the Amazon market segments (AWS, third-party seller services, subscription services, etc.). We also assume that the distribution in Germany is the same as it is globally.

When calculating total market sales, we combine data from the annual survey of the Federal Statistical Office with data from the monthly survey. However, as different methodological calculation procedures are used, deviations may occur, and the figures can only be determined approximately. However, the Federal Statistical Office applies extensive measures to ensure the highest possible data quality. It publishes detailed information on the procedure in a quality report (Statistisches Bundesamt, 2017b). We have always taken care to build consistent product categories so that the figures from Amazon can be compared with those of the market. However, the underlying products may not be exactly the same in all categories, as Amazon and the Federal Statistical Office use different classifications and designations. The Federal Statistical Office does not break down sales by product categories that are processed via distance selling (e.g., *E-Commerce*). All distance-selling sales are reported in a composite category. With the help of additional data from the e-commerce association bevh (2018), we can disaggregate distance-selling sales. Additional data from IfH Köln (Handelsverband Heimwerken, 2019) were used to determine online sales in the *DIY* category and data from Statista (2019) for the *Drugstore* category. The product category with the code

WZ08-4711 from the Federal Statistical Office is a composite category. According to a statement by a representative of the Federal Statistical Office, at least 75% of the products in category 47.2 (Einzelhandel mit Nahrungs- und Genussmitteln, Getränken und Tabakwaren (in Verkaufsräumen)) have to come from the food sector. Therefore, 75% of the sales for this category were allocated to the category *Groceries and Beverages*. The product category with the code WZ08-4753 contains products that are assigned to both the Amazon category *Kitchen, Household, & Home* and *DIY*. Since no further data are available on the structure of the category and since it is a small category in terms of sales, half of the sales were assigned to each of the two categories: *Kitchen, Household, & Home* and *DIY*.

The Amazon sales per category are calculated on the basis of bestseller ranks and product visibility on Amazon. However, there are also limitations in the calculation of the Amazon sales allocation to the categories. Since some categories on Amazon do not allow the usual method of obtaining data due to a specific structure limitation, the best possible estimate is calculated in these categories based on the metoda Visibility Index.

All figures in this paper refer to the German market. Future studies could look at other countries and also calculate the AMDI for them. This would also make it possible to compare the figures and illustrate how dominance in individual categories differs across countries. For the American market, figures can already be found for some categories. It can be seen that Amazon can claim even higher market shares in the USA than in Germany (Day & Gu, 2019).

A further subdivision of the categories that have been examined would provide even more detailed information about Amazon's market dominance. Feedback from readers of the E-Commerce Germany Report shows that there is interest in a deeper subdivision. A retailer of office supplies would like to know Amazon's market position in exactly this subcategory. However, since the *Office Supplies* category forms a category together with *Books*, it is difficult to draw conclusions about the *Office Supplies* sub-segment.

Future research could also include the influence and synergies of other Amazon business areas in determining market dominance. There are initial indications that the cloud division (AWS) also plays an essential role in Amazon's retail business. Cloud-based tools can be used to analyze the large amounts of data generated with each click on Amazon. The findings from the data can help Amazon gain valuable insights, allow it to personalize its services in a profound and individualized way, and lay the foundation for strategic decisions.

7.6.4 Conclusion

By combining several data sources, we were able to create more transparency regarding Amazon's market position in Germany. We have determined Amazon's market share in relation to the entire German retail market. In addition to comparing Amazon's total sales with the market as a whole, a category-specific analysis was a major goal of this study. Following the main product categories on amazon.de, we created ten segments in which we analyzed Amazon's market position in comparison to the total German retail market. We were able to determine that Amazon has a particularly high market share in the categories *Electronics & Computers* (24%) and *Toys & Baby, Sports & Leisure* (17.87%). However, in the categories *Apparel* (2.65%) and *Groceries & Beverages* (0.18%), Amazon has only achieved low market shares. Compared to the first half of 2019, Amazon increased sales by 35.08% in the second half of the year, whereas the total market only grew by 9.75% in the same period.

With the AMDI, we have created an indicator that illustrates Amazon's market dominance. The Index can have values between 1 (low dominance) and 10 (high dominance). Under the German Act Against Restraints of Competition, a company is presumed to be dominant if it has a market share of at least 40%. Thus, from this threshold, Amazon receives the highest Index value of 10.

By reflecting on our results by considering the two literature streams of platform economics and market share, we were able to gain valuable insights. The market share is the core element for determining the market power of a company. Therefore, the market share is particularly suitable for the creation of our AMDI. A high market share leads to greater firm performance and market power. This explains Amazon's strong focus on growth. The literature on platform economics shows that markets that are strongly influenced by the platform model often lead to WTA situations. Network effects and economies of scale play an important role here. We found that in dominant categories, Amazon more often sells products itself rather than through third-party sellers. With its hybrid platform model, Amazon can "cherry-pick" profitable product spaces and leave less attractive ones to third-party sellers. Due to the extensive data that Amazon generates with every click, it has deep insights into customer behavior and can, therefore, make superior decisions. Sellers often find themselves in a "swimming with sharks" dilemma. On the one hand, they need Amazon's reach and customer base to generate sales, but on the other hand, they lose direct access to customers. Amazon takes advantage of this dilemma by reducing product visibility from third-party sellers. As a result, it becomes increasingly difficult for sellers to attract customer's attention, which

Amazon is monetizing through ads on the platform. With this study, we enable sellers to better assess the market structure and dominance of Amazon in individual product categories. We hope that our findings will encourage sellers to analyze their market position in more detail and to develop a comprehensive platform strategy that enables long-term success.

Third Dissertation Article

Evaluation of the Effectiveness of the Amazon Product Listing Optimization Tool

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8 Evaluation of the Effectiveness of the Amazon Product Listing Optimization Tool

Abstract

With the growing popularity of the Amazon Marketplace and the increasing number of competing products, it has become difficult for sellers to gain visibility on the platform. The quality of the product presentation on the platform is a critical factor for visibility and sales performance. However, many sellers lack knowledge about which and to what extent product-page factors influence the conversion rate on Amazon. The Amazon Product Listing Optimization (APLO) tool helps sellers to optimize their product-page quality and, consequently, the conversion rate on Amazon. The tool analyzes the content of a specific Amazon product page and then provides individual improvement suggestions for the product-page quality.

The primary objective of this study is to evaluate the effectiveness of the APLO tool in supporting the implementation of product-page optimizations. Additionally, we assess how these product-page optimizations affect the sales rank of the products on Amazon and how satisfied users are with the current version of the APLO tool.

We used an experimental design to meet the primary study objective, in which the experimental group used the APLO tool and the control group did not. With a pretest–posttest design, we investigated whether the use of the tool and the intervention in the form of optimization suggestions have led to product-page improvements. Within 30 days, we checked the Amazon product pages at different predefined points in time using automatic re-crawling scripts to detect changes. Thus, we could also determine how long users need to implement the improvement suggestions. The last study objective was elaborated with an online survey integrated within the APLO tool website.

The product pages of sellers using the APLO tool showed significantly greater improvements than the product pages of sellers who did not use the tool. By improving the overall quality score of the product page by one percentage point, the Amazon sales rank could be improved by 0.996 percentage points. Based on all survey participants ($n = 102$), the tool achieved a net-promoter score (NPS) of 60.8%, so the overall satisfaction is high, and most of the users are promoters. Finally, we could show that the APLO tool is effective in supporting the implementation of product-page optimizations and in enhancing the sales rank on Amazon.

Keywords: online platform, intervention tool, application, evaluation, e-commerce, product-page optimization

8.1 Introduction

The Amazon Marketplace is one of the largest online retail platforms in the world. In Germany, 40% of all online sales are generated via Amazon (digital kompakt, 2020). Therefore, Amazon has a very dominant role in online retail. Amazon itself acts both as a platform provider as well as a retailer. However, third-party sales have increased steadily in recent years. In 2018, the global share of revenue generated by third-party sellers was 58% (Bezos, 2019). This shows that third-party sales have already exceeded first-party sales, and therefore third-party sellers play an increasingly important role for the whole Amazon ecosystem. In 2019, Amazon had over 2 million active sellers on the platform (Marketplace Pulse, 2020). The increasing number of sellers also leads to an increasing number of competing products. This challenges the individual retailer in many ways. The increasing product range makes it more and more difficult for sellers to gain visibility and generate sales on the platform (Li, H. et al., 2015). A merchant has to compete against other third-party sellers (Redmond, 2013) as well as against Amazon itself (Ryan et al., 2012; Zhu & Liu, 2018). The increase in sponsored products and advertising space on the search results pages also reduces the organic visibility of products (Molla, 2018). Therefore, it is increasingly important for Amazon sellers to convert product-page visitors into actual buyers and thus to increase the conversion rate. In this way, sellers could compensate for a loss in visibility. Beyond that, a better conversion rate could also help to re-stimulate visibility on the platform, as a product with a higher conversion rate is considered more relevant by Amazon (Purohit, 2020). A positive upward spiral is set in motion. The conversion rate is, therefore, one of the core metrics for every seller. On the Amazon platform, sellers can only influence a limited number of factors due to the predefined and rigid Amazon system. However, sellers could adjust some product-page factors to design an individual product page and to stand out from other products. Previous research has shown that factors such as reviews and ratings (Cezar & Ögüt, 2016; Sharma et al., 2019), visual presentation (Song & Kim, 2012), product information (Kim & Lennon, 2008; Ranganathan & Ganapathy, 2002), and shipping policies (Di Fatta, Musotto, & Vesperi, 2016; Lewis, Singh, & Fay, 2006) have an impact on the conversion rate and sales performance. By evaluating an extensive dataset with over 3,000 products in the first study of this dissertation, we were able to scientifically determine how the individual product-page factors affect the conversion rate. Synthesizing the results from the previous studies and existing literature, we were able to provide sellers with individual suggestions for optimizing their product pages on Amazon. In order to ensure the easy application of the results and to make them accessible for practice, we build a practical intervention tool in the form of an online application. The Amazon Product Listing Optimization (APLO) tool helps companies to optimize their product pages on Amazon to achieve higher conversion rates and better sales performance. Additionally, the APLO tool calculates an overall quality score for each product page. The overall quality score shows at a glance how well a product page is currently optimized (Google, 2019).

The objective of this study is to conduct an evaluation of the tool. We have three goals. First, we want to investigate the effectiveness of the tool intervention in supporting sellers to optimize their product pages. Second, we want to know how the product-page optimizations initiated by the APLO tool affect the sales rank of the product on Amazon. Third, we want to find out how satisfied users are with the current version and functionality of the tool and whether they are willing to pay for the tool.

