JUSTUS-LIEBIG-UNIVERSITÄT GIESSEN

Innovation Marketing: Aspects and Outlook in the Aera of Digitalization

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Doctoral Thesis

submitted to

Justus-Liebig-University Giessen

Department of Business Administration and Economics

Giessen, 1st of September, 2025

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List of Abbreviations

IM- Innovation Marketing

SLR- Systematic Literature Review

DI- Digital Innovation

B2C- Business-to-consumer

B2B- Business-to-business

DTM- Document by term matrix

AI- Artificial Intelligence

VR- Virtual Reality

USP- Unique Selling Proposition

CI- Consumer Innovativeness

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1 General Introduction

1.1 Relevance of Innovation Marketing

For decades, the development and launch of innovations have been central topics in both academic research and business practice (Gama and Magistretti, 2023; Vărzaru and Bocean, 2024). This focus is well justified, as many innovations continue to fail upon market introduction (Wang, 2023). High innovation failure rates are particularly detrimental to launching firms, which often have only one chance to succeed in the market (Kuester et al., 2018). While the reasons behind innovation failures are diverse, they are frequently linked to inadequate innovation marketing and ineffective consumer management (Al-Adwan, 2024; Xue et al., 2024).

Moreover, not only small firms but also large tech corporations are susceptible to innovation failures. A notable example is Samsung's launch of the Galaxy Fold. Despite its groundbreaking and futuristic design, the product was widely considered a failure due to issues with durability and robustness. Additionally, its $2,000 price point was seen as unjustifiable, further highlighting flaws in its marketing approach (retrieved on the 11th of June 2025 from: https://www.forbes.com/sites/gordonkelly/2019/07/04/samsung-galaxy-fold-release-upgrade-galaxy-note-10-s10-plus-note10/;https://www.theverge.com/2019/10/4/20898484/samsung-galaxy-fold-folding-test-failure-durability).

To date, the academic literature lacks a comprehensive conceptualization of innovation marketing. In this dissertation, innovation marketing (IM) is defined as the set of tactical marketing activities aimed at facilitating individual adoption and broader diffusion of an innovation (Peres et al., 2010). IM includes the extended marketing mix—product, price, promotion, place, people, physical evidence, and process (Kuester et al., 2018)—which together support successful commercialization of an innovation in a market. Despite the critical role IM plays in the survival of innovations and the long-term success of firms, research remains

fragmented, often narrowly focusing on isolated marketing tactics or specific aspects of innovation adoption.

At the same time, digitalization has accelerated innovation cycles and shortened time-to-market for innovative products and services (Tajudeen et al., 2022; Cannavale et al., 2025). Over the past decade, the number of firms engaged in innovation development and commercialization has surged (retrieved on the 11th of June 2025 from: https://www.mckinsey.com/capabilities/strategy-and-corporate-finance/our-insights/how-top-performers-use-innovation-to-grow-within-and-beyond-the-core). Start-ups, in particular, have led this surge (Ricap and Lundvall, 2021; Kitsios and Kamariotou, 2023). However, nearly 70% of start-ups fail within the first two to five years of market introduction of their innovations (retrieved on the 11th of June 2025 from: https://hbr.org/2021/05/why-start-ups-fail). The high failure rates are often attributable to consumer hesitation toward unfamiliar products or services offered by unknown companies (McKnight et al., 2002). Additionally, innovations of start-ups are associated with significant uncertainty, trust issues, and privacy concerns (Featherman and Pavlou, 2003). Therefore, effective commercialization strategies—and thus robust IM—are essential for their survival.

Digitalization has not only spurred more innovation but also gave a rise to a new type of innovations: digital innovations (DIs). These innovations are service innovations offering new and unique value propositions enabled by core digital technologies (Dotzel et al., 2013). For such innovations, uncertainty, lack of trust, and privacy concerns are especially acute (Eggers et al., 2022; Choung et al., 2022). Despite these challenges, DIs offer significant potential for firms and start-ups to disrupt existing markets, gain competitive advantage, and encourage consumers to switch from traditional to digital offerings.

However, in an attempt to minimize consumer uncertainty, start-ups often model their marketing programs for DIs too closely to those of non-digital alternatives (Kuester et al., 2018),

emphasizing points of parity rather than points of difference. This approach can be counterproductive, as it fails to provide compelling reasons for consumers to adopt DIs over conventional products. Consequently, this underscores the need for a distinct and well-crafted IM approach tailored to DIs.

Despite its growing importance, research on IM for DIs remains limited, leaving substantial opportunities for further investigation—not just on marketing for innovations, but specifically on the effective commercialization of DIs.

1.2 Research Questions, Overall Approach, and Outline of the Dissertation

Building on the academic and practical relevance of IM outlined in the previous chapter, the topic has received considerable attention in research over recent decades. Accordingly, this dissertation aims to review existing literature on IM (Paper 1) and address identified research gaps, particularly in relation to the IM of DIs (Papers 2 and 3). The overarching objective of this dissertation is to advance both theoretical and practical understanding of IM as a critical component within the broader framework of innovation adoption and diffusion (Rogers, 2003). Specifically, it seeks to deepen insights into the effective design of IM program, especially in the context of DIs. The following section introduces the core research questions addressed by this dissertation and outlines its overall methodological approach.

This dissertation is structured into five chapters. **Chapter 1** serves as the introduction, emphasizing the importance of IM and presenting the overarching structure and objectives of the research. **Chapters 2** through **4** each consist of an individual paper, two of which have been submitted to or accepted by peer-reviewed academic journals. Finally, **Chapter 5** summarizes the main findings, discusses theoretical contributions, explores managerial implications, and outlines limitations as well as directions for future research.

As previously noted, IM has garnered strong academic and practical interest, resulting in a diverse range of research questions, thematic areas, and methodological approaches (Hauser et al., 2006). These diverse foci and methods have contributed to a fragmented and complex research landscape, making it challenging for scholars and practitioners to identify central themes and obtain a comprehensive understanding of the research field. Furthermore, previous efforts to synthesize IM literature have often focused either on areas outside of the core marketing program (e.g., Evanschitzky et al., 2012) or on individual components of it (e.g., Brexendorf et al., 2015; Luchs et al., 2016). Given that the elements of the marketing mix do not function interdependently, a meaningful synthesis of the IM literature requires an integrative and holistic approach. Therefore, **Chapter 2** presents a comprehensive systematic literature review (SLR) of IM and addresses the first two research questions of this dissertation:

Research Question 1): What is the state of IM research regarding the topics studied?

Research Question 2): What are the research gaps and thus, future research directions within IM research?

To address the research questions outlined above, Paper 1 systematically reviews and synthesizes knowledge from 163 peer-reviewed articles on IM, offering several key contributions to the field. First, it provides a holistic overview of IM as an academic research domain. Second, the SLR tackles the complexity of the IM field by proposing a structured framework that categorizes and organizes the specific topics studied, thereby enabling scholars to gain a comprehensive understanding of the current state of knowledge. Third, the review offers an in-depth analysis of research trends, identifying patterns in studied topics over time, including commonly used dependent and independent variables and broader research foci. Finally, the SLR identifies significant research gaps and suggests directions for future research, among others emphasizing the need for research on innovations in the digital context.

Chapters 3 and **4** aim to deepen the understanding of the unique challenges and requirements of IM for DIs developed by start-ups. Paper 2, presented in **Chapter 3**, focuses on the critical role of initial trust perceptions in shaping consumers' adoption decisions for DIs. Specifically, it investigates how start-ups can design key elements of their marketing program to enhance the perceived trustworthiness of DIs and thereby increase adoption intention. More specifically, Paper 2 examines the influence of specific marketing elements—including customer ratings, benefit communication, and revenue models—on the trustworthiness of DIs. In doing so, it addresses the third research question of this dissertation:

Research Question 3): Which are the effective elements of the IM program to drive trustworthiness of DIs and, hence their adoption intention?

Furthermore, start-ups commercialize their DIs in the environment characterized by information asymmetry, where the start-up holds substantially more information than potential adopters. This imbalance creates a context in which consumers are faced with unknown products or services offered by unknown companies, leading to elevated levels of uncertainty and a lack of trust (Coulter and Coulter, 2003; Featherman and Pavlou, 2003). Drawing on the Signalling Theory (Spence, 1973), Paper 2 demonstrates that start-ups can mitigate lack of trust by using specific signals—heuristic cues that help potential adopters make inferences about the credibility and quality of DIs. According to Kuester et al. (2018), such signals may include disclosing the origin of the innovation, highlighting customer referrals in marketing communications, and ensuring personal data protection through transparent pricing strategies. To empirically investigate the effectiveness of these marketing signals in enhancing the perceived trustworthiness of DIs, Paper 2 draws on five experimental studies, involving a total of 728 participants. These studies explore how the specific design of marketing activities influences trust perceptions and, consequently, adoption intentions, addressing the following research question of this dissertation:

Research Question 4): How should start-ups design the specific elements of the IM program to drive trustworthiness of DIs and, hence their adoption intention?

Hence, Paper 2, presented in **Chapter 3**, examines the effectiveness of various elements of the IM program in enhancing the trustworthiness of DIs. Specifically, it investigates how the use of customer referrals and benefit communication within promotional activities, along with monetary and non-monetary revenue models in pricing strategies, influence trust perceptions of DIs. This paper makes several important contributions to the literature. First, it extends innovation adoption research into the rapidly growing and increasingly relevant domain of DIs. Second, it advances understanding of the adoption of start-up-led DIs (Kuester et al., 2018) by offering empirical evidence that start-ups can indeed overcome low initial trust if the elements of their marketing program are strategically designed. Third, it contributes to the literature on trust in digital environments (Schlosser et al., 2006) by highlighting trust as a central mediating factor between marketing signals and adoption intention.

Paper 3, outlined in **Chapter 4**, further deepens the understanding of DI commercialization by exploring the role of positioning and communication approaches. Drawing on the Porter's Positioning Framework (Porter, 1985), the paper investigates how start-ups can effectively position their DIs in the market. A key issue addressed in this paper is that, due to high levels of uncertainty, low trust, and privacy concerns, start-ups often avoid emphasizing the point of difference—namely, the digital nature of their DIs (Konya-Baumbach et al., 2019). Instead, they focus on points of parity with non-digital alternatives. While this approach may initially seem safer, it ultimately undermines the market survival of DIs due to insufficient differentiation and a lack of compelling reasons for consumers to switch from traditional products.

Thus, the need to position DIs around their point of difference is not merely beneficial—it is essential (Eggers et al., 2022). However, there remains a significant gap in the literature

regarding the specific tactics for an effective positioning and communications for DIs developed by start-ups. Given the inherent lack of trust and privacy concerns associated with DIs (Huang and Rust, 2013), these factors are likely to significantly influence the success of different positioning approaches.

Building on Porter's framework (Porter, 1985) and prior studies on digital product positioning (e.g., Kim et al., 2004), Paper 3 explores three strategic approaches: benefit-based positioning, cost-based positioning (focused on the revenue model), and value-based positioning (a combination of the two). Through this lens, Paper 3 addresses the fifth research question of this dissertation:

Research Question 5): Which benefit and/or revenue model should start-ups focus on to effectively position their DIs on a digital point of difference?

To further strengthen its research findings, Paper 3 incorporates the important perspective of customer segmentation, which—while widely acknowledged as essential in the broader context of innovation adoption (Rogers, 2003)—has been largely overlooked in the domain of DI adoption. Building on prior research suggesting that different adopter groups should be targeted with tailored messaging around unique selling propositions of innovations (Schuhmacher et al., 2018), Paper 3 takes this insight further by arguing that effective segmentation is imperative in the context of DIs, due to significant variation in adopters' openness to digital technologies (Kirk et al., 2015). Adopting the concept of Digital Nativeness (Prensky, 2001), the paper examines how different levels of familiarity with digital influence adopters' ability to cope with the uncertainties and perceived risks associated with DIs (Joiner et al., 2013). Specifically, Paper 3 investigates how the effectiveness of positioning and communication tactics that emphasize a digital point of difference may vary depending on the digital nativeness of the target audience—a critical dimension that has been completely

overlooked in existing literature**.** This focus leads to the formulation of the final research question of this dissertation:

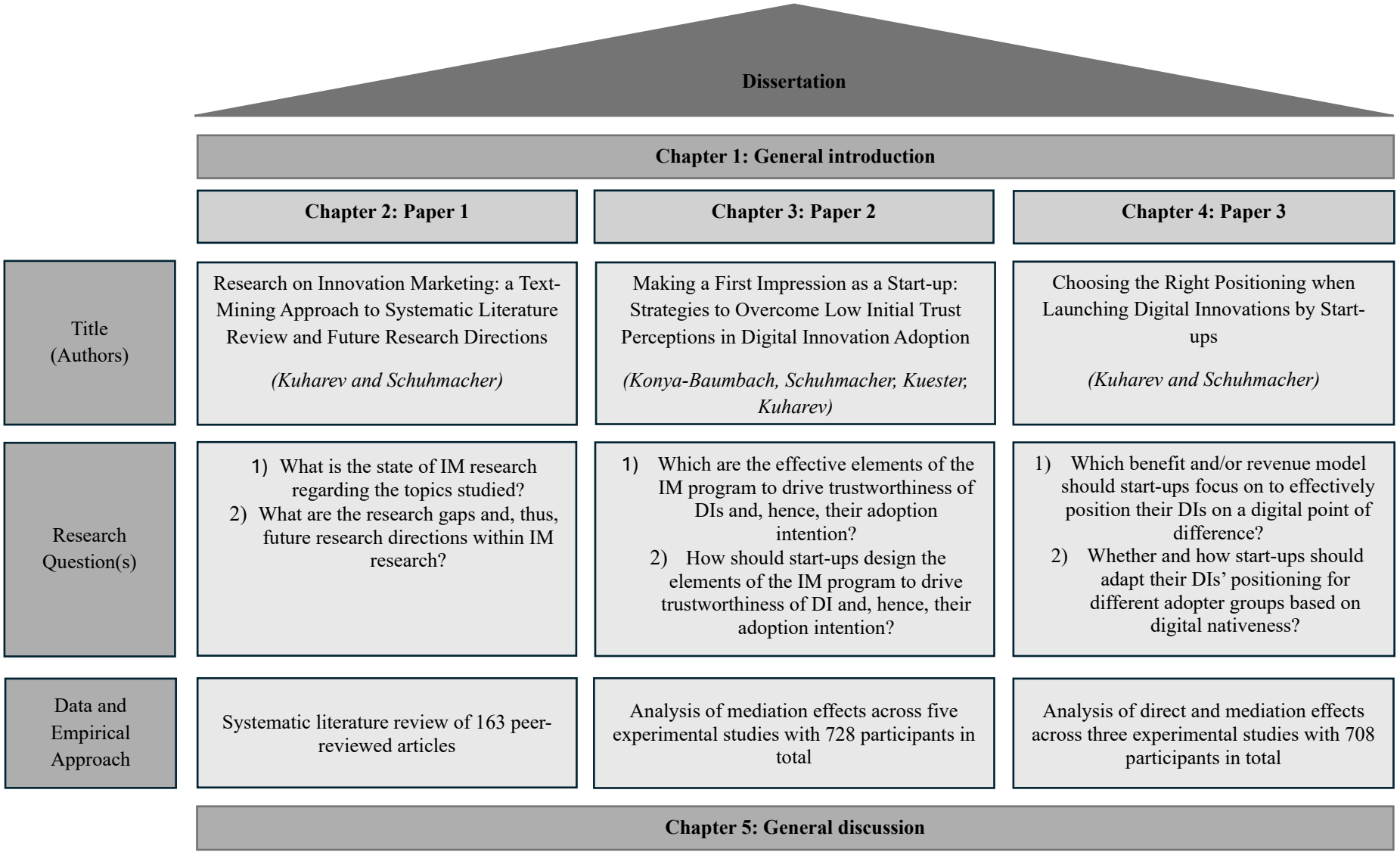
Research question 6): Whether and how start-ups should adapt their DIs' positioning for different adopter groups based on digital nativeness?

To address the research questions outlined above, Paper 3 employs an experimental design focused on different types of benefit-based and cost-based positioning strategies, examining their impact on adoption intention through the mediating roles of trust to DIs and privacy concerns, across two key adopter segments: digital natives and digital immigrants. Drawing on three experimental studies with a total of 708 participants, Paper 3 contributes to the literature in several important ways. First, it advances the body of research on the adoption of DIs by start-ups, particularly by building on previous studies (e.g., Kuester et al., 2018; Konya-Baumbach et al., 2019) that highlight the importance of trust for adoption of DIs. In doing so, it expands the scope by exploring the role of privacy concerns and analysing how digital nativeness shapes adopters' perceptions of and responses to DIs. Second, the paper offers key insights into the effective design of positioning strategies for DIs. It demonstrates that digital natives and digital immigrants perceive DIs differently, largely due to disparities in digital familiarity, experience, and risk tolerance. Consequently, Paper 3 addresses the critical issue of how to differentiate DIs from non-digital alternatives, emphasizing the need to highlight the digital core as a strategic point of difference. Third, the research paper makes a meaningful theoretical contribution by extending the Porter's positioning framework (Porter, 1985) into the DI context, an area where research remains limited. Building on the work of Kim et al. (2004), the paper confirms that start-ups can adopt a benefit-based, cost-based, or value-based positioning strategy, depending on their market context and target audience. Finally, Paper 3 provides a detailed analysis of the conditions under which each positioning strategy is most effective, offering practical guidance for start-ups aiming to improve the market success

of their DIs. These findings are not only theoretically significant but also offer valuable implications for managerial practice.

Chapter 5 concludes the dissertation by summarizing its core themes and findings, highlighting how the research advances current understanding of IM. The chapter also outlines the key theoretical contributions and managerial implications, discusses the main limitations of the dissertation, and proposes directions for future research. Figure 1.1 illustrates the overall structure of the dissertation.

Figure 1.1: Overall Structure of the Dissertation



2 Paper 1: Research on Innovation Marketing: a Text-Mining Approach to Systematic Literature Review and Future Research Directions

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Status: Reject in the Journal of the Academy of Marketing Science
Presented at: European Marketing Academy Conference (EMAC) 2018 in Glasgow, UK

Abstract

Innovation Marketing (IM) refers to the tactical marketing activities that contribute to the adoption and further diffusion of an innovation in a market. Due to the myriad of (digital) innovations launched today and their high failure rates, IM is a major driver of the innovation performance. Consequently, the marketing and innovation literature has witnessed a variety of IM studies, which are highly diverse in nature. This article offers a review of research on IM by combining the systematic literature review methodology with the text mining approach. We discuss commonalities and differences of the identified IM studies as well as identify ten common topics studied in IM research. We further develop a research framework, identify research gaps in the literature and suggest avenues for future research.

Keywords: *Innovation marketing, tactical marketing, literature review, text mining, topic modelling*

2.1 Introduction

IM refers to tactical marketing activities that contribute to the adoption and further diffusion of an innovation in a market (Peres et al., 2010). IM is claimed to substantially contribute to firms' long-term financial success (Bayus et al., 2003; Cefis and Marsili, 2006). An example of a successful IM campaign is, for instance, the benefit-based communication of "1,000 songs in your pocket" for the launch of the first iPod by Apple (retrieved on 5.06.2018 from: https://www.apple.com/newsroom). One of the main benefits of IM is that it helps companies to market the quality and functions of an unknown innovation to potential adopters. Nowadays, digitalization particularly triggers continuous innovation launches by companies (Bomsel and Le Blanc, 2004). Due to digitalization, the last decade has witnessed a 75% increase in the number of companies involved in innovation, and consequently, has resulted in a boom of innovation launches (Eurostat, 2017). However, this intensity and ever-growing complexity of innovations raises the requirements for IM (Lafferty et al., 2003), because companies only have one shot at the market. In contrast, high innovation failure rates set long-term survival of companies at risk (Anderson et al., 2015). Previous studies discuss the main reasons for innovation failure, one of which is incorrect IM (e.g., Barczak et al., 2009; Gourville, 2006). For example, the high price of $159 for the Apple Airpods at the time of their launch is considered to be such a wrong shot at the market (The Guardian 2016), which resulted in a negative word of mouth and unfavourable media reports (Forbes 2016).

The marketing literature has substantiated the importance of research on IM (e.g., Chandrasekaran and Tellis, 2007). IM studies address a multitude of different research questions and a variety of topics and research methods (Hauser et al., 2006). This variety makes it difficult to grasp core themes, to get a comprehensive view of the topics studied so far, and to unveil research gaps. Hence, this study aims to provide a systematic literature review to

capture core topics of IM research, to identify research gaps, and to suggest future research potential.

Overall, the literature on IM is highly fragmented, and there is no uniform conceptualization of the term ‘innovation marketing’ (Randhawa et al., 2016). Based on existing definitions (e.g., Castaño et al., 2008; Peres et al., 2010; Reinders, 2010; Goode et al., 2013; Heidenreich und Kraemer, 2015; Talke and Heidenreich, 2014), we define IM as follows: *1nnovation marketing represents all tactical marketing activities (marketing program) that contribute to the individual adoption and further diffusion of an innovation in a market.* Thus, with this definition of IM we focus on the "how" to launch an innovation in a market rather than on the "what", "where", "when", and “why" to launch (Frattini et al., 2013). The "how" can be classified according to the extended 7Ps (Kuester et al., 2018): product, price, promotion, place, people, physical evidence, and process.

Extant literature reviews and meta-analyses on innovation research focus on different aspects of innovation management. For instance, Troy et al. (2008) or Evanschitzky et al. (2012) provide a meta-analysis on strategic drivers of innovation market success. The study by Luchs et al. (2016) offers a review of innovation design literature. Concerning IM, there is no such review. So far, researchers have focused on single marketing activities, e.g., innovation preannouncement (Su and Rao, 2010) or branding of innovations (Brexendorf et al., 2015). However, we lack a systematic review of the literature on IM. Since marketing activities do not operate in isolation but provide a combination of signals to customers (Schuhmacher et al., 2018), there is a need for an overarching systematic literature review on IM research as called for by several researchers (e.g, Hauser et al., 2006; Chandrasekaran and Tellis, 2007).

Following the systematic literature review procedure proposed by Petticrew and Roberts (2006) we obtain our literature sample. Next, we analyze the literature sample concerning the empirical setting, i.e. we take a closer look at product and industry specifics and the research

design. This is followed by an examination of the retrieved studies using text mining to identify topics that comprise the IM research field. We take a deeper look into each topic, considering its tactical marketing activity, focus, and its development over time. Spanning all identified topics, we develop a clustering visualization based on two variables: (1) the focus of tactical marketing activity and (2) the dependent variable being either innovation adoption or diffusion. Finally, we identify research gaps and propose future research directions.

This article contributes to the marketing literature in several ways. First, we respond to the calls of researchers to provide a holistic overview of IM research (Hauser et al., 2006; Chandrasekaran and Tellis, 2007). Second, with our approach, we can understand the structure of IM research. Third, we dive deeper into each topic and identify patterns of their occurrence and development.

2.2 Procedure: Systematic Literature Review

IM research is a complex, fragmented, and rapidly developing field that requires a nontraditional approach to its review. We follow the classical literature review methodology proposed by Petticrew and Robers (2008). However, we also enhance it with text mining, which is claimed to be an appropriate tool for topic extractions within complex data sets (Basole et al. 2013). In our systematic literature review, we address two research questions: (1) What is the state of IM research regarding the topics studied? (2) What are the research gaps and, thus, future research directions within IM research?

We started our systematic literature review by searching for articles focusing on IM, as defined above. Thus, the criteria for inclusion of articles are determined by the tactical marketing program represented by the 7Ps, namely: product (e.g. features, brand, packaging, sizes), promotion (e.g., preannouncement, sales promotion, advertising, public relations), price (e.g., launch pric

e, discounts, allowances, payment method, credit terms), place (e.g., channels, coverage), people (e.g., participants, staff), process (e.g., service blueprint, process design), and physical evidence (e.g., service environment). Consequently, this review excludes studies with a focus on IM strategy (e.g. Hultink et al., 1999; Souder and Song, 1997; Steenkamp and Gielens, 2003), organizational factors (e.g. Eisend et al., 2016; Fernandez et al., 2016; van der Berg et al., 2014) and non-tactical marketing tools (e.g. Fueller et al., 2013; Nienaber and Schewe, 2014; Sridhar, 2012). Further, our literature search covers scholarly peer-reviewed journals and hence, does not include conference proceedings, books, dissertations, and press articles (Kozlenkova et al., 2013; Cleeren et. al., 2017). We ran an initial scoping of the literature in the following A+ and A marketing journals from 2010 until 2017: *Journal of Marketing, Journal of Marketing Research, Journal of the Academy of Marketing Science, Marketing Science, Management Science, Journal of Product Innovation Management, International Journal of Research in Marketing, Journal of Service Research, Journal of Retailing, Research Policy.* We scanned all articles' abstracts and identified 69 articles on IM research. We used these 69 articles to extract author-provided keywords. The overview of the most popular keywords is provided in the Table 2.1.

Table 2.1: Most Popular Keywords in the IM Literature in 2010-2017

Keywords	
Innovation	Service innovation
Adoption	Radical innovation
Diffusion	Innovation performance
Product innovation	Product innovativeness
Product newness	Resistance to innovations
Incremental new product	Technology and innovation
Breakthrough new products	Technological innovation
Customer-centric innovation	

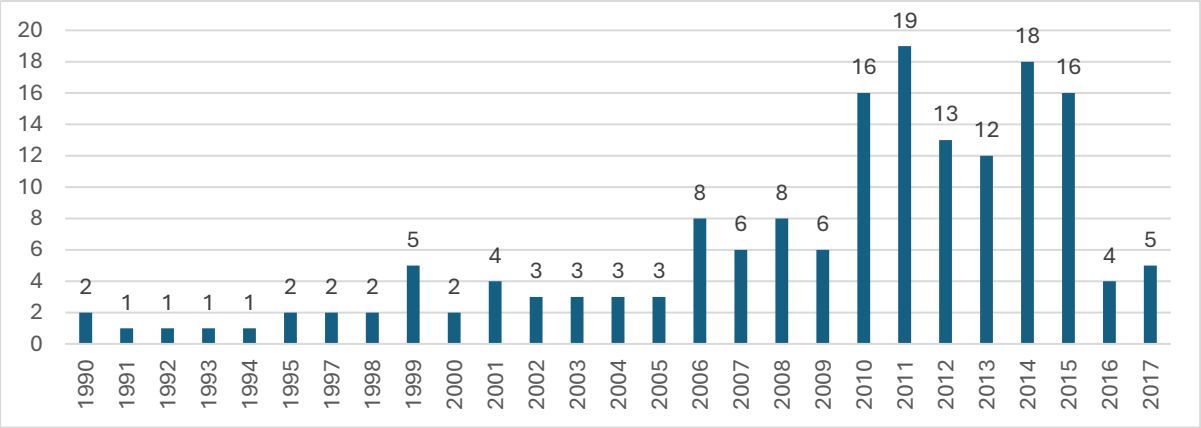
Based on these extracted keywords, we ran a journal-independent literature search. Here, we developed combinations consisting of the most popular keywords (e.g. innovation or new product) with other keywords addressing tactical marketing (e.g. launch or advertising), obtaining 81 keyword combinations. We used these keyword combinations to search within the EBSCOhost database "Business Source Complete" for further articles. For this search, we set the timeframe from 1990 to 2017. The starting date of 1990 was chosen based on the occurrence of the first article on IM (Thamhain, 1990). This search resulted in a total of 188 articles. Abstracts of each of these 188 articles were reviewed independently by both authors. Articles were eliminated from the sample that turned out not to cover IM as defined. This investigation resulted in a final sample of 163 articles from 38 different journals (see Appendix A1 for an overview of all studies).

2.3 Review of the IM Literature: Empirical Setting

2.3.1 Distribution of Articles over the Years

Analysing the appearance of articles on IM over the last 27 years, it can be clearly observed that the topic enjoyed very little focus throughout the nineties. At the beginning of the nineties, the appearance of relevant articles was minimal and started to increase towards the end of the decade. The timespan between the 2000 and 2015 has become an aera of IM research gradually increasing year by year and reaching its peak in 2010-2011 and 2014-2015. After 2015 the focus on IM in marketing literature has significantly dropped. Figure 2.1 showcases the distribution of all articles across the years.

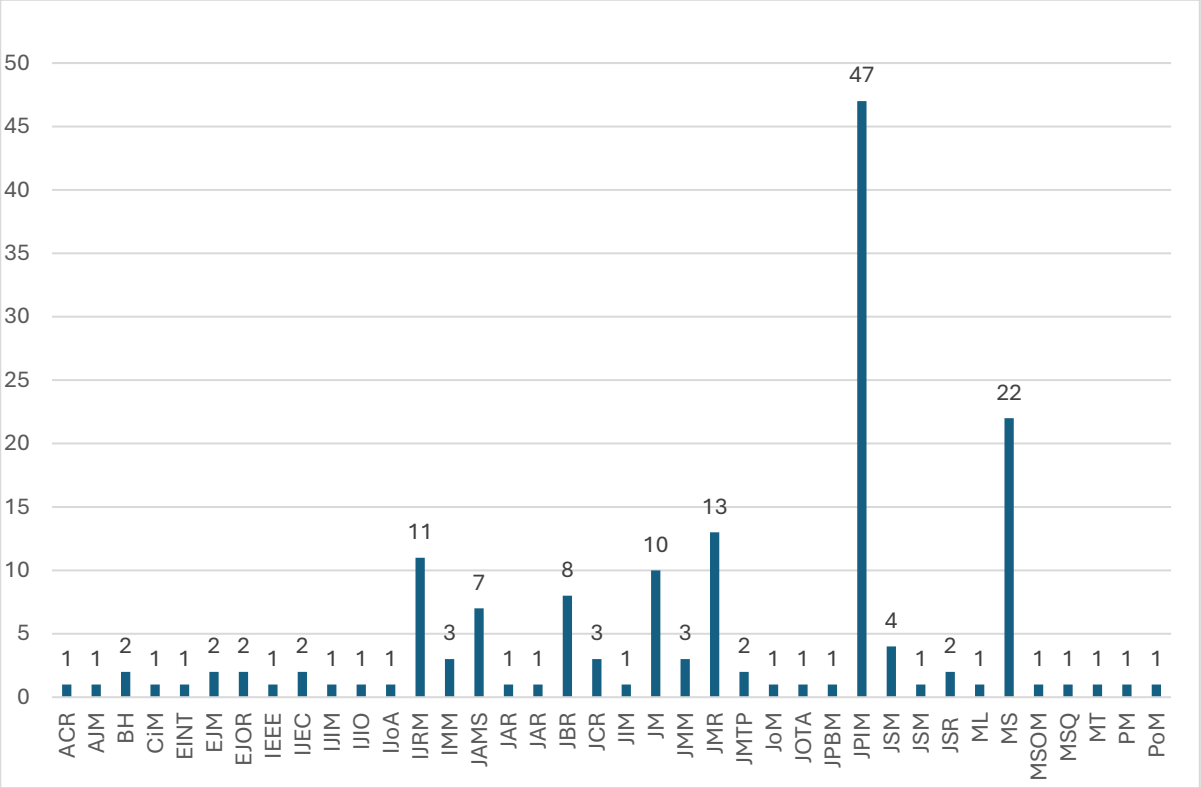
Figure 2.1: Distribution of IM Articles Between 1990 and 2017



2.3.2 Appearance of Articles in Marketing and Innovation Journals

The appearance of articles on IM in scientific journals across the years is diverse, ranging from A+ to C journals. However, we observe a large concentration of articles in A+ journals (48 articles): *Journal of Marketing*, Jo*urnal of Marketing Research*, *Journal of Consumer Research*, *Marketing Science*. Further, large concentration of articles is present in A journals (65 articles): *International Journal of Research in Marketing*, *Journal of Product Innovation Management* and J*ournal of the Academy of Marketing Science*. The remainder of the articles are published in B and C-ranking journals (Journal rankings retrieved 24.02.2017 from:https://www.vhbonline.org/fileadmin/vhb/Services/vhbrating/MARKVHB_Rating_2024_Area_rating_MARK.pdf). Figure 2.2 showcases the distribution of articles across the 38 scientific journals.

Figure 2.2: Distribution of IM Articles in Scientific Journals



2.3.3 Innovation Type and Industry

Concerning innovation type, our sample reveals an unbalanced focus on the product innovation context over the service innovation context (e.g., Avlonitis, 2001; Prins and Verhoef, 2007) and on the B2C sector over the B2B sector (e.g., Cooper and de Bretanis, 1991; Frambach et al., 1998). Specifically, 87% of the reviewed articles address product innovations, 10% investigate marketing for service innovations, 2% consider both product and service innovations, and the remaining 1% of articles do not specify the investigated innovation type. With regard to investigated sectors, 84% of the studies focus on the B2C sector, 10% on the B2B sector, 1% on the B2B and B2C sectors, and again, 5% do not specify the examined sector.

2.3.4 Methods Applied

Overall, we find that 62% of the studies follow a quantitative research approach, 7% a qualitative design and 30% of the articles are of a conceptual nature. The quantitative studies make use of a variety of different research designs, i.e., field studies (22%): surveys (44%) or experiments (33%). However, all studies employ single method approaches. Of the qualitative research setting, all the studies provide insights from expert interviews. Similarly, as with the quantitative studies, qualitative studies employ single method approaches.

2.3.5 Future Research with Regard to Empirical Setting

One concern of existing research is that the studies are heavily concentrated on B2C industries and on product innovations. More diverse research across product and service innovations as well as across B2B and B2C would allow a generation of more systematic and generalizable insights. This is substantiated by previous research claiming that tactical marketing decisions for product innovations in B2C should not be generalized for service innovations and B2B innovations (e.g. Steenkamp and Gielens, 2003). This is caused, for instance, by intangibility inherent in services or simultaneous production and consumption, which triggers implications for marketing communications (Avlonitis et al., 2001). Similarly, in the context of B2B markets IM becomes more personal due to key account management or personal sales interaction (White et al., 2007). Thus, in B2B markets the aspects of placing people or process in the 7 Ps become more relevant. Overall, expanding IM research into the B2B and service innovations context would allow to identify sector or/and category specific factors that substantiate current findings.

Furthermore, the proliferation of digitalisation in the marketplace gave rise to the appearance of DIs, which represent internet-enabled service innovations (Dotzel et al., 2013). So far, IM research has fully ignored this important development, even though the existing

insights on product and service innovations cannot be generalised to DIs, because DIs fundamentally differ in their nature (Kannan and Li, 2017) and the decision about their adoption usually takes place in an uncertain environment (Featherman and Pavlou, 2003), which does not apply to product innovations and service innovations. Hence, an expansion of the IM research into the area of DIs would be fundamental.

As shown above, a multitude of methods have already been used to analyse IM. Normally, the research question determines the data collection approach and analysis. As with many other areas, a key challenge will be to take this field of research to the next level. For example, researchers should make use of secondary data on IM activities and actual adoption data. Working with secondary data would add to the external validity of the results. In a similar vein, researchers collecting data via experiments should move away from lab experiments and combine these with real-life experiments. In this regard, multi-method studies and data triangulation will offer greater insights and more fine-grained managerial recommendations.