Based on an experimental setting, we compare the intervention with a control group to investigate the effectiveness of the APLO tool. The experimental group receives an intervention by using the APLO tool, whereas the control group does not use the APLO tool. The pretest–posttest design allows us to measure product-page quality before and after the intervention. We analyze the data with a repeated measures ANOVA and an additional post hoc test. To analyze a product page with the APLO tool, a user just has to enter the URL of the Amazon product page into our tool. Afterward, we crawl all relevant data from Amazon automatically, analyze them, and provide individual product-page improvement suggestions to the user. All queries and results are stored in a database. In order to evaluate the effectiveness of the tool, we check whether and when the user improved his or her product page. This is done by a fully automated re-crawling process. By querying the product page at predefined points in time following the initial analysis, we can also determine how quickly users integrate the improvement suggestions on Amazon. If users have implemented the APLO tool improvement suggestions, this is reflected in the individual score for each product-page factor and thus also in the resulting overall quality score.

With the APLO tool, we enable sellers to get evidence-based and decision-relevant information for the optimization of their Amazon product pages. We introduce the new measure of the overall quality score, which reflects the overall quality of a product page on Amazon in a single indicator. With an evaluation study, we show how effectively the tool can support the implementation of product-page improvement suggestions and thus increase the overall quality score of a product page. Additionally, we show that these optimizations have a significantly positive effect on the sales rank on Amazon. All users who have implemented at least one suggestion from the APLO tool increased their sales rank by an average of 21.93%. In this way, we can show that the APLO tool is not only effective in increasing the quality of the product page, but also leads to better sales performance. Through the additional online survey, we can determine how satisfied users are with the current version of the tool. It also enables us to identify further improvement possibilities of the tool from the users' point of view.

With this study, we also show how a digital online tool can be used to automatically generate data that enables a comprehensive evaluation study. With the help of social networks and online marketing campaigns, we were able to win a specific target group for the use of the tool in a short period of time and thus to generate a high-quality dataset. Through automatic re-crawling of Amazon product pages at predefined points in time, we were able to monitor implementation progress by the user automatically. Otherwise, this would only have been possible with high time investment and the associated costs.

8.2 Related Literature

8.2.1 Intervention Tools

The transfer of scientific knowledge into practice is often associated with several hurdles (Rynes et al., 2017). Often practitioners do not have access to scientific journals and demand an easier way to access and apply scientific findings (Crosier, 2004). Textbooks are, of course, one source, but they do not allow for an interactive and individual transfer of research results, which can significantly improve the application of them (Helic, Maurer, & Scerbakov, 2004). Related to our study, many sellers do not know which and how product-page factors can affect the conversion rate (ShopDoc, 2019). It is often difficult to obtain relevant data for product-page optimization potentials and to interpret them correctly. In addition, evidence-based conversion rate optimization suggestions for online platforms like Amazon Marketplace are hard to find. Especially in digital business areas, where technologies and practices often change, and information quickly becomes outdated, it is difficult for many companies to access relevant and up-to-date information (Carlsson, 2018). Various studies have shown that tools or applications have the potential to solve this problem (Fleming & Hawes, 2017; Gessner & Scott, 2009; Helic et al., 2004). Companies from different industries can benefit from apps that help them to implement and achieve their goals (Lozano, 2020).

To date, intervention tools in the form of online or mobile applications have been developed and tested particularly in the health sector. These apps address, for example, better nutrition (Nyström et al., 2018; Zarnowiecki et al., 2020), stress management (Hwang & Jo, 2019), or physical activity (Kramer et al., 2019). Most of the studies show that the apps could significantly improve the intended outcomes. Bessell et al. (2012) assess the effectiveness of an online intervention (Face IT) in reducing appearance concerns, depression, and anxiety. They conclude that the tool is effective in reducing these complaints. Chang, Cheng, and Kung (2019) use an app intervention to investigate whether stress can be reduced with it for newly employed nurses. The effectiveness of the app was proven in an experimental setting. In a subsequent survey, the participants expressed a high level of satisfaction and intention to use the app. Beal and Rosenblum (2018) examine whether an iPad app is better in helping students with visual impairments in solving mathematics problems than a traditional literacy medium is. The results show that the students solve more tasks correctly and show higher motivation when using the app.

However, intervention tools are also successfully used in the business field. A practical example is the Google Pagespeed Insights tool (Google, 2019). It helps users to optimize the loading speed of their websites. By demonstrating the website-specific potential for improvement, users are encouraged to optimize their website to achieve a higher loading speed. All these examples illustrate that apps and tools can help to achieve the desired outcome more efficiently and with higher user motivation.

With the APLO tool, we want to help Amazon sellers to improve their product detail pages and thus achieve a higher conversion rate. The tool should make it easier for sellers to recognize and implement evidence-based optimization potentials. We hypothesize a significantly larger improvement in the overall product-page quality score when participants use the APLO tool compared to a group that does not use the tool.

H1: Sellers who use the APLO tool will better improve their product pages than sellers who do not use the tool.

8.2.2 Product-Page Quality

Besides the cited literature about online tools in general, we will give an overview of the literature that underlies the content and desired outcome of our tool in the following section. In the first study of this dissertation, we already show how product-page factors can affect the conversion rate and sales performance of a product. The provided product information and overall product presentation on e-commerce websites are key success factors in online shopping (Blanco, Sarasa, & Sanclemente, 2010; Hong, Thong, & Tam, 2004). In the following, we take up the most important studies that are relevant in the context of the second objective of this study, where we investigate the impact of overall product-page quality on sales performance. We group product-page factors into four main groups: (1) *Reviews and Rating*, (2) *Visual Presentation*, (3) *Product Information*, and (4) *Shipping*.

Reviews and Rating. Concerning the first group, several studies show that a high number of reviews and recommendations have a positive impact on conversion rates (Cezar & Ögüt, 2016). Chevalier and Mayzlin (2006) investigate the effect of online book reviews on amazon.com. They found that an increase in reviews has a positive effect on sales on the platform. With a text-mining approach, Ludwig et al. (2013) found that the type, style, and tone of ratings can have varying effects on the conversion rate. The style of the reviews must match the type of product, and then reviews have the strongest positive effect on the conversion rate. The study by Zhu and Zhang (2010) goes in a similar direction. The researchers investigate the moderating effect of product and consumer characteristics on the impact of reviews on product sales. They found that online reviews have a stronger impact on the sales of less popular products. Sharma et al. (2019) investigate the influence of various factors on sales performance at Amazon and conclude that the number of ratings is the most important and significant predictor for sales. In addition to the number of ratings, the average rating or the proportion of positive ratings plays an important role for sales performance (Li, H. et al., 2015).

Visual Presentation. Moreover, the visual presentation is important for the sales performance of a product. Di et al. (2014) investigated if more product images affect a buyer's attention, trust, and conversion rate, and found positive evidence for all relationships. An increasing number of images offer customers a more comprehensive visual understanding of the product and are an effective way to increase the sell-through. Song and Kim (2012) stress that multiple product presentations can reduce mental intangibility and thus helps customers in their purchasing decision.

Product Information. Kim and Lennon (2008) compared visual and verbal product information. Although both types are important for positively influencing the customer's shopping experience, verbal information had a greater effect on purchase intention. Chen and Xie (2008) stress the importance of seller-created product information and conclude that buyer-created reviews can complement seller-created product information. Customer reviews offer a new user-oriented perspective and can help potential customers to better identify suitable products. Customer reviews enhance the product information provided by the seller, as these reviews often add new and additional information. Ranganathan and Ganapathy (2002) argue that information content is elementary for every website and that it should provide comprehensive descriptions of products and services. They found that information content is a crucial predictor of purchase intention and also serves as a differentiator between websites. Besides, Kim and Stoel (2004) state that information and content significantly contribute to the user's satisfaction. Thus, the completeness and amount of information are essential for the decision-making process of customers (Miranda & Saunders, 2003).

Shipping. Also, shipping policies could have different outcomes on the sales performance of a product. Di Fatta et al. (2016) found that free shipping is an important factor in e-commerce and has an impact on customer satisfaction. Lewis et al. (2006) add that free shipping could be very effective in the generation of additional sales. Not only shipping fees but also return shipping policies have consequences for the long-term success of a retailer (Bower & Maxham III, 2012). If customers can return an item for free, the post-return customer spending is much higher than when customers have to pay for their returns.

Although many studies examine the influence of individual factors, we argue that a combination of those leads to better sales performance (Blanco et al., 2010) as all these factors combined attribute to a higher quality of product presentation and service (Singh, Dalal, & Spears, 2005). Therefore, we merge them in a new measure called the overall quality score, and hypothesize, based on the previous literature, that an improvement in the overall quality score leads to a better sales performance on Amazon.

H2: An improvement in the overall quality score of a product page leads to a better sales performance on Amazon.

8.3 Data and Method

8.3.1 APLO Tool

The APLO tool analyzes the content of an Amazon product page and then makes suggestions for improving the product-page quality to increase the conversion rate and sales performance. Amazon sellers can analyze their product pages directly via our web-tool (aplo.stgaller-navigator.com). The website can be used on both desktop and mobile devices (see Figure 5). Additionally, the APLO tool will be integrated into the St.Galler Startup Navigator mobile application. When creating the APLO tool, we were guided by the Google Pagespeed Insights tool (Google, 2019). The Pagespeed Insights tool has similar functionality as the APLO tool. It allows website owners to analyze a website regarding page-speed problems and optimization possibilities. Therefore, the context is similar. With the APLO tool, we also offer a tool to improve an online presence. In the broadest sense, both tools aim to improve the user experience and finally to increase the conversion rate. The APLO tool analyzes product-page factors intending to improve product-page quality, whereas the PageSpeed Insights tool analyzes the content of a website to increase the page-loading speed. The structure and design of both tools are, therefore, very similar. To analyze an Amazon product page, a user simply needs to enter the web page address (URL) of the product in the upper section of the website. He or she then clicks on the "Analyze" button to start the analysis. In the next step, our tool crawls the Amazon website and extracts all the relevant information about the product page in real time. The evaluation is based on the previously presented literature about product-page factors and their impact on sales performance as well as on the results gained from a comprehensive data analysis of over 3,000 products on Amazon that we conducted in the first study of this dissertation. However, we not only know which factors affect the conversion rate, but also how. Using machine-learning techniques, we were able to determine the marginal effects that a factor has on the conversion rate. For example, we can make concrete suggestions on the length of the product description or the optimal number of bullet points. Based on the product listing data we extracted from Amazon, we could give sellers individual suggestions on how they could optimize product-page factors for their specific product. Additionally, we could also rank the suggestion based on the relevance and impact on the conversion rate. Table 12 shows all of the factors that are examined in our model and in the APLO tool. Of particular interest are the optimal values of a factor, showing which value a factor should have in the best case. For example, a product page should at best show seven product pictures. When a factor achieves this value, the conversion rate is affected in the best possible way. The relationship between the factors and the conversion rate can have various connections. Some relationships are linear; others are more complex.