2.4 In-depth Analysis of the IM literature: Text Mining and Topic Modelling

We use text mining for the analysis as well as synthesis of the literature sample to derive core topics of IM research. Traditionally, systematic literature reviews are based on manual coding and evaluation of literature, which leads to limitations for a comprehensive and profound analysis (Williams et al., 2009). In this regard, extant research argues that text mining can significantly improve literature reviews, enabling an analysis of unstructured full-text data more accurately and efficiently (Basole et al., 2013; Delen and Crossland, 2008). Given the complex and fragmented nature of IM research, we follow the previous research calls (Thomas et al., 2011; O'Mara-Eves et al., 2015) and conduct a text mining analysis.

So far, text mining has not been widely used to synthesize marketing literature. The few examples include, for instance, the systematic literature review on cause-related marketing

literature by Guerrero et al. (2016) or the review of Journal of Marketing Research by Huber et al. (2014). The use of text mining is more common in computer sciences (e.g. Basole et al., 2013; Mostafa, 2013) and natural sciences (e.g., Vazquez et al., 2011; Warrer et al., 2012).

Following the current standard, we used two specific text mining tools, namely clustering and topic modelling. The combination of these two tools allows us to uncover topic clusters in IM literature focusing on terms and their frequencies (Bragge et al., 2007; Delen and Crossland, 2008). Here, the fundamental assumption is that terms are defined by the context in which they occur and that terms that co-occur represent topics with specific meanings (Randhawa et al., 2016). For the analysis, we drew on the statistical computing package R Studio within R programming software (Sun, 2015).

The first step in text mining refers to pre-processing the literature and comprises transforming the source text to obtain raw text without formatting. Thus, we converted all articles' PDF files into TXT documents and removed figures and tables. The second step is transforming the text in each document by removing stop words, whitespace, punctuation, and numbers. The third step ensures that similar terms are not identified as being different. Hence, we ran stemming to prune all suffixes and prefixes to ensure that terms with the same root are captured as having the same meaning. As a result, we obtained the corpus of documents for text mining (Feinerer et al., 2008). Next, the number of similar terms in each document is counted and these frequencies are captured in a document-by-term classification matrix (DTM) (Feinerer et al,. 2008). The DTM is a bag-of-terms representation of the text corpus (Guerrero et al., 2016). A DTM is used to determine the occurrence of terms by document within the text corpus. The construction of a DTM is required to convert the text corpus into a mathematical object and to enable quantitative analysis (Solka, 2008). Previous studies have reported that a DTM may be sparse when documents from distinct subject areas are analyzed together. In such cases, transformations and penalty functions are used to reduce the influence of outlier

frequencies and the weight of terms that occur in all documents (Blei and Lafferty, 2009). In fact, we encountered this situation in our text corpus due to IM literature being highly fragmented across topics and conceptualizations. In our case the DTM is represented by 163 documents and 34,837 terms, showing a sparsity of 96%, which implies that from the large amounts of possible terms in all documents, only a few are used in individual documents. To reduce this sparsity, we followed the established procedure and used the term frequency~inverse document frequency (tf- idf) technique to remove all terms that occur frequently in one document but not in the overall corpus, i.e. only the terms with the frequencies greater than the median are kept (Grün and Hornik, 2011). In addition to the idf- weighting we made sure to exclude terms shorter than four characters (e.g. "one", "can") and also terms longer than ten characters, as we only expect stemmed terms to occur in our DTM. Further, we ran an explanatory analysis to uncover the most frequent terms (Guerreiro et al., 2016). We observed that there are five terms that occur over 2,500 times: "market" (tf= 3,690), "price" (tf- 3,590), "model" (tf- 2,996), "marketing" (tf- 2,669) and "innovation" (tf-2,561). The high frequency of these terms represents the general research focus. Interestingly, one element of the tactical marketing program, represented by the term "price" has equally a high frequency.

Traditionally, clustering algorithms are used to serve the purposes of text mining (e.g., Lu et al., 2012). Today, available algorithms include the cluster search based on latent semantic information in texts. In a document, the same terms can be used in relation to multiple topics at the same time, whereas different topics may also belong to a mixed membership set of topic clusters (Guerrero et al., 2016). Contextual meaning can be derived from observed proportions showing how much each cluster belongs to each document. Topics are then inferred from observable term frequencies via posterior inference (Grün and Hornik, 2011; Guerrero et al., 2016). Therefore, the possibility of uncovering a hidden structure of the topics instead of a list of terms is provided by the *topic modelling*. We consecutively ran both algorithm types.

First, we used cluster analysis within R Studio to identify underlying topics within IM research. For this study, we combined hierarchical and k-means cluster analyses. We used hierarchical agglomerative cluster analysis for the definition of the potential optimal number of topics and k-means cluster analysis for the optimality validation (Punj and Stewart, 1983). The hierarchical agglomerative clustering method is based on the identification of the Euclidean Distance, i.e., it starts by putting each term into its own cluster, measures the distances between all terms and groups the closest terms together. The Euclidean Distance is then calculated with the following formula (Kaufman and Roussew,1990):

$$D(X,Y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_n - y_n)^2},$$

where D refers to the distance between document X and document Y, document X has coordinates ($x_1, x_2, \ldots x_n$) and document Y has coordinates ($y_1, y_2, \ldots y_n$). Coordinates refer to term frequencies. We applied the algorithm to our DTM. Mathematically, our DTM is an 8,274-dimensional space where each document of the corpus is a point in this space. Therefore, the Euclidean distance D(X,Y) in our case would be the following:

$$D(X,Y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_{8274} - y_{8274})^2}.$$

To get the final cluster allocation of documents in our corpus in R Studio we ran *hclust* (Murtagh et al., 2011). The result of the *agglomerative hierarchical clustering* is visualized in a dendogram. Based on this visualization, we identified ten clusters that represent the topics of IM studies. To validate the number of clusters for our corpus we additionally ran a *k-means* cluster analysis that works via an upfront specification of the number of clusters (Wagstaff et al., 2001). We work with the assumption that the within-cluster distances, i.e., within cluster sum of squares (WSS), will be at maximum when k=1 and decrease as k will be increasing sharply at first and less sharply as k reaches the optimal value. We test different values of k from k-1 to 133 (134-1) and analyse cluster plots. We find an optimal value of k=10. Ten topic

clusters resulted in 72,4% total variance explained of the data distribution within our corpus, showing a very good fit of our model (Balcan et al., 2014).

Second, we made use of *topic modelling* to uncover the underlying semantic structure of the collection of documents (Blei and Lafferty, 2007). In other words, topic models are mixed membership models as each term can belong to multiple topics (Grun and Hornik, 2011). Consequently, each term has a different probability of belonging to a topic. The *Latent Dirichlet Allocation* (LDA) algorithm (Griffiths and Steyvers, 2004) allows identifying a latent conceptual structure of a topic given the terms in documents comprising it. It is common in research to treat each topic as a distribution over the terms and each document as a probabilistic mixture of the topics, with *n* number of topics and *n* being set up front (Griffins and Steyvers, 2004). We used *LDAGibbs* function of R Studio to run assignments of each term in a document to the *n* number of topics based on probabilities of each term to belong to a particular topic calculated as follows:

$$P(w_i) = \sum_{j=1}^{n} P(w_i \,|z_i = j)\; P\;(z_i = j),$$

with *n* being the number of topics, z_i being a latent variable indicating a topic from which *i*th term was drawn and P (w_i | z_j=j) being the probability of the term *w*; under the *j*th topic. P(z_i; = j) is the probability of choosing a term from topic *j* in the current document (Griffiths, 2002).

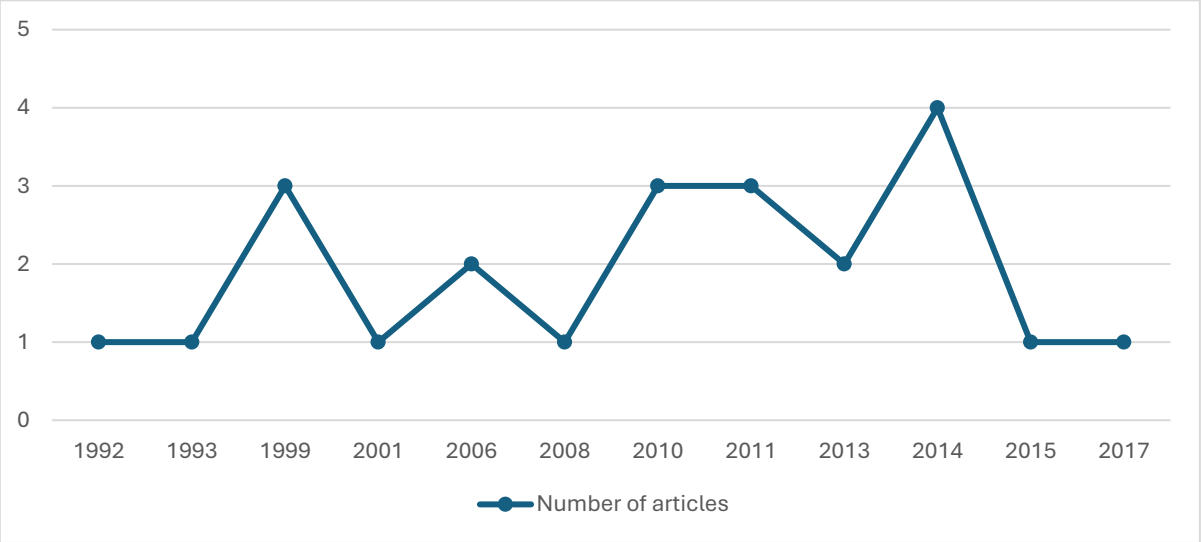
The output provides the final allocation of documents to topics based on documents-to-topics probabilities, i.e., probabilities of documents belonging to the topics. Therefore, *topic modelling* allows us to understand the latent structure of each topic defined by its most frequent terms and represented by the probabilities of each document belonging to the topic. Consequently, we derived a label for each of the ten topics.

2.5 Structure of IM Literature Based on Text-Mining: Ten IM Topics

In the following, we introduce each of the ten topics considering the tactical marketing focus, data source, most frequent terms, dependent variable, as well as topic development over time.

Topic # 1: IM drivers of innovation launch represents a topic covering IM activities aimed specifically at innovation market launch. The topic covers 23 articles. The top correlated terms within this topic are: "launch", "innovation", "customer", "development", "channel". The average posterior probability of articles in our corpus to belong to this topic is 0.68, which indicates a higher-than-average fit of the topic (Guerreiro et al., 2015). The majority of articles represent either conceptual studies or are based on field experiments and surveys. All articles investigate which tactical marketing tools contribute to the successful launch of an innovation in a market. However, studies differ in the tactical marketing variables investigated, i.e. "product", "pricing", "promotion", and "place". For example, di Benedetto (1999) investigates the impact of advertising, sales force, promotional activities, and distribution on innovation performance. In contrast, Easingwood (2006) focuses on pricing policies, distribution channels and communication. While the focus in this cluster is predominantly on product innovations, 21% of the articles investigate B2B industries (e.g., Di Benedetto, 1999; Gupta and Di Benedetto, 2006; Talke and O'Connor, 2011). Across the time frame from 1990 to 2017, the research attention is equally distributed reaching its peak in 2014. Figure 2.3 represents the distribution of articles across the timeframe.

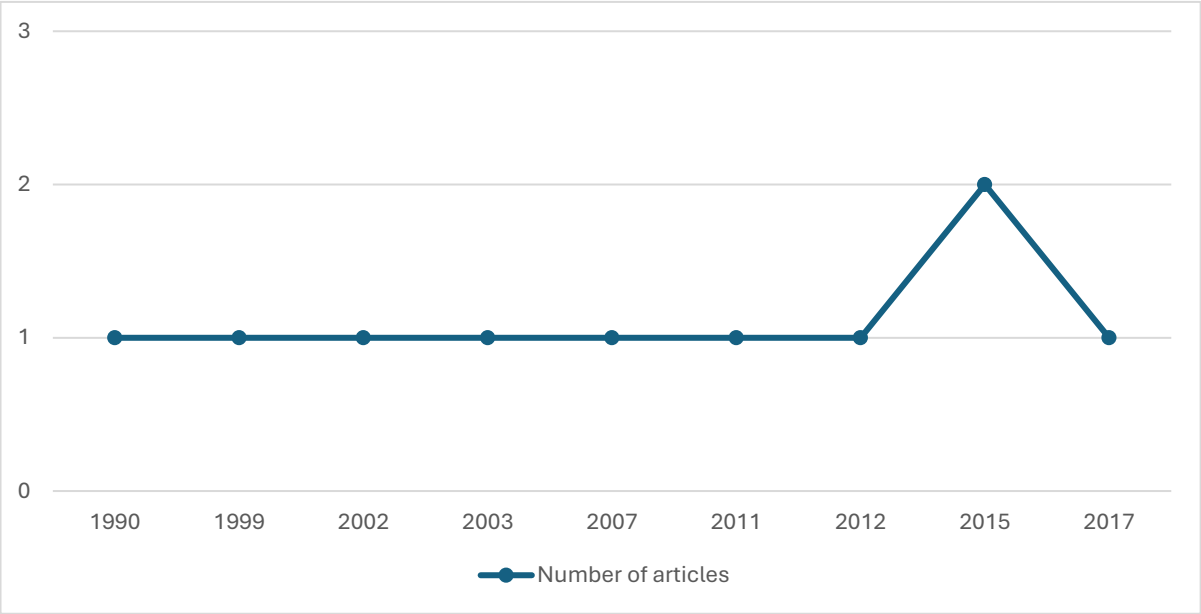
Figure 2.3: Timely Distribution of the Articles Belonging to Topic 1: IM Drivers of Innovation Launch



Topic # 2: IM drivers of innovation market take-off is represented by 11 articles that share the same dependent variable: innovation performance during market take-off. The terms "effect", "take-off', "price", "time", "consumer" are correlated with this topic. The average posterior probability of articles in our corpus to belong to this topic is 0.55, which indicates a lower-than-average fit of the topic (Guerreiro et al., 2015). However, this is expected due to the high variability of different factors investigated for this topic. The articles predominantly use existing industry panel data to analyze factors for successful innovation take-off. Studies within this topic show a rather narrow focus in terms of investigated independent variables, i.e., concentrating largely on pricing (Krishnan et al., 1999; Avagyan et al., 2011; Lowe and Barnes, 2012) and advertising (Delre et al., 2007; Barroso and Llobet, 2012 and Burmester et al., 2015). Other studies combine tactical marketing activities to examine simultaneously the impact of several activities on innovation take-off (Gielens and Steenkamp, 2003). 100% of the articles within this topic focus on B2C sector and product innovations. In terms of the evolution, IM research has covered tactical marketing tools' impact on innovation take-off since the early

1990 but received equally low attention of the scholars in the following years until 2017 (see Figure 2.4).

Figure 2.4: Timely Distribution of the Articles Belonging to Topic 2: IM Drivers of Innovation Take-off

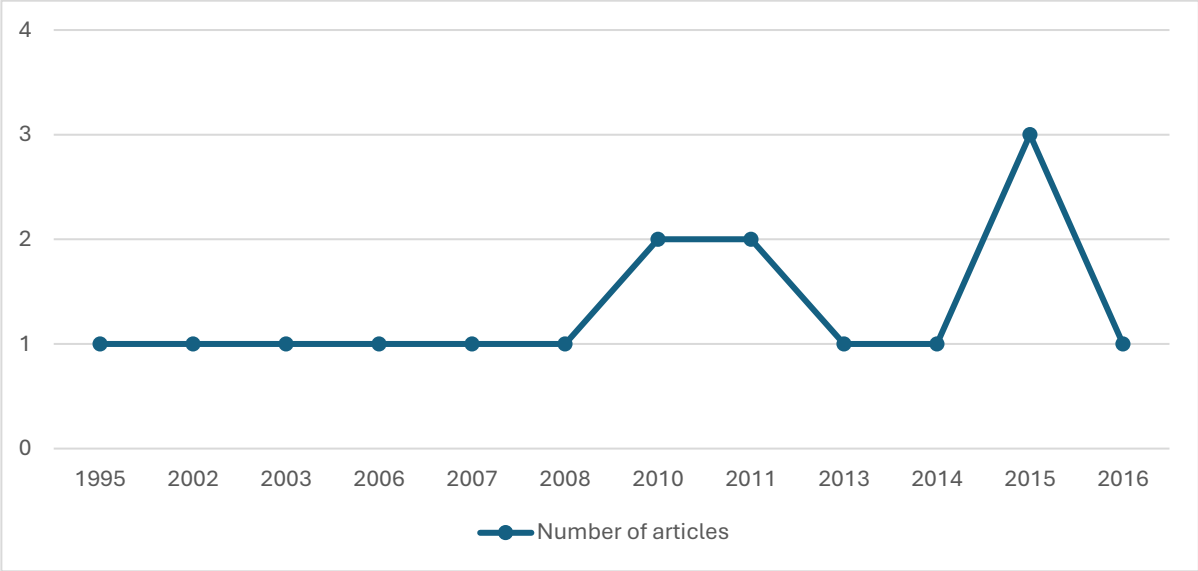


While topic #1 and topic #2 account mainly for the combined effect of several, at least two, tactical marketing activities, the remaining eight topics differ in their focus on single tactical marketing activities.

Topic # 3: Innovation pricing has received significant attention in IM literature. The topic focuses on the price "P" of the tactical marketing program. In total, 16 articles investigate innovation-pricing aspects using existing industry data as well as generating new insights via consumer experiments and surveys. The top 5 frequent terms with this topic are "price", "product", "market", "consumer", and "optimal". The average posterior probability of articles in our corpus to belong to this topic is 0.57, which indicates an average fit of the topic (Guerreiro et al., 2015). The studies address various pricing mechanisms. Studies compare the effectiveness of skimming vs. penetration pricing on innovation diffusion (e.g., Span et al.,

2014), investigate the specifics of dynamic price setting (e.g., Danaher, 2002; Handel and Mistra, 2015; Yu et al., 2016), and evaluate the effectiveness of discounts or upgrades in the context of innovation diffusion (e.g. Zhu et al., 2008; Avagyan et al., 2016). Overall, the research is predominantly concentrated on innovation diffusion with only a few studies looking into consumers' adoption as a dependent variable (e.g., Kuester et al., 2015). Furthermore, some of the articles investigated pricing of service innovations specifically (e.g. Danaher, 2002; Avlonitis and Indounas, 2006), however, the largest focus is put on product innovations. 100% of the studies focused on B2C sector within this topic. Since the early 1990s, researchers have been constantly investigating innovation pricing, however, the peak of interest falls into the period between 2009 to 2016 (see Figure 2.5).

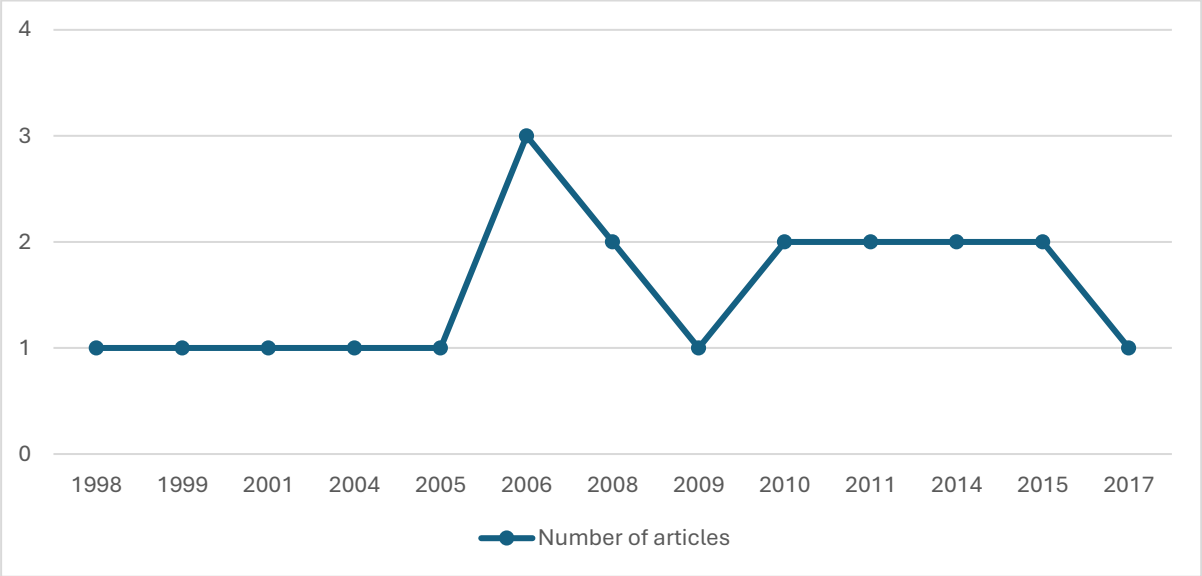
Figure 2.5: Timely Distribution of the Articles Belonging to Topic 3: Innovation Pricing



Topic # 4: Innovation promotion received significant attention in the literature and covers 21 articles. This topic discusses aspects of "promotion" by focusing on peculiarities of advertising for innovations as well as tools such as product simulation, visualization, and presentation (Castaño et al., 2008; Feiereisen et al., 2013; Brakus et al., 2014). This topic includes terms as "product", “advertising”, "visual", "simulation", "inform", "evaluation". The

average posterior probability of articles in our corpus to belong to this topic is 0.70, which indicates a strong fit of the topic and strong attribution of the articles to the topic (Guerreiro et al., 2015). The vast majority of articles within this topic are based on experiments. Within this topic, some of the studies investigate effective channels for promotion, e.g. role of TV commercials (Zigmond and Stipp, 2010), others address the content of adverts (e.g. Song and Parry, 2009) or endorsements (Lafferty et al., 2005). Another significant stream of research looks into experiential aspects of advertising by addressing analogies and mental simulations (Feiereisen et al., 2008), innovation presentations (Hoegg and Alba, 2011), where Mueller-Stewens et al., (2017) investigate gamified innovation presentations. Studies like the one of Zhao et al. (2014) address innovation usage simulation and its effect on adopters' innovation evaluation. Furthermore, Feiereisen et al. (2008) analyze the impact of alternative presentation formats (e.g., words vs. pictures) using various framing strategies (analogies vs. mental simulations) on product comprehension of various types of really new products (utilitarian vs. hedonic vs. hybrid). The majority of studies focus on B2C segments, i.e. consumer individual adoption using consumer experiments. Controversially, as the topic is mainly concentrated on adopters' experience with an innovation, service innovations have received just minimal attention so far (Storey and Easingwood, 1998). Also, the B2B context did not receive any significant research attention. Overall, the innovation promotion topic is a young research area with the first study appearing in the late 1990s (Thomke, 1998). Due to the availability of relevant technologies for experiential marketing, the main progress of this research topic is observed from 2006 (see Figure 2.6).

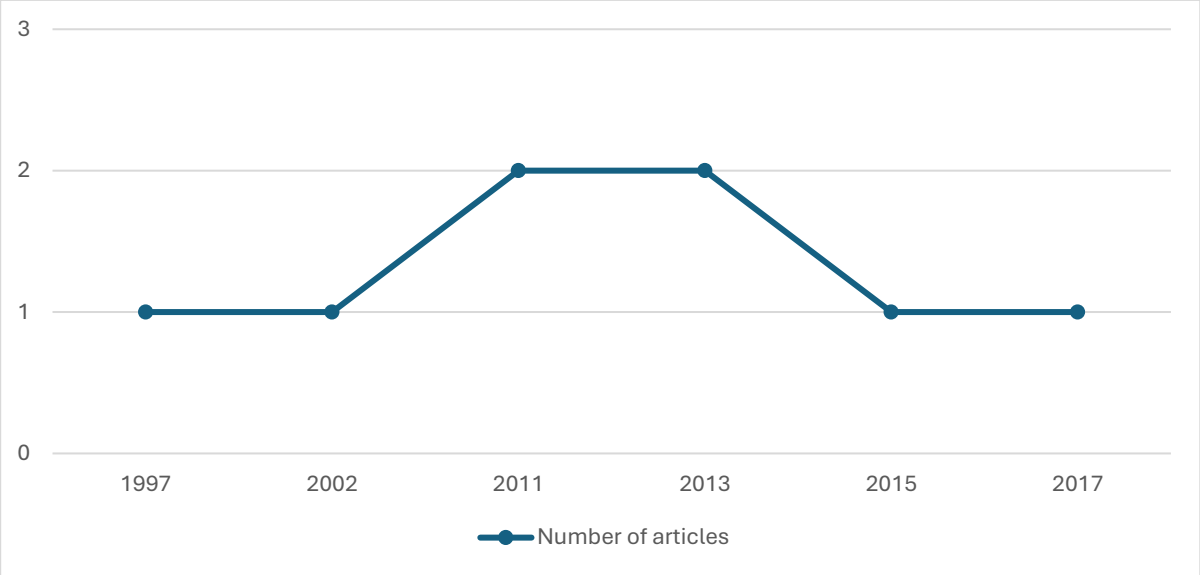
Figure 2.6: Timely Distribution of the Articles Belonging to Topic 4: Innovation Promotion



Topic # 5: Innovation design is represented by 8 articles and covers the "product" part of the 7Ps. "Product", "market", "design", "customer", and "perceived" are the terms highly correlated with the topic. The average posterior probability of articles in our corpus to belong to this topic is 0.58, which indicates an average fit of the topic (Guerreiro et al., 2015). Here, the research mainly uses consumer surveys and longitudinal data to investigate the impact of product and/or innovation characteristics on innovation adoption or innovation diffusion: e.g., newness of the product's design and features (e.g., Ziamou, 2002; ; Mugge and Dahl, 2013; Rubera et al., 2015) as well as other aspects of innovation design, e.g., design modularity (Lau et al., 2011) or contingent product design (Souder and Song, 1997). For instance, a study of Mugge and Dahl (2013) investigated the role of design newness and atypicality for radical and incremental innovations. Interestingly, the findings showcase that a lower level of design newness leads to more positive evaluations of radical innovations, whereas, for incremental innovations, there is no difference in the effect of design newness on innovation evaluations. Wood and Hoeffler (2013) investigate the role of the innovative design on innovation adoption through impression management, claiming that the willingness of adopters to appear innovative

and technology-savvy motivates them for adoption of innovative looking new technologies. All the studies have been fully focused on product innovations and the B2C sector. The evolution of the topic has been stable across late nineties until 2017 (see Figure 2.7).

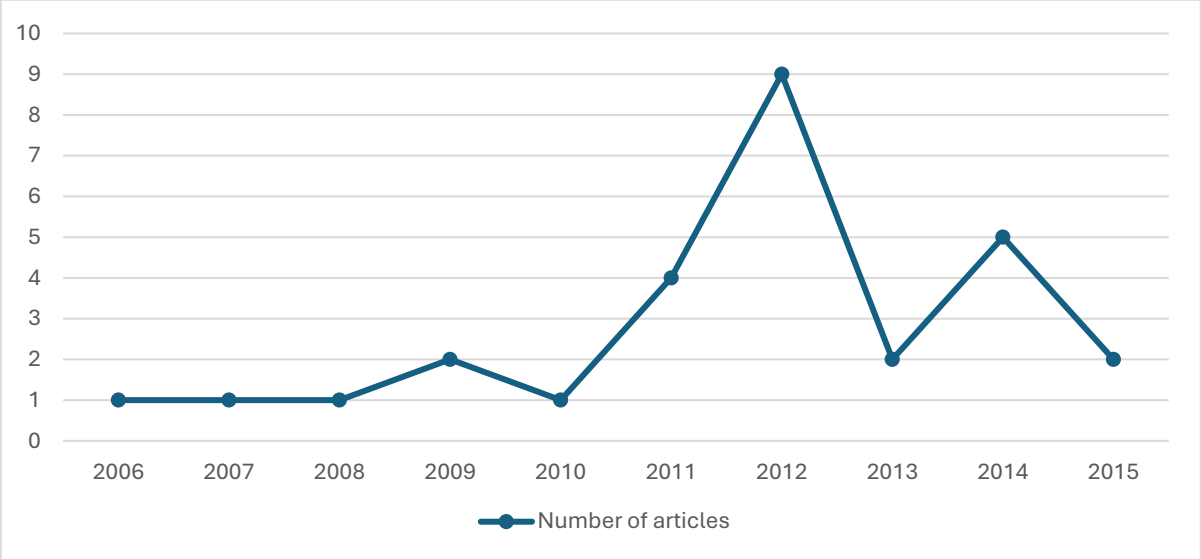
Figure 2.7: Timely Distribution of the Articles Belonging to Topic 5: Innovation Design



Topic # 6: Innovation marketing through social networks has received the strongest focus in the research within the investigated timeframe and contains 28 studies. The focus of this cluster is on the role of social media in the adoption of innovations, i.e., the topic focuses on the promotion of the tactical marketing program. The most frequent terms include "product", "adoption", "social", "consumer" and "network". The average posterior probability of articles in our corpus to belong to this topic is 0.68, which indicates a higher-than-average fit of the topic (Guerreiro et al., 2015). Specifically, articles address how firms can benefit from social networks to influence consumers' consideration of innovations. The studies mostly make use of consumer survey data and field experiments. Further, consumers' acceptance and adoption are the dependent variables studied. The research largely discusses word of mouth and social seeding (e.g. Bruce et al., 2012; Kawakami et al., 2012; Kawakami and Parry, 2013; Libai et

al., 2013; Huang et al., 2014), how targeting opinion leaders could help a more rapid innovation adoption (e.g. Aral, 2011; van Eck et al., 2011; Schweisfurth and Herstatt, 2015), and how management of social networks can stimulate consumer learning through online brand and product communities and reviews (Gruner et al., 2012; Gui et al., 2012). 100% of the studies focused on B2C segments. Also, the vast majority of the articles investigate product innovations, whereas service innovations receive only a limited focus (Andreassen and Streukens, 2009). Similarly, as with the previous topic, IM through social networks is a young topic. The first article was published in 2006 (Sussan et al., 2006), and the research topic has developed rapidly since then peaking in 2012 (see Figure 2.8).

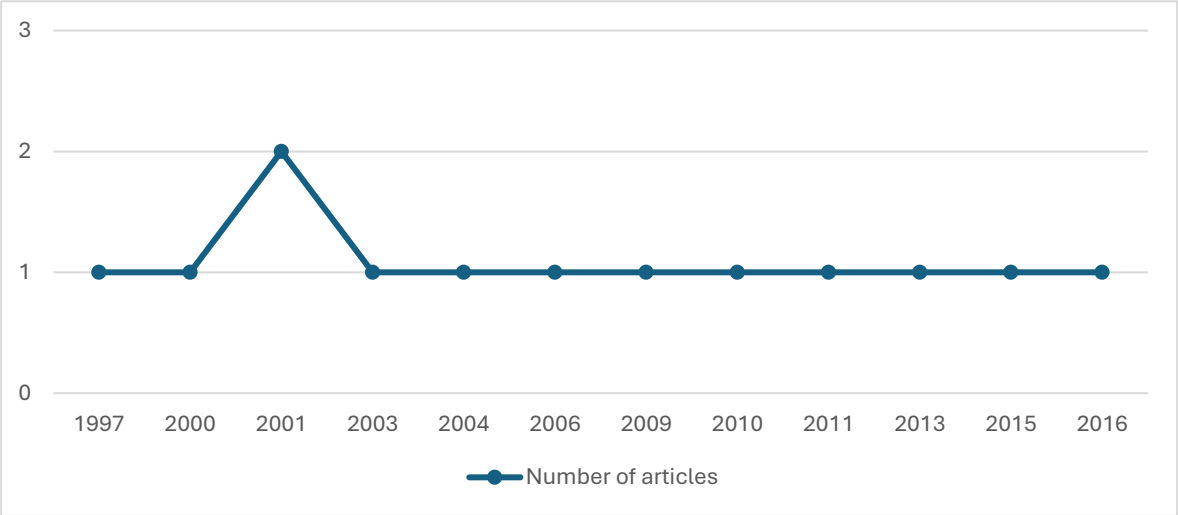
Figure 2.8: Timely Distribution of the Articles Belonging to Topic 6: Innovation Marketing Through Social Networks



Topic # 7: Innovation preannouncement comprises 11 articles and focuses on the "promotion" part of the tactical marketing program. The corresponding frequent terms are highly correlated with this topic: "product", "preannouncement", "market", "firm", "inform". The average posterior probability of articles in our corpus to belong to this topic is 0.55, which indicates an average fit of the topic (Guerreiro et al., 2015). Mainly, studies use secondary panel data. The research investigates consumers' adoption behaviour as a dependent variable.

More specifically, design aspects of preannouncement campaigns are investigated, e.g., communication signals during the preannouncement (Bayus et al., 2000; Jung, 2011; Popma et al., 2005; Su and Rao, 2010; Ofek and Turut, 2013) or the optimal timing of preannouncement (Lilly and Walters, 1997; Bayus et al., 2001; Le Nagard-Assayag et al., 2001; Wu et al., 2004; Schatzel and Calantone, 2006). For example, Popma et al. (2005) use content analysis to investigate a range of actual preannouncements of different innovations and provide insights on the design of new product preannouncements. Further, Schatzel and Calantone (2005) investigate whether the intensity of preannouncement is a prerequisite for innovation success through the creation of market anticipation. Three studies investigate preannouncements in the B2B sector (Bayus et al., 2000; Popma et al., 2003; Schatzel and Calantone, 2006). However, no studies investigate service innovations. The topic has been continuously investigated since the late 1990s (see Figure 2.9).

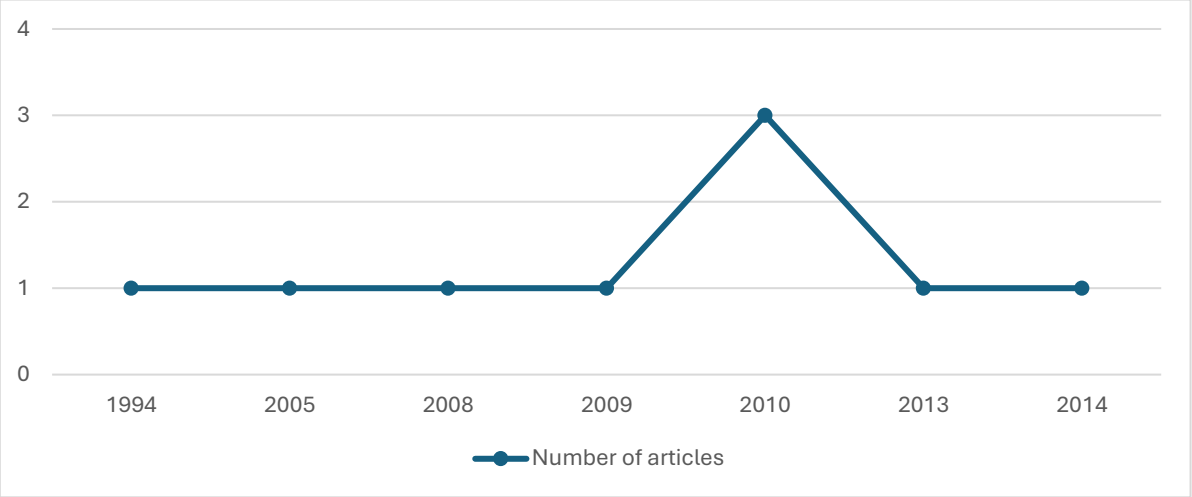
Figure 2.9: Timely Distribution of the Articles Belonging to Topic 7: Innovation Preannouncement



Topic # 8: *Innovation branding focuses* on "product" aspects of the marketing program and consists of 9 articles. Innovation branding is associated with the following frequent words: "brand", "product", "market", "extension", "category". The average posterior probability of

articles in our corpus to belong to this topic is 0.71, which indicates a good fit of the topic (Guerreiro et al., 2015). Studies belonging to this research topic predominantly rely on data gathered via consumer experiments. Consequently, the research focuses on consumer acceptance and adoption. Marketing program activities investigated are, for example, co-branding (e.g. Corkindale and Belder, 2009; Besharat et al., 2010) and brand extensions (Sheinin and Schmitt, 1994; Klink and Athaide, 2010; Goedetier et al., 2015). More specifically, Besharat (2010) investigates the effectiveness of co-branding vs. brand extensions on consumer attitudes towards innovations. The researcher shows that the presence of a high-equity brand positively impacts consumer evaluations of a new product. However, the findings of the study also show that there is no significant difference in consumer evaluations depending on the exact branding strategy. Goedetier et al. (2015) study of the impact of brand prototypically on adopters' acceptance of brand extensions and showcase that brand prototypicality positively impacts consumer acceptance of new product not only in close but also in “distant” product categories. All the studies belonging to the topic address B2C segments. Only two studies focus on service innovations (Halliday and Trott, 2010; O’Cass et al., 2013). In terms of the development over time, research on innovation branding was initiated in the early 1990s with no spark for more research at the beginning. However, in the early 2000s, researchers addressed innovation branding again, which progressed since then (see Figure 2.10).

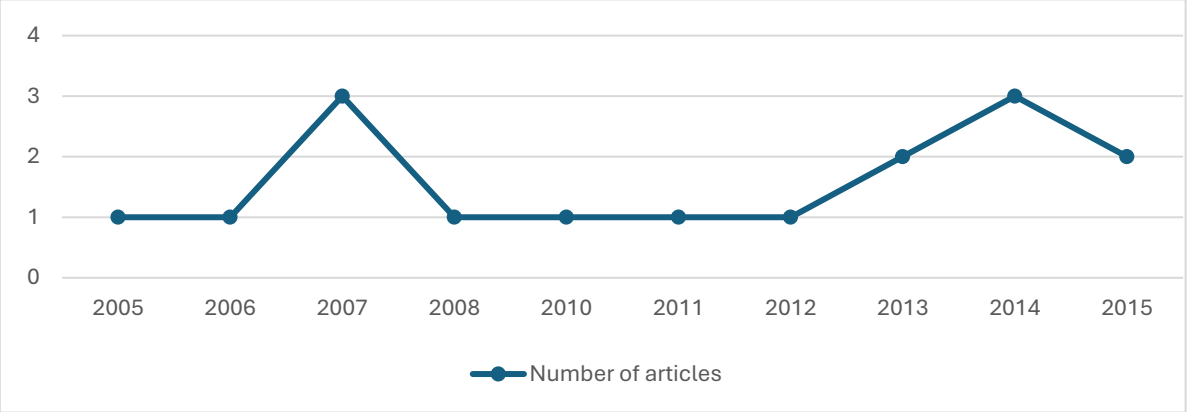
Figure 2.10: Timely Distribution of the Articles Belonging to Topic 8: Innovation Branding



Topic # 9: Innovation communications signalling product features is represented by 17 articles, which address the product "P" of the marketing mix. The characterizing frequent terms here are the following: "product", "detail", "quality", "learn", "model". The average posterior probability of articles in our corpus to belong to this topic is 0.65, which indicates a higher-than-average fit of the topic (Guerreiro et al., 2015). Based mainly on consumer experiments, the majority of articles in this topic investigate how feature-based communication influences consumers' acceptance. Besides others, researchers focus on what features should be communicated, e.g. quality, originality and usefulness (Li et al., 2014), familiarity (Zhou and Nakamoto, 2007; Ziamou et al., 2012; Nam et al., 2010), product reliability (Bakshi et al., 2015) and innovativeness (Calantone et al., 2006; Fu and Elliott, 2013; Stanko et al., 2014). Furthermore, studies investigate how feature-based communication helps to accelerate consumers' learning about innovation (Narayan and Machanda, 2007; Alexander et al., 2008; Ziamou and Veryzer, 2005) as well as to reduce consumer uncertainty regarding innovation (Narayan et al., 2005; Reinders et al., 2010; Nakata and Weidner, 2011; Talke and Heidenreich, 2013). From the 17 articles three articles focus on service innovations (Boxer and Reketeyye, 2011; Ordanini et al., 2014; Nylen and Holmstroem, 2015). All articles focus on the B2C sector.

The distribution of the articles across the timeframe shows that the topic of product features communications for innovations is a relatively new research stream emerging in the early 2000s and constantly developing since then (see Figure 2.11).

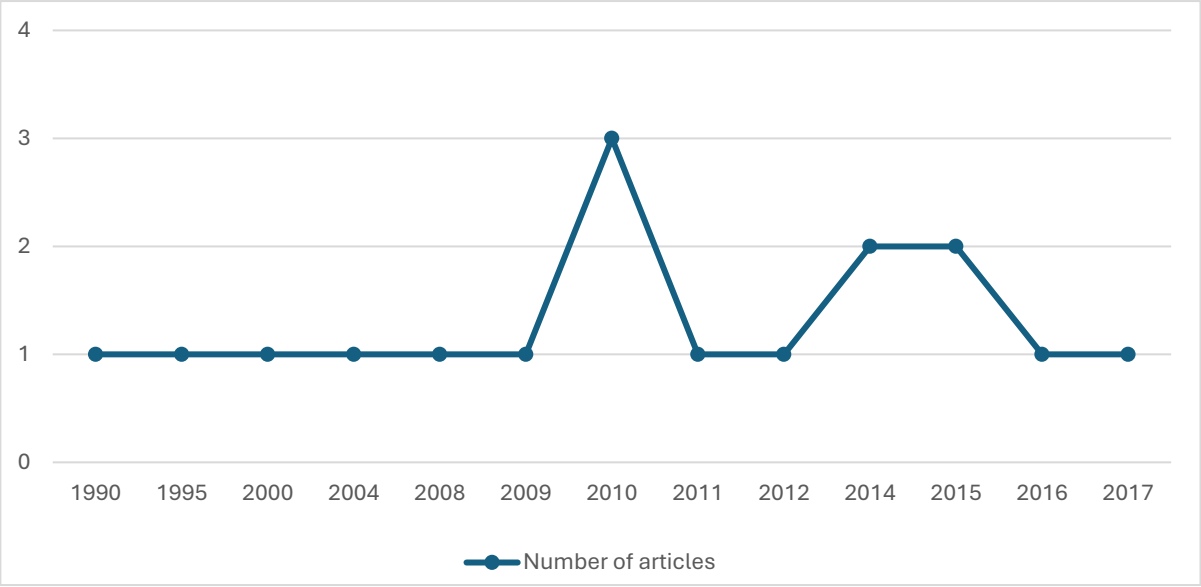
Figure 2.11: Timely Distribution of the Articles Belonging to Topic 9: Innovation Communications Signalling Product Features



Topic #10: Innovation frontline employee management is represented by 17 articles. The main focus here is on the "people" part of the marketing program with the corresponding frequent terms: "sales", "success", "effort", "performance", "innovation". The average posterior probability of articles in our corpus to belong to this topic is 0.65, which indicates a higher-than-average fit of the topic (Guerreiro et al., 2015). The studies investigate how frontline employee management drives innovation diffusion. For the analysis, researchers mostly use managerial surveys and expert interviews. First, findings demonstrate the role of frontline sales force in innovation diffusion (Hultink and Atuahene- Gima, 2000; Beuk et al., 2014). Further, some studies investigate tools to trigger frontline employee effectiveness, e.g. motivation and leadership (Cadwalader et al., 2010; Van der Borgh and Schepers, 2014) and empowerment (Sok and O'Cass, 2015). Other studies look into frontline employee characteristics, e.g. age and experience (Fu, 2009) or team innovativeness (Thamhain, 1990). Furthermore, a number of scholars address the issue of cross-functional integration of the frontline teams with other

functional teams in the light of the new product performance (Troy et al., 2008; Calantone and Rubera, 2011; Santos-Vijande et al., 2016; Grimpe et al., 2017). Within this topic we observe a more significant focus on service innovations compared to other topics (Cadwalader et al., 2010; Melton and Hartline, 2010; Karlsson and Skalen, 2012; Hidalgo and Alvano, 2015; Sok and O'Cass, 2015; Santos-Vijande et al., 2016). However, the focus on the B2B context is still very limited and represented just by two articles (Fu, 2009; Santos-Vijande et al., 2016). In regard to the development over time, the topic has received some attention already in the nineties, further developed in the beginning of the 2000s, however, the peak of studies is observed around 2010-2016 (see Figure 2.12).

Figure 2.12: Timely Distribution of the Articles Belonging to Topic 10: Innovation Frontline Employee Management

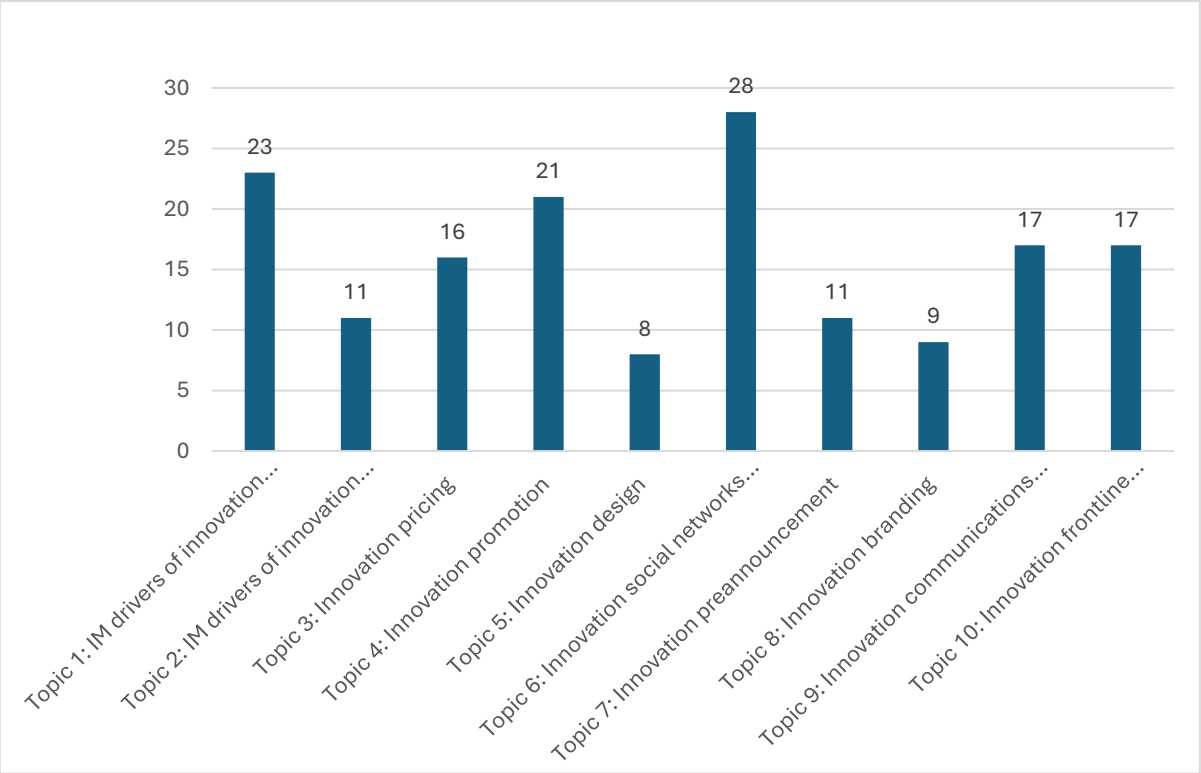


2.6 Avenues for Future Research

Although the research on IM has progressed significantly in the last 27 years and covers a wide spectrum of topics, some research areas receive only limited attention or are so far ignored by researchers (see Figure 2.13). The results of our analysis of IM research demonstrate that the evolution of the extant IM studies has been taking place in a disorganized manner. The researchers have been using inconsistent approaches and foci. Therefore, IM literature

resembles scattered pieces rather than a comprehensive research field. Essentially, following aligned perspectives and consistent foci would help to address a broader spectrum of issues, to achieve more generalizable insights, and to generate a more robust understanding of IM. Aiming for such a development, we propose the following future research avenues.

Figure 2.13: Distribution of IM Articles per Topic



2.6.1 Focus of Tactical Marketing Program

The results of our analysis demonstrate that different elements of the tactical marketing program for innovations have not been investigated to the same extent. More specifically, we observe the majority of focus on Product, Promotion and Price and People – "Ps" of the tactical marketing program. Whereas, Place, Process, and Physical evidence have received very limited attention.

Product. The Product- P of the marketing mix has been studied extensively, where the studies focused on the aspects of product features (Topic # 9), innovation branding (Topic # 8)

and innovation design (Topic # 5). As innovations represent products and services that are novel to adopters (Dotzel et al., 2013), future research could investigate the role of additional services like warranties, product service, innovative trial, and usage opportunities that would help to address adopters' uncertainty and adoption barriers.

Price. The Price- P of the marketing mix has been also studied significantly in the IM research field, not only individually (Topic # 3), but also in combination with other Ps like promotion and product (Topic # 1 and Topic # 2). However, the research has been focusing mainly on the classical aspects of pricing (i.e. monetary price). Whereas, with the proliferation of service innovations and digital innovations (Huang and Rust, 2013), future research should put more attention to the aspects of dynamic pricing (e.g., pay per use, subscription) and non-monetary pricing mechanisms (freemium or free-of-charge pricing).

Promotion. The Promotion- P of the marketing mix is one of the most extensively studied areas in the last decades. As the Pricing P, the aspects of promotion were oftentimes studied individually (Topic # 4, Topic # 6 and 7), but also in combination with other Ps like pricing and promotion (Topic # 1 and 2). A particular focus was put on social media promotion (Topic # 6). Nevertheless, we see still some room for future research, particularly in the digital area by addressing the aspects of Influencer, Affiliate, and Content marketing that could be helpful in overcoming the initial uncertainty with innovations and foster their trial.

Place. Contrary to Promotion, the Place- P of the marketing mix has been one of the least studied areas, which is very surprising, as a strong distribution strategy is crucial for innovation market success (Sikdar and Vel, 2010). We could observe that, in general, the research has been predominantly focused on the aspects and drivers of adopters' acceptance of innovations as one of the key issues in the research, ignoring other crucial aspects of the marketing mix. Hence, future research has significant potential by addressing the distribution of innovations, mainly the aspects of classical distribution, as stationary places like specialist

dealers and stores. However, digitalisation and proliferation of service innovations offer even more opportunities for investigation due to the emergence of online platforms and marketplaces. Which is particularly interesting for the research, because it allows to drastically reduce the intermediate steps in the distribution process and provides companies opportunities for direct-to-consumer sales.

People. The People P is a somewhat studied area of the marketing mix, still with a significant potential for future research. Whereby, clearly, the research should put more focus on service innovations, where frontline personnel play a crucial role. Here, the research should investigate aspects of necessary employee trainings and also measures to empower personnel to become ambassadors of innovations and play an active role in shaping adopters' perceptions of innovations. The same principles of personnel acting as ambassadors would equally benefit product innovations as well. Another area requiring attention would be the challenges and peculiarities of the online sales processes (e.g. online advisors, video demonstrations, chatbots), both for product and service innovations, due to the proliferation of digital technologies and digital innovations

Process. The Process- P is one of the least studied elements of the tactical marketing program in the innovation marketing literature. This can be driven by the fact that, equally, the focus on service innovations has been fairly limited. Future research should address the classical aspects of the process related to new service development. Another significant research opportunity would be the involvement of adopters in the innovation co-creation processes, which might positively impact general uncertainty and adoption barriers of service innovations. Furthermore, as digitalisation offers numerous new opportunities for the development of service innovations and digital innovations (Kannan and Li, 2017), future research could also investigate the potential for innovative process design leveraging online platforms and digital technologies (e.g., virtual reality, artificial intelligence, machine learning).

Physical evidence. The Physical evidence-P is another least studied element of the tactical marketing mix within the marketing literature. Similar to the process "P", the lack of focus could be attributed to the general lack of focus on service innovations. However, the initial significant research opportunity would be to investigate the classical aspects of environment design for both product innovations and service innovations. Nowadays, companies strive not only to sell a product or service to a customer, but to deliver an experience (Nasermoadeli et al., 2013), where the store layout, design, packaging, signage, displays and staff appearance play a vital role. In addition, addressing the aspects of experience would help companies to target uncertainty and lack of trust to innovations. Furthermore, digitalisation provides additional aspects of physical evidence like the representation of the online environment of a product or service innovation, e.g. online presence, online ratings and reviews, social media profiles and customer testimonials.

2.6.2 Single vs. Multiple IM Tactical Activities

Studies on IM tactical activities predominantly address single IM tactical activities (Topic # 3, Topic # 4, Topic # 5, Topic # 6, Topic # 7. Topic # 8, Topic # 9. Topic # 10). Fewer topics examine multiple IM activities (Topic # 1 and Topic # 2). However, the fundamental logic of marketing is that marketing activities are not perceived in isolation, but in coexistence with each other. Logically, the signalling value of the entire marketing program needs to be accounted for by IM research (Kuester et al., 2018; Schuhmacher et al., 2018). Consequently, future studies need to broaden the scope towards the simultaneous investigation of several tactical marketing activities. This is in line with recent developments, where studies suggest investigating bundles of marketing activities and their impact on innovation adoption (Schuhmacher et al., 2018).

2.6.3 Innovation Adoption vs. Diffusion

Five of the ten IM topics focus on innovation diffusion (Topic # 1, Topic # 2, Topic # 3, Topic # 5, Topic # 10). These topics provide valuable insights on the role of innovation pricing, design, and product configuration, front-line employee management, as well as some combinations of tactical marketing activities for innovation diffusion. So far, research has developed a more diverse knowledge on different IM activities' impact on innovation adoption (Topic # 4, Topic # 6, Topic # 7, Topic # 8, and Topic # 9). Consequently, future research should study the performance of those marketing tools in the context of innovation diffusion, considering distribution, branding, experiential marketing, communications, innovation preannouncement, or social networks marketing. This is essential, as innovation diffusion represents a more complex phenomenon than the sum of individual adoptions. Based on Rogers' (1969) innovation diffusion model, an important element here is the presence of various adopter categories. However, there is no empirical justification that the size of adopter categories and their composition are constant for all innovations (Peterson, 1973). Therefore, it is valuable to extend the current research to a wider range of products and industries as well as across different adopter groups to be able to draw generalizations for the research field.

2.6.4 Innovation Focus

Our study showcases that the IM research is heavily skewed towards product innovations. The lack of focus is not justified; hence, we call for future research to address service innovations more seriously. First, service innovations differ from product innovations in their nature, therefore, the insights generated for product innovations can be applied to services only to a limited extent (Edwards et al., 2015). Second, service innovations have intangibility in their nature (Couter and Couter, 2003), which makes it more difficult for

potential adopters to overcome the initial uncertainty and substantiate the importance of certain marketing mix elements like process and physical evidence.

2.6.5 Customer Focus

Our research also demonstrated an unequal focus on B2C compared to B2B segments. This is expected, as a large number of innovations are launched in B2C segments, and the human adoption patterns are complex. However, nowadays a lot of innovations are also introduced in the B2B area (Lilien, 2016), whereby the research insights generated about adoption patterns in B2C segments cannot be transferred and applied in B2B segments, which creates a major research gap.

2.6.6 Digitalization of Innovations

Nowadays, digitalization drives a flood of innovation launches by companies (Bomsel and Le Blanc, 2004). Furthermore, this rise of digital innovations originates not only from established companies but also from start-ups (Kuester et al., 2018). These DIs result in the appearance of new business model designs. For example, we see an emergence of new revenue model designs around them, e.g., the freemium, hidden revenue models, and others (Lui et al., 2014; Fleisch et al., 2015). So far, it is unclear how these different designs drive customer acceptance, adoption, and ultimately diffusion. Hence, there is a need for future research that accounts for the developments and provides insights on how to effectively design IM for DIs.

2.7 Overarching Structure of IM research: IM Research Areas

Based on the results of the text mining analysis, we developed an IM research framework based on two dimensions: focus of tactical marketing activities (single vs. multiple) and the dependent variable (innovation adoption vs. diffusion) (see Figure 2.14). Based on these

two dimensions, the ten identified IM research topics are grouped into a four-quadrant matrix and thus, into four different research areas.

The first research area, i.e. the left bottom quadrant of the matrix, represents five topics covering single tactical marketing activities and their impact on innovation adoption: *Innovation promotion* (Topic # 4), *Innovation social networks marketing* (Topic # 6), *Innovation preannouncement* (Topic # 7), *Innovation branding* (Topic # 8), *Innovation communications signalling new product features* (Topic # 9). Thus, these five topics share the focus on one specific marketing tactic but differ in the investigated marketing Ps.

The second research area, i.e. the right bottom quadrant, also represents topics on a single tactical marketing activity; however, here studies examine how the respective activity drives innovation diffusion. The following three topics determine this research area: *Innovation pricing* (Topic # 3), *Innovation design and product configuration* (Topic # 5) as well as *Innovation front line employee management* (Topic # 10).

The third research area, i.e. the right upper quadrant of the matrix, represents topics with studies on multiple tactical marketing activities and their impact on innovation diffusion. Two topics are part of this research area: *IM drivers of innovation market take-off* (Topic # 1) and *IM drivers of innovation launch* (Topic # 2). Unlike the first two research areas, this third research area investigates how several marketing activities simultaneously impact either innovation launch or take-off.

The left upper quadrant of the matrix represents the research area of studies on multiple tactical marketing activities influence on innovation adoption. Between 1990 and 2017, no study investigated this research area.

Figure 2.14: Overarching IM Research Framework

Multiple tactical marketing activities

Single tactical marketing activities

Topic # 1: IM drivers of innovation launchc

Topic # 2: IM drivers of innovation take-off

Topic # 8: Innovation branding

Topic # 4: Innovation promotion

Topic # 6: Innovations social networks marketing

Topic # 9: Innovation communications signalling product features

Topic # 7: Innovation preannouncement

Topic # 3: Innovation pricing

Topic # 5: Innovation design

Topic # 10: Innovation frontline employee management

Innovation adoption

Innovation diffusion

2.8 Conclusion

IM has received increased attention from marketing researchers over the last decades. Consequently, the number of articles on IM has grown exponentially, resulting in a highly fragmented research field. For example, so far there is no common understanding of IM. In addition, despite the relevance of innovation development and the successful launch of innovations, we have no holistic understanding of extant research and necessary future research directions. So far, literature reviews in the IM field only focus on single tactical marketing activities (e.g. Bouten et al., 2011; Libai et al., 2013; Avagyan et al., 2016). However, to be able to conduct more meaningful research, researchers need to build on and combine insights from existing studies. Hence, this study provides an important review on the state of knowledge on IM research from 1990 to 2017.

First, due to the lack of a comprehensive definition of IM in the literature we proposed a definition of IM based on the works of the researchers in the IM research field (Castaño et al., 2008; Goode et al., 2013; Heidenreich and Kramer, 2015; Reinders, 2010; Talke and Heidenreich, 2014). Following that, we combined the systematic literature review methodology (Petticrew and Roberts, 2008) and text mining approach (Randhawa et al., 2016) to synthesize published IM articles to present a comprehensive review of the research field. The results demonstrate that IM research is fragmented with an unbalanced focus on certain tactical marketing program aspects. In addition, we identified ten core research topics varying in investigation breadth and depth. We classify these topics into four main research areas of IM literature depending on their focus: single tactical marketing activities focused on either innovation adoption or diffusion and multiple tactical marketing activities focused on innovation diffusion. In general, the majority of IM studies focus predominantly on single tactical marketing activities triggering customers' innovation adoption.

However, marketing activities do not operate in isolation; they serve as signal vehicles to communicate particular signals to potential customers (Schuhmacher et al., 2018). Thus, future studies must not concentrate on single activities but need to examine the combined signal value of different tactical marketing activities (Hultink et al., 1999; Lee et al., 2011). Further, based on the diffusion theory (Rogers, 1983), research needs to collect, use or combine data to investigate more aspects of IM in the context of innovation diffusion.

Taken together, this review offers researchers an understanding of the IM research structure, several research gaps and future research directions. Given the increasing intensity and complexity of innovation launches (Lafferty et al., 2005), research on IM will continuously attract researchers to the IM research field. Our study provides all researchers a starting point for a comprehensive understanding of IM research. Due to the use of a systematic research methodology, our study reduces the bias associated with traditional literature reviews (Randhawa et al., 2016). Overall, we call researchers to broaden IM knowledge beyond IM for product innovations in B2C industries to also service innovations and B2B industries as well as beyond "traditional" marketing mix variables to account for digital marketing and revenue models. Finally, we stress the ongoing trends of DI launches in the marketplace and call for comprehensive research of marketing tactics considering peculiarities of DIs like their intangibility and digital nature (Couter and Couter, 2003; Featherman and Pavlou, 2003).

2.9 Limitations

Inevitably, this literature review is not without limitations. First, our results are a representation of existing published research and exclude ongoing debates and conference proceedings as well as not-yet-published articles, inclusion of which might have enhanced our empirical base. Second, although this paper makes use of the full texts of published articles instead of only titles and abstracts, the results are still an outcome of a particular algorithm

employed by a software with a limited output (terms and probabilities) but a broad room for interpretation. Third, the cross-sectional nature of some of the studies (e.g. investigating several marketing Ps or other factors) limited ability of the text mining mechanisms to 100% correctly allocate studies to topics, limiting our ability to make correct inferences. Finally, conducting a broad review of the literature required a larger focus on the breadth rather than depth. Hence, the possibility of organising a wide range of knowledge and making single literature streams clearer and more tangible came at expense of being able to investigate each topic at depth.

3 Paper 2: Making a First Impression as a Start-up: Strategies to Overcome Low Initial Trust Perceptions in Digital Innovation Adoption

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Status: Published in the International Journal of Research in Marketing
Presented at: Academy of Marketing Science World Marketing Congress in 2019 in Edinburgh, UK

Abstract

High failure rates of DIs by start-ups indicate that consumers' initial trust perceptions are make-or-break for their survival. Hence, start-ups have to design adequate business models to manage consumers' initial trust perceptions of DIs. Five experiments explore how start-ups can signal trustworthiness in order to overcome low initial trust perceptions and boost adoption. We find three specific design strategies of start-ups' digital business models – customer ratings, benefit communication, and revenue model – to be effective to overcome low initial trust perceptions and to increase adoption of DIs of start-ups. The findings demonstrate that initial trust serves as a critical mediator in the relationship between these design strategies and consumers' adoption intention. Additionally, the revenue model chosen has differential effects on privacy concerns, which mediate the relationship between revenue model and initial trust. The present empirical insights help start-ups to craft business model design strategies for successful DI launch.

Keywords: *Start-up, digital innovation, digital business model, initial trust, privacy concerns, adoption intention*

3.1 Introduction

Increasingly, companies focus on developing and launching DIs (Huang and Rust, 2013). DIs are Internet-enabled service innovations (Dotzel et al., 2013), such as the online cloud-service Dropbox at the time of its market introduction in 2008, which revolutionized the established file storage industry. DIs can change the way people live, work, and communicate (Higgins, 2015). Recent research even indicates that these digital advancements create notable gains in consumer welfare, which traditional accounts of economic activities do not seem to capture (Brynjolfsson et al., 2018). As DIs are drivers of future economic success, researchers call for research on consumers' acceptance of DIs (Kannan and Li, 2016; Kuester et al., 2018; Kunz and Hogreve, 2011). Start-ups have become especially important in launching DIs but more than 90% of these endeavors fail (Marmer et al., 2011). This failure rate indicates that start-ups seldom get a second chance to make a first impression but also makes successful DIs by start-ups notable.

Ultimately, the success of an innovation depends on consumers adopting it (Hauser et al., 2006). At the same time, achieving a high level of DI acceptance is challenging for companies (Prins et al., 2009). Whether consumers eventually adopt a DI largely depends on their first impression of the DI's trustworthiness. Uncertainty generally surrounds innovations (Meuter and Ostrom, 2000) and this uncertainty is pronounced in case of DIs due to their digital nature (Coulter and Coulter, 2003; Featherman and Pavlou, 2003). This uncertainty may find expression in privacy concerns, fear for data misuse, and in doubts regarding performance (Featherman and Pavlou, 2003; Meuter, and Ostrom, 2000). Consumers' unfamiliarity with the launching company further aggravates these conditions (McKnight et al., 2002) as in the case when the DI is launched by a start-up. The initial touchpoint in a consumer's journey represents a critical stage in this regard (Lemon and Verhoef, 2016). Nevertheless, research about consumers' initial perceptions of DIs – especially initial trust perceptions – is scant. Prior

research indicates that trust may help to resolve perceptions of uncertainty (Ha and Stoel, 2009; Morrison and Firmstone, 2000; Nienaber and Schewe, 2014). This finding holds also for services (Coulter and Coulter, 2003) and in the digital environment (Kannan and Li, 2017). In fact, some researchers found evidence for a general positive influence of trust on the use of electronic services (Beldad et al., 2010) and e-commerce (Ha and Stoel, 2009; McKnight et al., 2002; Morrison and Firmstone, 2000; Nienaber and Schewe, 2014).

However, in case of an unknown product such as a DI by an unknown start-up prior customer experiences do not exist. McKnight et al. (2002, p. 335), define trust in an "unfamiliar trustee", with whom consumers have had no prior experiences, as initial trust. Initial trust may constitute a valuable piece of information in this otherwise information-poor adoption decision setting. In these settings, start-ups face the challenge to generate initial trust for their DIs to boost consumer adoption. Based on the Signaling Theory (Spence 1973), this study proposes that start-ups can signal trustworthiness via specific business model design strategies when launching DIs.

Empirical evidence obtained in the context of e-commerce suggests that consumers use any information available to form initial trust about an unknown e-vendor (McKnight et al., 2002; Schlosser et al., 2006). In the case of a DI by an unknown company, consumers have no prior experiences and lack comprehensive information. So far, there is no research on the creation of consumers' initial trust in the DI start-up context. Our research addresses this deficiency by investigating how to overcome low initial trust perceptions to boost adoption.

Due to the digitalization, we see a rise of new forms of business models. Especially start-ups launching DIs make use of specific design strategies for business models. In their explorative study, Kuester et al. (2018) investigate go-to-market strategies for DIs of start-ups. They propose trust to serve as a mediator in the relationship between the DI's signals of trustworthiness, including customer ratings and payment modalities, and DI adoption. For

example, Google's or Facebook's revenue model is based on consumers 'paying' services with their data. But little is known about *whether* and *how* these business model design strategies are able to overcome the low initial trust perceptions of start-ups' DIs. By investigating the influence of different design strategies for digital business models on initial trust perceptions, we close this research gap.

The present work provides valuable contributions to the extant literature. First, this study extends adoption research to the growing field of DIs. Specifically, this study contributes to research on adoption of start-ups' DIs (Kuester et al., 2018) by showing the necessity of overcoming consumers' low initial trust perceptions for successful commercialization of DIs by start-ups. Second, the present findings expand current knowledge on the role of trust in the online context (Schlosser et al., 2006). The insights highlight the importance of initial trust perceptions in the go-to-market strategies–adoption relation. Specifically, the findings establish initial trust as a critical mediator in the relationship between design strategies of digital business models functioning as signals and adoption intentions. Finally, our work contributes to the effectiveness of the design of digital business models by illustrating that start-ups are able to overcome low initial trust perceptions regarding their DIs with the targeted use of specific strategies. Using signaling theoretical reasoning, we test the effectiveness of different business model design strategies as trustworthiness signals: customer ratings, benefit communication, and revenue model.

3.2 Adoption of DIs

Research on innovation adoption has long been established in the field of marketing (e.g., Taylor and Todd, 1995; for an overview, see Arts et al., 2011). However, adoption research has not kept pace with digitalization. Most adoption studies focus on researching product innovations (Feiereisen et al., 2013; Müller-Stewens et al., 2017). Other studies are concerned

with service innovations (Prins et al., 2009), with very little research pertaining to digital services (Ha and Stoel, 2009) or specifically accounting for the role of trust (Nienaber and Schewe, 2014). Research on the adoption of DIs and the design of effective digital business models in this regard is scarce. Although the adoption and commercialization of DIs is a genuine consumer research and marketing topic, research on DIs mainly originates in information systems (Featherman and Pavlou, 2003; Hampton-Sosa, 2017). Only a few studies derive recommendations for the commercialization of digital products (Talke and Snelders, 2013) or digital services (Prins and Verhoef, 2007). Although more and more start-ups are launching DIs (Marmer et al., 2011), researchers have neglected the special context of DI adoption by an unknown company, as represented by a start-up.

Our study embraces a multidisciplinary vantage point and bridges the gap between marketing and information systems by exploring how start-ups can overcome initially low trust perceptions of their DIs. Reviewing relevant literature in these fields, Table 3.1 depicts quantitative studies on the adoption of (digital) innovations and shows how the present study contributes to the existing body of adoption research.

Although the number of DIs using innovative digital business models is increasing, especially by start-ups, research on go-to-market strategies for DIs is largely lacking. As an exception, Kuester et al. (2018) investigate go-to-market strategies for DIs of start-ups but point out that there is no "[...] study that explores the marketing mix components of EIs [e-innovations] or of innovations launched by start-ups" (Kuester et al. 2018, p. 67). Furthermore, the majority of studies that investigate the marketing of innovations focuses on promotion (Fruchter and van den Bulte, 2011; Hariharan et al., 2015; Le Narad-Assayag and Manceau, 2001) and pricing (Kuester et al. 2015; Park et al., 2011).