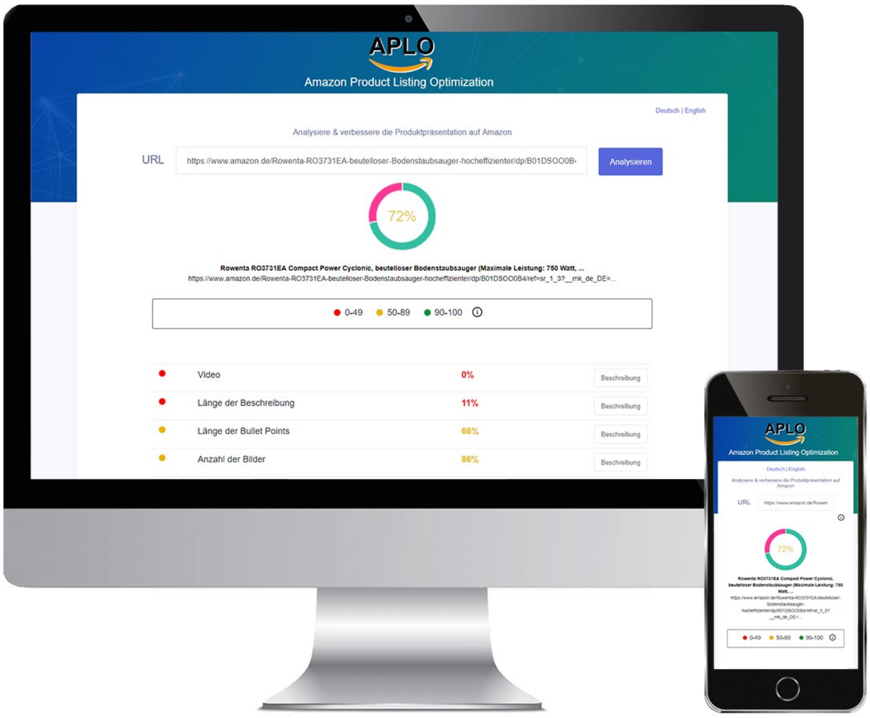
Table 12: Amazon Product-Page Factors

Product-page factors	Description	Suggestion	Relationship	Optimum
Number of images	Images illustrate a product and help the customer with product selection.	Increase the number of images. The product page shows less than seven images. Use the maximum number of images to present the product in the best possible way.	Linear	7
Video	A video can be added next to pictures to present a product even more vividly.	Add a video. A video makes it possible to present your product even more vividly and to convey emotional elements.	Binary	1
Number of ratings	Evaluations and reviews from existing customers help prospective customers with product selection.	Increase the number of ratings. Ideally, you will have 80 or more reviews for the product.	Linear	80
Average rating	The average rating indicates how satisfied customers are with the product. A customer can award between 1 and 5 stars.	Improve your rating. The average rating of the product should be 4.5 stars or higher. Try to improve your product quality so that customers give better ratings.	Non-Linear	> 4.5
Number of bullet points	Bullet points describe the most important product information in the area above the fold without scrolling.	Increase the number of bullet points. Use all five bullet points to describe the product in the best possible way.	Linear	5
Length of bullet points	The length of the bullet points indicates the number of characters of all bullet points. More information could help customers to make a better purchase decision and thus leads to a better conversion rate.	Reduce/increase the number of characters in the bullet point fields.	Non-linear	900–1100 characters
Length of description	The length of the description indicates the number of characters of the entire description. More information could help customers to make a better purchase decision and thus leads to a better conversion rate.	Reduce/increase the number of characters in your product description.	Non-linear	1900–2100 characters
A+ content	A+ content enables a more comprehensive and attractive description.	Add A+ content. With the help of A+ content, you can describe your product more appealingly (including pictures). A+ content can only be used by vendors or brand owners.	Binary	1 (= A+ content existing)
Fulfillment by Amazon (Prime)	Fulfillment by Amazon (FBA) enables sellers to have their own goods shipped by Amazon. Thereby, a product receives the Prime Badge. Customers appreciate this service because fast and reliable handling is guaranteed.	Use Fulfillment by Amazon (FBA). You are currently not using Amazon shipping, and the product is, therefore, not Prime eligible. With Prime, you can increase your conversion rate.	Binary	1 (= FBA)

After processing and analyzing the extracted data, the user receives an overview of the results. In the first part of the result page, the user sees an overall quality score, which reflects the quality of the product page in a single indicator (see Figure 5). The score ranges from 0 to 100, where 100 represents a perfectly optimized product page. Values between 0 and 49 represent a poor product-page quality, between 50 and 89, an average quality, and values above 90 stand for a high degree of optimization. An overview section shows the user all the analyzed factors. Each product-page factor is provided with a score that shows the user how well the respective factor is already optimized, again ranging from 0 to 100. In the second part of the result page, the user also receives detailed improvement suggestions for all factors that achieve a score of less than 100. Such an improvement suggestion could be, for example, to add a longer product description or to add missing product images.

After the test results section on the APLO website, we show more data and key figures for each product category in which the analyzed product is classified on Amazon. The data in this section are taken from the results of the second study of this dissertation. We show which market share Amazon has in comparison to the entire German retail market (online + offline), and we also provide the Amazon Market Dominance Index (AMDI) to show Amazon's market power in the respective category. This gives retailers a first insight into the attractiveness of individual categories on Amazon. We also show figures like the average price point and Prime availability for products in the category. The vendor/seller share illustrates the share of first-party and third-party sales in a category. We also list the ten most visible brands on Amazon for each category. Finally, we summarize the most important findings for each category in three key points. All data refer to Amazon's German Marketplace.

Figure 5: Amazon Product Listing Optimization Tool Website



8.3.2 Study Design and Procedure

Field studies can be used to observe processes in natural environments and put them into context. In information system research, design artifacts and their solutions can be investigated with real users (Hevner, March, Park, & Ram, 2004; Nunamaker, Chen, & Purdin, 1990). By using a mixed-methods approach combining quantitative data from an experimental setup and qualitative data from a survey, comprehensive insights into user interaction with the APLO tool can be gained (Klein & Myers, 1999).

Experimental procedure

To assess our hypotheses, we conduct an online experiment. The experimental group receives an intervention via the APLO tool in the form of suggestions for improvements for their Amazon product page. The control group is made up of randomly selected Amazon product pages that did not receive an intervention.

The study took place from March to May 2020 and lasted 60 days in total. The participants in the experimental group accessed the tool via the website and could use it without any restrictions. During the same period, the product pages of the control group were randomly selected and tested using the APLO tool.

With a pretest–posttest procedure, we can determine, for both the experimental and the control group, how the overall quality score of the respective product pages change. In the experimental group, the first query from a seller via the tool gives us the pretest values immediately before the intervention takes place. We save the provided URL the seller entered via our tool to check, after predefined points in time, whether the company changed the product page on Amazon based on our suggestions. After each initial request with our tool, a script starts the automatic re-crawling process. Through this, all product pages are automatically re-tested, and the latest results for each factor are calculated. All results are saved in a database. Since we re-crawl the product pages several times during the investigation period, multiple posttests are performed. This allows us to monitor whether and when sellers are actually implementing the recommended improvements to the product page.

We carried out the same procedure for all products in the control group. We randomly selected 161 product pages from Amazon and analyzed them with the APLO tool. Consequently, the sellers in the control group, compared to the experimental group, did not receive any improvement suggestions from the tool. All the products for the control group were added to our database with a control group identifier and went through the same re-crawling process as the product pages from the experimental group did. Thus, we were able to determine changes and improvements for these product pages as well. By including a control group, we can strengthen the validity of our results. This approach allows us to control for random changes on the product pages that are not caused by the APLO tool intervention.

Finally, we determined how strongly the product pages had changed over time, comparing the experimental and control group. As a result, we can determine the effectiveness of the APLO tool with regards to the actual impact on product-page quality. In the end, our tool is successful when the sellers implement our suggestions to increase their business success.

The first (initial) analysis of a product page by the APLO tool is the baseline measurement (T = 0) of all product-page factors. It takes place immediately before the intervention (output of improvement suggestions). After the first analysis, we automatically re-crawl the product page at nine points in time: 2:30 hours (T1), 12 hours (T2), one day (T3), two days (T4), three days (T5), five days (T6), ten days (T7), 20 days (T8), and 30 days (T9) after the initial analysis. The collection of data takes place on a rolling basis. In the beginning, the frequency of observations is higher because we assume that some users will implement the improvement suggestions shortly after the intervention. A high frequency enables us to determine the time of implementation of the optimizations more precisely. Already on the same day of the baseline measurement, we re-crawl product pages two times to assess whether the proposed improvements have already been implemented. Some suggestions can be integrated by sellers easily and with little expenditure of time. For example, the number of bullet points or the number of product images can be adjusted quickly by the seller. The first automatic re-crawling takes place 2:30 hours after the intervention. The second check takes place after 12 hours. However, not all suggestions from the tool can be implemented within such a short period of time. The number of ratings or participation in the "Fulfillment by Amazon" (FBA) service requires a longer time for implementation. Therefore, we also re-crawl each product page 10, 20, and 30 days after the first analysis and check if the user has implemented further improvements. By doing this, we can additionally determine how many days users need to integrate the suggested improvements.

Online experiments are particularly suitable for a large number of participants and long study durations for which another research method would be very time-consuming and costly (Reips, 2002). Automatic digital processing allows us to carry out a large number of experimental sessions at a low cost. Since all processes and requests of the examined APLO tool are entirely digital, all data generated in this context can be easily and cost-efficiently stored in a database.

Online survey

Besides evaluating whether an information system works, a comprehensive evaluation should also determine how and why it works (Pries-Heje, Baskerville, & Venable, 2008). With an online survey, we can ask tool users about their satisfaction with the tool and gain deeper insights. Our online survey is a self-administered questionnaire where participants complete the questionnaire independently (Healey, Baron, & Ilieva, 2002). Users are invited to participate in the survey on the APLO tool website after the test result section.