Table 3.1: Selected Studies on Quantitative Adoption Research

Selected studies	Research field	Focus	Innovation context?	Focus on digital?	Including trust?	Start-up context?	On design of digital business model components?
Karahanna et al. 1999, MISQ Yu et al. 2017, CHB	information systems	information technology	no	yes	no	no	no
Hoeffler 2003, JMR Wood & Moreau 2006, JM Herzenstein et al. 2007, JMR Castaño et al. 2008, JMR Alexander et al. 2009, JMR Feiereisen et al. 2013, JPIM Kuester et al. 2015, IJRM Müller-Stewens et al. 2017, JM Schuhmacher et al. 2018, JPIM	marketing	products	yes	no	no	no	no
Krieger et al. 2003, JSM Prins et al.2009, IJRM	marketing	Services	yes	no	no	no	no
Nienaber and Schewe 2014, IJIM	marketing	Services	yes	no	yes	no	no
Parry & Kawakami 2015, JPIM	marketing	products	yes	yes	no	no	no
Meuter et al. 2005, JM	marketing	Services	yes	yes	no	no	no
Featherman & Pavlou 2003, IJH-CS Hampton-Sosa 2017, CHB	information systems	services	yes	yes	no	no	no
Talke & Snelders 2013, JPIM	marketing	products	yes	yes	no	no	promotion
Prins & Verhoef 2007, JM	marketing	services	yes	yes	no	no	promotion
Ha and Stoel 2009, JBR	marketing	services	yes	yes	yes	no	no
Pavlou & Fygenson 2006, MISQ	information systems	services	yes	yes	yes	no	no
Present study	*marketing*	*services*	*yes*	*yes*	*yes*	*yes*	*promotion revenue model*

3.3 Signalling Trustworthiness

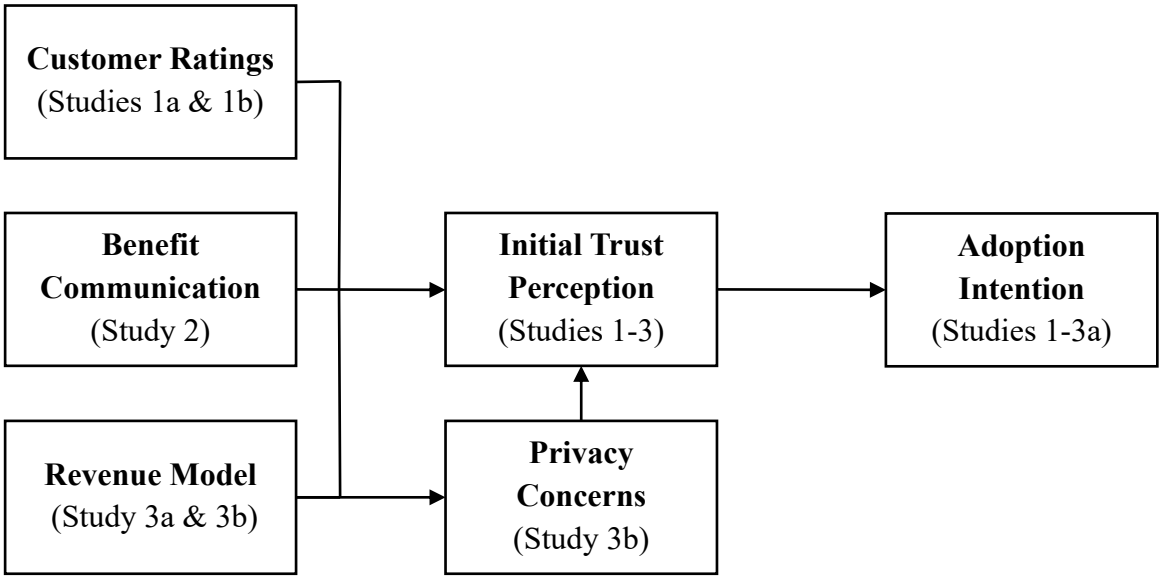
The present study draws on the Signaling Theory (Spence, 1973) to explore how start-ups can overcome consumers low initial trust perceptions of their DIs. Signaling theory describes how a signal sender and receiver may behave under asymmetric information. Signal senders are better informed than outsiders about an individual (Spence, 1973) or an organization (Ross, 1977). These insiders may communicate their information to other parties in form of a signal (Connelly et al., 2011). To be effective, signals need to be observable to these outsiders and costly to the effect that obtaining this signal is more expensive for low than high quality actors (Connelly et al., 2011; Spence, 1973). Signal receivers may then interpret signals to draw conclusions, for example, about the expected quality of the signal sending individual (Spence, 1973) or company (Ross, 1977). As a result, signal receivers are able to gain information so that information asymmetries between signal sender and receiver decrease.

Based on this logic, there are two main mechanisms to reduce information asymmetries between start-ups offering DIs and potential consumers. On the one hand, start-ups can actively provide information to consumers by sending specific signals (Kuester et al., 2018). Start-ups may send these signals to signal the innovation's quality (Schuhmacher et al., 2018) or the trustworthiness of their DIs (Kuester et al., 2018). Such signals can reduce perceived information asymmetry, which in turn reduces uncertainty, to favorably impact innovation adoption (Kuester et al., 2018). On the other hand, consumers can actively search for signals to reduce their uncertainty accruing from information disadvantages with regard to a start-up's DI in their decision about adopting the DI. For example, in e-commerce, consumers look for and use any information available to form initial trust perceptions about an unknown e-vendor (McKnight et al., 2002; Schlosser et al., 2006). Consequently, the receiver interprets the signal to make a decision based on the information obtained from the signal.

In the following, we apply signaling theory to explain how start-ups launching a DI can use design strategies of digital business models as signals for trustworthiness. Start-ups can mitigate information asymmetries that exist at the time of launching a DI thereby enhancing initial trust perceptions and, ultimately, adoption. Whereas start-ups know the true quality of their DI, consumers may not. In fact, DIs by start-ups imply high levels of uncertainty for consumers because of the DIs' digital nature (Coulter and Coulter, 2003; Featherman and Pavlou, 2003), its complexity or (in)compatibility (Boulding and Kirmani, 1993; Rogers, 2003), its novelty (Meuter et al., 2000), its intangibility (Huang and Rust, 2013), and due to perceived liabilities of start-ups (Baum and Silverman, 2004; Huyghebaert and van de Gucht, 2007). Regarding consumers' decision-making process with regard to DIs, signals may serve as heuristic cues that help consumers to make inferences about the respective DI.

Kuester et al. (2018) argue that several signals can signal trustworthiness such as revealing the DI's origin, ensuring data safety or stressing customer referrals. The present study specifically investigates customer ratings, revenue model, and benefit communication regarding their effectiveness in serving as trustworthiness signals. Initial trust perceptions induce behavioral reactions of consumers such as purchase behavior (e.g., McKnight et al., 2002) and adoption intention which refers to a "consumer's expressed desire to purchase a new product in the near future" (Arts et al., 2011, p.135). Based on previous findings on trust in general (Wu et al., 2011), we argue that the higher the initial trust perception the higher the adoption intention for a DI by a start-up. Figure 3.1 provides an overview of the organizational framework of all studies.

Figure 3.1: Organizational Framework



3.4 Study 1: The Influence of Customer Ratings on Initial Trust Perceptions

In Study 1, we investigate the effectiveness of customer ratings to overcome low initial trust. First, we are interested whether the number of available favorable customer ratings impacts perceived initial trust, and in turn, adoption. In this regard, we compare the effect of having a low number versus a high number of positive customer ratings (Study 1a). Second, we explore the impact of the (positive) valence of customer ratings (Study 1b).

3.4.1 Study 1a: The Impact of the Number of Available Positive Customer Ratings

Given the specific context of DIs by start-ups, we propose positive customer ratings as a signal to communicate trustworthiness. Customer ratings are used to signal the quality of a company and/or product (Dellarocas, 2006). De Langhe et al. (2015) found consumers to use the average rating but also the number of ratings as direct quality cues. We argue that the number of positive customer ratings can serve as an effective trustworthiness signal for start-ups' DI. Applying signaling theory logic (Connelly et al., 2011; Spence, 1973), a small number of

positive customer ratings is less costly for both start-ups offering low quality or high quality DIs. Thus, signaling trustworthiness via a small number of positive customer ratings will be less effective and unlikely to favorably impact low initial trust. In contrast, over time start-ups offering high quality DIs will automatically receive a high number of positive customer ratings. Hence, by showing a high number compared to a low number of positive customer ratings, start-ups are better able to signal the trustworthiness of their DI. We hypothesize:

Hypothesis 1: A DI by a start-up with a high number of positive customer ratings leads to higher initial trust perceptions than a DI by a start-up with a small number of positive customer ratings, ultimately resulting in higher adoption intentions.

3.4.1.1 Method

Participants and design. Augmented reality (AR) is often a central application of DIs, specifically for start-ups (Soldamatic, 2017). For the purpose of this study, we thus chose an AR-based city guide developed by a start-up and available for three international cities. The DI was not available for any major European city at the time of the study, making it unlikely that participants knew the guide, which we coined *CityTour AR*. For our experiment, we used the visualization of the available app modifying its name and visuals. We recruited participants via a European online consumer panel and randomly assigned them to the 2 (number of positive customer ratings: low vs. high) x 1 between-subjects factorial design. We obtained 212 completed questionnaires. Following Buchanan and Scofield (2018), we used the character reading limit to estimate reading time and measured time spent on filling out the survey to detect speeders (Mason and Suri, 2012). Excluding 11 speeders from our data resulted in a final sample of 174 participants (51.1% female, average age: 47.9 years) allocated equally across cell sizes.

Procedure. We asked all participants to imagine that their next trip would be a city trip and while preparing for the trip they were searching on the Internet and in their app store for a digital, app-based city guide. Further, they were asked to imagine that they would go to their app store to search for suitable city guides. We then highlighted one search result: an innovative digital, AR-based city guide called *CityTour AR*. We informed the participants that *CityTour AR* is the first product by the start-up *CityTour* explaining that the app offers the visualization of city tours using AR. We further instructed the participants to read the app store description of *CityTour AR*. We implemented the manipulation of customer rating into the visualization of *CityTour AR* in a way typical for an app store. In both conditions, the participants saw an overall positive, average customer rating score of 4.5 stars for *CityTour AR*. We selected the score of 4.5 based on the ratings of other city tour apps. Furthermore, in the condition 'low number of customer ratings', the participants learned that so far two people had rated the *CityTour AR* app. In the condition 'high number of customer ratings', participants were informed that the score was an average of 8,786 customer ratings. Prior to this manipulation, we checked average low numbers and high numbers of similar apps already available in the market.

After exposure to the app store description of *CityTour AR*, the participants completed four 7-point items measuring consumers' intention to adopt the DI and rated their initial trust in *CityTour AR* (see Appendix for the measurements). Further, participants completed manipulation checks regarding the customer ratings using a 7-point scale (1 = "disagree strongly" and 7 = "agree strongly"). Participants evaluated control variables and provided sociodemographic information. After completing the questionnaire, we thanked and dismissed the participants.

3.4.1.2 Results

Manipulation check. CityTour AR was perceived to be new (M = 4.72). As intended, participants in the low number of customer ratings condition indicated that fewer users had rated the app (M = 4.83) compared to participants in the high number condition (M = 3.59; F = 30.016, p < .001). Further, participants understood that *CityTour AR* is the first product by the start-up *CityTour* (M = 5.40), indicated the customer ratings as positive (M = 4.79), the DI (M = 5.07) and its launch as realistic (M = 5.09), and that they were not familiar with the app (M = 1.29).

Main result. An ANOVA shows no significant effect of the number of positive customer ratings on initial trust perceptions ($M_{\text{LowNumber}}$ = 4.25; $M_{\text{HighNumber}}$ = 4.31; F (1, 172) = .072, p > .05). An ANCOVA with the covariates perceived usefulness ("Overall, I think CityTour AR is useful.") and product category relevance ("Online services are relevant for me.") yielded the same pattern of results, (F (1,172) = .154, p > .05). Thus, we do not find support for H_1.

Researchers have shown that trust perceptions positively affect purchase intentions in various contexts (Buettner and Goeritz, 2008; Schlosser et al., 2006). As hypothesized, we expect the number of positive customer ratings to influence adoption intentions via perceived initial trust. Accounting again for the two control variables, we examined this mediation by carrying out a mediation analysis using the bootstrap test (5,000 resamples) by Preacher and Hayes (2004). In line with our H_1, we find a significant, positive impact of initial trust perception on adoption intention (b = .490; p < .001) (see Table 3.2). Consistent with our previous results, the overall indirect path from the customer rating to adoption intention through initial trust is not significant (b = .034) with a 95% confidence interval including zero [-.147; .195]. Holding initial trust constant, the direct path between customer ratings and adoption intention is also not significant (b = -.037; [-.362; .289]; p > .05). The number of

positive customer ratings has no impact on adoption intention, neither directly nor indirectly via perceived initial trust.

Table 3.2: Mediation Model for the Effect of Number of Positive Customer Ratings (NCR) on Adoption Intention (AI) Through Perceived Initial Trust (PIT)

Regression analysis				*Bootstrap analysis*[a]	
Effect	*b*	*T*	*p*	*Indirect effect*	*95% CI*
NCR[b] → *PIT*	.069	.392	.696	.034	–.147 .195
PIT → *AI*[c]	.490	6.805	.000		
NCR → *AI*	-.037	-.221	.825		

[a] based on 5,000 bootstrap resamples
[b] dummy-coded (0 = low number of customer ratings, 1 = high number of customer ratings)
[c] R^2=.638; we further controlled for perceived usefulness and product category relevance

3.4.2 Study 1b: Valence of Customer Ratings

In light of of these results, we propose that being able to show positive customer ratings – independent of the number of ratings – increases initial trust perceptions compared to not being able to show any customer ratings at all. In other words, signaling customer ratings does not seem to depend on the number of available ratings, but on the positive valence of these ratings. Therefore, we aim to test the notion that communicating positive customer ratings as compared to communicating no customer rating helps to overcome low initial trust perceptions.

3.4.2.1 Method

Participants and procedure. For this follow-up study, we chose the same AR-based city guide app as in the main experiment, *CityTour AR* by the start-up *CityTour*. All else being equal, this time the participants could not see any customer rating in the visualization of the app. Again, we recruited participants via a European online consumer panel. After exposure to the app store description of *CityTour AR*, the participants completed the same questionnaire as in the main experiment (see Appendix A2 for measurements). Overall, we recruited 101 participants.

Following the same procedure as in the main study, we excluded 11 speeders from further analysis, resulting in an additional sample of 90 participants (37.8% female, average age: 48.5 years).

3.4.2.2 Results

Manipulation check. As intended, the participants in the no customer ratings condition indicated that less users had rated the app compared to participants in the customer rating condition ($F = 5.375$, $p < .05$). Further, participants understood that *CityTour AR* is the first product by the start-up *CityTour* ($M = 5.41$) and indicated its launch as realistic ($M = 5.14$) but that they were not familiar with the app ($M = 1.27$).

Main result. An ANCOVA including the two covariates product category relevance and perceived usefulness shows a significant impact of providing positive customer ratings compared to having no customer ratings at all ($M_{NoRatings} = 3.87$; $M_{Ratings} = 4.28$, $F = 4.973$, $p < .05$). The impact of initial trust on adoption intention remains positive ($b = .434$) and significant ($p < .001$) in the mediation analysis (Preacher and Hayes 2004) (see Table 3.3). The indirect path from customer ratings to adoption intention via initial trust is significant ($b = .170$) with a 95% confidence interval excluding zero [.047; .310]. Holding initial trust constant, the direct path between customer ratings and adoption intention is not significant ($b = -.201$; [-.500; .067], $p > .05$), providing evidence for an indirect only (i.e., full) mediation (Zhao et al., 2010).

Table 3.3: Mediation Model for the Effect of Existence of Positive Customer Ratings (ECR) on Adoption Intention (AI) Through Perceived Initial Trust (PIT)

Regression analysis				*Bootstrap analysis*[a]	
Effect	*b*	*t*	*p*	*Indirect effect*	*95% CI*
ECR[b] *CR*[b] → *PIT*	.390	2.667	.008	.170	.047 .310
PIT → *AI*[c]	.434	6.854	.000		

ECR → AI	-.201	-1.328	.185

[a] based on 5,000 bootstrap resamples
[b] dummy-coded (0 = no customer ratings, 1 = customer ratings)
[c] R^2=.568; we further controlled for perceived usefulness and product category relevance

3.4.3 Discussion

Contrary to both our expectation and prior research (De Langhe et al., 2015), the number of positive customer ratings is a design strategy of a digital business model that affects neither consumers' perceived initial trust nor their adoption intention. In fact, consumers seem to weigh the average positive rating more heavily than the actual number of ratings (De Langhe et al., 2015). Thus, showing positive customer ratings, independent of the number of available ratings, turns out to be an effective signal to communicate the trustworthiness of a start-up's DI, ultimately boosting adoption intention. We demonstrate that the strategy of showing positive customer ratings compared to not providing customer ratings at all does not directly but indirectly influence adoption intention via initial trust perceptions.

3.5 Study 2: The Influence of Benefit Communication on Initial Trust Perceptions

Research has highlighted message content in communications as a signal driving innovation adoption (Schuhmacher et al., 2018; Talke and Snelders, 2013). Following this notion, we propose that the design of message content can be a signal to communicate the trustworthiness of a start-up's DI. The extant literature identified different types of message content when introducing innovations (Lee et al., 2011), one of them being benefit-based message content. Benefit-based ads express the subjective and symbolic benefits of a product and can demonstrate fit with consumer needs. Several studies show the effectiveness of benefit-based message content over other message content types (e.g., Lee and O'Connor, 2003; Talke and Snelders, 2013). For example, Lee and O'Connor (2003) find that communicating

innovation benefits to consumers is an effective signal for persuading consumers to abandon the old technology. However, research has neither distinguished the signaling value of different types of benefits nor explored their effectiveness for signaling trustworthiness.

Following the notion of Lee and O'Connor (2003), for start-ups' DIs the digitalization of a former offline service may represent a new technology. Thus, when communicating the benefit of the DI, start-ups can signal to potential consumers that the DI is beneficial because of its digital nature and emphasize aspects such as transparency, speed, or simplicity as genuine digital benefits. This way, start-ups aim to persuade potential consumers to abandon the offline services and turn to the DI. For example, the digital nature of AirBnB allows the guest to connect to the local host even prior to a trip, a potential benefit to be used when launching AirBnB. Communicating such digital benefits can evoke positive customer experiences.

However, Kuester et al. (2018) propose that start-ups should specifically emphasize the origin of their innovation to signal a DI's trustworthiness. With regard to start-ups' DIs, an origin-based benefit could refer to the product category or industry that the DI originates from. Typically, DIs do not create new product categories but rather innovate in existing product categories. For example, AirBnB originates from the tourism industry, hence, an origin-based benefit communication to signal trustworthiness for AirBnB could have been to communicate integrity, a benefit often communicated by hotels.

Again, in the case of a start-up's DI launch consumers face a situation of high uncertainty. We propose that potential consumers look for trustworthiness signals, which can communicate the origin of a DI (Kuester et al., 2018). Benefit communication based on the origin of the DI refers to aspects of the innovation consumers are familiar with, which should lead to higher trustworthiness perceptions. However, digital benefits refer to the new aspect of the DI based on the fact, that it is of digital nature and, thus, communicating digital benefits could reinforce

the feeling of uncertainty towards a DI from a start-up. Hence, we hypothesize that an origin-based benefit is more effective in overcoming low initial trust perceptions than a digital benefit:

Hypothesis 2: The communication of an origin-based benefit compared to a digital benefit leads to higher initial trust perceptions, which ultimately results in higher adoption intentions.

3.5.1 Method

To test H_2, we ran a quasi-field experiment in cooperation with an insurance start-up, which we refer to as *Insutech* to anonymize the start-up. *Insutech* is about to launch a DI, which is a smart app to help consumers keeping an overview of their portfolio of insurance products and to offer consumers new products geared towards their needs using machine learning algorithms. *Insutech* targets consumers aged 20 to 50 years. Having recently ensured sufficient financing, the founders of *Insutech* decided to run banner ads to promote their smart app. As banner ads provide limited space for content, they decided to communicate one benefit only. In the realm of the cooperation with *Insutech*, we set out to investigate the effectiveness of different benefits in the banner ads.

3.5.2 Pilot

We invited consumers from the targeted age group to join us for an interview to find out about the perceived key benefit of the smart *Insutech* app, randomly recruiting 19 participants (53% female, average age 34 years). As we expected, the participants either focused on benefits that referred to the insurance aspect of the app, i.e., the origin of the app, or to the digital aspect of the *Insutech* app. Specifically, the following origin-based benefits came up: safe, trustworthy, personal, and contactable. Of these benefits, *personal* was mentioned most often (7). With regard to digital benefits, interviewees mentioned simple, fast, objective, transparent, flexible with *transparent* mentioned most often (11). We also assessed that neither *personal* was

perceived as a digital benefit nor *transparent* was perceived as an origin-based benefit. Based on this pilot, we decided to test two specific benefits: 1) *personal* as an origin-based benefit and 2) *transparent* as a digital benefit. An advertisement agency designed a banner ad accordingly.

3.5.3 Participants and Design

For the experiment we used a 2 (benefit: personal vs. transparent) x 1 factorial between-subjects online experiment with 93 individuals recruited from a European consumer panel (47.3% female, average age: 36.9 years). Detecting speeders as before, we excluded two participants resulting in a final sample of 91 individuals. We randomly assigned the participants to one of the two groups resulting in nearly equal cell sizes.

3.5.4 Procedure

The study simulated the launch of the smart *Insutech* app using a mock banner ad. All participants first read the standardized introductory information before we asked them to imagine the following situation: “Imagine you surf the Internet and then the following banner ad for a new, digital app called XYZ (real name disguised due to non-disclosure agreement with *Insutech*) pops up. XYZ is a smart insurance broker, which is available as a digital application.” The banner ad showed one sentence at the top, for the origin-based benefit “Good to know that digital becomes personal.” and for the digital benefit “Good to know that being insured becomes transparent.” Furthermore, the banner showed a screen shot of a smartphone with the name of the smart *Insutech* app and the tagline “the smart insurance specialist” as well as “Check, manage, and optimize your insurances for free”. The banner also informed that the app is available in the app store and in the play store. The remainder of the questionnaire used the same questions as in Study 1 (see Appendix A2 for measurements).

3.5.5 Results

3.5.5.1 Manipulation check

We again ran manipulation checks using 7-point Likert scales finding that participants perceived the smart service as new ($M = 5.00$). Participants perceived the service in the personal benefit condition as more personal ($M_{Personal} = 4.86$, $M_{Transparent} = 3.28$, $F\ (1, 89) = 32.123$, $p < .001$) and in the transparent benefit condition as more transparent ($M_{Transparent} = 4.62$, $M_{Personal} = 3.23$, $F\ (1, 89) = 25.898$, $p < .001$). Finally, participants perceived the scenarios to be realistic ($M = 4.31$) and were not familiar with the app ($M = 1.32$).

3.5.5.2 Main effect

An ANOVA of participants' initial trust perceptions shows a main effect of the benefit communication in the hypothesized direction. We find higher initial trust perceptions in the origin-based benefit condition using *personal* as a benefit ($M = 4.37$) than in the digital benefit condition using *transparent* as a benefit ($M = 3.20$; $F\ (1, 89) = 32.323$, $p < .001$, *partial η2* = .268). Thus, we find support for H_2. To check the robustness of our findings, we conducted again an ANCOVA including the two covariates product category relevance and perceived usefulness, supporting the results of the ANOVA. Furthermore, we expect that benefit communication implies higher adoption intentions because the signal communicated leads to higher perceived initial trust. We examined the proposed relationship by carrying out a mediation analysis again using the bootstrap test (5,000 resamples) (Preacher and Hayes 2004) (see Table 3.4). We find a positive (b = .470) and significant (p < .01) impact of perceived initial trust on adoption intention. In support of the proposed mediation, the overall indirect path from benefit communication to adoption intention through initial trust is significant (b = .477) with a 95% confidence interval excluding zero [.142; .835]. Holding initial trust constant, the direct path between the benefit communication and adoption intention is significant and negative

(b = -.685; [-1.245; -.125]), providing evidence for a competitive mediation. Competitive mediation occurs when both the indirect and the direct effect are significant and have opposing signs (Zhao et al., 2010).

Table 3.4: Mediation Model for the Effect of Benefit Communication (BC) on Adoption Intention (AI) Through Perceived Initial Trust (PIT)

Regression analysis				*Bootstrap analysis*[a]		
Effect	*b*	*t*	*p*	*Indirect effect*	*95% CI*	
BC[b] → *PIT*	1.014	5.122	.000	.477	.142	.835
PIT → *AI*[c]	.470	3.516	.001			
BC → *AI*	-.685	-2.431	.017			

[a] based on 5,000 bootstrap resamples
[b] dummy-coded (0 = digital benefit, 1 = origin-based benefit)
[c] R^2=.476; we further controlled for perceived usefulness and product category relevance

3.5.6 Discussion

Signalling an origin-based benefit results in higher initial trust perceptions than signaling a digital benefit. More generally, signaling a benefit that refers to the origin of the product category, such as being personal in our case, increases the initial trust perception compared to a benefit related to the digitalization of the offline service, such as being transparent in our case. Initial trust perceptions, in turn, positively affect adoption intentions. Hence, to overcome low initial trust perceptions, start-ups should focus on communicating origin-based benefits. At the same time, communicating a digital benefit directly results in slightly higher adoption intention than an origin-based benefit. However, not accounting for initial trust perceptions as a mediator between the communicated benefit type and adoption intention could mislead start-ups in their focus on benefits in ad campaigns. Accounting for the strong impact of initial trust perceptions on adoption intention, start-ups should not neglect the power of benefits signaling the fundamental advantages of the origin of the digital service. Focusing on the roots of the product

category and thus providing an origin-based benefit can help to overcome low trust perceptions of DIs by start-ups, which then drives consumers' adoption intentions.

3.6 Study 3: The Influence of the Revenue Model on Initial Trust Perceptions

Study 3 explores the effectiveness of the revenue model in increasing initial trust perceptions of a start-up's DI. When designing a business model, start-ups can employ different revenue models, including pay-per-use or hidden revenue models (Gassmann et al., 2014). We refer to the first as monetary revenue model and to the latter as data-based revenue model. Depending on the revenue model, consumers 'pay' for a DI with different currencies. We refer to a monetary revenue model as a model in which a start-up charges a monetary price and refrains from collecting or selling usage data. In contrast, we define a data-based revenue model as a model in which a start-up charges no monetary price but collects or sells usage data. For example, Facebook offers its digital services free of charge while selling usage data to third-party providers. In this sense, consumers 'pay' with their data. We address the question of which of the two revenue models has a greater impact on perceived initial trust and, ultimately, on adoption. In Study 3a, we investigate whether the design strategy of the revenue model impacts perceived initial trust, and in turn, adoption intention. In doing so, we compare the effect of applying a monetary versus a data-based revenue model. In Study 3b, we focus on the role of privacy concerns in the revenue model–initial trust relationship.

3.6.1 Study 3a: The Impact of the Revenue Model

Research investigating the signaling value of prices reveals that prices serve a dual role as both indicator for a monetary sacrifice and for quality (Kardes et al., 2004; Suri et al., 2007). The proposed positive link between price and perceived quality can be explained by the "you get what you pay for" heuristic (Kardes et al., 2004). This heuristic reduces consumers' effort

associated with judging quality in the absence of quality information (Shah and Oppenheimer, 2008). Völckner and Hofmann's (2007) meta-analysis reveals that consumers are more likely to draw positive price-quality inferences if they are unfamiliar with the product, as is the case for DIs by start-ups. At the same time, the higher the launch price, the higher the amount of money that consumers lose when the product turns out to be a bad buy (DelVecchio and Smith, 2005; Ram and Sheth, 1989). Thus, for start-ups' DIs about which consumers have little knowledge, charging a price can potentially backfire on initial trust perceptions.

There is a lack of research on how consumers perceive 'data money'. Bhat's (2015) study indicates that consumers increasingly perceive giving away data to third party-providers as unethical and as a sacrifice, even though it is common practice. Thus, we argue that in contrast to paying a price, consumers do not perceive data money as a quality signal but rather as a sacrifice. A data-based revenue model should be less effective as a signal for trustworthiness. In other words, we expect that consumers perceive start-ups that do not charge a price but require consumers to pay with their data as less trustworthy. In sum, a DI by a start-up charging a monetary price in a monetary revenue model should lead to higher initial trust perceptions than a DI of a start-up charging a data price in a data-based revenue model. Thus, we hypothesize:

Hypothesis 3: A DI by a start-up using a monetary revenue model leads to higher initial trust perceptions than a DI by a start-up using a data-based revenue model.

3.6.1.1 Method

Participants and design. As in Study 1, we used *CityTour AR* as the DI recruiting 177 participants per e-mail sent to students and staff of a major European business school. Detecting speeders as before, we excluded four participants from the data analysis, obtaining a final sample of 173 individuals (71.3% female; M_{age} = 33.10). Those were randomly assigned to a 2

(revenue model: monetary vs. data-based) x 1 between-subject factorial design. The cell size was 83 in the monetary revenue model condition and 90 in the data-based revenue model condition.

Procedure. The procedure of the experiment was similar to the one employed in Study 1. In addition to general information on *CityTour AR's* functionalities, participants were provided with the pricing and data safety policy of *CityTour A*R. In the monetary revenue model condition, the price for the app was set at 10.99€ based on prices for competitive city tour apps available in app and play stores. Furthermore, participants received the following information: "Charging you a price of 10.99€, we are able to assure you that your data will not be sold to third-party providers." In the data-based revenue model condition, there was no monetary price charged for the use of the *CityTour AR* app but a data price. The description read: "We offer you *CityTour AR* free of charge. However, based on this pricing policy, we want to inform you, that we sell your usage data to third-party providers." The remainder of the questionnaire was the same as in Study 1 (see Appendix A2 for measurements) with adjusted manipulation checks.

3.6.1.2 Results

Manipulation check. Participants perceived the DI as new (M = 4.37). As intended, participants in the monetary revenue model condition indicated that the DI was not for free and participants in the data-based revenue model condition indicated that the DI was for free ("The use of *CityTour AR* is for free", M_{Price} = 1.07, M_{Data} = 5.52, F (1, 171) = 313.741, p < .001). Further, participants rated the data safety higher in the monetary revenue model condition (M = 1.77) than in the data-based revenue model condition (M = 6.36) as assessed by the item "My personal and usage data of the *CityTour AR* app will be sold to third-party providers." (F (1, 171) = 358.169, p < .001). Finally, the scenarios were perceived as realistic (M = 4.84) and participants indicated to not be familiar with *CityTour AR* (M = 1.05).

Main effect. In line with H_3, an ANOVA of participants' initial trust perceptions showed a main effect of monetary price as compared to the data price. We found higher initial trust perceptions in the monetary revenue model condition ($M = 3.33$) than in the data-based revenue model condition ($M = 2.39$; $F(1, 171) = 24.135$, $p < .001$, *partial* $\eta 2 = .124$). Again, an ANCOVA with the two covariates product category relevance and perceived usefulness yielded similar results. Furthermore, we expect that the revenue model signal does not imply higher adoption intentions as long as the signal does not lead to higher perceived initial trust. A mediation analysis (Preacher and Hayes 2004) revealed a positive significant impact of initial trust on adoption intention (see Table 3.5). In support of our prediction, the overall indirect path from the revenue model signal to adoption intention through initial trust is significant (b = .505) with a 95% confidence interval excluding zero [.310; .799]. Holding initial trust constant, the direct path between the revenue model signal and adoption intention is not significant (b = -.229; [-.612; .155]), providing evidence for an indirect only ("full") mediation (Zhao et al. 2010).

Table 3.5: Mediation Model for the Effect of Revenue Model (RM) on Adoption Intention (AI) Through Perceived Initial Trust (PIT)

Regression analysis				*Bootstrap analysis*[a]	
Effect	*b*	*t*	*P*	*Indirect effect*	*95% CI*
RM → PIT	.911	5.440	.000	.505	.310 .799
PIT → AI[c]	.554	6.734	.000		
RM → AI	-.229	-1.179	.240		

[a] based on 5,000 bootstrap resamples
[b] dummy-coded (0 = monetary price, 1 = data price)
[c] R^2=.599; we further controlled for perceived usefulness and product category relevance

3.6.2 Study 3b: The Role of Privacy Concerns in the Revenue Model-Trust Relationship

Due to data protection regulations such as the European Union's General Data Protection Regulation (GDPR) effective as of May 2018, companies have to state general terms and conditions whether and how they use usage data. For example, the music-streaming service

Spotify specifies in their app store description that they collect usage data for market research purposes ("This app features Nielsen's audience measurement software which will allow you to contribute to market research [...]") and the e-commerce company Zalando explains website visitors: "We want you to have the best user experience possible. To help us deliver this, we use tools to track and analyse user behaviour and compile statistics." Given the implications for consumers' privacy concerns, it seems warranted to zoom in on the central issue of how start-ups can overcome low initial trust for their DI by focusing on the chosen (monetary or data-based) revenue model. We expect that the revenue model–initial trust relationship is mediated by privacy concerns. We argue that choosing a monetary revenue model and indicating that usage data will not be collected and used, perceived privacy concerns will be lower and, in turn, increase initial trust. In contrast, employing a data-based revenue model and indicating that usage data is collected and used, privacy concerns will be higher, impacting initial trust negatively.

3.6.2.1 Method

Participants and design. For the purpose of this experiment, we used an interior design planner, which was developed by a start-up. This planner displays 2D and 3D perspectives of living spaces including furnishing to allow consumers to order selected furniture directly. At the time of the experiment, this interior design planner, which we coined *mydesign3D* from the start-up *mydesign*, was available in the U.S., but not in any European country making it unlikely that participants knew it. We used the visual appeal of the original website with a modified name and the translated description for our experimental setup. Again, we recruited participants via a European online consumer panel and randomly assigned them to a 2 (revenue model: monetary vs. data-based) x 1 between-subject factorial design. Of the 227 participants, we

excluded 27 speeders as before, resulting in a final sample of 200 participants (59.5% female; M_{age} = 42.72).

Procedure. The procedure of the experiment was similar to Study 3a. In addition to general information on *mydesign3D*'s functionalities, we provided participants with the pricing and data safety policy of *mydesign*. In the monetary revenue model condition, the price for the DI was set at 14.99€. Furthermore, participants received the following information: "To provide you with the best possible user experience, we want to assure you that we do not use tools to collect nor to analyze your user behavior." In the data-based revenue model condition, there was no monetary price charged for the use of *mydesign3D* but a data price. Compared to Study 3a, we used a subtler manipulation for the data-based revenue model manipulation of data-sharing, closely based on the way that European companies, such as Spotify or Zalando, nowadays have to display according to the GDPR. The description read: "We want to provide you with the best possible user experience. Thus, we make use of tools to collect and analyze your user behavior." We then assessed privacy concerns using a scale by Liao et al.,2011, while the remainder of the questionnaire was the same as in Study 3a (see Appendix A2 for measurements).

3.6.2.2 Results

Manipulation check. As intended, participants in the monetary revenue model condition indicated that the DI was not for free and in the data-based revenue model condition participants indicated that the DI was for free ("The use of mydesign3D is for free", MPrice = 1.63, MData = 6.10, F (1, 198) = 427.949, p < .001). Finally, the scenarios were perceived as realistic (M = 5.31) and participants indicated to not be familiar with mydesign3D (M = 1.34).

Main effect. An ANOVA of participants' privacy concerns showed a main effect of monetary price as compared to the data price. We found lower privacy concerns in the monetary

revenue model condition (M = 3.22) than in the data-based revenue model condition (M = 4.32; $F(1, 198) = 21.847$, $p < .001$, partial $\eta 2 = .089$). Again, an ANCOVA with the two covariates product category relevance and perceived usefulness yielded similar results.

Further, we ran a mediation analysis (Preacher and Hayes, 2004) finding a positive significant impact of privacy concerns on initial trust perceptions (see Table 3.6). In fact, the overall indirect path from the revenue model signal to initial trust perceptions through privacy concerns is significant (b = .345) with a 95% confidence interval excluding zero [.175; .548]. Holding privacy concerns constant, the direct path between the revenue model signal and initial trust perceptions is not significant (b = -.084; [-.376; .209]), providing evidence for an indirect only ("full") mediation (Zhao et al. 2010).

Table 3.6: Mediation Model for the Effect of Revenue Model (RM) on Perceived Initial Trust (PIT) Through Privacy Concerns (PC)

Regression analysis				*Bootstrap analysis*[a]	
Effect	*b*	*t*	*P*	*Indirect effect*	*95% CI*
RM → PC	-1.265	-5.632	.000	.345	.175 .548
PC → PIT[c]	-.273	-6.238	.000		
RM → PIT	-.084	-.564	.574		

[a] based on 5,000 bootstrap resamples
[b] dummy-coded (0 = monetary price, 1 = data price)
[c] R^2=.436; we further controlled for perceived usefulness and product category relevance

3.6.3 Discussion

The findings show that consumers indeed seem to perceive paying with usage data as a sacrifice, as previous research shows (Bhat, 2015). The results additionally reveal that the data sacrifice weights heavier than the money sacrifice in terms of the implied privacy concerns as well as initial trust perceptions. Charging a monetary price is effective in establishing trust for a DI by a start-up. Specifically, consumers perceive the DI by a start-up to be more trustworthy

when the start-up charges a monetary price for its DI in the realm of a monetary revenue model instead of obtaining it free of charge but knowing that the company collects and usage data. Following the logic of signaling theory (Spence, 1973), we demonstrate that a monetary revenue model specifically excluding data collection reduces privacy concerns and, thus, more effectively signals trustworthiness leading to higher perceived initial trust and, ultimately, boosting adoption intention of a start-up's DI as compared to a data-based revenue model.

3.7 Overall Discussion and Research Contribution

Although trust has been an important research topic in both information systems and e-commerce (Wu et al., 2011), previous studies paid little attention to how trust is incorporated into consumers' decision-making processes, particularly in the context of the adoption of DIs by start-ups. Due to the digital nature of DIs by start-ups, these innovations are surrounded by substantial uncertainty originating from privacy concerns, fear of data misuse, or doubt regarding performance (Featherman and Pavlou, 2003; Meuter et al., 2000). Perceptions of uncertainty are further aggravated by consumers' unfamiliarity with the unknown company (McKnight et al., 2002) as represented by the start-up. Thus, because these innovations imply high levels of uncertainty for consumers (Coulter and Coulter, 2003), consumers' initial trust perceptions of DIs constitute an important prerequisite, and potentially a heuristic cue, for DI adoption. At the same time, it is far from straightforward for start-ups to generate initial trust because effective trust-building strategies, such as using well-established brand names, are not available for start-ups. Hence, consumers are even more dependent on signals, like heuristic quality cues, to make initial trust inferences as well as adoption decisions. We therefore conducted five consumer experiments specifying how start-ups can overcome low initial trust perceptions and boost adoption by designing specific aspects of digital business models as signals of trustworthiness.

We demonstrate that initial trust presents itself as a critical source of information for consumers in the otherwise information-poor initial phase of the DI adoption process. The present study contributes to previous research on innovation adoption of start-ups' DIs (Kuester et al., 2018) empirically demonstrating the necessity of overcoming consumers' low initial trust perceptions for successful commercialization of DIs launched by start-ups.

Furthermore, this study highlights the mediating role of initial trust perceptions in signal-adoption intention relations. So far, research claims and investigates a direct impact of signals on consumer acceptance and adoption (Schuhmacher et al., 2018). In situations of poor information such as making adoption decisions for a DI by a start-up, this study establishes initial trust perception as a critical mediator in the relationship between design strategies of digital business models functioning as signals and adoption intentions. Finally, we illustrate that start-ups are able to overcome low initial trust perceptions regarding their DIs with the targeted use of specific signal strategies. Our findings indicate that consumers seem to consider individual design strategies of digital business models as heuristic cues in making their judgments about initial trust regarding DIs. Specifically, we cover multiple strategies for start-ups to overcome initially low trust perceptions of their DIs. Hence, applying signaling theory (Spence, 1973), our study contributes to the effectiveness of the design of specific digital business models.

First, we find that consumers show higher initial trust when a start-up's DI exhibits positive customer ratings than when it does not. Our findings contribute to prior research on the role of average customer ratings and the number of customer ratings (De Langhe et al., 2015) by indicating that the overall positive rating of the DI seems to serve as a trustworthiness signal, independent of the total number of ratings.

Second, we extend research investigating the influence of message content on adoption intention (Lee and O'Connor, 2003). Even though studies highlight the importance of benefit-

based communication for innovations (Talke and Snelders, 2013), research has not explored the differential effectiveness of different benefits. We shed a first light on the type of benefits that help to overcome low initial trust. Specifically, we show that the communication of origin-specific benefits, such as being personal for an insurance-related DI, leads to higher initial trust perceptions than focusing on digital benefits, such as transparency for an insurance-related DI.

Third, we see a rise in the use of data-based revenue models in contrast to monetary revenue models. Start-ups tend to implement data-based revenue models, seemingly offering their DI for free, with the intention to increase consumer adoption. Our study takes a first step in investigating the effectiveness of such data-based revenue models finding that in order to overcome low initial trust perceptions of DIs start-ups are better off refraining from data-based revenue models and usage data collection. Intriguingly, employing a monetary revenue model seems to result in lower privacy concerns and ultimately higher initial trust perceptions than employing a data-based revenue model where consumers 'pay' with their data.

In summary, our findings expand current knowledge on the role of trust in the online context and extend adoption research to the growing field of DIs. Our study identifies multiple design strategies of digital business models for start-ups to overcome initially low trust perceptions of their DIs. By taking the perspective of the consumer adoption process (Arts et al. 2011), we hone our understanding of the consumer decision making with regard to DI adoption.

3.8 Managerial Implications

As digitalization continues to advance, consumers increasingly have access to DIs by start-ups. At the same time, consumer journeys are getting more complex and comprehensive (Anderl et al., 2016; Lemon and Verhoef, 2016). Accordingly, consumers' perceptions of the trustworthiness of DIs by start-ups at initial touchpoints play an increasingly important role.

We show that trustworthiness can serve as a competitive advantage online, especially for start-ups. Our work offers useful implications for start-ups launching DIs regarding specific design strategies of digital business models and their signaling power. Specifically, start-ups should pay close attention to three digital business model design strategies: customer ratings, benefit communication, and revenue model.

First, our studies reveal that the (positive) valence impacts initial trust perceptions and adoption intention independent of the amount of positive ratings available. Hence, start-ups introducing a DI should highlight and specify some positive customer ratings on their websites, in app stores or press released and do not need to invest money to achieve a high number of positive customer ratings. Actually, several start-ups apply this strategy. For example, the Swedish Surplus Food App *Karma* offers a platform for customers to connect to restaurants and cafes to solve the problem of food waste. Karma does not emphasize its positive average customer ratings, but rather focuses on individual customer ratings by citing favorable comments to signal Karma's trustworthiness. One such citation reads: "This smart way of reducing food waste is smart and beneficial for both restaurants and cafes but also for us customers. I follow a few places and I'm really satisfied! Strongly recommended!"

Second, when communicating the benefits of their DIs, start-ups should bear in mind that some benefits are more helpful than others in increasing initial trust while other benefits are more effective in boosting adoption intention. Start-ups should carefully calibrate the communication of these benefits to the targeted audience, depending on their primary goal: increasing adoption intentions via increased initial trust perceptions or directly. Since start-ups mostly depend on both directly boosting short-term acceptance to reach a critical mass of consumers and establishing a sustainable high adoption rate via overcoming low initial trust in the long-term, they could consider communicating both benefits at the same time. For example, the healthcare innovation *Liveline* from Iceland offers a platform to keep a full record of

personal data gathered in place and always updates the newest data while being accessible from anywhere. In their communication, *Liveline* focuses on both types of benefits: full visibility and accessibility as digital benefit and security as origin-based benefit.

Third, when deciding on a revenue model for their DI, start-ups should be aware that selling their users' data to third parties is counterproductive as a signal for trustworthiness. By charging a monetary price for the DI instead of using consumer data, there will be less privacy concerns with regard to the DI by the start-up. Lower privacy concerns imply higher initial trust perceptions, which drive DI adoption rates as compared to charging a 'data price'. Thus, start-ups should aim to follow a monetary revenue model and, more importantly, should state clearly that they refrain from private data collection and usage if the establishment of trust is the start-up's primary objective. In this case, start-ups should even use their strong data protection policies as a unique selling proposition in their marketing communication. An example of a start-up following this strategy is the Swiss-based messenger app *Threema*. Instead of offering their services with a data-based revenue model, they follow a monetary revenue model. The start-up specifically highlights on its website that it is exclusively financed by app purchases and, thus, does not sell any data to a third party. Ultimately, if start-ups consider offering a "free" service option in the realm of a data-based revenue model to lure consumers and to eventually get them to convert to a monetary priced service option, the "free" service option can potentially backfire.

3.9 Further Research

The present research focuses on how to overcome low initial trust perceptions for start-ups' DIs. In our first study, we find that the number of positive customer ratings is not effective in signaling the trustworthiness of a DI by a start-up. Future research should test whether these results also hold true for the opposite case of low customer ratings. Additionally, our results

find no difference in the impact of a low number compared to a high number of customer ratings on initial trust perceptions. Further, research should explore whether there is a possible (inverted) U-shaped relationship between the number of customer ratings and perceived initial trust.

In our study on benefit communication, the competitive mediation opens up space for further research on the direct effect of digital benefit communication on adoption intention. According to Zhao et al. (2010), competitive mediations may point to a yet unidentified mediator in the direct path. It is thus likely that there is a potential mediator accounting for this direct effect, for example, perceived simplicity (Rogers, 2003). Future research should aim to explore potential mediators. Moreover, competitive mediation potentially indicates that a moderator has not been taken into account (Demming et al., 2017), suggesting a moderated mediation. First, in line with previous literature, innovativeness could be such a potential moderator. On the one hand, product innovativeness might moderate the mediation (Kuester et al., 2015) because the more radical an innovation, the more uncertain the situation for potential consumers and thus, the stronger the mediation through initial trust. Accordingly, the more incremental an innovation, the weaker the mediation via initial trust. On the other hand, consumer innovativeness might moderate the mediation (Schuhmacher et al., 2018) rendering the mediation more pronounced for less innovative consumers and weaker for more innovative consumers. Hence, for less innovative consumers, origin-based benefits should positively influence adoption intention, whereas for more innovative consumers, digital benefits should be more beneficial. Second, this study is the first to address the effectiveness of communicating different types of benefits when launching a DI. Future research could explore the effectiveness of other types of benefits that can be communicated to signal trustworthiness.

Study 3 sheds light on the effectiveness of different revenue models for DIs by start-ups. In addition to the revenue models we tested, other digital revenue models exist including freemium, subscription, or advertisement-based revenue models (Gassmann et al., 2014).

Future research could explore the effectiveness of these different revenue models with regard to perceived initial trust, adoption intentions, or other behavioral outcomes. In addition, researchers could explore consumers' perceptions of paying with their usage data when using DIs and identify factors that influence these perceptions, such as, consumer innovativeness or digital fluency.

With regard to the generalization of our findings, it is possible that our results depend on the type of DI. Thus, future research should validate the present findings for other DIs.

4 Paper 3: Choosing the Right Positioning when Launching Digital Innovations by Start-ups

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Status: No submission

Abstract

Digital Innovations (DIs) are an important driver of market success in the digital era. A significant number of DIs is launched by start-ups in existing product categories disrupting available product offerings. However, the disruption is rarely reflected in the positioning of DIs, which becomes detrimental for their survival due to the lack of focus on the core competitive advantage: being digital. As a result, adopters fail to differentiate DIs from existing services and adopt them. Our three experiments explore how DIs should be positioned to foster their adoption. Drawing on Porter's positioning framework, we find that the positioning of DIs can be focused on benefits or costs, but also that a combination of both (value-based positioning) is equally effective in driving adoption intention. Furthermore, we suggest that considering a target group based on digital nativeness is crucial in finding the right positioning strategy. Based on our insights, we offer important managerial implications for start-ups launching DIs.

Keywords: *Digital innovations, adoption intention, start-up, positioning, porter, trust, privacy concerns, digital nativeness*

4.1 Introduction

Today, start-ups are continuously launching DIs in the marketplace (Kuester et al., 2018). Particularly widely spread are solutions powered by artificial intelligence (AI) (Kim et al., 2021). Overall, DIs are referred to as service innovations that offer new and unique value propositions enabled by inherent digital technologies (Dotzel et al., 2013; Konya-Baumbach et al., 2019). However, many of these DIs fail when it comes to customers' adoption – a phenomenon that has been attracting the attention of several scholars in the past decade (e.g., Marmer et al., 2011; Mikti et al., 2019; Setzke et al., 2021). Specifically, extant research finds that issues related to marketing (Poddar and Agarwal, 2019) as well as a lack of trust and privacy concerns are key reasons for start-ups' DI failure (Nienaber and Schewe, 2014; Kuester et al., 2018; Konya-Baumbach et al., 2019; Eggers et al., 2022). In recent years a particular attention in research has been given to issues around the lack of trust and uncertainty with AI-enabled DIs (Schmidt et al., 2020; Choung et al., 2022).

In pursuit of addressing the lack of trust and privacy concerns due to start-ups being new and DIs being digital (Huang and Rust, 2013), particularly when enabled by unknown technologies like AI (von Eschenbach, 2021), start-ups tend to promote DIs similarly to their non-digital alternatives. Consequently, start-ups focus their positioning and communication on the category origin to signal trustworthiness (Kuester at al., 2018), which, in turn, was found to increase DI adoption (Konya-Baumbach et al., 2019). Meanwhile, start-ups frequently disregard their DIs' unique digital characteristics and thus, fail to differentiate them from existing offerings. In other words, start-ups communicate their DIs based on points of parity to existing, non-digital offerings instead of focusing on points of difference based on the inherent digital technologies. For example, the start-up *Shyp* developed a digital delivery service that allows its users to ship items by taking a picture and making a couple of clicks on their smartphone (McCracken, 2018). At the time of the market launch, the start-up did not focus on

the point of difference, which was the digital imaging technology accompanied by machine learning that enabled the creation of a shipment order by taking a picture of the shipping item with a smartphone. Digital imaging technology allowed to collect the necessary data about the shipment from the picture, and machine learning allowed the preparation of suitable pick-up and packaging. Instead, the start-up focused on points of parity regarding category origin-based claims and positioned the DI as the "cheapest, fastest and easiest delivery service" - failing to differentiate from traditional delivery services by e.g. providing a digital-based reason to believe and by these means failing to survive in the market in the long run.

We argue that focusing the positioning of DIs and their communication solely on their category origin is not sufficient for their long-term survival due to several reasons. Firstly, DIs of start-ups do not offer the same benefits as their category alternatives per definition. DIs offer new benefits enabled by digital technologies (Dotzel et al., 2013), hence, the major point of difference for DIs is digital. The lack of focus on the point of difference in communications may lead adopters to see no value in switching from traditional services to the start-ups' DIs. Secondly, since DIs and start-ups are unknown to potential adopters, both must occupy the right space in their minds (Cennamo, 2021) and strive for a unique positioning. Finally, as new start-ups, products and services are constantly booming in the marketplace, start-ups need to ensure that their positioning is distinct from their (non-)digital alternatives to avoid market failure (Matthyssens et al., 2009). For example, the start-up *Chip* successfully addressed positioning issues when launching its money-saving app. In the positioning of the app, *Chip* ensured a clear focus on the digital point of difference, i.e. AI that enabled intelligent automatic saving and investing. The start-up communicated the DI as "an App that enables building one's wealth powered by AI" and highlighted the uniqueness of the app due to the digital component. Proper positioning based on the digital point of difference helped the start-up *Chip* to survive in the market and win over 500,000 adopters to date (retrieved 08.11.2024 from: www.getchip.uk).

For a long time, adopters' uncertainty about a start-up and its DI due to their newness and thus, due to lack of trust and privacy concerns have been a major reason for start-ups to avoid focusing on their digital point of difference (Konya-Baumbach et al,. 2019). Meanwhile, the number of DIs launched in the market rapidly increased, and adopters became more familiar with digitalization (Hasan et al., 2021). Therefore, we propose that start-ups not only can but must position their DIs based on the digital point of difference (Eggers et al., 2022). Some start-ups are already starting to do so, abandoning the traditional monetary-based revenue model and adopting new digital-enabled revenue models, such as free-of-charge and freemium (Waitzinger et al., 2015). However, currently, we lack an understanding of how a digital point of difference should translate into an effective positioning of start-ups' DIs to signal trustworthiness and reduce privacy concerns. Hence, our research aims to examine how start-ups should position their DI when focusing on a digital point of difference to enhance adopters' trust and privacy concerns. Extant research refers to possibilities of focusing on either benefit (benefit-based positioning), revenue model (cost-based positioning) or a combination of both (value-based positioning) in the positioning of DIs. Hence, we formulate the first research question: Which benefit and/or revenue model should start-ups focus on to effectively position their DIs on a digital point of difference?

Based on the diffusion logic (Rogers, 2003), the essential element of positioning of an innovation is segmentation according to specific adopter characteristics. Extant studies show that different adopter groups should be addressed differently when communicating USPs of innovations (Schuhmacher et al., 2018). In the context of DIs, this need is even more aggravated, since adopters differ in their openness to digital technologies (Kirk et al., 2015). Specifically, digital nativeness drives differences in attitudes and openness towards digital and is defined by the level of exposure and experience with digital technologies (Prensky, 2001). Furthermore, digital nativeness determines adopters' ability to cope with uncertainties and risks in digital

(Joiner et al., 2013). Therefore, we expect different adopter groups to experience different levels of trust and privacy concerns due to their digital nativeness when dealing with start-ups' DIs. Consequently, we propose that the effectiveness of DIs' positioning based on a digital point of difference also depends on the digital nativeness of adopters. However, existing research on the relationship between digital nativeness and the effectiveness of positioning strategies, particularly revenue models, is scant. Hence, the second research question we formulate is: whether and how start-ups should adapt their DI's positioning for different adopter groups based on digital nativeness?

To answer our research questions, we conducted a multi-method, multi-study research. First, we run an exploratory study to analyse the actual positioning and communication of DIs launched by start-ups. We use the results of our exploratory study to identify how positioning translates into the communication of DIs by start-ups. Second, we run three experimental studies to assess the effectiveness of different positionings based on digital points of difference on the intention to adopt a start-up's DI. Consequently, we investigate how the communication of an effective positioning for DIs should be designed when targeting adopter groups varying in the degree of their digital nativeness.

Our research contributes to the extant literature in several ways. First, we extend the existing research on the adoption of DIs launched by start-ups and address previous calls for research (e.g. Arts et al., 2011). We expand upon previous studies (e.g. Kuester et al., 2018; Konya-Baumbach et al., 2019) that confirmed the role of trust in the adoption of DIs by exploring privacy concerns and analysing differences between adopter groups driven by digital nativeness. We shed light on how the positioning of DIs should be designed because digital natives and digital immigrants perceive DIs differently due to the differences in their knowledge and experience with DIs. Further, we address the important topic of DIs' positioning, which is detrimental for DIs' differentiation from non-digital offerings with a focus on the digital core

and make a crucial extension of Porter's positioning framework (Porter, 1985) into the digital context. We build upon the work of Kim et al. (2004), who found that in the digital realm, there is no need for companies to strictly follow either one positioning strategy or another, as claimed initially by Porter (1985). We provide further evidence that in the context of DIs start-ups can focus on one of the positioning strategies (benefit-based or cost-based positioning) or a combination of the both (value-based positioning). In addition, we explain in detail the conditions for a choice of a specific positioning for start-ups and discuss the importance of considering digital nativeness of the target group in the design of specific positioning strategies.

4.2 Literature Review on DIs

4.2.1 Adoption of DIs

Innovation adoption research has a long-established history (Arts et al., 2011). Traditionally, most focus has been put on product innovations (Chiesa and Frattini, 2011; Chesbrough, 2017; Schulz and Voelckner, 2020). Whereas, in more recent years, research on service innovation adoption gained momentum as scholars have recognized the unique characteristics and challenges associated with diffusing these types of innovations (Edwards et al., 2015; Moretz et al., 2021, Chen et al., 2022; Heidenreich et al., 2024). However, despite growing digitalization in all areas, research on DIs, which encompasses service innovations enabled by digital technologies, is still a fairly new field of study. Contemporary research on DIs stems from the fields of marketing, but also information systems, which have been at the forefront of exploring the impact and adoption of digital technologies. Most marketing studies focus on drivers of adoption behaviour (Prins and Verhoef, 2007; Shen, 2015; Mahardika et al., 2019; Heidenreich et al., 2024), whereas, most information systems studies focus on the development and management of digital technologies (e.g. Kazan et al., 2018; Koutsikouri et al., 2018; Drehsler et al., 2020; Liu et al., 2023), DI strategy development (e.g. Keen and

Williams, 2013; Wiredu et al., 2021; Saleem et al., 2023) and new organizational structures and capabilities related to digitalization (e.g. Tumbas et al., 2017; Chan et al., 2019; Mendling et al., 2020; Rosario, 2022). Furthermore, even though most DIs are launched by start-ups, still only a few studies examine specific implications for start-ups when launching DIs (Kuester et al., 2018; Konya-Baumbach et al., 2019).

When individuals consider adopting DIs, they often weigh potential benefits against potential risks and uncertainties (Mou et al., 2017). Prior research suggests that trust helps to resolve overall uncertainty, particularly in the digital context (Kannan and Li, 2017). As adoption of DIs takes place in an environment of uncertainty, the research of Konya-Baumbach et al. (2019) confirmed that addressing trust positively impacts adoption intention for DIs in such a setting. Hence, start-ups must cater for the necessity to build trust when designing the positioning for their DIs.

In a similar vein, DIs are often associated with the collection and processing of personal data, hence, privacy concerns arise as adopters worry about the unauthorized access, potential misuse, or sharing of their personal information by start-ups (Saura et al., 2021). Privacy concerns become particularly aggravated with the widespread use of data-based revenue models, where adopters pay with their data for the usage of DIs (Gassmann et al., 2014). Previous research has provided some significant evidence on the effects of privacy concerns on certain behaviours, e.g. overall adoption of online services (Baruh et al., 2017), readiness to pay premium to ensure protection of privacy with online services (Tsai et al., 2011), as well as negative impact on the overall trustworthiness of DIs and their adoption (Konya-Baumbach et al., 2019). However, in the present research, we claim that start-ups can address these adoption issues by carefully designing their positioning to reduce privacy concerns.

Scholars have drawn upon the Signalling Theory (Spence, 1973) to prove the necessity of sending specific signals to address the lack of trust or privacy concerns (Ha and Stoel, 2008;

Kuester et al., 2018; Casado- Aranda et al., 2019; Konya-Baumbach et al., 2019). For example, a study by Chang and Fang (2013) provides evidence that trustworthiness can be created via website design and features. Other studies show the relevance of lean brand names, customer-centric promotion, and customer support (Kuester et al., 2018) as well as customer ratings and communicated benefits (Konya-Baumbach et al., 2019). In a similar vein, the research by Konya-Baumbach et al. (2019) indicates that privacy concerns can be addressed by the choice of the revenue model. Therefore, we conclude that the extant research on the adoption of DIs focuses on some specific elements of tactical marketing. However, current research is missing an overarching view on the commercialisation of DIs from a rather strategic marketing standpoint, addressing positioning, segmentation of adopters and corresponding communications.

4.2.2 Positioning of DIs by Start-ups

Overall, the concept of positioning has an established history in research and represents a specific design of the company's offering to occupy a distinctive space in the minds of the target market through a unique point of difference (Matthyssens et al., 2009; Kotler and Keller, 2016). Over decades, Porter's positioning concept (Porter, 1985) has been at the forefront of research with three distinctive positioning strategies, i.e. benefit-based, cost-based and value-based positioning. Later on, new forms of value creation developed and fostered research on combinations of the single strategies (Kim et al., 2004). Proliferation of digitalization further strengthened this notion, focusing on maximization of all components of product value, i.e. benefits and costs (Kim, 2005). However, despite different conceptualisations researchers have been consistent in the claim that the success of a positioning is determined by the ability to generate competitive advantage over the competition (Clancy and Trout, 2002; Porter, 2008; Akpoyomare et al., 2013; Haseeb et al., 2019).

When it comes to the positioning of DIs, research is scant. Existing literature focuses on the challenges of start-ups to obtain a distinct positioning (Kumaraswamy et al., 2018) due to overall uncertainty and lack of trust (Saura et al., 2021; Eggers et al., 2022). Scholars claim that start-ups mostly focus on origin/category signals instead of core signals related to digital technologies (Kuester et al., 2018). More specifically, scholars highlight that start-ups largely focus on specific benefits, communication signals, and pricing schemes (Kuester et al., 2018; Konya-Baumbach et al., 2019; Eggers et al., 2022) to convey the trustworthiness element in their positioning. However, so far, the research on DIs ignores the focus on core digital signals in the positioning.

4.2.3 Segmentation of Adopters in the Context of DIs by Start-ups

Segmentation of adopters has been at the forefront of innovation adoption literature, supported by the notion that the lack of understanding of adopters' needs drives market failure of innovations (Bartels and Reinders, 2010). Some researchers investigated adopters' characteristics concerning the adoption of new products (e.g. Lassar et al., 2005), whereas a significant number of studies focused on the concept of consumer innovativeness (CI) (e.g. Goldsmith and Hofacker, 1991; Im et al., 2005; 2007; Steenkamp and Gielens, 2003; Li et al., 2015; Zhang et al., 2020). Today, we know that so-called actualized CI drives innovative behaviour for a specific innovation.

Drawing upon the Innovation Diffusion theory (Rogers, 2003), research differentiates the extent to which innovation adoption of an individual precedes that of other adopters (Bartels and Reinders, 2011). In this regard, scholars differentiate between high and low CI adopters, where high CI adopters, i.e. innovators, demonstrate adoption behaviours ahead of the rest of the adopters and low CI adopters, i.e. imitators, adopt innovations later in time (Rogers, 2003; Bass, 2004). Most studies focus on innovators and consider them pivotal to the success of

innovation diffusion. Innovators are characterized as technology-savvy, capable of dealing with uncertainties surrounding innovations and showing a positive attitude towards and a high willingness to try innovations (e.g. Rogers, 2003; Bartels and Reinders, 2011; Flores and Jansson, 2021; Seyed et al., 2021). Imitators receive less attention in innovation research, which is partially attributable to the so-called "pro-innovation" bias (Rogers, 2003), where the research is mostly triggered by the focus on drivers of innovation diffusion (Goldenbert and Oreg, 2007). The existing research on adopters low on CI focuses on adopter characteristics and drivers of their late adoption behaviour. Imitators are said to be traditionalists, sceptical of innovations and require uncertainty to be eliminated before adopting an innovation (Rogers, 2003; Matzler et al., 2014). From a demographic perspective, Im et al. (2003) claim that adopters low on CI have lower incomes, lower levels of education and are older. Generally, research on actualized CI suggests a significant positive relationship between demographic characteristics and adoption intention (Gielens and Steenkamp, 2007; Hirunyawipada and Paswan, 2006; Im et al., 2007).

Literature still lacks an understanding of the implications of CI in the context of DIs. We propose to leverage the concept of digital nativeness as a specification of CI in the context of DIs for a better understanding of DI adoption, which builds upon the principles of actualized CI considering adoption behaviour patterns. Digital nativeness determines how potential DI adopters perceive information about digital innovations and cope with risks and uncertainties around them (Kirk et al., 2012; Joiner et al., 2013). In this regard, Prensky (2001) delineates two user groups based on the level of usage and exposure to digital products: digital natives and digital immigrants. Digital natives represent adopters who grew up in a networked world with access to ubiquitous digital technologies and the ability to use them in a sophisticated way (Palfrey and Gasser, 2008). Prensky (2001) further defined digital natives as born after 1980 and accustomed to the rapidly changing and rapid world of digital. In contrast, digital

immigrants are defined as adopters who were not born into the digital era but have become a part of it by adapting to or coping with digital technologies consciously (Prensky, 2001; Vodanovich et al., 2010). Consequently, digital immigrants tend to have less expertise in digital (Kirk et al., 2015), take longer to process new digital technologies, and have a higher probability of being overwhelmed, causing more negative attitudes towards DIs (Liu and Schrum, 2009). Most research on digital nativeness originates either from studies on education (e.g. Hesper and Eynon, 2010; Ng, 2012; Wilson et al., 2022; Badgi and Bulsara, 2023) or information technologies (e.g. Akcayir et al., 2016; Sadiku and Shadare, 2017; Wang et al., 2019; Agardi et al., 2022; Ashrafi and Easmin, 2023). Few marketing researchers, for example, Hoffmann et al. (2014) investigate attitudes to digital technologies based on digital nativeness and claim that digital immigrants show a lower level of trust and a more negative attitude in comparison to digital natives. Ebermann et al. (2016) examine the role of digital nativeness in DI adoption and justify a positive relationship between the two phenomena. More specifically, the researchers confirm that digital nativeness predicts positive attitudes towards DIs and that, furthermore, positive attitudes towards DIs drive the adoption intention. In addition, the scholars investigate the effect of design elements of DIs that address specific motivational affordances of digital natives (e.g. autonomy, self-identity, challenge, reward, socio-psychological needs) on attitudes to DIs. However, the researchers only focus on digital natives and don't consider digital immigrants in their study.

4.3 Pre-Study: Identifying Positioning Strategies for DIs by Start-ups

To develop a specification of a positioning based on digital points of difference for our conceptual model, we ran a preliminary study to identify positioning strategies that are deployed by start-ups when launching DIs. To do so, we applied the historical method approach proposed by Eisenhardt (1989), which implies a collection of evidence from case studies for theory

derivation. More specifically, we followed the approach of Golder (2000) to properly specify the scope: to collect, document, and analyse evidence on the positioning of DIs by start-ups.

As a first step, we searched for start-ups having launched DIs by 2024 with the Google search engine using combinations of the keyword *start-up* with the terms: *digital innovations*, *internet innovations*, *e-innovations, online innovations, service innovations, online products, online services, digital services, digitalised services, e-services, digital applications, online applications, internet applications, internet services, innovative online services.* The Google search generated several databases like CrunchBase, Startbase or Seedtable, which we used to further search for DIs by start-ups. We continued the search within the databases using the same keywords to compile the initial list of start-ups. The initial list contained 146 start-ups. First, we excluded start-ups that were no longer in the market to only focus on successful positioning strategies. Then, both authors carefully analyzed the generated list to only keep those start-ups which DIs comply with the definition of a DI by Dotzel et al. (2013), resulting in a list of 104 start-ups. Next, we visited websites of each start-up, screened them and collected the following information: the exact description of the DI, its positioning, the key claim, and communication of the positioning. Using the collected description of DIs we evaluated the target market (B2B or B2C), target adopter segment (digital natives, digital immigrants or both) and product category (existing or new). Finally, we analyzed the positioning claims of DIs and their communication according to the type of claim (benefit, cost (revenue model) or both) as well as their focus (origin-based or digital).

Our final sample consisted of 104 start-ups presented in the Appendix A3, out of which 68% belong to B2C, 25% to B2B and 7% represent both industries. Most start-ups in the sample offered DIs in existing product categories (73%) and 27% opened up new product categories. The analysis of the positioning claims revealed that 49% of start-ups focus solely on benefit-based positioning. Out of all start-ups focusing on benefit-based positioning, in line with our

reasoning, 70% of start-ups still focus on category origin benefits of DIs. For example, the start-up *Foodvisor* launched a DI that helps to eat smarter and healthier by analysing nutrients in the food and providing personalized nutrition plans. At the launch, the start-up positioned the App as "more than just a calorie counter", as "an App that will help you to eat healthier" (retrieved 11.11.2024 from: www.foodvisor.io), clearly focusing on the category-origin benefits.

The remaining 30% of start-ups focused on digital benefits, which are largely either technological or motivational. *Technological benefits* (80%) represent the capabilities of a product or service to expand available offerings beyond existing boundaries due to the technology it is based on (Veryzer, 1998). For example, the start-up *Tibber* provides a digital service that allows the optimization of electricity consumption in a household based on real-time tracking and analytics. The positioning of the DI *Tibber* communicates as "Make energy consumption smarter using digital technology" (retrieved 11.11.2024 from: www.tibber.com), clearly emphasizing the benefit of more economical usage of electricity at home, thanks to the digital technology behind the DI. Whereby, *motivational benefits* (20%) represent still digitally enabled benefits that address the question of how a product conveys a specific meaning through the achievement of customer goals, pertaining values and life themes (Bagozzi and Dholakia, 1999; Baustella et al., 2012). Generally, motivational benefits aim at enhancing daily experiences or improving life quality through technological advancements fostering sense of purpose and motivation. In case of motivational benefits, the digital technology is meant as an enabler of the benefit, however, start-ups do not explicitly mention the exact digital technology behind. For example, start-up *Neuroflow* introduced an App that helps adopters to take control of their whole health, both physical and mental and positioned it as "be the best you with Neuroflow" (retrieved on 11.11.2024 from: https://www.neuroflow.com/for-individuals/) providing a higher meaning to personalised activities to strengthen adopters' mind-body connection.