With the increasing adaptation of computers and the Internet, online surveys have also become increasingly important for research in recent years and decades. The first online surveys were applied in the 1990s. Evans and Mathur (2018) provide a comprehensive and systematic overview of the development of online surveys and their advantages and disadvantages. A major advantage of an online survey, especially compared to a paper survey, is its flexibility (Evans & Mathur, 2005). Online surveys can be conducted in different formats (e-mail, embedded, link to URL). For the present survey, the embedded form was the best solution. Since only the participants who had actually used the tool were eligible for our survey, we integrated the survey directly into the APLO tool website. In this way, we can profit from the advantage of an online survey to make it directly accessible for a specific target group. The APLO tool website is available in German and English. Therefore, we were able to provide the survey language that was suitable for the individual user. Users could choose the correct language directly on the website. Moreover, an online survey can be conducted easily, quickly, and cost-efficiently (Evans & Mathur, 2005). The automatic, digital data collection also allows for faster processing and analysis (van Selm & Jankowski, 2006). Technological innovations and tools also enable a simple yet comprehensive survey to be created (van Selm & Jankowski, 2006; Wright, 2005). For the survey in this study, we used the tool "Typeform." It is characterized by the fact that it can be integrated particularly seamlessly into a website and is optimally displayed on desktop computers as well as on mobile devices. In addition, the design and layout are simple, which makes it easy for participants to fill out the forms. Online surveys also offer a high degree of convenience, as participants can fill out the survey at any time. Furthermore, participants are not exposed to time pressures when filling out the questionnaire. With the help of online surveys, different types of questions (e.g., multiple-choice, open-ended questions, etc.) can be implemented. The order in which questions are answered can be better controlled in online surveys and the required answers can be defined (Evans & Mathur, 2018). By combining quantitative and qualitative questions, as well as open-ended questions, we were able to obtain rich and diverse data (Altintzoglou, Sone, Voldnes, Nøstvold, & Sogn-Grundvåg, 2018; Mauceri, 2016). The questionnaire consists of ten questions that can be filled out directly on the website. More information about the individual measurements can be found in section 8.3.4 of this study. Online surveys could also have potential weaknesses. A low response rate is a common problem. Here, we try to achieve a higher response rate by addressing the right target group and directly pointing tool users to the survey.

8.3.3 Participants and Recruitment

Gregori and Baltar (2013) investigate the use of new technologies for data collection. Social networks play a crucial role here. People are spending more and more time on social platforms, which makes it appropriate to address them here. Social networks have considerably changed the way people contact, communicate, and share information (Cheung, Xiao, & Liu, 2014). People in online networks reveal a lot about their interests. This enables advertisers and researchers to target their audience more effectively. The combination of social media sites and online experiments and surveys is, therefore, an excellent way to achieve higher participation rates (Gregori & Baltar, 2013). To make users aware of the APLO tool and the survey, we used four different channels.

(1) *Facebook groups* are great for connecting people with similar interests. Several groups deal specifically with topics related to selling on the Amazon Marketplace. We shared a post in six groups in which we introduced the tool and also specifically drew attention to the corresponding survey.

(2) *Facebook ads* allow for reaching a specific target group with paid ads. Through predefined targeting settings, we specifically addressed people who were interested in the Amazon Marketplace. Other settings covered location (Germany), age (18–60), and gender (all genders). The APLO tool ad was delivered across the entire Facebook ad network, including Instagram and the Facebook Display network.

(3) With *Google ads,* we were able to target people who were looking for Amazon optimization opportunities through specific keywords. Using the Google Keyword Planner tool, we first conducted a keyword analysis to identify suitable search terms. In the second step, we created a search network campaign with these keywords for users located in Germany. In total, we spent around €500 for all paid advertisements.

(4) A *print ad* in the E-commerce Germany Report allowed us to target Amazon sellers who are less active in social networks and search engines. The E-commerce Germany Report deals with topics around Amazon's market position and therefore has a very relevant readership to promote the APLO tool.

In total, we had 486 visitors on the APLO tool website in the 30-day data-collection period. Of all website visitors, 377 (77.57%) conducted a product-page analysis with the APLO tool. Users who conducted an analysis with the APLO tool in the 30-day period between March and April 2020 were participants in the online experiment. The control group was built by randomly selecting 161 product pages from Amazon. Each product page analyzed with the APLO tool was re-analyzed at nine points in time within a period of 30 days, and the respective values were stored in the database. This results in a total study duration of 60 days, so that even product pages that were analyzed for the first time on day 30 could go through a re-crawling period of 30 days (see Figure 6). Due to incorrect queries by the re-crawling script, 230 product pages from the intervention group and 20 pages from the control group had to be removed from the dataset (see Figure 7). So, in the end, there were 147 participants (product pages) in the experimental group and 140 in the control group. One hundred and two users of the tool took part in the online survey. It was active over a period of 60 days. In total, the users spent one minute and 38 seconds on average on the tool website. During the 30-day collection period, 11.7% of the visitors were returning visitors to the APLO tool website.

Figure 6: Timeline of the Study

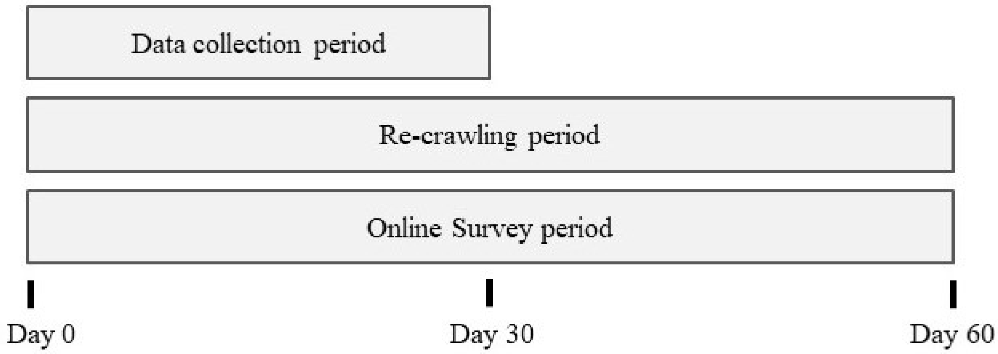
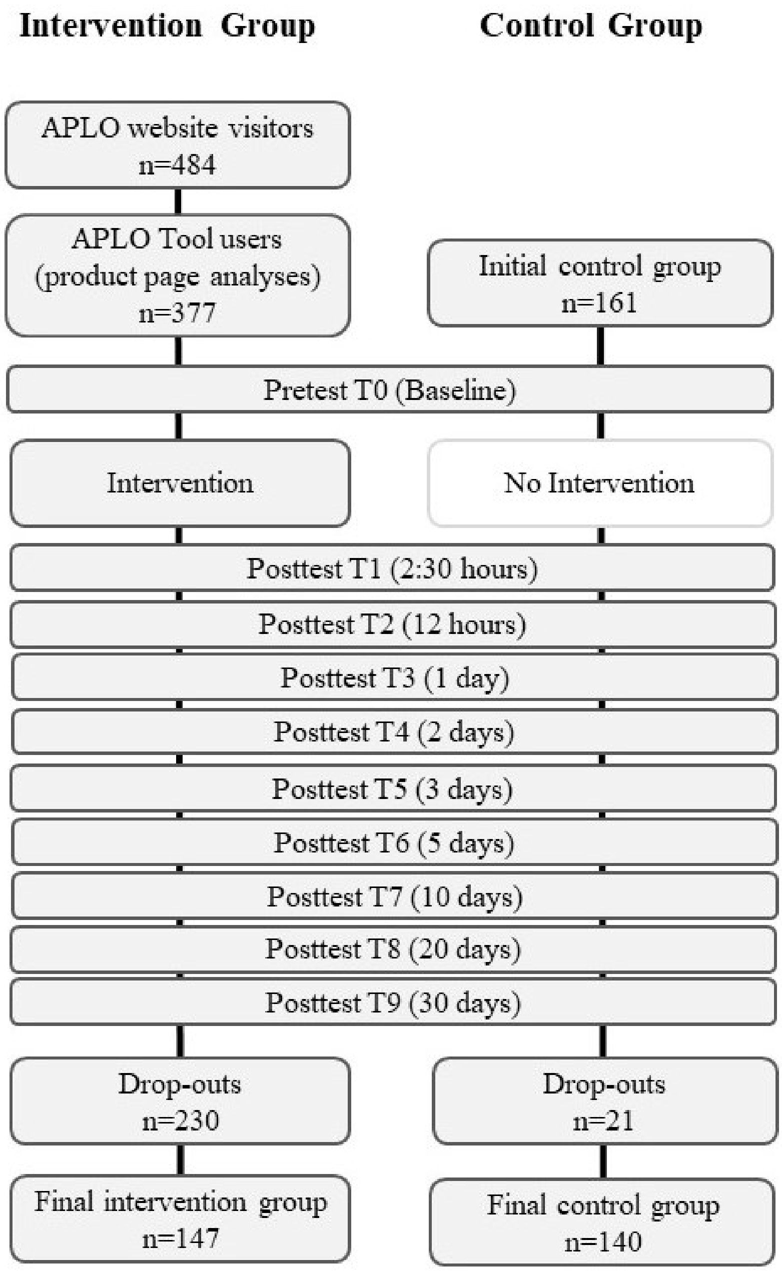


Figure 7: Participant Flow Through the Study



8.3.4 Measurements

Overall quality score. The goal of the APLO tool is to help Amazon sellers to improve their product listing and ultimately achieve higher conversion rates. With the APLO tool, the user gets improvement suggestions to optimize his or her Amazon product page. We measure the effectiveness of the tool by checking whether a user actually implements the product-page optimization suggestions by the APLO tool. For this, we use the overall quality score, which shows on a scale from 0 to 100 how well the product page is currently optimized. In classifying the score, we were guided by Google's PageSpeed Insights online service for optimizing website-loading speeds (Google, 2019). Values below 50 show that a product page is not yet well optimized. Values above 90 indicate a good product-page quality on Amazon. The overall quality score is composed of the nine individual product-page factor scores and thus reflects the quality of the product presentation in a single indicator. An overall quality score change reflects a change in the product page and is thus a core parameter for determining the effectiveness of the tool.

Sales Rank. The Amazon sales rank is another important measure to investigate our second RQ. By crawling and extracting product-page data from amazon.de, we also stored the sales rank for each product. The Amazon sales rankings are based on the sales on amazon.de and are updated hourly (Amazon, 2020g). Amazon does not disclose the exact sales figures for individual products. However, the sales rank indicates how well a product is selling compared to other products of the same category on Amazon (Li, Ch'ng, Chong, & Bao, 2016). Therefore the sales rank can be used as a proxy for sales performance, as many other studies have already done (e.g., Brynjolfsson, Hu, & Smith, 2003; Chevalier & Mayzlin, 2006). The score is reversely related to product sales. The higher the sales, the lower the sales rank (Amblee & Bui, 2011). The bestseller lists and ranks always refer to a specific category or subcategory. Therefore, the rank for two products from different categories says nothing about how well a product is selling compared to a similar product in another category. In order to correctly analyze the effect of the product-page quality on the sales rank, we use the change rates of both factors.