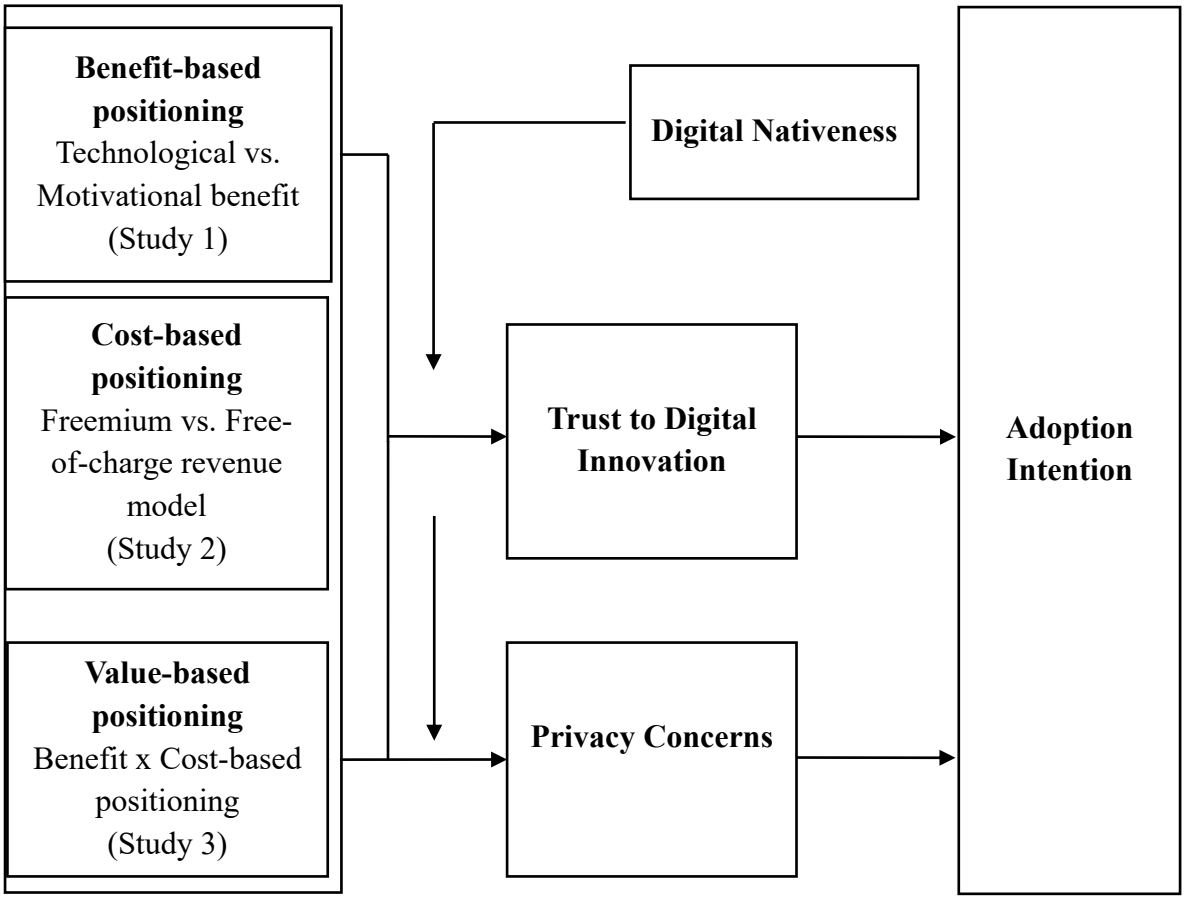
Apart from benefit-based positioning, 51% of the overall sample communicated both benefits and costs in their positioning, i.e. following a value-based positioning. Value-based positioning of DIs represents a distinctive benefit provided at a specific price (monetary or data-based). Here, the majority of start-ups also focus on category origin benefits with a combination of a free-of-charge revenue model (83%), where 20% choose a combination with a freemium revenue model, and the remainder a monetary price revenue model. For example, the innovative digital trip planner *Fineway* was positioned as a "free instant trip planner for everyone" that "frees travellers from wasting time and money on travel ever again" (retrieved 11.11.2024 from: www.fineway.ai). In its positioning, *Fineway* clearly stresses the benefit of convenience and easiness of travel planning, while offering it free of charge. Only 17% of start-ups focused on digital benefits combined with a certain revenue model. Here, the majority (60%) chose a technology-based benefit combined with a freemium or a free-of-charge revenue model. For example, the start-up *Cleo* launched their DI, an AI-based solution offering intelligent assistance to help manage personal finances, focusing on a technology-based benefit and a free-of-charge revenue model. The DI *Cleo* was communicated as: "Meet the world's first AI money Pro" (retrieved 12.11.2024 from: www.meetcleo.com). The remainder of start-ups focused on motivational benefits in combination with a freemium or a free-of-charge revenue model.

However, we noticed that no start-up solely focuses on cost-based positioning. Further, we found that start-ups that choose to communicate a certain revenue model also communicate a certain benefit, which is always a non-cost-related benefit. For example, the start-up *Evernote* followed a freemium revenue model when launching their organizer App but focused on convenience as a key benefit in communication. The communication read: "Your second brand. Capture everything that is, was or could be important, and access it on all your devices" (retrieved 11.11.2024 from: www.evernote.com). The DI was offered as a basic version free of charge and as a premium version. The basic version included digital note-taking, some limited

memory space, a search function, and a document attachment, and was offered for free. Whereas, the premium version included all the basic features as well as multiple device synchronization, increased memory space, Google calendar connection, and the addition of due dates and reminders.

While many start-ups do not focus on a digital point of difference, we claim that start-ups that focus on a digital point of difference can develop trust and reduce privacy concerns, leading to DI adoption under specific circumstances. Hence, we propose a conceptual framework for start-ups' benefit-based, cost-based, and value-based positioning focusing on a digital point of difference (Figure 4.1). In Study 1, we investigate the effectiveness of a benefit-based positioning strategy based on a digital point of difference with a direct mention of digital technology (technological benefit) and without a direct mention of digital technology (motivational benefit). Whereas in Study 2, we take a closer look into how a cost-based positioning (freemium vs. free of charge revenue models) drives the adoption intention of DIs. Then we run an additional Study 3, where we combine the above benefit-based and cost-based positioning and investigate a value-based positioning strategy in the context of the adoption of a DI by a start-up. Within each of the three studies, we account for the moderating effects of trust to DI and privacy concerns and additionally investigate digital nativeness exploring the effectiveness of each positioning strategy for digital natives vs. digital immigrants.

Figure 4.1: Conceptual Framework



4.4 Study 1: Benefit-Based Positioning of DIs

4.4.1 Hypothesis Development

Prior research stressed the importance of message selection in driving innovation adoption (Song and Parry, 2009; Schuhmacher et al., 2018; Lee et al., 2021). Benefit-based messages are particularly effective in persuading adopters to switch from old technologies (Lee and O'Connor, 2003) and reducing adoption risks (Talke et al., 2011; Talke and Snelders, 2013). However, existing studies overlooked benefit-based communication for DIs specifically, focusing on feature-based positioning (Hyatt, 2001).

However, most recent research highlights the significance of emphasizing benefits in DIs commercialization. Start-ups increasingly prioritize highlighting DIs benefits over features. Yet, the question of which benefits to emphasize remains crucial. Konya-Baumbach et al. (2019)

claim the positive impact of category-origin benefits on DIs adoption due to the better-perceived trustworthiness. However, solely focusing on these benefits and overlooking digital points of difference of DIs potentially endangers DIs' market survival (Namibisan et al., 2017).

Focusing on a digital point of difference, start-ups can highlight technological benefits of DIs to showcase their advantages over non-digital alternatives and encourage adoption. However, it is essential to consider adopters' readiness for digital technology to avoid uncertainty, anxiety, and diminished trust (Liu and Tao, 2022). Taking into consideration potential adopters' concerns, start-ups can ensure the digital point of difference by focusing on motivational benefits. Motivational benefits are digitally enabled benefits that address the achievement of adopters' goals, values, and life themes (Baustella et al., 2012). Although motivational benefits are enabled by certain digital technologies, they do not directly mention the digital technology and can help with adopters' anxiety. However, motivational benefits do not exactly convey how the DI drives the achievement of adopters' life goals and values. Hence, the achievability of motivational claims can easily be questioned by adopters.

In contrast, with the rapid proliferation of digital technologies adopters' exposure to them promptly emerged (Ameen et al., 2021). Furthermore, adopters are gradually becoming more familiar with digital technology and its applications (Fernandes and Oliviera, 2021). Also, it seems that due to the media's promotion of the relevance and significance of digital technologies, customers react to buzzwords such as AI or digital technology. Further, increased familiarity with digital technologies reduces uncertainty and can further drive the trustworthiness of DIs (Kaya et al., 2019). Hence, nowadays, adopters can exhibit a good level of trust in technological benefits. Given that overall trust in DIs influences their adoption (Konya-Baumbach et al., 2019), we hypothesize that technological benefits are more effective in driving DI adoption due to their ability to foster greater trust compared to motivational benefits:

Hypothesis 1a: Benefit-based positioning focusing on the digital point of difference of DIs by start-ups based on a technological benefit leads to higher trust in DIs compared to a motivational benefit, resulting in higher adoption intention.

In addition to trust, privacy concerns have emerged as a key focus in DIs' adoption research in recent years. Scholars have found that adopters express concerns regarding data misuse (Ha and Stoel, 2009), uncertainty regarding personal data processing (Dinev and Hart, 2006), and reluctance to share personal data (Pavlou et al., 2007) when engaging with DIs. Therefore, start-ups must consider adopters' privacy concerns when designing positioning strategies for their DIs. Given adopters' anxiety about digital technologies (Dutta and Sarma, 2020), we suggest that emphasizing technological benefits in DIs positioning may aggravate uncertainties surrounding privacy. In contrast, the communication of motivational benefits is unlikely to provoke such concerns, as motivational benefits do not directly reference digital technology, thereby reducing adopters' anxiety. Previous research has demonstrated that privacy concerns significantly impact adoption intention for DIs (Gupta et al., 2011). Therefore, we hypothesize that focusing on motivational benefits in DI positioning will be more effective in driving adoption intention due to lower privacy concerns, whereas, in turn, technological benefits would have a stronger impact on privacy concerns*:*

Hypothesis 1b: Benefit-based positioning focusing on the digital point of difference of DIs by start-ups based on a technological benefit leads to higher privacy concerns with DIs compared to a motivational benefit, resulting in lower adoption intention.

When designing the positioning of DIs, start-ups must consider the differing perceptions of DIs between digital natives and immigrants, as these perceptions impact the effectiveness for both groups. Digital natives, who grew up in a digitalized world and actively use digital technologies (Prensky, 2001), tend to be more technology-savvy and inclined to engage with DIs (Palfrey and Gasser, 2008). They are typically well-informed and familiar with

technological products and show a high level of trust in digital technologies (Hoffmann et al., 2014). In contrast, digital immigrants tend to have less expertise in digital (Kirk et al., 2015) and are more often overwhelmed by digital technologies causing overall high uncertainty and suspicion towards DIs (Liu and Schrum, 2009), resulting in a lower level of trust to DIs. Therefore, we hypothesize that the effectiveness of the benefit-based positioning will differ for digital natives and immigrants due to their different levels of trust:

Hypothesis 2a: Benefit-based positioning focusing on the digital point of difference of DIs by start-ups based on a technological benefit (motivational benefit) leads to higher (lower) trust in DIs and thus, higher (lower) adoption intention for digital natives (digital immigrants).

Overall differences in perceptions of DIs between digital natives and digital immigrants also extend to their privacy concerns. Although both groups are aware of privacy issues related to DIs (Hoffmann et al., 2015), their behaviours towards DIs differ significantly based on the existing research evidence. More specifically, digital natives, being familiar with DIs and the technologies behind them, are less deterred by privacy concerns and actively use DIs (Engels, 2019). Consequently, communication of technological benefits is unlikely to negatively impact their privacy-related concerns towards DIs, hence, their adoption intentions. Conversely, technological benefits are highly likely to drive privacy concerns of digital immigrants and negatively influence their actual behavior towards DIs (Filho et al., 2021). Moreover, given their generally negative perceptions, scepticism, and anxiety towards digital technology (Liu and Schrum, 2009), focusing on motivational benefits instead of technological ones should help alleviate privacy concerns of digital immigrants driven by digital technology. Therefore, while technological benefits may be more effective when targeting digital natives, motivational benefits should be more effective when targeting digital immigrants. Hence, we hypothesize:

Hypothesis 2b: Benefit-based positioning focusing on the digital point of difference of DIs by start-ups based on a technological (motivational) benefit leads to lower (higher) privacy concerns resulting in higher (lower) adoption intention for digital natives (digital immigrants).

4.4.2 Study Design and Data

To test our hypotheses, we conducted an experimental study. We chose as the DI an email solution with innovative features enabling smarter and more effective management of emails, which we called *SuperMail*. The DI *SuperMail* was not available in Europe at the time our study was conducted, thus, we assumed a low probability for participants to know it. For the experiment, we used webpage screenshots and modified them to suit our manipulation. We collaborated with a professional marketing research agency to recruit participants via a European online consumer panel to increase the validity and heterogeneity of our sample. All participants were randomly assigned to the 2 (benefit-based positioning: technological benefit vs. motivational benefit) x 1 between-subjects factorial design resulting in nearly equal cell sizes.

In the experimental context, participants were exposed to a screenshot of the website of the DI *SuperMail* developed by a start-up *Brainly*. In the technological benefit positioning condition, the communication read as "*The App SuperMail gives superpower to your inbox thanks to the integrated artificial intelligence and enables a more efficient, intelligent, and professional email communication*". Whereas, in the motivational benefit-based positioning condition the communication was designed as *"Be the best version of yourself in everything you do. The App SuperMail gives superpower to your inbox and enables a more efficient, intelligent and professional email communication*". After the positioning claims participants could read the description of the main features of the DI such as identification and triage of important emails, read reports for timely follow-up, right time automatic reminders, which were

similar in both experimental conditions. Appendix A5.a provides an overview of the manipulation.

Following the description of the DI *SuperMail* participants were asked to rate their adoption intention on a 7-point items Likert scale adopted from Castaño et al. (2008). Further, participants were asked to rate their trust to *SuperMail (*adapted from Sekhon et al., 2014) and privacy concerns (adapted from Liao et al., 2011). Furthermore, participants were asked to complete manipulation checks regarding the benefit manipulation they were exposed to using a 7-point Likert scale (1= "disagree strongly" and 7="agree strongly") as well as digital nativeness. The measurement of digital nativeness was adapted from Stokburger and Plank (2014), addressing expertise, access, and use of digital technologies as well as age of adopters (see Appendix A4 for all the measurements). Lastly, participants evaluated control variables and provided sociodemographic information. Upon completion of the questionnaire, we thanked the participants.

4.4.3 Sample and Measurement

Targeting only employed participants we obtained 193 complete responses to our questionnaire. As an initial step, we assessed the speed of questionnaire completion of each participant to exclude speeders. Based on Buchanan and Scotfield (2018), we estimated the average time of completion by using the number of characters in the questionnaire (10,381) and a standard character reading per minute (987), resulting in 10,5 minutes reading time. 9 responses were provided within a shorter time and were excluded from the final data set. Hence, our final sample resulted in 184 participants. The demographics show that 57% of the sample is female, with an average age of 45 years. Table 4.1 provides a detailed overview of the sample.

Table 4.1: Characteristics of the Sample Study 1

Variable (N=184)	Frequency	Percentage
Gender:		
1) Male	79	48
2) Female	105	52
Age (average)	45	N/a
Education		
1) Secondary school	5	2
2) College	42	22
3) High school	49	26
4) Bachelor	21	11
5) Master/ Specialist diploma	54	29
6) Phd	7	3
7) N/a	4	2
8) Other	2	1
Profession		
1) Currently employed	64	35
2) Self employed	9	5
3) University/school student	9	5
4) Not employed	9	5
5) Retired	9	5
6) N/a	27	15
7) Other	55	30
Marital status		
1) Single	42	22
2) Partnership	42	22
3) Married	77	41
4) Divorced	15	8
5) N/a	6	3
6) Other	2	1
Monthly net income (Euro)		
1) below 500	1	1
2) 501-1.000	8	4
3) 1.001-2.000	18	9
4) 2.001- 3.000	29	15
5) 3.001- 4.000	53	28
6) 4.001-5.000	32	17
7) Over 5.000	15	8
8) N/a	7	3

We started our analysis by assessing item reliability using factor analysis. All item loadings were significant ($p < .001$) and greater than 0.7. Our results also demonstrated internal consistency according to Cronbach alpha values around 0.9, supporting a very good construct reliability. Kaiser-Meyer-Olkin values are also greater than 0.7, implying a large proportion of variance to be shared between our items. Judging on the overall results, we assume appropriate validity and reliability of our instruments. Appendix A4 provides a summary of measurement statistics.

Next, we ran manipulation checks using 7-point Likert scale, where participants acknowledged that the DI was developed by a start-up (M=6.19) and were not familiar with it before the study (M=1.44). In the technological benefit- based positioning condition participants understood that the performance of *SuperMail* is enabled by a digital technology (AI) ($M_{Technology}$=6.13, $M_{Motivation}$=4.30, F(1,92)=52.536, p<.001). Whereas, in the motivational benefit-based positioning condition, participants perceived *SuperMail* as allowing them to achieve a life goal- to be more successful in what they do ($M_{Motivation}$=5.27, $M_{Technology}$=4.32, F(1,90)=29.711, p<.001). Finally, participants confirmed the scenarios to be realistic (M=4.47).

4.4.4 Results

Analysis of Variance (ANOVA) reveals no significant direct effect of benefit-based positioning on adoption intention (M_{TBB}=4.83, M_{MBB}=3.83, F(1,183)=.151, p=.689). Nevertheless, with our first hypothesis, we expect to observe an indirect effect of benefit-based positioning on adoption intention via trust to DIs (Hypothesis H1a) and privacy concerns (Hypothesis 1b). To test both hypotheses, we ran a mediation analysis using the bootstrap test (5000 resamples) by Preacher and Hayes (2004). During the mediation analysis, we controlled for several variables. First, we controlled for domain-specific adopter innovativeness (Kaushik and Rahman, 2015) to account for the impact of certain adopters being more innovative than

others which would drive higher trust and lower privacy concerns to DIs overall. Second, we controlled for product innovativeness (Tsai et al., 2015) to ensure that perceived innovativeness of the DI that we chose for manipulation does not affect our participants' trust and privacy concerns, hence, the findings can be applied to other DIs. Thirdly, we accounted for DI performance uncertainty to consider the overall uncertainty that adopters have with technological products and services (Dholakia, 2001). The overall indirect path from the benefit-based positioning on adoption intention through trust to DI is significant and positive (b=.319) with a 95% confidence interval excluding zero [.518; .604]. Holding trust constant, the direct effect of benefit-based positioning on adoption intention is again not significant and negative (b= -.208; [-1.145; .253]), thus, we confirm a significant indirect effect via trust to DIs as hypothesized and find support for hypothesis 1a. However, the indirect path from benefit-based positioning on adoption intention through privacy concerns is not significant (b= -.005; [-.068; .034], thus, we find no support for our hypothesis 1b (see Table 4.2).

Table 4.2: Mediation Model for the Effect of Benefit-Based Positioning (BBP) on Adoption Intention (AI) Through Trust to Digital Innovation (TDI) and Privacy Concerns (PC)

Regression analysis				*Bootstrap analysis*[a]		
Effect	*b*	*T*	*P*	*Indirect effect via Trust*	*95% CI*	
BBP[b] → *TDI*	-.506	-2.344	.020	.319	.518	.604
TDI → *AI*	.630	9.567	.000	*Indirect effect via Priv. Concerns*		
BBP → *PC*	-.078	-.303	.762	-.005	-.068	.034
PC → *AI*	-.066	-1.195	.233			
BBP → *AI*[c]	-.208	-1.145	.253	*Total indirect effect*		
				.314	0.15	.607

[a]based on 5,000 bootstrap resamples
[b]dummy-coded (0 = Motivational benefit-based positioning, 1 = Technological benefit-based positioning)
[c]R^2=.801; we further controlled for domain-specific innovativeness, product innovativeness and performance uncertainty.

Next, we ran a moderated mediation for trust to DI and privacy concerns with the moderator digital nativeness to test Hypotheses 2a and b (see Table 4.3). The overall moderated effect of benefit-based positioning on trust is significant: b= -1.854, p=.001. Moreover, the indirect effect on adoption intention via trust is positive and significant for digital natives (b=.603) with a 95% confidence interval excluding zero [.308; .946]. For digital immigrants, though, the indirect effect via trust is negative, but also significant (b= -.459) with a 95% confidence interval excluding zero [-.897;-.042], resulting in an overall significant index of moderated mediation via Trust b=-1.062 with a confidence interval excluding zero [-1.647; -.539]. Hence, we support our hypothesis 2a. Further, we investigated the moderated effect of benefit-based positioning on privacy concerns and found also a significant, but negative effect (b=-2.331; p=.000). However, the overall indirect effect of benefit-based positioning on adoption intention via privacy concerns for digital natives is positive but not significant (b=.015) with the confidence interval containing zero [-.069;.086]. Similarly, for digital immigrants the effect is although negative (b= -.439) also not significant with the confidence interval containing zero [-.250;.153], resulting in an overall non-significant index of moderated mediation via privacy concerns (b=-.059) with a confidence interval containing zero [-.319; .219]. Therefore, we don't find support for our hypothesis 2b.

Table 4.3: Moderated Mediation Model for the Effect of Benefit-Based Positioning (BBP) on Adoption Intention (AI) Through Trust to Digital Innovation (TDI) and Moderator Digital Nativeness (DN)

Regression analysis				*Bootstrap analysis indirect effect via Trust*[a]			
Effect	*b*	*T*	*P*	*Digital Nativeness*	*Effect*	*95% CI*	
BBP[b] → *TDI*	-.105	-4.279	.000	Digital Natives	.603	308	.946
DN[c] → *TDI*	-1.118	-3.026	.002	Digital Immigrants	-.459	-.897	-.042

BBP x DN → TDI	1.854	4.075	.001
TDI → AI[d]	.583	9.076	.000
BBP → AI	2.031	3.044	.002
BBP → PC	.592	2.031	.043
DN → PC	1.061	2.413	.016
BBP x DN → PC	-2.331	-4.332	.000
PC → AI	-.042	-.792	.429

Index of moderated mediation via Trust

Effect	95% CI	
-1.062	-1.647	-.539

Bootstrap analysis indirect effect via Privacy concerns

Digital Natives	.015	-.069	.086
Digital Immigrants	-.439	-.250	.153

Index of moderated mediation via Privacy Concerns

Effect	95% CI	
-.059	-.319	.219

[a]based on 5,000 bootstrap resamples
[b]dummy-coded (0 = Motivational benefit-based positioning, 1= Technological benefit-based positioning)
[c]dummy-coded (0 = Digital Natives, 1 = Digital Immigrants)
[d]R^2=.801; we further controlled for domain-specific innovativeness, product innovativeness and performance uncertainty.

4.4.5 Discussion

Benefit-based positioning proves effective in the commercialization of DIs, but start-ups must carefully select the type of benefit to emphasize. We find that benefit-based positioning can drive adoption intention of DIs by start-ups through trust to DIs but not through privacy concerns. In line with our expectations, technological benefits aren't necessarily associated with lower trustworthiness for adopters compared to motivational benefits. With digital products becoming integral to adopters' daily lives, they generally seem not to exhibit distrust towards digital products anymore (Dornberger and Schwaeferts, 2021). However, there are still significant differences in trust formation to DIs among different adopter groups that implies the need for start-ups to tailor positioning benefits accordingly. Specifically, digital natives show higher intention to adopt DIs due to higher trust when targeted with technology-based positioning communication, whereas digital immigrants exhibit higher intention to adopt DIs

when targeted with motivational benefit-based positioning communication. Although, privacy concerns are still present for digital natives and immigrants, when benefit-based positioning is communicated, but they don't seem to drive significant differences in adoption behaviour.

4.5 Study 2: Cost-Based Positioning of DIs

4.5.1 Hypothesis Development

The proliferation of DIs and their zero marginal cost of production opened numerous opportunities for the emergence of new revenue models (Kim et al., 2004; Waitzinger et al., 2015). Furthermore, in the quest for differentiation from non-digital offerings, start-ups prefer free-of-charge or freemium revenue models, where a freemium revenue model represents a combination of a monetary-price-based and a free-of-charge revenue model. However, opting for such models necessitates an alternative source of revenue, which typically requires commercialization of adopters' data in one way or another (Konya-Baumbach et al., 2019).

While the benefit of using DIs at no monetary cost has been enticing for adopters, it has also raised uncertainty among them (Pavlou et al., 2007). Contemporary research suggests that particularly young and digitally savvy adopters prefer free-of-charge services, as they perceive an irrationally high value of free-of-charge offers, mostly driven by the zero-price effect phenomenon (Niemand et al., 2019). Although it has become an established practice for start-ups to include disclaimers about the collection of personal data, still certain adopters feel concerned about which data monetization practices start-ups follow (Han et al., 2020), leading to a lower level of trust for free-of-charge services. At the same time, recent research showcases that some adopters might not be prepared to pay extra for the stricter privacy practices of start-ups (Plangger and Montecchi, 2020). Hence, it remains highly arguable how exactly adopters perceive the free-of-charge revenue model. Simultaneously, a recent stream of research emerged exploring adopters' perceptions of the freemium revenue model (e.g., Seufert, 2013;

Schreiner and Hess, 2015). Studies have found that the freemium revenue model generally provides a good level of information and transparency regarding free and paid versions (Kumar, 2014; Niemand et al., 2015), which can positively impact adopters' trust. Additionally, the provision of different options for adopters to choose from can further increase the credibility of the start-up. Considering that overall trust in DIs by start-ups influences their adoption (Kuester et al., 2018), we hypothesize that a cost-based positioning focusing on a freemium revenue model is more effective in driving DI adoption due to greater trust compared to a free-of-charge revenue model:

Hypothesis 3a: Cost-based positioning of DIs by start-ups focusing on a digital point of difference based on a freemium revenue model (free-of-charge revenue model) leads to higher (lower) trust, resulting in higher (lower) adoption intention.

The choice of a revenue model is inevitably interlinked with privacy concerns. Despite a wide spread of free-of-charge revenue models, they naturally lead to scepticism around the commercial model behind those services (Martin et al., 2017). More specifically, users perceive free-of-charge revenue models as being linked with a high price in the form of providing their personal data, with limited awareness of the real cost and opportunities to influence how their data is managed by the start-up providing the DI (Bamberger et al., 2020). Furthermore, adopters feel a risk of personal data misuse because they possess less information than the start-up about how exactly collected data is handled (Al-Natour et al., 2020). Additionally, oftentimes start-ups do not provide clarity on the exact data collected, which further aggravates privacy concerns (Hermalin and Katz, 2006). However, freemium revenue models do not fall under the same level of scrutiny due to their ability to generate revenue from monetary sources, providing potentially a stronger security of personal data (van Angeren et al., 2021). Furthermore, with freemium revenue models, many start-ups still make the effort to provide transparency about

exact data handling practices for each of the freemium options (Han et al., 2019), potentially reducing adopters' privacy concerns.

Previous research has demonstrated that privacy concerns significantly impact DIs adoption intentions (Gupta et al., 2011). Therefore, we hypothesize that focusing on a freemium revenue model in DI positioning should be more effective in driving adoption intention due to lower privacy concerns compared to a free-of-charge revenue model:

Hypothesis 3b: Cost-based positioning of DIs by start-ups focusing on a digital point of difference based on a freemium revenue model (free-of-charge revenue model) leads to lower (higher) privacy concerns, resulting in higher (lower) adoption intention.

As there are differing perceptions of DIs between digital natives and immigrants, these perceptions significantly impact the effectiveness of DIs' positioning. Therefore, start-ups should take the distinction between digital nativeness and digital immigrants into account when selecting the appropriate cost-positioning strategy for their DI. Digital natives, being technologically savvy and generally well-informed and familiar with technological products, tend to have a high level of trust in digital technology and DIs overall (Hoffmann et al., 2014). In addition, digital natives are typically aware of the free-of-charge revenue models that start-ups use and their implications on personal data (Lupton, 2021), hence, free-of-charge revenue models should not negatively impact their trust. Additionally, as digital natives are grown up in the digitalized world having interminable access to DIs and digital services (Palfrey and Gasser, 2008), they tend to have a so-called "free mentality" (Dingli et al., 2015). This implies, that digital natives are inclined towards a belief that digital services should be offered free of charge. Hence, a freemium business model might cause perceptions of unfairness to digital natives due to the need to pay a monetary price for the premium version of a DI and have only a limited version of it free of charge. Therefore, we assume that a free-of-charge revenue model would more positively impact the trust of digital natives compared to the freemium revenue model.

In contrast, digital immigrants often lack expertise with DIs and are less aware of data monetization strategies (Kirk et al., 2015). Furthermore, digital immigrants prefer services, where they can be sure of straightforward and honest marketing approaches (Nicolas, 2009), hence, the usage of a free-of-charge revenue model can aggravate their distrust to DIs. Whereas the freemium revenue model provides a better transparency regarding available options and how personal data is used. Thus, a freemium revenue model would likely result in greater trust in DIs among digital immigrants compared to a free-of-charge revenue model. Therefore, we hypothesize:

Hypothesis 4a: Cost-based positioning of DIs by start-ups focusing on a digital point of difference based on a freemium revenue model (free-of-charge revenue model) leads to lower (higher) trust resulting in a lower (higher) adoption intention for digital natives (digital immigrants).

Similarly, we expect that both digital natives and digital immigrants exhibit different privacy concerns when confronted with revenue models of DIs, that shape their adoption intention to DIs. As digital natives are more familiar with DIs, i.e. technologies integrated and monetization practices, they are generally less concerned about data privacy (Engels, 2019), hence a usage of a free-of-charge revenue model will not imply high privacy concerns for digital natives. Therefore, a free-of-charge revenue model will drive adoption intention for digital natives through low privacy concerns. Furthermore, digital natives are not only not concerned about their privacy, but also they are not prepared to pay extra for better privacy protection (Bordonaba-Juste et al., 2020). Hence, more data security with freemium revenue model that would also keep privacy concerns of digital natives low, should still not result in a higher adoption intention for freemium.

Conversely, as digital immigrants have a lack of experience with DIs and understanding of the data monetization practices (Filho et al., 2021), they would exhibit high privacy concerns

with free-of-charge revenue models, as those revenue models do not provide full transparency on the handling of personal data. Whereas freemium revenue models offer a premium version that often guarantees the security of personal data, which can help to reduce privacy concerns of digital immigrants. Although freemium still also provides an option for a free-of-charge usage that assumes personal data monetization, we expect that provision of transparency on available options and a premium version will keep privacy concerns of digital immigrants low. Therefore, we propose that a freemium revenue model would be more effective for targeting digital immigrants due to lower privacy concerns compared to a free-of-charge revenue model. Hence, we hypothesize:

Hypothesis 4b: The difference in privacy concerns between a cost-based positioning of DIs by start-ups focusing on a digital point of difference based on a freemium revenue model compared to a free-of-charge revenue model is less pronounced for digital natives compared to digital immigrants, resulting in a lower adoption intention for digital natives for a freemium revenue model compared to digital immigrants.

4.5.2 Study Design and Data

We conducted another experimental study to test hypotheses 3 and 4. Here, we used the same DI as in Study 1: *SuperMail*. For Study 2, we modified website screenshots to suit our manipulation. We recruited a different set of participants via a European online consumer panel. All participants were randomly assigned to a 2 (Cost-based positioning: Freemium vs. Free-of charge) x 1 between-subjects factorial design resulting in nearly equal cell sizes.

As in Study 1, in the experimental context, the participants were exposed to the screenshot of a fictitious website with an overall description of features of the *SuperMail*: information about the revenue model of the DI and a disclaimer about start-up's privacy policy at the bottom of the page, which was in line with how start-ups communicate pricing schemes.

Therefore, in the freemium experimental condition, some basic features were provided being free of charge and the basic features plus some additional features of *SuperMail* were offered for a fee of €9.99. The corresponding disclaimer provided information about third-party cookies and access to personal data for third parties depending on the chosen option. Whereas, in the free-of-charge experimental condition the usage was claimed to be for free with the disclaimer highlighting that the start-up allowed third-party cookies and corresponding access to third parties to personal data. Appendix A5.b provides a visualization of the manipulations. The remainder of the questionnaire was the same as in the Study 1.

Targeting only employed participants and excluding speeders (Buchanan and Scotfeld, 2018), we obtained 200 complete responses to our questionnaire. 51% of the sample was female with an average age of 48 years. Table 4.4 provides a detailed overview of the sample.

Table 4.4: Sample Description for the Study 2

Variable (N=200)	**Frequency**	**Percentage**
Gender:		
1) Male	98	49
2) Female	102	51
Age (average)	48	N/a
Education		
1) Secondary school	15	7
2) College	65	32
3) High school	41	20
4) Bachelor	9	4
5) Master/ Specialist diploma	60	30
6) Phd	3	1
7) N/a	3	1
8) Other	4	2
Profession		
1) Currently employed	80	40
2) Self employed	10	5
3) University/school student	20	10
4) Not employed	10	5
5) Retired	30	15
6) N/a	30	15
7) Other	10	5

Marital status		
1) Single	39	19
2) Partnership	55	27
3) Married	92	46
4) Divorced	10	5
5) N/a	3	1,5
6) Other	1	0,5
Monthly net income (Euro)		
1) below 500	7	3
2) 501-1.000	15	7
3) 1.001-2.000	17	8
4) 2.001- 3.000	30	15
5) 3.001- 4.000	44	22
6) 4.001-5.000	39	20
7) Over 5.000	9	5
8) N/a	17	8

We ran manipulation checks using 7-point Likert scale, where participants acknowledged that the DI was developed by a start-up (M=6.29). Additionally, participants were not familiar with it before the study (M=1.34). In the freemium condition participants perceived an advanced version of *SuperMail* to be offered against a monetary price, whereas, a basic version to be offered free of charge ($M_{Freemium}$=6.09, $M_{Freeofcharge}$=2.47, F(1,199)=8.100, p<.001). Whereas, in the free-of-charge condition, participants understood that *SuperMail* was offered at no monetary cost, however, personal data was collected and commercialized ($M_{Freeofcharge}$=5.37, $M_{Freemium}$=4.31, F(1,199)=3.207, p<.001).

4.5.3 Results

Analysis of Variance (ANOVA) reveals a significant direct effect of the cost-based positioning on adoption intention ($M_{Freemium}$=4.12, $M_{Freeofcharge}$=3.37, F(1,199)=2.275, p=.024). To test hypotheses H3a and H3b, we ran a mediation analysis using the bootstrap test (5,000 resamples) by Preacher and Hayes (2004). As in the Study 1, we controlled for domain-specific innovativeness, product innovativeness and performance uncertainty. The overall indirect path from the cost-based positioning on adoption intention through trust to DI is positive (b=.038), but not significant with a 95% confidence interval including zero [-.020; .149]. Thus, we cannot

confirm a significant indirect effect of the cost-based positioning via trust to DIs. Hence, H3a is not supported. However, the indirect path from cost-based positioning on adoption intention through privacy concerns is significant and positive (b= .175; [.040; .368]. This relation is a partial mediation due to a remaining significant direct effect of cost-based positioning on adoption intention (Zhao et al. 2010). Thus, we find support for hypothesis 3b (see Table 4.5).