Online survey measures. Using a survey, we want to find out how satisfied customers are with the current artifact of the tool and what willingness they have to pay for the tool. The survey is designed to answer the third RQ. In the first question of the survey, we use the net-promoter score (NPS) measure to evaluate the loyalty of our users (Reichheld, 2003). With the question "How likely are you to recommend this tool to a friend or a colleague?" we can determine the number of promoters and detractors among our users. On a scale from 0 to 10, promoters are the users who select 9 or 10 (very likely to recommend). Users who select the value of 7 or 8 are considered passively satisfied. Detractors choose a value between 0 and 6. These users are very unlikely to recommend the tool. By subtracting the percentage of detractors from the percentage of promoters, the final NPS score is calculated. Companies that have very loyal customers achieve scores of 75% and more (Reichheld, 2003). The NPS can be measured easily and has high relevance. A high NPS is a reliable indicator of loyalty and growth because, through a recommendation, a user puts his or her reputation at risk. The user only bears this risk if he or she is truly loyal and satisfied (Reichheld, 2003). Based on the next three questions, we built a joint construct for user satisfaction (see Table 13). We asked participants about their general satisfaction with the tool (satisfaction), of the likelihood that they would reuse the tool (retention), and how useful they found the additional information (additional facts). All items are measured on a 7-point scale. The user satisfaction item can also be used as a countercheck to the first question (NPS), as we expect a high correlation for the results. We also investigated the user's understanding by asking whether the suggestions had been clearly formulated. In addition, we used two questions to examine user satisfaction with the tool's functionality. In two open questions, we allowed participants to tell us what they particularly liked about the tool and where they saw potentials for improvement. The next question focuses on the users' willingness to pay. Participants can choose an amount between €0 and €50. There are eight predefined choices (€0, €5, €10, €15, €20, €30, €40, or €50). Then we asked the user what the tool needs to provide so that he or she would pay more for it. Survey participants could answer this question in a text box. Finally, we gave the participants the opportunity to provide free feedback or comments on the last survey page.

Table 13: Online Survey Items for APLO Tool Evaluation

Variable	Questions	Scale
NPS	How likely are you to recommend this tool to a friend or a colleague?	11-Point Scale
User satisfaction		
Satisfaction	How satisfied are you generally with the tool?	7-Point Scale
Retention	How likely is it that you will use the tool again?	7-Point Scale
Additional facts	Is the additional information (facts & figures) on your product category useful for you?	7-Point Scale
Understanding	Are the tool's suggestions clear to you?	7-Point Scale
Tool functionality	What do you like about this tool?	Text
	What can we improve in this tool? Which functions would you like?	Text
Willingness to pay	How much would you be willing to pay for the tool per month?	8 Choices
	What would the tool need to provide so that you would pay more for it?	Text

8.3.5 Statistical Analysis

Power analysis (powered on the overall quality score) revealed that 40 product pages were sufficient to investigate the effect of our intervention with the APLO tool (power = 0.80; $\alpha = 0.05$; effect size = 0.25). We compared the four product-page characteristics of overall quality score, price, FBA (product is shipped by seller or Amazon), and brand product (product has brand content on Amazon) at baseline by an independent sample *t* test to detect baseline differences between the intervention and control group. The intervention effects on the product pages' overall quality score were examined by conducting a repeated measures ANOVA. We use time as the within-factor (differences between pretest and posttests) and condition (intervention group, control group) as between factor. As the repeated measures ANOVA is an omnibus statistical test, we additionally examined a post hoc test to identify when exactly the users implemented the improvement suggestions. To receive valid results from a mixed ANOVA analysis, our data had to meet several assumptions. In our preliminary analysis, we calculated descriptive statistics of sample characteristics and checked the normality of key variables. The Shapiro–Wilk test of normality revealed significant results, meaning the assumption of normality was violated. However, the graphical analyses of normality revealed a moderate deviation from normality. Moreover, the repeated measures ANOVA is a relatively robust procedure referring to the violation of normality (Glass, Peckham, & Sanders, 1972; Lumley, Diehr, Emerson, & Chen, 2002). Therefore, we undertook no corrections. The dataset had no outliers. The Greenhouse–Geisser adjustment was used to correct for violations of sphericity (Salkind, 2007). There was homogeneity of the error variances, as assessed by Levene's test ($p > .05$).

8.4 Results

In total, we conducted the study with 287 product pages. The intervention group included 147 analyzed product pages and the control group 140. The baseline characteristics of the intervention and control group did not show significant differences in the four analyzed factors of overall quality score, price, FBA, and brand product, with *p* values between $p = .074$ and $p = .984$.

Table 14 shows the basic descriptive statistics for all of the analyzed product-page factors of the intervention group at time T0 and T9.

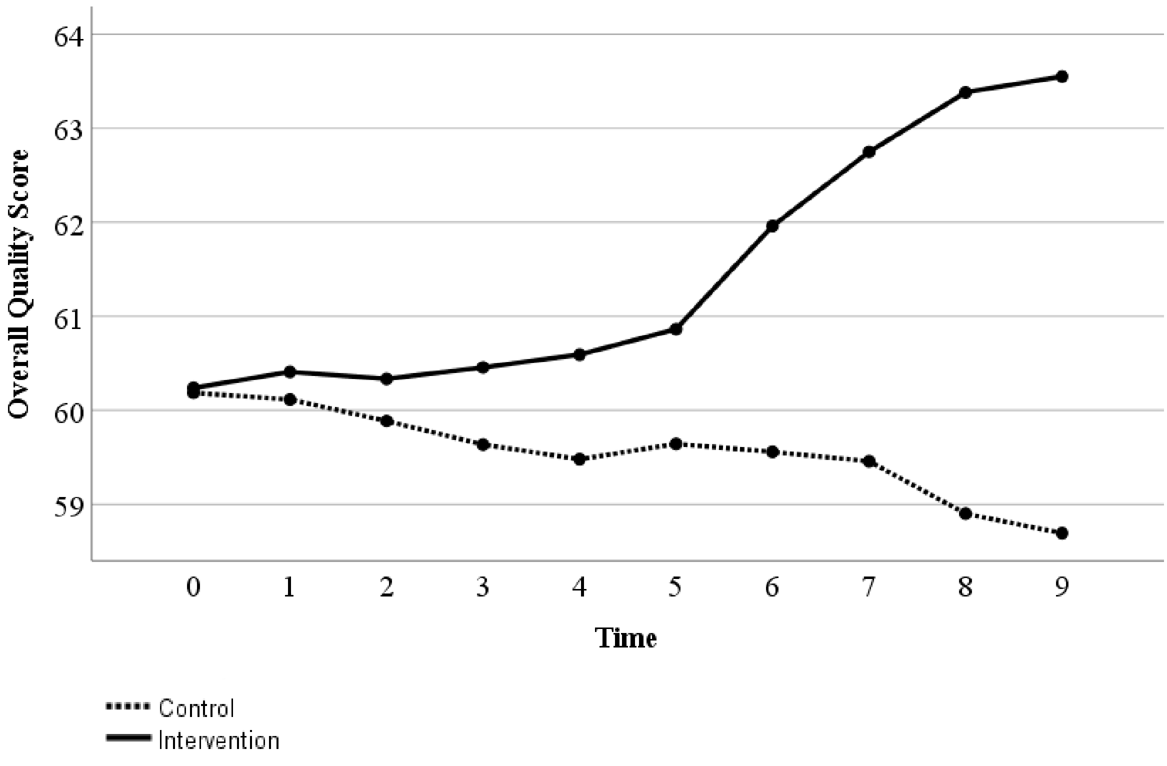
Table 14: Descriptive Statistics for the Intervention Group

	T0			T9		
Product-page factors	**Mean (*SD*)**	**Min.**	**Max.**	**Mean (*SD*)**	**Min.**	**Max.**
Overall quality score	60.24 (21.06)	13	97	63.55 (19.43)	14	97
Number of images	5.19 (2.35)	0	7	5.66 (1.87)	0	7
Video	0.13 (0.34)	0	1	0.14 (0.34)	0	1
Number of ratings	536 (2227)	0	18.057	544 (2230)	0	18.057
Average rating	3.84 (1.55)	1	5	3.94 (1.46)	1	5
Number of bullet points	4.80 (1.66)	0	11	4.84 (1.62)	0	11
Length of bullet points	834 (520)	0	2264	910 (476)	0	2264
Length of description	2012 (2107)	0	15.046	2078 (2141)	0	15.046
A+ content	0.46 (0.50)	0	1	0.50 (0.50)	0	1
Fulfillment by Amazon (Prime)	0.65 (0.48)	0	1	0.73 (0.44)	0	1

Intervention effects on product-page quality

With a repeated measures ANOVA, we analyzed the two-way interaction effects. It showed that the intervention group had a significant increase in the overall quality score (Greenhouse–Geisser $F(2.16, 616.04) = 19.67$, $p < 0.001$; partial $\eta^2 = 0.065$) compared to the control group. Additionally, we tested the simple main-effects of the between-factor (group). A Welch post hoc test showed that the two groups differed significantly 30 days after the intervention ($p < .05$) (see Appendix 2). The overall quality score increased from an average of 60.24% (T0) to 63.55% (T9) in the intervention group. In the control group, however, the score decreased from 60.19% (T0) to 58.69% (T9) (see Figure 8). In order to check whether users implemented some of the tool's improvement suggestions directly after the intervention, we conducted posttests immediately on the same day of the intervention (T1 and T2). However, the intervention group showed no significant improvements at these points in time compared to the control group. Besides, we tested simple main-effects of the within-factor (time). The control group showed a statistically significant effect of time on overall quality scores, Greenhouse–Geisser $F(2.81, 390.40) = 4.29$, $p < .05$, partial $\eta^2 = .03$. Also, the intervention group showed a statistically significant effect of time on overall quality scores, Greenhouse–Geisser $F(1.83, 266.60) = 17.25$, $p < .001$, partial $\eta^2 = .11$. With a pairwise comparison, we identified where exactly the differences were (see Appendix 3). In the control group, significant effects were found between baseline T0 and T9 (1.49, $p = .048$). In the intervention group, significant effects were found between baseline T0 and T7 (−2.51, $p = .001$), T8 (−3.14, $p < .001$), and T9 (−3.13, $p < .001$).

Figure 8: Overall Quality Score Change Over Time Between the Intervention and Control Group



Effect of product-page quality enhancement on sales rank on Amazon

With linear regression analysis, we investigated how a change in the quality of the product presentation (overall quality score) affects the change in the sales rank on Amazon. The data must meet several assumptions in order to obtain valid results and allow for correct interpretation. The linear relationship between the variables was checked with a scatter diagram and was given. Based on casewise diagnostics, six outliers were identified and excluded from the analysis. The model had no auto-correlation as the value of the Durbin–Watson statistic was 1.792. The variance equality of the residuals was checked with a scatter diagram and was given. We checked the normal distribution of the residuals visually with a histogram and a P-P-plot. The normal distribution was not optimal but was still acceptable.

The results indicate that the overall quality score significantly predicts the sales rank on Amazon ($F(1, 136) = 350.696$, $p < .000$), with an R^2 of .721. If the product-page quality (overall quality score) improves by one percentage point, the sales rank improves by 0.996 percentage points. Seventy-two percent of the spread of the sales rank change is explained by the change in the overall quality score. According to Cohen, this is a strong effect.

Online survey

The online survey gave us insights into the user's satisfaction, user's understanding, tool functionality, and willingness to pay for the APLO tool. Based on all survey participants ($n = 102$), we could determine an NPS of 60.8% for the APLO tool. This results from 71.6% of the APLO tool users being promoters and 10.8% being detractors. The average score for user satisfaction was 5.83 on a 7-point scale, where 7 represents *highly satisfied*, and 1 represents *not satisfied at all*. For reliability analysis, Cronbach's alpha (Cronbach, 1951) was calculated to assess the internal consistency of the subscale, which consists of three questions (see Table 13). The internal consistency of the construct is good, with Cronbach's alpha = .816. The average user's understanding of the tool was high, with an average score of 5.48 on a 7-point scale. For the evaluation of the open questions, we conducted a qualitative content analysis following Mayring (2002). In order to systematically evaluate the statements of the participants, the statements given for the two open questions on tool functionality were grouped into categories with similar content (Mayring, 2015). The inductive category formation was applied. We were also able to put the categories into hierarchical order. The category with the most similar statements comes first. The following content categories were formed based on the statements referring to the question regarding what users liked about the tool: (1) content (suggestions), (2) design, and (3) simplicity. An example of a statement from the content category is the feedback of a user, who points out that the suggestions are well explained. As an example of the design category, another user notes that the clarity of the outcomes and suggestions is positive. Statements from the "simplicity" category emphasize positive aspects about the usability and speed of the tool. For the question regarding what we could still improve on the tool or which functions were desired, we were able to group the answers into four categories: (1) analysis of variants, (2) keyword-based statistics, (3) quality analysis of texts, and (4) knowledge database. Due to the complex structure of some variant articles on Amazon, the APLO tool may have problems retrieving and extracting all of the factors from the Amazon website. The user will then get an error message. In the category "analysis of variants," we have summarized all of the statements of those users who raised an issue regarding analyzing variant products. Other users would like to have statistics on keywords, for example, how often a keyword appears on the product page and which keywords are used by competing products. Another desired feature would be a qualitative text analysis, for example, for the product description. Lastly, users mentioned that an additional knowledge database could complement the tool and would be helpful to gain even more in-depth knowledge about optimization possibilities.

The average willingness to pay per month for the current version of the APLO tool was €5.55. Overall, 66.7% of the users had a willingness to pay for the tool, whereas 30.40% would not pay for the current version of the tool. Three participants did not provide an answer to this question. Most of the users (43.1%) would pay up to €5 per month and 8.9% of the users were willing to pay €15 or more. In order for users to pay more for the tool, it would have to offer even more functionality. Several users would like to have a wider range of functions and further analysis of the data. An ongoing analysis of the product pages with an individual dashboard was mentioned. Other users would like to see real improvements to the product page through the tool and not just suggestions. Also, the simultaneous analysis of multiple products was required for a higher willingness to pay.

8.5 Discussion and Conclusion

8.5.1 Discussion

This study investigated the effectiveness of the APLO tool in supporting sellers in the implementation of product-page optimizations on Amazon. We also examined after how many days significant product-page changes can be observed. The analyses demonstrated that the APLO tool improvement suggestion intervention had a significant effect on product-page quality 30 days after the intervention compared to the control group. Thus, the APLO tool is effective in supporting the implementation of product-page optimizations. The overall quality score was increased in the intervention group from an average of 60.24% (T0) to 63.55% (T9) within the 30-day study period. From all 147 users of the intervention group who had used the tool, 50 (34%) actually implemented improvements on their product page within a period of 30 days after the initial tool analysis. A look at the individual product-page factors and how they have changed within the 30-day period shows that users particularly optimized two factors: number of images and the length of bullet points. This is reasonable, as these are two factors that can be implemented easily and quickly. In contrast, the number of ratings had only increased slightly. Sellers have fewer options here to influence this factor directly.

As already shown in the literature section, recommendation tools can generate positive outcomes. With this study, we can enhance this research stream by showing that an online recommendation tool can also effectively contribute to improvements in the context of online retail platforms. By comparing overall quality score changes in the intervention group, we found significant changes starting at T7 compared to baseline (T0). Contrary to our assumption, we could not find a significant improvement in product-page quality on the same day or one day after the intervention. This shows that the users of the tool did not immediately implement the suggestions. One reason for this could be that users test the tool purely informatively at first use. The implementation of the suggestions will then take place at a later date. In some cases, the administration of Amazon product pages is done externally by a service provider. Possibly, the user of the tool is not the one who can implement the suggestions directly. This causes a further time delay.

What is also remarkable is that the overall quality score in the control group even dropped slightly within the 30-day study period from 60.19% (T0) to 58.69% (T9) (see Figure 8). This indicates that the product page may lose quality without ongoing optimization, and it emphasizes the importance of the APLO tool.

Additionally, we investigated how these product-page optimizations affect the sales rank on Amazon. As numerous studies have already shown, improvements in product-page quality can increase purchase intention and conversion rates. With this study, we re-evaluated this relationship and show that the product-page improvements achieved through the APLO tool suggestions significantly improved the sales rank. All of the users who implemented at least one suggestion from the APLO tool increased their sales rank by an average of 21.93%. If the product-page quality (overall quality score) improves by one percentage point, the sales rank improves by 0.996 percentage points.

This illustrates that an improvement in the overall product-page quality leads to an almost equal improvement in the sales rank. This underlines our assumption that the enhancement of overall product-page quality contributes to an improvement in sales performance. In addition to some studies that examine individual factors, we can thus show that a comprehensive and integrated view of product-page quality is important for improving sales performance.

Based on an additional online survey, we gained even more insights into the users' satisfaction with the tool and possible improvements. The results show that a knowledge base or an online learning area could be integrated next into the APLO tool to increase understanding and, thus, the implementation rate of the suggestions. For example, some users do not know how to increase the number of ratings for a product. A knowledgebase could offer extensive explanations and instructions that could provide high added value for the user. In the long run, the tool could develop into a comprehensive digital analytics and learning tool that supports Amazon sellers in various ways.

The APLO tool improvement suggestions can also act as reference points or goals for tool users (Imschloss & Lorenz, 2018). Studies show that such reference points can help to achieve the desired outcome (Heath, Larrick, & Wu, 1999). Loss aversion also plays a role in this context. The fear of having a poor conversion rate or not having fully exploited the potential, and thus losing sales, could encourage users to implement the suggestions. Through the online survey, we also found that users would like to see a concrete indicator that shows how many percentage points the conversion rate can be increased by optimizing a specific factor. The quantification of a concrete conversion rate loss or potential gain could strengthen the loss-aversion effect. The integration of gamification elements could also increase the implementation rate of the suggestions by setting goals and receiving virtual rewards for achieving them (Antonaci, Klemke, Stracke, & Specht, 2017; Tondello, Premsukh, & Nacke, 2018, January 3-6). An individual dashboard for every user, in which the product-page quality of his or her own products can be tracked over time would also be of added value for the users. Over two-thirds of all survey participants had a willingness to pay for the tool. This is a very positive signal and important for a sustainable future development of the tool.

With this study, we could also show how an online experiment and a remote recruitment and data-collection process with marketing via social media and online advertising platforms can be used to address a specific target group in a short time and generate high-quality research data (Reips, 2002). Our digital, technical infrastructure enabled us to record extensive data and real-world behavior.

8.5.2 Implications

Sellers can use the APLO tool to quickly and easily get product-specific and evidence-based suggestions for product-page improvements. This allows sellers to gain an advantage on the platform and differentiate themselves from other sellers and products. This leads to a higher conversion rate and, thus, to better sales performance. For Amazon, the conversion rate is an essential indicator of the attractiveness of a product from the customer's perspective (Purohit, 2020). Products with a higher conversion rate are presented more visibly on the category and search result pages as well as on the entire platform. With the APLO tool, we provide individual improvement suggestions for a specific product. By crawling the respective product page on Amazon, we obtain nine relevant product-page factors and analyze them in terms of our evidence-based findings. In the next step, we create individual optimization suggestions for the retailer weighted according to optimization potential. This allows the seller to prioritize the optimization activities. In addition, the tool gives users additional metrics about the specific category in which the product is listed on Amazon. Therefore, the APLO tool not only enables the assessment of the product-page quality but also gives a better understanding of the product category characteristics on Amazon. With the APLO tool, we can save users time by providing a comprehensive evaluation of all relevant product-page factors on a single website. Users no longer need to obtain information about individual product-page factors from different sources. Thus, we reduce the search costs of the tool users.

Considering that online recommendation tools constitute a promising, cost-effective way to improve a desired outcome, the findings of this study should be of interest to other business areas and app designers. While some intervention tools already exist, especially in the health sector (e.g., Coughlin & Stewart, 2016; Direito, Jiang, Whittaker, & Maddison, 2015; Safran Naimark, Madar, & Shahar, 2015), there are many other business areas where online or mobile intervention applications could be useful and still have vast potential. For example, in the entrepreneurship area, the process of building a venture could be accompanied by an intervention tool that stimulates improvement potential based on real-time business data. This could also increase the motivation of tool users (Read & Kukulska-Hulme, 2015).

8.5.3 Limitations and Future Research

In this section, we would like to highlight the limitations of this study and some future research possibilities. With the APLO tool, we address a specific user group. There is a self-selection of users who are sellers on the Amazon Marketplace. For other users, the APLO tool does not offer any benefit at the moment. Sellers select themselves by using the tool. However, by promoting the tool through various online and offline channels (see chapter 8.3.3), we have tried to attract a diverse and representative group of Amazon sellers. In addition, the present study was conducted exclusively with sellers of the German Marketplace (amazon.de). An extension to international Amazon Marketplaces could provide further insights. A comparison of whether the key figures differ between international Marketplaces may be instructive. Therefore, this study is subject to these restrictions, which may affect the generalizability of the results and conclusions.

With a posttest period of 30 days, users may not be able to implement all of the suggestions, although they have the intention of doing so. Possibly the follow-up period for measurement is too short. For example, the production of a product video may take longer than 30 days. Although users may already be working on the implementation of this suggestion, we have not yet been able to determine any implementations in our investigation period. The measurement of the effectiveness of the tool could be negatively affected, even though users are working on product-page improvements. On the other hand, it can also happen that the factors of "average rating" and "number of ratings" are positively influenced without the users actively encouraging this improvement. Thus, the positive and negative effects on the measurement of effectiveness could, to a certain extent, compensate each other. Therefore, we assume that the distortion of the results is minimal. Besides, the experimental setting of this study with a control group allows us to largely exclude that the effects are due to coincidental changes in the product page.