Table 4.5: Mediation Model for the Effect of Cost-Based Positioning (CBP) on Adoption Intention (AI) Through Trust to Digital Innovation (TDI) and Privacy Concerns (PC)

Regression analysis				*Bootstrap analysis*[a]		
Effect	*b*	*T*	*P*	*Indirect effect via Trust*	*95% CI*	
CBP[b] → *TDI*	.239	1.515	.131	.038	-.020	.149
TDI → *AI*	.160	1.676	.095	*Indirect effect via Priv. Concerns*		
CBP → *PC*	-.693	-.359	.000	.175	.040	.368
PC → *AI*	-.253	-3.219	.001			
CBP → *AI*[c]	.475	2.275	.024	*Total indirect effect*		
				.214	.077	.407

[a]based on 5,000 bootstrap resamples
[b]dummy-coded (0 = Free- of-charge based cost positioning, 1 = Freemium based cost positioning)
[c]R^2=.660; we further controlled for domain-specific innovativeness, product innovativeness and performance uncertainty

Next, we ran a moderated mediation for trust to DI and privacy concerns with the moderator digital nativeness to test Hypotheses 4a and b. Firstly, we don't observe a significant effect of cost-based positioning on trust for digital natives and immigrants (b= -.051; p=.878). Furthermore, the indirect effect of cost-based positioning on adoption intention through trust is not significant for digital natives (b=.042) with a 95% confidence interval containing zero [-.021;.165]. Similarly, the indirect effect of cost-based positioning also not significant for digital immigrants (b= -.033) with a 95% confidence interval containing zero [-.067; .190], resulting in an overall non-significant index of moderated mediation: b= -.008 with a 95% confidence interval containing zero [-.165;1.353]. Holding trust constant, a direct effect of cost-

based positioning on adoption intention is non-significant (b=.258, p=.673) as well. Hence, we do not find support for hypothesis 4a. Further, we investigated the indirect path from cost-based positioning on adoption intention via privacy concerns for both adopter groups. Firstly, we observe a non-significant effect of cost-based positioning on privacy concerns for both adopter groups (b=.344; p=.328). However, the indirect effect of cost-based positioning on adoption intention via privacy concerns is significant and positive for digital natives (b=.204) with a 95% confidence interval excluding zero [.040; .448]. Also, we find a significant and positive effect for digital immigrants (b=.117) with a 95% confidence interval excluding zero [.029; .327]. Hence, the overall moderated mediation is significant (b= -.086) with a 95% confidence interval excluding zero [-.011;-.021]. Interestingly, we find a slightly stronger effect for digital natives compared to digital immigrants, but for both adopter groups the effects go in the same direction. Hence, we find no support for our hypothesis 4b (see Table 4.6).

Table 4.6: Moderated Mediation Model for the Effect of Cost-Based Positioning (CBP) on Adoption Intention (AI) Through Trust to Digital Innovation (TDI), Privacy Concerns (PC) and Moderator Digital Nativeness (DN)

Regression analysis			
Effect	*b*	*T*	*P*
CBP[b] → *TDI*	.306	.646	518
DN[c] → *TDI*	.095	.375	.707
CBP x DN → *TDI*	-.051	-.153	.878
TDI → *AI*[d]	.164	1.707	.089
CBP → *AI*	.258	.422	.673
CBP → *PC*	-1.157	-2.033	.046
DN → *PC*			
CBP x DN → *PC*	.011	.036	.978
PC → *AI*	.344	.846	.328

Bootstrap analysis indirect effect via Trust[a]			
Digital Nativeness	*Effect*	*95% CI*	
Digital Natives	.042	-.021	.165
Digital Immigrants	-.033	-.067	.190

Index of moderated mediation via Trust		
Effect	95% CI	
-.008	-.165	1.353

Bootstrap analysis indirect effect via Privacy concerns:			
Digital Natives	.204	.040	.448
Digital Immigrants	.117	.029	.327

Index of moderated mediation via Privacy Concerns

-.250	-3.169	.001	Effect	95% CI	
			-.086	-.011	-.121

[a]based on 5,000 bootstrap resamples
[b]dummy-coded (0 = Free- of- charge- based cost positioning, 1= Freemium- based cost positioning)
[c]dummy-coded (0 = Digital Natives, 1 = Digital Immigrants)
[d]R^2=.757; we further controlled for domain-specific innovativeness, product innovativeness and performance uncertainty

4.5.4 Discussion

Our study findings reveal that a cost-based positioning strategy influences the adoption intention of DIs primarily through privacy concerns, rather than through trust to DIs by start-ups. Consistent with our expectations, it appears that privacy concerns are particularly increased when DIs are offered under a free-of-charge revenue model. Consequently, we observed a lower adoption intention for a free-of-charge revenue model due to increased privacy concerns. Moreover, the choice of a cost-based positioning also directly impacts adoption intention. There's a general reluctance towards free-of-charge revenue models as well as a preference for the freemium revenue model. A trend that is consistent with prior research findings (Han et al., 2020).

However, we discovered some unexpected findings in relation to the effect of a cost-based positioning on adoption intention via trust or privacy concerns for digital natives and digital immigrants. First, there seems to be no significant indirect effect of cost-based positioning via trust for adopter groups. Furthermore, both digital natives and digital immigrants appear to demonstrate similar levels of privacy concerns in case of different cost-based positionings. Despite previous claims suggesting otherwise (Engels, 2019; Bordonaba-Juste et al., 2020), our research shows that digital natives do not exhibit a greater level of indifference towards revenue models and do not trust the free-of-charge model more, compared to digital immigrants. Digital natives seem to care about their privacy, which shapes their adoption behaviour. More specifically, our findings indicate that, digital natives show a higher

adoption intention towards a freemium-based cost positioning, which implies that they trust it more and are less concerned about it than digital immigrants.

4.6 Study 3: Putting it Together - Value-Based Positioning for DIs by Start-ups

We run a further study to investigate the combined effect of a benefit-based and a cost-based positioning. Within this study, we aim to investigate effective combinations of a benefit-based and cost-based positioning for driving adoption intention of DIs by start-ups considering trust and privacy concerns for digital natives and immigrants.

4.6.1 Hypotheses Development

4.6.1.1 Value-Based Positioning

The results of our Study 1 indicate that, in general, a benefit-based positioning focusing on technological benefits is more effective in driving adoption intention than a positioning based on motivational benefits. More specifically, technological benefits enhance trust, leading to higher adoption intention. This finding suggests that adopters have become more knowledgeable and comfortable with digital technologies, whereby the anxiety and distrust often associated with technological innovations has been reduced.

However, within a value-based positioning start-ups simultaneously must account for the communication and impact of a revenue model. We assume that the revenue model might impact the effect of the benefit-based positioning on trust and hence on adoption intention, as the communication of a revenue model might increase overall uncertainty with a DI. However, the effect might vary depending on the exact benefit and revenue model chosen.

More specifically, for a technological benefit, the communication of a freemium revenue model can strengthen the positive effect on trust, as a freemium model provides a higher transparency on handling of adopters' personal data (Kumar, 2014). However, communication of a free-of-charge revenue model might lead to a higher uncertainty with the technological

benefit due to the unclear data commercialisation behind (Pavlou et al., 2007) and, further, it can create too much exposure to pure digital cues for adopters leading to a higher scepticism. For a motivational benefit, we expect a freemium revenue model to equally positively impact trust and adoption intention due to provision of a good level of information about the purchasing options and their credibility (Niemand et al., 2015). Whereas a free-of-charge revenue model would negatively impact the level of trust with motivational benefit, due to lack of transparency about exact data monetisation practices (Han et al., 2020). Finally, as there is a higher level of trust to technological compared to motivational benefits, we expect a freemium revenue model to enhance it further, whereas a free-of-charge revenue model to undermine it, since adopters might already feel uncertain about achievement of motivational benefits, they might feel more uncertain with those provided free-of-charge. Thus, we hypothesize:

Hypothesis 5a: The positive effect of a benefit-based positioning, which is stronger for a technological vs. a motivational benefit, on trust and, consequently, adoption intention is impacted by a cost-based positioning, whereby the effect is weaker for a technological vs. a motivational benefit with a freemium compared to a free-of-charge cost-based positioning.

Privacy concerns generally play a significant role in influencing adoption of DIs (Gupta et al., 2011). However, our results indicate that a benefit-based positioning does not elicit privacy concerns. Even a communication focused on technological benefits does not appear to provoke worries about personal data handling. On the other hand, existing research and our findings suggest that privacy concerns are primarily pronounced and drive adoption intention when start-ups focus on a cost-based positioning, as adopters feel anxious about the commercialization of their personal data (Martin et al., 2017). Hence, we anticipate a cost-based positioning to impact the relation between the benefit-based positioning and privacy concerns and, further, adoption intention. More specifically, a communication of a cost-based positioning alongside a benefit-based positioning will generally cause higher privacy concerns, when start-ups focus on a free-

of-charge revenue model compared to a freemium revenue model due to commercialisation of personal data (Han et al., 2020). Furthermore, a communication of a cost-based positioning might lead adopters to have higher privacy concerns with a technological benefit-based positioning compared to a motivational benefit, because the focus on a revenue model and digital technology in communication might make adopters more uncertain and concerned about how their personal data will be handled. Whereas, such an effect might be weaker for a motivational benefit because adopters will only be exposed to a digitalised revenue model and not the digital technology itself. Therefore, we hypothesize:

Hypothesis 5b: The relation between a benefit-based positioning and privacy concerns and, consequently, adoption intention is impacted by a cost-based positioning, driving higher privacy concerns with a technological vs. motivational benefit, whereby the impact of a cost-based positioning is stronger for a free-of-charge compared to a freemium cost-based positioning.

4.6.1.2 Value-Based Positioning for Different Adopter Groups

Previous research (e.g., Hoffmann et al., 2014) and our studies confirm significant differences in attitudes and perceptions between digital natives and digital immigrants. The proliferation of digital technologies and new avenues for value creation have made adopters more discerning, with both groups aiming to maximize overall value in their choices (Kautish and Sharma, 2019). Digital natives are primarily attracted to digital services that enhance their lives, while digital immigrants tend to prefer solutions they can trust and effectively control the risk (Vodanovich et al., 2010).

Further, our findings from Studies 1 and 2 show that technological benefits are more effective than motivational benefits in fostering trust and, subsequently, adoption among digital natives due to their familiarity with and awareness of digital technologies (Palfrey and Gasser,

2008). However, when it comes to revenue models, digital natives appear concerned about commercialization practices behind DIs, contrary to the prevailing beliefs in the literature (e.g. Dingli et al., 2015). Therefore, a communication of a benefit-based positioning together with a revenue model is expected to negatively impact trust and, consequently, adoption intention for digital natives. Furthermore, digital natives tend to prefer a freemium vs. a free-of -charge revenue model, as it offers a greater transparency regarding data monetization practices (Niemand et al., 2015). Therefore, the negative impact of a revenue model on the positive effect of a benefit-based positioning on trust might be weaker in a combination with a freemium compared to a free-of-charge revenue model. Further, due to digital natives' overall awareness and familiarity with digital technologies, we expect a technological benefit to still drive higher trust compared to a motivational benefit, when combined with a freemium revenue model as opposed to a free-of-charge revenue model.

In contrast, digital immigrants often exhibit an overall anxiety and distrust toward DIs (Kirk et al., 2015). Therefore, the most effective strategy to build trust among digital immigrants is to focus on motivational benefits that do not prominently emphasize digital technology. However, as digital immigrants are less aware of data monetisation practices (Kirk et al., 2015). a communication of a benefit-based positioning together with a revenue model might negatively effect trust of digital immigrants and, consequently, adoption intention. More specifically, as digital immigrants tend to prefer solutions that deliver highest transparency (Nicolas, 2009), the negative impact of a revenue model communication together with the benefit-based positioning on trust to be weaker for a freemium revenue model compared to a free-of-charge revenue model. Whereas, the personal data monetisation with the free-of-charge revenue model might more negatively impact the relationship between the benefit-based positioning and trust. Hence, we hypothesize:

Hypothesis 6a: For digital natives the positive effect of a benefit-based positioning, which is stronger for a technological vs. a motivational benefit, on trust and, consequently, adoption intention is decreased by a cost- based positioning, whereby the decreasing effect is stronger with a free-of-charge compared to a freemium cost-based positioning.

Whereas, for digital immigrants the positive effect of a benefit-based positioning, which is stronger for a motivational vs. a technological benefit, on trust and, consequently, adoption intention is decreased by a cost- based positioning, whereby the decreasing effect is stronger with a free-of-charge compared to a freemium cost-based positioning.

Previous research has established the impact of privacy concerns on DI adoption (e.g., Martin et al., 2017; Bamberger et al., 2020), whereby digital natives and immigrants exhibit different levels of privacy concerns toward DIs, with digital immigrants appearing more sensitive to the technological aspects of DIs (Filho et al., 2021). However, the appearance of privacy concerns seems to be related to the exact type of positioning communicated by start-ups. For example, a benefit-based positioning communication (either motivational or technological benefit) does not seem to provoke privacy concerns for either digital natives or digital immigrants, whereas, a cost-based positioning appears to drive significant privacy concerns for both adopter groups. Hence, in general, a cost-based positioning might impact the effect of a benefit-based positioning on privacy concerns and adoption intention. More specifically, for digital natives, the effect of a benefit-based positioning on privacy concerns might be stronger for a combination with a free-of-charge revenue model compared to a freemium, as digital natives appear to be concerned with their data privacy and prefer solutions with a better data handling transparency. Furthermore, despite digital natives being usually familiar with digital technologies and actively using them (Engels, 2019), the communication of a technological benefit together with a cost-based positioning might cause stronger privacy concerns than a combination of a motivational benefit.

Digital immigrants are naturally even more concerned about their data privacy than digital natives (Filho et al., 2021), therefore, a communication of a cost-based positioning alongside a benefit-based positioning might also cause stronger privacy concerns. Furthermore, the effect of a benefit-based positioning on privacy concerns might be also stronger for a combination with a free-of-charge revenue model compared to a freemium, as digital immigrants generally tend to be more concerned when a DI involves commercialisation of personal data. Moreover, as digital immigrants generally tend to have anxiety, scepticism and negative perceptions towards digital technologies (Liu and Schrum, 2009) the impact of a cost-based positioning communication will be aggravated for the technological benefit compared to a motivational benefit. Thus, we hypothesize:

Hypothesis 6b: For digital natives the relation between a benefit-based positioning and privacy concerns and, consequently, adoption intention is impacted by a cost-based positioning, driving higher privacy concerns with a technological vs. motivational benefit, whereby the impact of a cost-based positioning is weaker for a freemium compared to a free-of-charge cost-based positioning.

Equally, for digital immigrants the relation between a benefit-based positioning and privacy concerns and, consequently, adoption intention is impacted by a cost-based positioning, driving higher privacy concerns with a technological vs. motivational benefit, whereby the impact of a cost-based positioning is weaker for a freemium compared to a free-of-charge cost-based positioning.

4.6.2 Study Design and Data

We conducted an experimental study, where we used a different DI as in the Studies 1 and 2, a DI we called *HeimWerk*. The DI *HeimWerk* represents a solution that enables smaller repairs at home with the help of video streaming via a smartphone. As before, we recruited participants

via a European online consumer panel. All participants were randomly assigned to the 2 (Benefit-based positioning: technological vs. motivational) x 2 (Cost-based positioning: freemium vs. free of charge) between-subjects factorial design resulting in nearly equal cell sizes.

As in the previous studies, the participants were exposed to a screenshot of the website with an overall description of *HeimWerk's* features, the benefit it delivers, information about the revenue model of the DI, and a disclaimer about personal data handling at the bottom of the page. Therefore, for example, in the technological benefit-based and freemium experimental condition it was claimed that the DI enables an on-the-spot repair of smaller issues without long waiting and unnecessary appointments thanks to the various digital technologies behind it. Additionally, some basic features were provided free of charge and some additional advanced features were provided for a fee of €9.99. The corresponding disclaimer provided information about third-party cookies and access to personal data for third parties depending on the chosen option. Whereas, in the motivational benefit-based and free-of-charge experimental condition it was claimed that the DI enables an on-the-spot repair of smaller issues without wasting time that can be used for more important things in life. Also, the usage was claimed to be for free with the disclaimer highlighting that the start-up allowed third-party cookies and corresponding access to third parties to personal data. The remainder of the questionnaire was the same as in the Study 1 and 2. Appendix A5.c provides a visualization of the manipulation used in the experiment.

4.6.3 Sample and Measurement

Excluding speeders according to the procedure in Studies 1 and 2 (Buchanan and Scotfeld, 2018), we obtained 315 complete responses to our questionnaire. 45% of the sample was female with an average age of 48 years. Table 4.7 provides a description of the sample.

Table 4.7: Description of the Sample Study 3

Variable (N=314)	Frequency	Percentage
Gender:		
1) Male	170	54
2) Female	142	45
3) N/a	2	1
Age (average)	48	N/a
Education		
1) Secondary school	57	18
2) College	99	31
3) High school	66	21
4) Bachelor	21	6
5) Master/ Specialist diploma	50	15
6) Phd	6	2
7) N/a	5	2
8) Other	0	0
Profession		
1) Currently employed	124	39
2) Self employed	22	7
3) University/school student	10	3
4) Not employed	16	5
5) Retired	21	6
6) N/a	23	7
7) Other	99	33
Marital status		
1) Single	67	21
2) Partnership	68	21
3) Married	135	43
4) Divorced	32	10
5) N/a	5	2
6) Other	8	2
Monthly net income (Euro)		
1) below 500	16	5
2) 501-1.000	36	11
3) 1.001-2.000	48	15
4) 2.001- 3.000	43	13
5) 3.001- 4.000	82	26
6) 4.001-5.000	31	9
7) Over 5.000	0	0
8) N/a	9	2

We ran manipulation checks using 7-point Likert scale, where participants acknowledged that the DI was developed by a start-up ($M=5.99$, $F(1,314)= 77.343$, $p<.001$)). Additionally, participants were not familiar with the DI before the study ($M=1.21$, $F(1,314)=26.785$, $p<.001$). In the freemium-based positioning condition, participants perceived

an advanced version of *HeimWerk* to be offered against a monetary price, whereas a basic version to be offered free of charge ($M_{Freemium}$=6.15, $M_{Freeofcharge}$=2.89, F(1,314)=21.753, p<.001). Whereas, in the free-of-charge-based positioning condition participants understood that *HeimWerk* is offered at no monetary cost, however, personal data is collected and commercialised ($M_{Freeofcharge}$=5.62, $M_{Freemium}$=4.34, F(1,314)=6.712, p<.001). Additionally, in the experimental conditions where participants were exposed to the motivational benefit, they understood the motivational aspect (M_{MBB}=6.22, M_{TBB}=4.46, F(1,314)=32.665, p<.001). Whereas, whenever participants were exposed to the technological benefit, they understood that the benefits of the DI are enabled by digital technologies (M_{TBB}=5.95, M_{MBB}=3.52, F(1,314)=34.654, p<.001).

4.6.4 Results

To test our hypotheses, we ran several moderated mediation bootstrap tests (5000 resamples) by Preacher and Hayes (2004) and, consequently, examined the effective combinations of benefit and cost-based positionings effecting trust and privacy concerns for digital natives and immigrants using planned contrasts analysis. As in the Study 1 and 2, we controlled for domain-specific innovativeness, product innovativeness, and performance uncertainty.

First, we confirm a positive significant effect of benefit-based positioning on trust (b=.658; p=.005). We also observe a direct significant positive effect of benefit-based positioning on adoption intention (b=.630; p=.001). Next, we investigate the indirect effect of a value-based positioning (as an interaction effect of a benefit-based and cost-based positioning) on adoption intention via trust. However, we don't find a significant interaction effect between the benefit-based positioning and the freemium cost-based positioning (b= -.430) with the confidence interval containing zero [-.870;.010]. However, we find a significant negative effect

for the interaction between the benefit-based positioning and the free-of-charge cost- based positioning (b= -.581) with the confidence interval excluding zero [-.954;-.206]. Following the non-significant effect of the benefit-based positioning with the freemium cost-based positioning, the overall moderated mediation is non-significant (b=.150) with the confidence interval containing zero [-.437;.709], which is not in line with our hypothesis 5a. Table 4.8 provides a summary of findings.

Table 4.8: Interaction Effect of Benefit-Based Positioning (BBP) on Adoption Intention via Trust to Digital Innovation (TDI) and Privacy Concerns (PC) with the Cost-Based Positioning (CBP)

Regression analysis				*Bootstrap analysis indirect effect via Trust*[a]			
Effect	*b*	*T*	*P*	*Cost-based positioning*	*Effect*	*95% CI*	
BBP[b] → *TDI*	.658	2.819	.005	Freemium	-.430	-.870	.010
CBP[c] → *TDI*	1.571	6.633	.000	Free-of-charge	-.581	-.954	-2.065
BBP x CBP → *TDI*	.170	.516	.606	*Index of moderated mediation via Trust:*			
CBP → *PC*	-.117	-4.495	.000	Effect		95% CI	
BBP → *PC*	.105	.416	.677	.150		-.437	.709
BBP x CBP → *PC*	.008	.023	.981	*Bootstrap analysis indirect effect via Priv.concerns:*			
BBP → *AI*	.630	3.844	.001	Freemium	-.004	-.049	.025
TDI → *AI*	.883	18.563	.000	Free-of-charge	-.004	-.049	.021
PC → *AI*	-.040	-.844	.399	*Index of moderated mediation via Priv. concerns:*			
				Effect		95% CI	
				-.0003		-.050	.046

[a]based on 5,000 bootstrap resamples
[b]dummy-coded (0=Motivational benefit-based positioning, 1= Technological benefit-based positioning)
[c]dummy-coded (0=Free-of-charge based cost positioning, 1=Freemium-based cost positioning
[d]R^2=.814; we further controlled for domain-specific innovativeness, product innovativeness and performance uncertainty.

Next, we take a closer look into the effects of the combinations of a benefit-based and a cost positioning on trust and run a planned contrast analysis. The overall effect of the value-

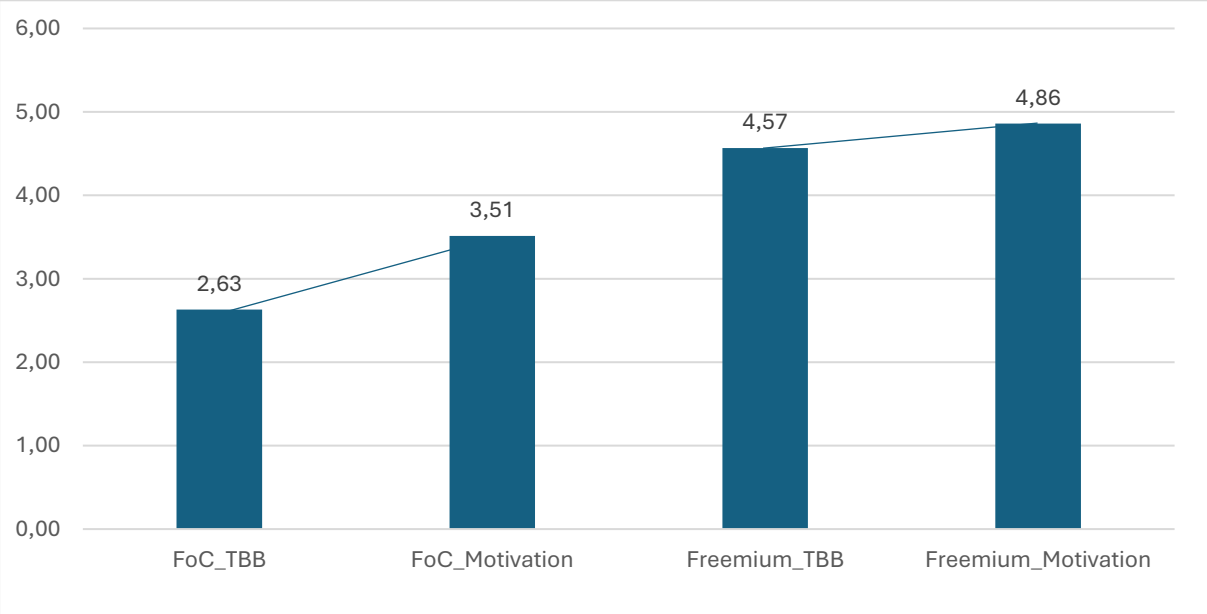
based positioning on trust is significant and positive ($F(3,311)=28.573$, $p<.05$)). Further, a combination of a motivational benefit and a freemium revenue model has the strongest positive effect on trust (M=4.86; SD=2.04) (see Table 4.9). However, this effect is almost equal to the effect of a combination of a technological benefit with a freemium revenue model (M=4.56; SD=1.82), where the planned contrast analysis indicates no significant difference between the two effects $t(3,311)=0.29$; $p=.782$), which is in line with the results of our moderated mediation analysis. Whereas trust is significantly lower for a combination of a motivational benefit with a free-of-charge revenue model (M=3.51; SD=1.68) and a technological benefit with a free-of-charge revenue model (M=2.63; SD=1.08). Whereby, the means differences are significant with $t(3,311)=2.22$;$p=.00$ for the combination of a free-of-charge and motivational benefit and $t(3,311)=1.34$;$p=.00$ for the combination of a free-of-charge and technological benefit, which is also in line with our moderated mediation analysis. We illustrate the effects in the Figure 4.2, that visually shows almost equal effects for both types of benefit-based positioning in a combination with freemium cost-based positioning. Whereas, we observe a significant difference for the benefit-based positioning in a combination with a free-of-charge cost-based positioning. Taking all findings together, we are not able to find support for our hypothesis 5a.

Table 4.9: Planned Contrasts Analysis of Different Combinations of Benefit and Cost-Based Positioning on Trust to Digital Innovation

	N	*Mean*	*St.Dev.*	*Mean difference*			
				TBB&FoC	TBB&Fr.	Mot&FoC	Mot&Fr.
TBB&FoC	80	2.63	1.08	-	-1.935*	-.881*	-2.228*
TBB&Freemium	82	4.56	1.82	1.935*	-	1.054*	-.292
Motivation&FoC	78	3.51	1.68	.881*	-1.054*	-	-1.347*
Motiv.&Freem.	75	4.86	2.04	2.228*	.292	1.347*	-

FoC= Free-of-charge cost-based positioning
TBB= Technological benefit-based positioning
Motivation= Motivational benefit-based positioning

Figure 4.2: The Effect of Different Combinations of Benefit and Cost-positioning on Trust to Digital Innovation



Then, analysing the effects via privacy concerns, we first, as before, run the mediation analysis. We observe an overall non-significant effect of benefit-based positioning on privacy concerns (b=.105;p=.677) and a non-significant effect of privacy concerns on adoption intention (b= -.040;p=.399). Analysing the indirect effects, we find a non-significant overall indirect effect of a value-based positioning (as interaction of benefit and cost-based positioning)

on adoption intention via privacy concerns. More specifically, the interaction effect of a benefit-based positioning with the freemium cost-based positioning is negative (b=-.004) and not significant [-.049;.025], whereas the interaction effect of a benefit-based positioning with the free-of-charge cost-based positioning is also negative (b= -.004) and not significant [-.041;.021]. Moreover, contrary to our expectations, both effects are quite similar, resulting in a non-significant moderated mediation (b=-.0003) with the 95% confidence interval including zero [-.050; .046] (see Table 4.8). Hence, the found effects do not support the hypothesized direction.

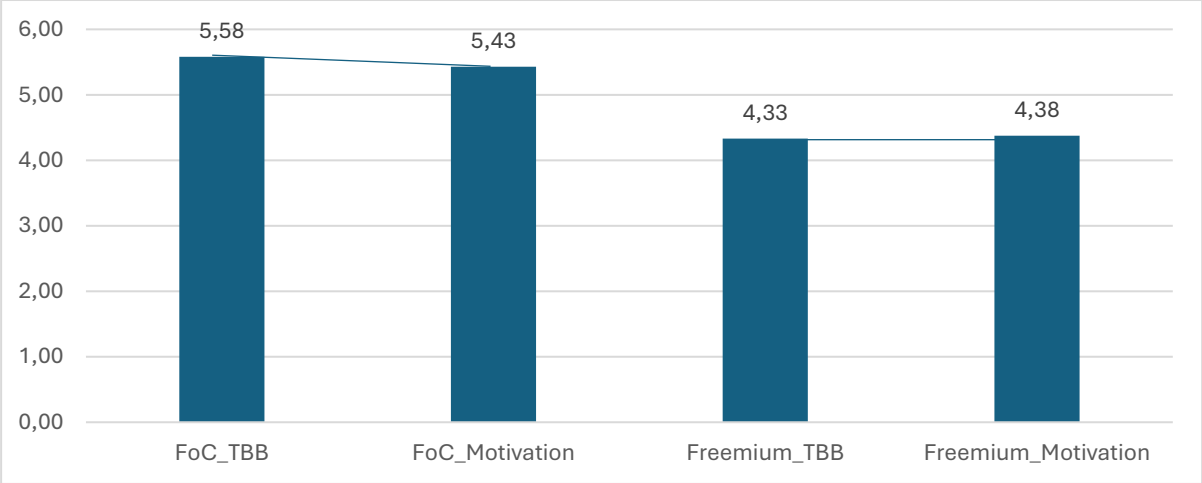
However, we also ran a planned contrast analysis to investigate individual effects of different combinations of benefit and cost-based positioning on privacy concerns. We observe that the effect of a benefit-based positioning on privacy concerns is significantly stronger when combined with a free-of-charge revenue model vs. freemium revenue model. Whereby, it is the highest for the combination with a technological benefit (M=5.58;SD=1.56) compared to a motivational benefit (M=5.43;SD=1.54). However, the means difference is not significant t(3,311)=.1548, p>.05. Although the combination of a benefit-based positioning with a freemium revenue model has a weaker effect on privacy concerns, still the means difference is also not significant between a technological (M=4.33; SD=1.85) and a motivational (M=4.37;SD=1.89) benefit combined with a freemium t(3,311)=-.044, p>.05 (Table 4.10). As before, we illustrate the effects in the Figure 4.3, which shows significantly higher level of privacy concerns for the combinations of benefit-based positioning with a free-of-charge compared to freemium cost-based positioning. However, in line with our mediation analysis we observe hardly any difference in privacy concerns for the effects of technological vs. motivational benefits combined with a free-of-charge revenue model as well as for the similar combinations with a freemium revenue model. Hence, we don't find support to our hypothesis 5b overall.

Table 4.10: Planned Contrasts Analysis of Different Combinations of Benefit and Cost-Based Positioning on Privacy Concerns

	N	*Mean*	*St.Dev.*	*Means difference*			
				TBB&FoC	TBB&Fr.	Mot&FoC	Mot&Fr.
TBB&FoC	80	5.58	1.56	-	1.255*	.1548	1.210*
TBB&Freemium	82	4.33	1.85	-1.255*	-	-1.100*	-.044
Motivation&FoC	78	5.43	1.54	-.154	1.100*	-	1.056*
Motivation&Freem.	75	4.37	1.89	-1.056*	.0443	-1.210*	-

FoC= Free-of-charge cost-based positioning
TBB= Technological benefit-based positioning
Motivation= Motivational benefit-based positioning

Figure 4.3: The Effect of Different Combinations of Benefit and Cost-Positioning on Privacy Concerns



Next, we investigate the value-based positioning (as interaction effect between benefit and cost-based positioning) for digital natives and digital immigrants and run a moderated moderated mediation bootstrap analysis (5000 resamples) by Preacher and Hayes (2004). Consequently, we also investigate the effects of single combinations of benefit and cost-based positioning on trust and privacy concerns for both adopter groups using planned contrast analysis.

Firstly, we confirm a significant positive effect of a value-based positioning on trust for digital natives and immigrants (b=.834; p=.056). Then we investigate the indirect effects. For digital natives we observe a weaker negative effect of freemium compared to free-of-charge cost-based positioning, resulting in a stronger positive effect of benefit-based positioning on adoption intention via trust (b= 1.603) with a 95% CI excluding zero [1.111; 2.105]. Whereas, we observe a stronger negative effect of free-of-charge resulting in a lower effect of benefit-based positioning on adoption intention via trust (b= -.941) with a 95% CI excluding zero [-1.396; -.489]. For digital immigrants, we also observe a weaker negative effect of freemium compared to free-of-charge cost-based positioning, resulting in a stronger effect of benefit-based positioning on adoption intention via trust (b= -.853) with a 95% CI excluding zero [.165; 1.527] and a stronger negative effect of free-of-charge cost-based positioning resulting in lower effect of benefit-based positioning (b= -.204) with a 95% CI excluding zero [-.778; -.368]. Therefore, we are able to confirm a significant overall moderated mediation (b=1.720) with the confidence interval excluding zero [.637;2.804] (see Table 4.11), largely supporting the hypothesized direction for the hypothesis 6a.

Table 4.11: Tripple Interaction for the Effect of a Benefit-Based Positioning (BBP) on Adoption Intention via Trust to Digital Innovation (TDI) and Privacy Concerns (PC) with the Cost-Based Positioning (CBP) and the Moderator Digital Nativeness (DN)

Regression analysis				*Bootstrap analysis indirect effect via Trust*[a]				
Effect	*b*	*T*	*p*	*Digital Nativeness*	*Cost-based positioning*	*Effect*	*95% CI*	
BBP[b] → *TDI*	-1.899	-2.837	.004	Digital Natives	Freemium	1.603	1.111	2.105
					Free-of-charge	-.941	-1.396	-.489
CBP[c] → *TDI*	3.681	5.350	.000					
DN[c] → *TDI*	-.529	-1.531	.126	Digital Immigrants	Freemium	- .853	1.527	.165
					Free-of-charge	-.204	-.778	-.368
BBP x CBP → *TDI*	-2.697	-2.819	.005					
BBP x DN → *TDI*	.834	1.916	.056	*Index of moderated moderated mediation via Trust*				

CBP x DN → TDI	-1.417	-3.195	.001
BBP x CBP x DN → TDI	1.947	3.151	.001
BBP → PC	1.352	1.856	.064
DN → PC	1.140	2.940	.003
CBP → PC	-1.912	-2.476	.013
BBP x CBP → PC	.561	.522	-.601
BBP x DN → PC	-.860	-1.760	.079
CBP x DN → PC	.531	1.066	.286
BPB x CBP x DN → PC	-.403	-.580	.561
BBP → AI	.039	.267	.789
TDI → AI	.883	18.563	.000
PC → AI	-.040	-.844	.399

		Effect	*95% CI*	
		1.720	.637	2.804
Bootstrap analysis indirect effect via Priv.concerns:				
Digital Natives	Freemium	.040	-.123	.040
	Free-of-charge	.034	-.111	.024
Digital Immigrants	Freemium	.023	-.038	.107
	Free-of-charge	.024	-.018	.078
Index of moderated moderated mediation via Privacy Concerns				
		Effect	*95% CI*	
		.016	-.080	.114

[a]based on 5,000 bootstrap resamples
[b]dummy-coded (0 = Motivational benefit- based positioning, 1= Technological benefit- based positioning)
[c]dummy-coded (0= Free-of-charge based cost positioning, 1= Freemium based cost positioning)
[d]dummy-coded (0 = Digital Immigrants, 1 = Digital Natives)
[e]R^2=.825; we further controlled for domain-specific innovativeness, product innovativeness and performance uncertainty.