Currently, we calculate the influence of the individual product-page factors on the conversion rate for the entire German Amazon Marketplace. A category-specific analysis could provide deeper insights into whether factors differ in specific categories. Studies show that product categories can differ in their characteristics (Redmond, 1995). For example, the number of images could be more important in the category of *Fashion* than in the *Books* category.

In this study, we focus on the evaluation of the effectiveness of the tool. In the next step, the design and structure of the tool could be analyzed in more detail in a design science research study. A comprehensive usability study could provide further insights into how to improve the usefulness of the tool even further. Different user-centered design methods play an important role here and could be used to conduct a usability study with a design science research approach (Schnall, Rojas, Travers, Brown, & Bakken, 2014).

8.5.4 Conclusion

Synthesizing the results from the previous studies, we build a practical intervention tool, implemented in the form of an online application. The *Amazon Product Listing Optimization (APLO) tool* should help companies to optimize their product listings on Amazon to achieve a higher conversion rate. With the APLO tool, we focus on the improvement in digital venture coaching. With the help of our tool, retailers get assistance and evidence-based optimization suggestions for their Amazon product pages. A retailer only has to provide a web address for the Amazon product page in our tool and automatically receives an evaluation for the respective product. Better access and distribution of decision-relevant information to the core target group of startups and retail-focused companies is the primary goal of the APLO tool. With an experimental intervention study, we investigate the effectiveness of the tool in the field. Sellers who use the APLO tool could significantly improve the quality of their product pages. These quality enhancements also lead to improvements in the sales rank on Amazon. Thus, the APLO tool effectively helps sellers to improve their product-page quality and sales performance.

Appendices

Appendix 1: Implementation Details of Algorithms

Our neural network consisted of a total of seven input layers. The first of these handled the current and previous month's conversion rate; the second input layer handled all legitimacy-enhancing variables, and the five additional dealt with the five categorical variables. In so doing, we followed Guo and Berkhahn (2016) and condensed these highly dimensional features using entity embeddings to improve the predictive ability of the network. The two input layers for the conversation rates and the legitimacy variables were combined with the concatenation layer. After this concatenation layer, we stacked three dense layers with 128, 128, and 32 neurons and used a rectified linear unit (relu) activation function that can be considered as standard choice (Chollet, 2018). In order to fight overfitting, we added a dropout layer with a dropout rate of 0.3 after each dense layer. Across all bootstrap samples, we trained the neural networks on a mean squared error loss function using an Adam optimizer over 50 epochs with a batch size of 5. The architecture of the overall network and its parametrization were chosen after an intense cross-validation procedure.

For training the gradient boosted decision trees, we have chosen a loss function that is well-suited for nearly poisson distributed data as our conversion rates and that minimizes the negative log-likelihood. We trained each tree ensemble for 200 rounds, using a minimum loss reduction of 10 for regularization, a maximal tree depth of 10, a minimum child weight of 0.2, and a learning rate of 0.1. Again, all these parameters were identified by an intensive cross-validation procedure.

Appendix 2: Robust Test of Equality of Means

		Statistic[a]	df1	df2	Sig.
Overall Quality Score T0	Welch-Test	,000	1	282,805	,984
Overall Quality Score T1	Welch-Test	,013	1	282,647	,908
Overall Quality Score T2	Welch-Test	,031	1	282,798	,859
Overall Quality Score T3	Welch-Test	,105	1	282,728	,746
Overall Quality Score T4	Welch-Test	,197	1	282,303	,658
Overall Quality Score T5	Welch-Test	,240	1	281,667	,625
Overall Quality Score T6	Welch-Test	,960	1	279,208	,328
Overall Quality Score T7	Welch-Test	1,843	1	277,998	,176
Overall Quality Score T8	Welch-Test	3,435	1	278,156	,065
Overall Quality Score T9	Welch-Test	4,033	1	278,999	,046

a. Asymptotically F distributed

Appendix 3: Pairwise Comparison

control	(I)Time	(J)Time	Mean difference (I-J)	Std. error	Sig.[b]	95% Confidence Interval for Difference[b]	
						Lower Bound	Upper Bound
1	T0	T1	,071	,079	1,000	-,191	,334
		T2	,300	,186	1,000	-,319	,919
		T3	,550	,225	,717	-,201	1,301
		T4	,707	,263	,363	-,169	1,583
		T5	,543	,289	1,000	-,419	1,505
		T6	,629	,296	1,000	-,357	1,614
		T7	,729	,379	1,000	-,534	1,991
		T8	1,286	,415	,105	-,095	2,666
		T9	1,493*	,447	,048	,005	2,980
	T1	T0	-,071	,079	1,000	-,334	,191
		T2	,229	,169	1,000	-,334	,791
		T3	,479	,212	1,000	-,228	1,186
		T4	,636	,252	,579	-,204	1,476
		T5	,471	,279	1,000	-,457	1,399
		T6	,557	,286	1,000	-,396	1,510
		T7	,657	,372	1,000	-,582	1,896
		T8	1,214	,424	,216	-,197	2,625
		T9	1,421	,457	,101	-,099	2,942
	T2	T0	-,300	,186	1,000	-,919	,319
		T1	-,229	,169	1,000	-,791	,334
		T3	,250	,132	1,000	-,189	,689
		T4	,407	,241	1,000	-,395	1,210
		T5	,243	,290	1,000	-,722	1,208
		T6	,329	,298	1,000	-,662	1,319
		T7	,429	,381	1,000	-,841	1,698
		T8	,986	,434	1,000	-,459	2,431
		T9	1,193	,467	,525	-,362	2,747
	T3	T0	-,550	,225	,717	-1,301	,201
		T1	-,479	,212	1,000	-1,186	,228

		T2	-,250	,132	1,000	-,689	,189
		T4	,157	,209	1,000	-,537	,852
		T5	-,007	,285	1,000	-,956	,942
		T6	,079	,290	1,000	-,886	1,044
		T7	,179	,376	1,000	-1,073	1,430
		T8	,736	,431	1,000	-,701	2,172
		T9	,943	,465	1,000	-,606	2,492
	T4	T0	-,707	,263	,363	-1,583	,169
		T1	-,636	,252	,579	-1,476	,204
		T2	-,407	,241	1,000	-1,210	,395
		T3	-,157	,209	1,000	-,852	,537
		T5	-,164	,193	1,000	-,808	,480
		T6	-,079	,231	1,000	-,849	,691
		T7	,021	,333	1,000	-1,087	1,130
		T8	,579	,396	1,000	-,741	1,898
		T9	,786	,433	1,000	-,657	2,229
	T5	T0	-,543	,289	1,000	-1,505	,419
		T1	-,471	,279	1,000	-1,399	,457
		T2	-,243	,290	1,000	-1,208	,722
		T3	,007	,285	1,000	-,942	,956
		T4	,164	,193	1,000	-,480	,808
		T6	,086	,126	1,000	-,334	,505
		T7	,186	,322	1,000	-,886	1,257
		T8	,743	,351	1,000	-,427	1,913
		T9	,950	,393	,756	-,357	2,257
	T6	T0	-,629	,296	1,000	-1,614	,357
		T1	-,557	,286	1,000	-1,510	,396
		T2	-,329	,298	1,000	-1,319	,662
		T3	-,079	,290	1,000	-1,044	,886
		T4	,079	,231	1,000	-,691	,849
		T5	-,086	,126	1,000	-,505	,334
		T7	,100	,299	1,000	-,896	1,096
		T8	,657	,336	1,000	-,460	1,775

		T9	,864	,377	1,000	-,391	2,119
	T7	T0	-,729	,379	1,000	-1,991	,534
		T1	-,657	,372	1,000	-1,896	,582
		T2	-,429	,381	1,000	-1,698	,841
		T3	-,179	,376	1,000	-1,430	1,073
		T4	-,021	,333	1,000	-1,130	1,087
		T5	-,186	,322	1,000	-1,257	,886
		T6	-,100	,299	1,000	-1,096	,896
		T8	,557	,269	1,000	-,338	1,452
		T9	,764	,318	,797	-,296	1,825
	T8	T0	-1,286	,415	,105	-2,666	,095
		T1	-1,214	,424	,216	-2,625	,197
		T2	-,986	,434	1,000	-2,431	,459
		T3	-,736	,431	1,000	-2,172	,701
		T4	-,579	,396	1,000	-1,898	,741
		T5	-,743	,351	1,000	-1,913	,427
		T6	-,657	,336	1,000	-1,775	,460
		T7	-,557	,269	1,000	-1,452	,338
		T9	,207	,175	1,000	-,377	,791
	T9	T0	-1,493*	,447	,048	-2,980	-,005
		T1	-1,421	,457	,101	-2,942	,099
		T2	-1,193	,467	,525	-2,747	,362
		T3	-,943	,465	1,000	-2,492	,606
		T4	-,786	,433	1,000	-2,229	,657
		T5	-,950	,393	,756	-2,257	,357
		T6	-,864	,377	1,000	-2,119	,391
		T7	-,764	,318	,797	-1,825	,296
		T8	-,207	,175	1,000	-,791	,377
2	T0	T1	-,170	,114	1,000	-,549	,209
		T2	-,095	,138	1,000	-,555	,365
		T3	-,218	,179	1,000	-,812	,377
		T4	-,354	,241	1,000	-1,154	,446
		T5	-,626	,278	1,000	-1,551	,299

		T6	-1,721	,521	,055	-3,456	,014
		T7	-2,510*	,576	,001	-4,426	-,595
		T8	-3,143*	,612	,000	-5,180	-1,105
		T9	-3,313*	,649	,000	-5,474	-1,152
	T1	T0	,170	,114	1,000	-,209	,549
		T2	,075	,077	1,000	-,182	,332
		T3	-,048	,134	1,000	-,494	,399
		T4	-,184	,210	1,000	-,884	,516
		T5	-,456	,254	1,000	-1,300	,388
		T6	-1,551	,509	,122	-3,243	,141
		T7	-2,340*	,564	,003	-4,215	-,465
		T8	-2,973*	,602	,000	-4,977	-,969
		T9	-3,143*	,640	,000	-5,273	-1,013
	T2	T0	,095	,138	1,000	-,365	,555
		T1	-,075	,077	1,000	-,332	,182
		T3	-,122	,152	1,000	-,629	,384
		T4	-,259	,222	1,000	-,997	,480
		T5	-,531	,240	1,000	-1,330	,269
		T6	-1,626	,512	,082	-3,330	,078
		T7	-2,415*	,566	,002	-4,299	-,531
		T8	-3,048*	,604	,000	-5,058	-1,037
		T9	-3,218*	,642	,000	-5,353	-1,082
	T3	T0	,218	,179	1,000	-,377	,812
		T1	,048	,134	1,000	-,399	,494
		T2	,122	,152	1,000	-,384	,629
		T4	-,136	,162	1,000	-,676	,404
		T5	-,408	,216	1,000	-1,127	,311
		T6	-1,503	,492	,119	-3,139	,132
		T7	-2,293*	,559	,003	-4,152	-,433
		T8	-2,925*	,598	,000	-4,916	-,934
		T9	-3,095*	,649	,000	-5,256	-,935
	T4	T0	,354	,241	1,000	-,446	1,154
		T1	,184	,210	1,000	-,516	,884

		T2	,259	,222	1,000	-,480	,997
		T3	,136	,162	1,000	-,404	,676
		T5	-,272	,172	1,000	-,845	,301
		T6	-1,367	,476	,211	-2,952	,217
		T7	-2,156*	,547	,006	-3,976	-,337
		T8	-2,789*	,587	,000	-4,743	-,836
		T9	-2,959*	,639	,000	-5,086	-,832
	T5	T0	,626	,278	1,000	-,299	1,551
		T1	,456	,254	1,000	-,388	1,300
		T2	,531	,240	1,000	-,269	1,330
		T3	,408	,216	1,000	-,311	1,127
		T4	,272	,172	1,000	-,301	,845
		T6	-1,095	,461	,845	-2,629	,438
		T7	-1,884*	,537	,027	-3,669	-,099
		T8	-2,517*	,580	,001	-4,445	-,589
		T9	-2,687*	,631	,002	-4,786	-,588
	T6	T0	1,721	,521	,055	-,014	3,456
		T1	1,551	,509	,122	-,141	3,243
		T2	1,626	,512	,082	-,078	3,330
		T3	1,503	,492	,119	-,132	3,139
		T4	1,367	,476	,211	-,217	2,952
		T5	1,095	,461	,845	-,438	2,629
		T7	-,789	,289	,321	-1,751	,173
		T8	-1,422*	,390	,017	-2,720	-,123
		T9	-1,592*	,465	,036	-3,140	-,044
	T7	T0	2,510*	,576	,001	,595	4,426
		T1	2,340*	,564	,003	,465	4,215
		T2	2,415*	,566	,002	,531	4,299
		T3	2,293*	,559	,003	,433	4,152
		T4	2,156*	,547	,006	,337	3,976
		T5	1,884*	,537	,027	,099	3,669
		T6	,789	,289	,321	-,173	1,751
		T8	-,633	,286	1,000	-1,583	,317

		T9	-,803	,383	1,000	-2,077	,472
	T8	T0	3,143*	,612	,000	1,105	5,180
		T1	2,973*	,602	,000	,969	4,977
		T2	3,048*	,604	,000	1,037	5,058
		T3	2,925*	,598	,000	,934	4,916
		T4	2,789*	,587	,000	,836	4,743
		T5	2,517*	,580	,001	,589	4,445
		T6	1,422*	,390	,017	,123	2,720
		T7	,633	,286	1,000	-,317	1,583
		T9	-,170	,217	1,000	-,893	,553
	T9	T0	3,313*	,649	,000	1,152	5,474
		T1	3,143*	,640	,000	1,013	5,273
		T2	3,218*	,642	,000	1,082	5,353
		T3	3,095*	,649	,000	,935	5,256
		T4	2,959*	,639	,000	,832	5,086
		T5	2,687*	,631	,002	,588	4,786
		T6	1,592*	,465	,036	,044	3,140
		T7	,803	,383	1,000	-,472	2,077
		T8	,170	,217	1,000	-,553	,893

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

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List of Publications

Research papers

Knape, D., Hess, M., Blohm, I., Wincent, J., Grichnik, D. (2020). Predicting success of product introductions with online legitimacy on digital marketplaces: A machine learning approach. *Preparing Submission for Journal of Product Innovation Management*.

Knape, D., Hess, M., Grichnik, D. (2020). Amazon's market power decoded by the Amazon Market Dominance Index. *Published as a working paper on www.alexandria.unisg.ch*

Knape, D. (2020). Evaluation of the effectiveness of the Amazon Product Listing Optimization tool. *Published as a working paper on www.alexandria.unisg.ch*

Reports

digital kompakt (Ed.). (2020). E-Commerce Germany: Marktreport für Amazon & Co. Deep Dive Amazon Business. Berlin.

digital kompakt (Ed.). (2019). E-Commerce Germany: Marktreport für Amazon & Co. Deep Dive Fashion. Berlin.

digital kompakt (Ed.). (2018). Amazon Watch: Datenbasierter Analyse-Report für die reale Marktdominanz von Amazon. Berlin.

Tools

Knape, D. (2020). Amazon Product Listing Optimization (APLO) tool. *Published as an online tool on aplo.stgaller-navigator.com*

Dominic Knape

Curriculum Vitae

Personal Information

Full Name:	Dominic Alexander Knape
Date of birth:	29.12.1992 in Munich
Citizenship:	German
Languages:	German (Native), English (Advanced, Level C1), Latin (Latinum), Chinese (Level A1)

Education

Since 03.2017	**University of St. Gallen (HSG)**, **Switzerland**: Ph.D. in General Management, Focus: Entrepreneurship & Online Platforms
09.2015 – 02.2017	**University of St. Gallen (HSG), Switzerland:** Master studies in Business Management, degree: Master of Arts HSG, GPA 5.59/6, Focus: Entrepreneurship & Digital Business
03.2015 – 07.2015	**Johannes Kepler University (JKU), Linz (Austria):** Master studies in Web Sciences (Web Business & Economy)
04.2014 – 07.2014	**Technical University of Munich (TUM), Munich**: Course: Business Plan Advanced
10.2011 – 10.2014	**Ludwig-Maximilians-Universität (LMU), Munich:** Bachelor studies in Business Administration, degree: Bachelor of Science, GPA 1.9, Major: Management, Marketing and Innovation, Minor: Media and Communication
09.2003 – 06.2011	**Graf-Rasso-Gymnasium, Fürstenfeldbruck**: General University Entrance Qualification (Allgemeine Hochschulreife)

Scholarships

04.2013 – 09.2014	**UnternehmerTUM, Munich**: Scholarship in the entrepreneurial qualification program Manage&More

Professional Experience

Since 03.2017	**DK Limitless GmbH (Fürstenfeldbruck, Germany):** CEO & Founder, Building a high-quality jewelry brand called CHAMOON® Jewelry. Building an affordable jewelry brand called BONNYBIRD. Responsible for Design, Purchasing, Marketing & Sales
Since 03.2017	**University of St. Gallen HSG (Switzerland)**: Research Associate at the Chair for Entrepreneurship, Startup Coach at Startup@HSG Lab, Responsible for the Entrepreneurial Talents Program
05.2013 – 12.2016	**Kadocom (Fürstenfeldbruck, Germany)**: CEO & Co-Founder, International Distribution – Responsible for the planning and technical implementation of e-commerce projects and online marketing campaigns
04.2013 – 07.2013	**Siemens AG (Munich, Germany):** Innovation Project in Teamwork: Development of Vision Scenarios for 2030
09.2012 – 12.2012	**DLA GmbH (Munich, Germany)**: Working Student in the Online Marketing Department, Search Engine Optimization and Online Marketing
12.2011 – 10.2014	**CHIP Xonio Online GmbH (Munich, Germany)**: Working student as Video Producer, Video Creation (Shooting, Editing, and Dubbing) for the website www.chip.de

Since 03.2011	**Digital Kreativ (Fürstenfeldbruck, Germany)**: CEO & Founder, Web Design and Video Production: Creation and Optimization of Websites, Performance Marketing, E-Commerce, Video Creation, Graphic Design
07.2011 – 09.2011	**NMZ Media (Regensburg, Germany):** Internship, Video Editing, Cutting, Lighting, and Sound
07.2009 – 01.2012	**Axel Gerstl (Biburg, Germany):** System Administrator, Web Design, Online Marketing, Administration and Maintenance of the Online Shop and ERP system

■ Teaching Experience

Fall Semester 2017/18/19	**Lean Startup,** Teaching Assistance and Lecturer, Master Level, University of St.Gallen, Best Evaluation: 1,1
August 2019	**Entrepreneurial Champions Program,** Selection and supervision of the five best founders at HSG, Support program, San Francisco & Silicon Valley, In collaboration with swissnex San Francisco
Spring Semester 2019	**Digital Startup,** Teaching Assistance and Lecturer, Master Level, University of St.Gallen & ETH Zurich
Spring Semester 2018	**High Tech Start-Up Management,** Teaching Assistance and Lecturer, Master Level, University of St.Gallen & ETH Zurich, Evaluation: 1,6
2017-2020	Supervision and consultancy of over 50 founders from the University of St.Gallen
2017-2020	Thesis Supervision at the University of St.Gallen

■ Media Coverage (*Selection of most important*)

Handelsblatt. Übermacht Amazon. Publication Date Nov. 7, 2018; P.1, 4-5 (Major German Newspaper featuring Amazon Watch Report as Cover Story)

Handelsblatt. Bequemlichkeit schlägt Gewissen. Publication Date Oct. 18, 2019; P. 23 (Major German Newspaper featuring E-Commerce Germany Report)

Wirtschaftswoche. Amazon erlöst hierzulande im ersten Halbjahr 12 Milliarden Euro – ein Drittel aller Online-Umsätze. Publication Date Dec. 02, 2019. (Wirtschaftswoche Blog featuring E-Commerce Germany Report)

Internetworld. Amazon kommt im Modehandel nicht aus den Schuhen. Publication Date Oct. 28, 2019. (Internetworld Online featuring E-Commerce Germany Report)

■ Practical Skills

- Good knowledge in Microsoft Office, Adobe Illustrator, Adobe InDesign, Adobe After Effects, Adobe Premiere, Sony Vegas, Apple Final Cut Pro
- Very good knowledge in Adobe Photoshop, graphic design and image editing
- Good knowledge of programming languages HTML and CSS
- Very good knowledge of Content-Management-System Wordpress; E-Commerce-Software Shopware, Shopify and Modified ecommerce; ERP Software JTL Wawi and db-Fakt

■ Extracurricular Activity

Associations:	Co-founder Coding Academy at the University of St.Gallen, Member of the Family Business Club at the University of St.Gallen, Member of the Investment Club (HIC) at the University of St.Gallen
Voluntary Engagement:	Active member of the voluntary fire department Fürstenfeldbruck (2006 –2011), Participation at RoboCup German Open 2010