As before, to confirm the exact single combinations of benefit-based and cost-based positioning on trust for digital natives and immigrants, we run a planned contrast analysis. For digital natives, the overall effect of a benefit-based positioning on trust is stronger when combined with a freemium cost-based positioning, in line with the hypothesized direction. More specifically, the effect is increased for a technological benefit (M=6.17;SD=1.83) as compared to a motivational benefit (M=4.47;SD=0.64) with a significant means difference t(3,311)=-1.699, p<.05. Furthermore, interestingly, we observe an adverse effect when a benefit-based positioning is combined with a free-of-charge revenue model for digital natives. Mainly, the effect of a technological benefit (M=2.77;SD=1.00) is decreased compared to a motivational benefit (M=4.03;SD=1.38), with the significant means difference as well

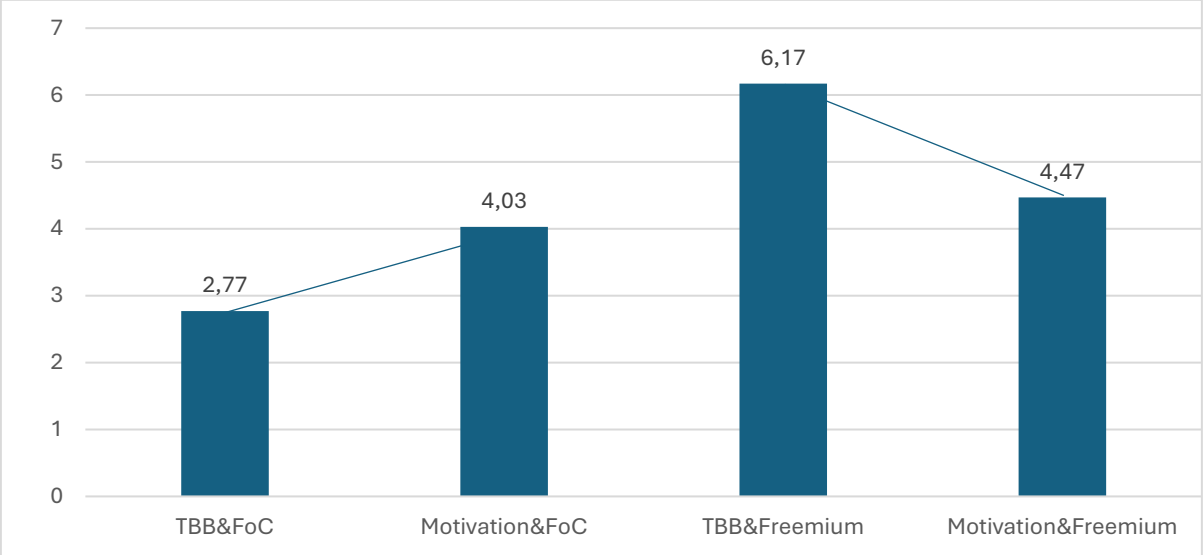
t(3,311)=-1.291, p<.05. Table 4.12 provides results of the planned contrasts analysis for digital natives. We further illustrate the effects in Figure 4.4 and observe that freemium cost-based positioning has a weaker negative effect on the effect of the benefit-based positioning on trust compared to a free-of-charge cost-based positioning, hence, significantly higher trust for technological vs. motivational benefit-based positioning. However, for the combination with a free-of-charge cost-based positioning, contrary to our expectations, we observe a stronger effect on trust for motivational vs. technological benefit-based positioning. Hence, overall, we can partially support our hypothesis 6a for digital natives.

Table 4.12: Planned Contrasts Analysis of Different Combinations of Benefit and Cost-based Positioning on Trust to Digital Innovation for Digital Natives

Target group: Digital Natives	*N*	*Mean*	*St.Dev.*	*Means difference*			
				TBB&FoC	TBB&Fr.	Mot&FoC	Mot&Fr.
TBB&FoC	43	2.77	1.00	-	-3.427*	-1.291*	-1.727*
TBB&Freemium	38	6.17	1.83	3.427*	-	2.136*	-1.699*
Motivation&FoC	43	4.03	1.38	1.291*	-2.136	-	.437
Motivation&Freem.	44	4.47	0.64	1.727*	-1.699*	.437	-

FoC= Free-of-charge cost-based positioning
TBB= Technological benefit-based positioning
Motivation= Motivational benefit-based positioning

Figure 4.4: The effect of Different Combinations of Benefit and Cost-Based Positioning on Trust to Digital Innovation for Digital Natives



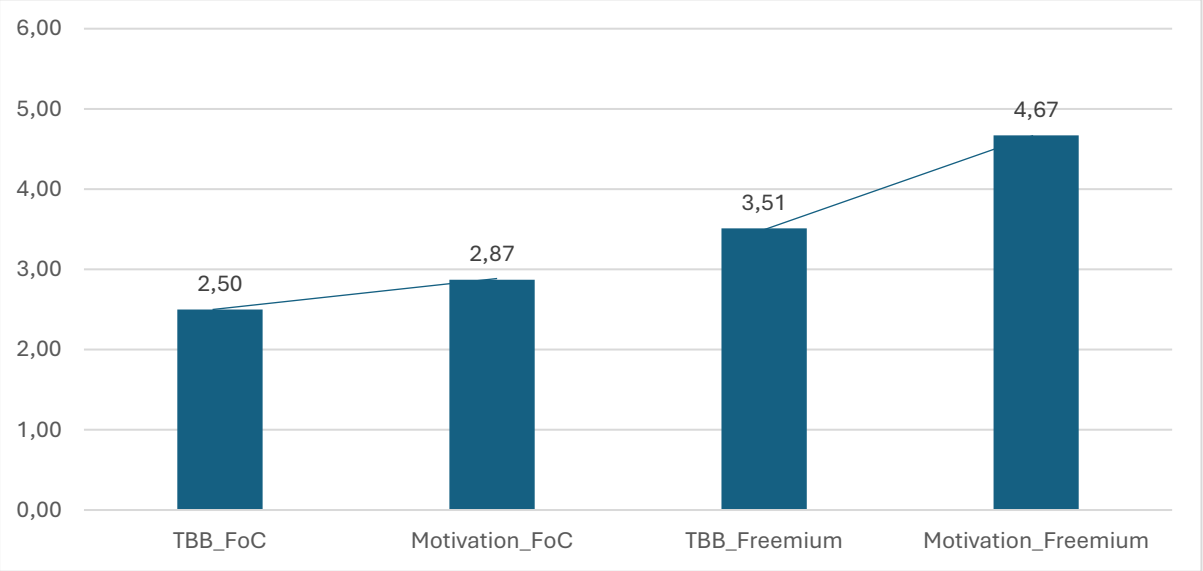
Next, we take a closer look at the effectiveness of different combinations of a benefit and cost-based positioning on trust for digital immigrants with the planned contrasts analysis. Firstly, in line with our hypothesis, we observe a stronger effect of a benefit-based positioning on trust when combined with a freemium revenue model. More specifically, the effect is stronger for a motivational (M=4.67;SD=2.12) as compared to a technological (M=3.51;SD=1.83) benefit with a significant means difference t(3,311)=-1.164, p<.05 (Table 4.13). A similar direction of the effect remains for the combination with a free-of-charge revenue model, where the effect for a motivational benefit (M=2.87;SD=1.81) is higher than a technological benefit (M=2.50;SD=1.17), however, with no significant means difference t(3,311)=-.371, p>.05. We also illustrate the effects on the figure 4.5 and clearly observe a weaker negative effect of a freemium cost-based positioning on the effect of benefit-based positioning on trust vs. free-of-charge cost-based positioning. Whereby, the effect on trust is higher for motivational vs. technological benefit-based positioning in a combination with freemium. However, we confirm no significant difference between the two types of benefit-based positioning in a combination with free-of-charge. Therefore, we can partially support our hypothesis 6a for digital immigrants.

Table 4.13: Planned Contrasts Analysis of Different Combinations of Benefit and Cost-Based Positioning on Trust to Digital Innovation for Digital Immigrants

Target group: Digital Immigrants	*N*	*Mean*	*St.Dev.*	*Means difference*			
				TBB&FoC	TBB&Fr.	Mot&FoC	Mot&Fr.
TBB&FoC	35	2.50	1.17	-	-1.014*	-.371	-2.178*
TBB&Freemium	37	3.51	1.83	1.014*	-	.642	1.164*
Motivation&FoC	37	2.87	1.81	.371	-.642	-	-1.806*
Motivation&Freem.	37	4.67	2.12	2.171*	-1.164*	1.806	-

FoC= Free-of-charge cost-based positioning
TBB= Technological benefit-based positioning
Motivation= Motivational benefit-based positioning

Figure 4.5: The Effect of Different Combinations of Benefit and Cost-Based Positioning on Trust to Digital Innovation for Digital Immigrants



Next, we analyse the effects via privacy concerns. As before, we first analyse the overall indirect effects using the moderated mediation analysis for both adopter groups. For digital natives, we don't observe any significant effects of benefit-based positioning on adoption intention via privacy concerns depending on a cost-based positioning. Furthermore, the effects

are relatively similar (b= .040) with a 95% CI containing zero [-.123; .040] for freemium and (b= .034) with a 95% CI containing zero [-.111; .024] for free-of-charge. Also, for digital immigrants we observe similar effects with (b=.023) with a 95% CI containing zero [-.038; .107] for freemium and (b= .024) with a 95% CI confidence interval containing zero [-.018; .078]. Hence, we don't find a significant overall interaction between benefit and cost-based positioning on adoption intention via privacy concerns (b=.016) with a confidence interval containing zero [-.080;.111] (Table 4.11), which does not support our hypothesis 6b.

To confirm the effects, we ran again a planned contrasts analysis of different combinations of a benefit-based and a cost-based positioning on privacy concerns. For digital natives, we observe an overall stronger effect on privacy concerns for a combination with a free-of-charge revenue model. Whereby, the effect is increased for a technological benefit (M=5.43;SD=1.68) compared to a motivational benefit (M=4.83;SD=1.53), however, the means difference is not significant t(3,311)=.605, p>.05. A similar effect is observed for a combination of a benefit-based positioning with freemium, whereby the means difference is still not significant t(3,311)=.530, p>.05. Table 4.14 provides a summary of all effects. We illustrate the effects in the figure 4.6. We observe a significantly stronger effect on privacy concerns for the combinations of a benefit-based positioning with free-of-charge cost-based positioning compared to those with freemium cost-based positioning. However, there are no significant differences for technological and motivational benefits. Hence, we cannot confirm our hypothesis 6b for digital natives.

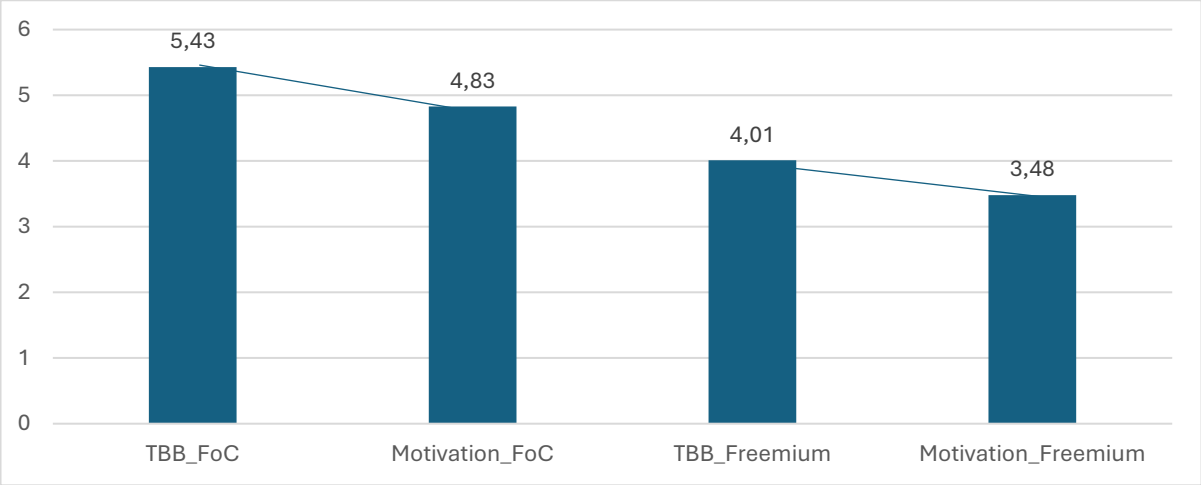
Table 4.14: Planned Contrasts Analysis of Different Combinations of Benefit and Cost-Based Positioning on Privacy Concerns for Digital Natives

Target group: Digital Natives	*N*	*Mean*	*St.Dev.*	*Means difference*			
				TBB&FoC	TBB&Fr.	Mot&FoC	Mot&Fr

TBB&FoC	43	5.43	1.68	-	1.419*	.605	1.949*
TBB&Freemium	38	4.01	1.76	-1.419*	-	-.814*	.530
Motivation&FoC	43	4.83	1.53	-.605	.814*	-	1.345*
Motivation&Freem.	44	3.48	1.72	-1.949*	-.530	-1.345*	-

FoC= Free-of-charge cost-based positioning
TBB= Technological benefit-based positioning
Motivation= Motivational benefit-based positioning

Figure 4.6: The Effect of Different Combinations of Benefit and Cost-Based Positioning on Privacy Concerns for Digital Natives



Lastly, we analyze the same effects for digital immigrants. The effect of a benefit-based positioning on privacy concerns is stronger for a combination with free-of-charge revenue model as compared to a freemium revenue model. More specifically, the effect is increased when a technological benefit is combined with a free-of-charge revenue model (M=6.17;SD=1.21) as compared to a combination of a motivational benefit with a free-of-charge revenue model (M=5.76;SD=1.41), however, with a non-significant means difference t(3,311)=-.408, p>.05. Whereas, a similar direction of the effect is observed for the combinations with a freemium revenue model. Whereby, a technological benefit (M=5.29;SD=1.62) still causes higher privacy concerns compared to a motivational benefit

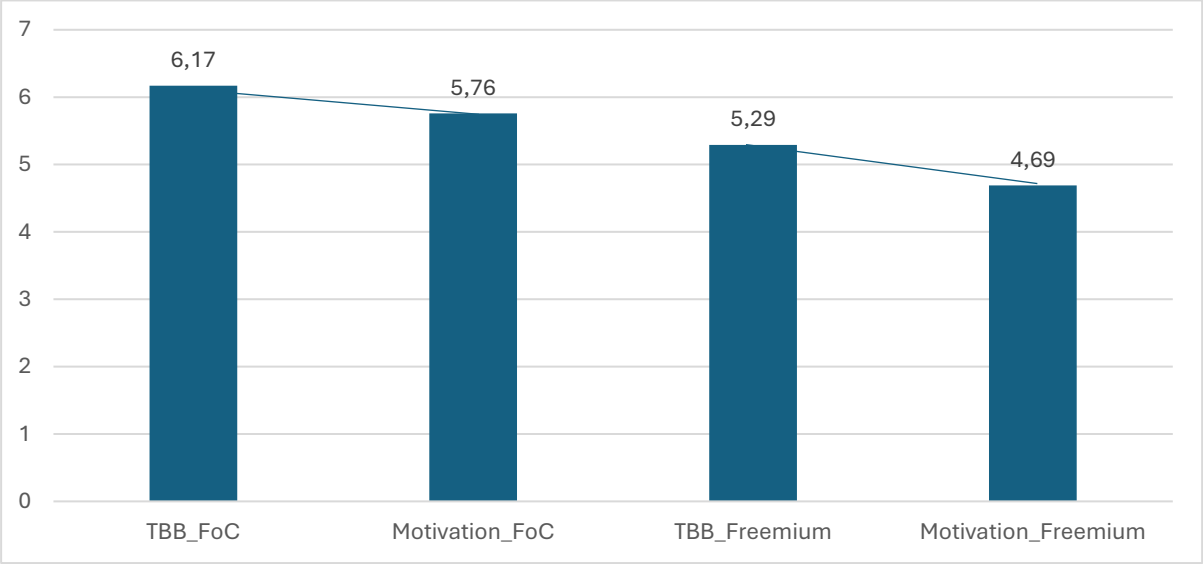
(4.69;SD=1.90) with a still non-significant means difference t(3,311)= -.593, p>.05. Table 4.15 provides an overview of the effects for digital immigrants. We also illustrate the effects on the figure 4.7. We clearly observe a stronger effect of the combination of benefit-based positioning and free-of-charge compared to freemium cost-based positioning on privacy concerns. Also, for both conditions the effect is stronger for the technological vs. motivational benefit, however, the differences are not significant. Hence, we don't find support for hypothesis 6b for digital immigrants.

Table 4.15: Planned Contrasts Analysis of Different Combinations of Benefit and Cost-Based Positioning on Privacy Concerns for Digital Immigrants

Target group: Digital Immigrants	*N*	*Mean*	*St.Dev.*	*Means difference*			
				TBB&FoC	TBB&Fr.	Mot&FoC	Mot&Fr.
TBB&FoC	37	6.17	1.21	-	.881*	.408	1.474*
TBB&Freemium	38	5.29	1.62	-.881*	-	-.473	.593
Motivation&FoC	35	5.76	1.41	-.408	.473	-	1.066*
Motivation&Freem.	37	4.69	1.90	-1.474*	-.593	-1.066*	-

FoC= Free-of-charge cost-based positioning
TBB= Technological benefit-based positioning
Motivation= Motivational benefit-based positioning

Figure 4.7: The Effect of Different Combinations of Benefit and Cost-Based Positioning on Privacy Concerns for Digital Immigrants



4.6.5 Discussion

In line with the objective of our additional study, we examined the effectiveness of a value-based positioning, which combines different configurations of benefit-based and cost-based positioning, on adoption intention through trust and privacy concerns for digital natives and immigrants. First, we confirmed a significant effect of a value-based positioning on trust. Notably, we observed an overall stronger effect on trust and adoption intention when benefit-based positioning was combined with a freemium revenue model as opposed to a free-of-charge revenue model. However, somewhat unexpected, we further observed a higher effect on trust for a combination with a motivational benefit, as opposed to a technological benefit. This finding suggests that, while adopters typically exhibit higher trust in DIs when start-ups emphasize a technological benefit within the benefit-based strategy, a value-based strategy that combines a technological benefit with a revenue model may still induce some distrust. This effect could be attributed to the fact that a value-based approach emphasizing a technological benefit and freemium revenue model communicates a number of digital cues at once, which can create additional uncertainty for adopters.

However, with regards to privacy concerns, we found no significant effect of a value-based positioning on privacy concerns. This suggests that communicating a cost-based positioning together with the benefit-based positioning does not induce privacy concerns and a negative impact on adoption intention. We, thus, conclude that while privacy concerns have long impacted DI adoption, the communication of a cost-based positioning together with a benefit-based positioning for DIs will not drive privacy concerns and a negative impact on adoption intention.

Further, analysing these effects for digital natives and immigrants, we found significant differences between both adopter groups for the effect of a value-based positioning on adoption intention via trust. More specifically, a combination of a motivational benefit and a freemium model proved more effective in driving adoption intention among digital immigrants due to increased trust. In contrast, for digital natives, a combination of a technological benefit and a freemium model led to higher trust and higher adoption intention, aligning with our previous findings. However, interestingly, the communication of a free-of-charge revenue model together with the benefit-based positioning has a very strong negative effect on trust, whereby even for the motivational benefit-based positioning trust to DI remains low as long as free-of-charge revenue model is communicated alongside the benefit.

Lastly, with regard to the indirect effects of a value-based positioning via privacy concerns, we identified no significant differences in the effects for both adopter groups. Furthermore, in line with the findings for the overall indirect effect of a value-based positioning on adoption intention via privacy concerns, our analysis showcased, that although a cost-based positioning impacts privacy concerns, once a benefit-based positioning is communicated together with the cost-based positioning the effect on privacy concerns becomes non-significant. Furthermore, interestingly, the same effect is observed for both adopter groups despite their differences. Thus, we conclude that the addition of a benefit-based positioning to the cost-based positioning does

not cause a rise of privacy concerns, and consequently, negative effect on adoption intention for digital natives and immigrants.

4.7 Overall Discussion and Research Contribution

While the importance of effective marketing strategies driving adoption of DIs has been widely discussed in the contemporary literature (e.g. Mikti et al., 2019; Setzke et al., 2021), research has yet to address effective positioning strategies for DIs developed by start-ups that would foster differentiation of DIs from their non-digital alternatives. This gap is understandable. On one hand, without a clear differentiation, adopters may see little benefit in switching from familiar, non-digital services to new DIs (Matthyssens et al., 2009). On the other hand, start-ups must select positioning strategies that address adopters' potential anxiety, concerns, and lack of trust in DIs (Mou et al., 2017). Therefore, identifying the right positioning strategy to achieve strong differentiation, strengthen trust and reduce privacy concerns is a complex challenge. To explore this, we conducted three experiments to examine positioning strategies for start-ups' DIs, focusing on factors that shape adopters' perceptions of these innovations.

Our research demonstrates that in order to drive adoption intention for DIs, start-ups must select positioning strategies that address adopters' trust, privacy concerns, and digital nativeness. In doing so, we contribute to the existing research on DI adoption (Prins and Verhoef, 2007; Shen, 2015; Mahardika et al., 2019) and expand upon prior studies focused on trust in the context of DIs (e.g., Kuester et al., 2018; Konya-Baumbach et al., 2019) by examining the roles of privacy concerns and digital nativeness.

Our findings suggest that start-ups may follow a benefit-based, cost-based, or a value-based strategy; however, not all strategies are equally effective, as their success is highly context-dependent. Addressing the efficiency of positioning strategies, our study reinforces

previous research on the importance of trust and privacy concerns as mediators between DI positioning and adoption intention. We find that the mediating effects of trust and privacy concerns vary according to the specific positioning strategy. More specifically, trust can be influenced by a benefit-based positioning, while privacy concerns are more triggered by a cost-based positioning. In the case of a value-based positioning—a combination of benefit- and cost-based approaches—only trust appears to mediate the overall relationship between the positioning and adoption intention. Interestingly, the combination of a benefit-based positioning with a cost-based positioning does not drive significant privacy concerns and does not seem to negatively impact adoption intention, which is a new insight in the research on adoption of DIs.

Further, our study also highlights the moderating role of digital nativeness in the indirect relationship between positioning and adoption intention through trust. Until now, the influence of digital nativeness has been largely overlooked in the research on DI adoption. However, given the distinct experiences and familiarity with DIs across different adopter groups, digital nativeness is essential for the understanding of the effectiveness of different positioning strategies. Specifically, because digital natives have grown up with constant access to digital technologies, we find that positioning strategies utilizing digital cues positively impact their trust and, in turn, their adoption intention. Conversely, digital immigrants tend to show lower trust when presented with digital claims in positioning, which negatively affects adoption intention. Instead, digital immigrants respond more positively to motivational positioning claims, where digital context is less explicit. Hence, we extend the previous research insights on digital nativeness to the context of DI adoption. Additionally, we discover some new and somehow contradictory insights in relation to the cost-based positioning and privacy concerns for digital natives and immigrants. With the rise of data-based revenue models, commonly deployed by start-ups for DIs, previous studies have suggested that digital natives and immigrants differ in their attitudes toward privacy (e.g. Lupton, 2021). Although prior research

indicates that digital natives value privacy, it also claims that these concerns do not significantly impact their adoption behaviour (Bordonaba-Juste et al., 2020). However, our study challenges these prevailing assertions. Our findings reveal that privacy concerns among both digital natives and immigrants are increased in the context of a free-of-charge revenue model, negatively impacting their adoption intention. In contrast, both groups exhibit lower privacy concerns towards a freemium model, leading to a greater likelihood of adoption. Hence, the topic is rather controversial and requires a further empirical investigation.

4.8 Managerial Implications

The widespread digitalization of the marketplace and the proliferation of DIs offer extensive opportunities for value creation (Kim et al., 2004). Start-ups play a key role in this transformation, serving as primary drivers of new value propositions through the development of DIs (Konya-Baumbach et al., 2019). DIs deliver novel benefits that traditional products cannot, effectively disrupting existing non-digital offerings in the marketplace (Brynjolfsson et al., 2018). However, start-ups often struggle to effectively differentiate their DIs and emphasize their core digital advantages. Consequently, while they may overcome high uncertainty and concerns associated with DIs, they frequently struggle to achieve high adoption rates, as adopters may not clearly see distinct benefits of DIs over non-digital alternatives.

Our research offers valuable insights and strategic guidance for start-ups on designing positioning strategies that highlight digital as a core competitive advantage. Specifically, we suggest that start-ups can leverage on the three primary positioning strategies to drive DI adoption: a benefit-based, a cost-based, or a value-based positioning. Additionally, our findings underscore the importance of considering factors such as trust in DIs, privacy concerns, and—critically—the digital nativeness of the target audience when developing positioning strategies.

First, benefit-based positioning focuses on emphasizing a specific benefit as the primary differentiator (Porter, 1985), a strategy that is generally effective in driving DI adoption (e.g., Talke and Snelders, 2013; Schuhmacher et al., 2018). To achieve a meaningful differentiation from non-digital alternatives, start-ups should highlight a technology-based benefit, explicitly naming the digital technology that enables this benefit. However, directly referencing the digital technology may cause uncertainty for some adopters; in such cases, start-ups can shift their focus to a motivational benefit, which communicates the unique advantages enabled by the digital technology without explicitly mentioning it. Our research indicates that, over time, adopters are becoming more familiar with digital technologies (Fernandes and Oliveira, 2021), leading to increased trust in these technologies. Thus, when addressing the general population, start-ups can emphasize a technology-based benefit, which positively impacts both trust and adoption intention. Furthermore, a focus on technology-based benefits does not appear to raise privacy concerns, suggesting that start-ups do not need to address these concerns explicitly when following a benefit-based positioning. However, addressing their communications to specific adopter groups, it is important to tailor the benefit approach. When targeting digital natives or early adopters, start-ups should emphasize a technology-based benefit, as it effectively fosters trust and encourages adoption. Conversely, when addressing digital immigrants or the late majority, focusing on a motivational benefit may be more effective, as this approach tends to build greater trust within these groups, ultimately driving adoption intention.

Second, start-ups may opt for a cost-based positioning strategy, which differentiates DIs from non-digital alternatives through a digitalized revenue model. In this approach, start-ups can choose between freemium or free-of-charge models, where adopters' personal data is used instead of direct monetary payments (Al-Natour et al., 2020). Consistent with prior studies, our research indicates that a cost-based positioning inherently raises privacy concerns, making the

choice of revenue model critical based on its impact on these concerns. Specifically, our findings show that a freemium revenue model in the cost-based positioning positively influences privacy perceptions, thereby encouraging adoption. Additionally, our studies suggest that freemium model also enhances adopters' trust in DIs, further increasing adoption intention. Hence, generally start-ups should prioritise a freemium revenue model when following a cost-based strategy. Contrary to prior research suggesting significant differences in privacy attitudes between adopter groups, our findings reveal that digital natives and digital immigrants exhibit similar types of attitudes regarding the implications of free-of-charge models on personal data. Both groups appear to prioritize data privacy over the benefit of a free digital service. Therefore, with the cost-based positioning, start-ups can also confidently prioritize a freemium revenue model regardless of whether they are targeting the broader market or segmenting by adopter type, such as digital natives (early adopters) or digital immigrants (late majority).

Lastly, start-ups can adopt a value-based positioning strategy, which integrates both benefit and cost positioning simultaneously. We generally recommend following this strategy, as it allows start-ups to deliver maximum value to adopters by providing optimal benefits at effective costs. Previous research supports this approach, indicating that adopters prefer solutions that offer the highest value (Huber et al., 2001). In line with our insights regarding the effectiveness of both benefit- and cost-based positioning strategies, start-ups should focus on a combination of technological benefits and a freemium revenue model when targeting the overall market with a value-based positioning strategy. This combination positively influences adopters' trust, subsequently driving their adoption intention for DIs. Furthermore, start-ups should tailor their value-based strategy slightly when targeting different adopter groups, in line with our recommendations for benefit-based positioning. More specifically, start-ups should emphasize a combination of technological benefits and a freemium revenue model when targeting digital natives. In contrast, when targeting digital immigrants, a focus on motivational benefits

alongside a freemium revenue model is likely to be most effective. Such tailored combinations will enhance trust within each respective adopter group and encourage adoption intention.

4.9 Limitations and Future Research

Our study examines effective positioning strategies that leverage a digital point of difference, enabling start-ups to differentiate their DIs from non-digital alternatives while addressing adopters' trust, privacy concerns and digital nativeness. Given the existing gap in positioning conceptualizations specifically for DIs, we developed a positioning framework for DIs based on the Porter's framework (1985). In doing so, we identified the nuances of benefit, cost, and value-based positioning strategies that are particularly relevant for DIs. However, we acknowledge that future research should validate our positioning framework and findings within different research contexts and with other types of DIs.

In our study on the benefit-based positioning, we offered new insights into the effectiveness of technological benefits over motivational ones in fostering trust in DIs and driving adoption intention, despite the fact that the underlying technology is explicitly mentioned. This finding challenges the prevailing claims in prior research regarding adopters' general anxiety about digital technologies (Huang and Rust, 2013). Therefore, future research should seek to validate our findings using other types of DIs.

Regarding the cost-based positioning, we expanded existing research on revenue models (e.g., Kim et al., 2004; Waitzinger et al., 2015; Konya-Baumbach et al., 2019) by focusing explicitly on digitalized revenue models. Our results indicate a notable preference among adopters for a freemium revenue model while showing a tendency to avoid free-of-charge models, even among digital natives. This finding is surprising, given previous research suggesting that digital natives are less concerned about privacy and are driven by a "free mentality," which posits that digital services should be available at no cost despite implications

for personal data (Dingli et al., 2015). Future studies should confirm this unexpected finding. Additionally, subsequent research could further explore other digital revenue models, such as subscription-based or advertisement-based models (Gassmann et al., 2014), to broaden our understanding of how different digitalised revenue models impact adoption intention.

5 General Discussion

The final chapter of this dissertation summarizes the main findings, provides theoretical contributions and managerial implications, highlights strengths and limitations, outlining potential for future research.

5.1 Summary of Main Findings

The overarching aim of this dissertation is to advance both theory and practice in IM, recognizing it as a key driver of innovation success in the marketplace (Barczak et al., 2009; Poddar and Agarwal, 2019). Accordingly, this dissertation seeks to deepen the theoretical and practical understanding of how to design effective IM strategies and tactics that support the successful market launch of innovations.

Today, IM represents a broad and multifaceted research field, which makes it challenging for both scholars and practitioners to draw upon existing knowledge and apply it effectively. The field lacks a unifying focus, often overlooks important contemporary developments—such as the emergence of DIs—and tends to concentrate on isolated marketing activities (e.g., innovation preannouncement (Su and Rao, 2010) or branding (Brexendorf et al., 2015)) rather than adopting a holistic perspective on the IM program. Hence, the goal of the Paper 1 **(Chapter 2)** was to reveal the structure of this fragmented field, develop an overarching framework, and identify key research gaps. To this end, a SLR of 163 peer-reviewed articles published over a span of 27 years (1990–2017) was conducted. This SLR provides a comprehensive overview of core themes in IM research, identifies significant research gaps, and outlines future research directions.

Firstly, the SLR examined the empirical contexts of the sampled articles. The analysis revealed a predominant focus on B2C industries and product innovations, which limits the generalizability of findings given the fundamental differences between product and service

innovations (e.g., intangibility and simultaneous production and consumption of services (Avlonitis et al., 2001)). Similarly, applying B2C findings to B2B contexts is problematic due to the more personal and relationship-driven nature of B2B marketing (White et al., 2007). Future research should thus redirect attention toward service innovations and B2B contexts to address this imbalance. Moreover, the review found a marked lack of research on DIs—despite their unique characteristics (Kannan and Li, 2017) and the inherently uncertain environments in which decisions about DIs are made (Featherman and Pavlou, 2003). This represents another critical gap warranting future research.

Secondly, the SLR employed advanced methods, such as text mining and topic modelling, to perform a more nuanced analysis of the IM literature. Unlike traditional approaches based on manual coding, these statistical techniques offer more accurate and efficient evaluations of large, unstructured datasets. This approach allowed for a systematic identification of core research topics, their thematic focus, and development patterns. Understanding this structure facilitated the creation of a comprehensive framework for the IM field and highlighted underexplored areas requiring further investigation.

The analysis revealed that IM research encompasses ten core topics, which vary in focus between individual marketing elements and more integrated approaches investigating multiple elements of IM program. For instance, numerous studies have examined single elements such as innovation branding (e.g., Corkindale and Belder, 2009; Goedertier et al., 2015), promotion (e.g., Lafferty et al., 2005; Zigmond and Stipp, 2010), social network marketing (e.g., Aral, 2011; Kawakami and Parry, 2013; Huang et al., 2014), preannouncement (e.g., Bayus et al., 2000; Jung, 2011; Ofek and Turut, 2013), and communication strategies highlighting product features (e.g., Zhou and Nakamoto, 2007; Ziamou et al., 2012), which primarily address innovation adoption. Other studies, such as those on pricing (e.g., Zhu et al., 2008; Lowe and Barnes, 2012; Avagyan et al., 2016), design (e.g., Ziamou, 2002; Lau et al., 2011; Mugge and

Dahl, 2013), and frontline employee management (e.g., Cadwalader et al., 2010; Van der Borgh and Schepers, 2014; Sok and O'Cass, 2015), focus on innovation diffusion. Others explore multiple marketing elements in tandem—such as drivers of innovation launch (e.g., di Benedetto, 1999; Easingwood, 2006) and take-off (e.g., Delre et al., 2007; Burmester et al., 2015). However, a notable research gap exists in studies examining multiple marketing elements in relation to innovation adoption—an area that future research could meaningfully explore.

Finally, a deeper analysis of the individual tactical marketing elements (the so-called "Ps") revealed further imbalances in research focus. Elements such as pricing, promotion, and product have received considerable attention, though even for those areas future research opportunities remain—particularly concerning non-monetary pricing mechanisms for innovations and DIs (e.g., data-based revenue models, pay-per-use, subscriptions), and digital promotion strategies (e.g., influencer or affiliate marketing). Conversely, other elements—place, people, process, and physical evidence—have been largely neglected, despite their growing relevance in the digital era. Future studies should address issues such as digital platforms and e-commerce for distribution (place), digital touchpoints like online advisors and chatbots (people), the use of technologies like AI or VR (process), and digital indicators of quality and trust such as online ratings and testimonials (physical evidence).

In response to these gaps, Paper 2 (**Chapter 3**) focuses specifically on IM for DIs, addressing their proliferation and the growing role of start-ups in launching them (Kannan and Li, 2017; Brynjolfsson et al., 2018; Kuester et al., 2018). Recognizing the increased uncertainty that characterizes DI adoption (Meuter et al., 2000), Paper 2 employs the Signalling Theory (Spence, 1973) to investigate which tactical marketing elements help start-ups mitigate low initial trust and encourage adoption. Five experimental studies examine the effectiveness of

three key marketing tools—customer ratings, benefit communication, and revenue models—in signalling the trustworthiness of DIs offered by start-ups.

Specifically, the first study includes two experiments with a total of 264 participants from a European consumer panel, exploring the impact of customer ratings on perceived trust and adoption intention. Experiment 1 tests the number of ratings, while Experiment 2 focuses on their valence. The findings reveal that the quantity of positive ratings has no significant impact on adoption. However, a positive valence alone increases trust perceptions and adoption intention—indicating that showcasing favorable ratings, even if few, is an effective trust-building tactic for DIs by start-ups.

The second study, involving 91 participants, investigates how benefit communication affects perceived trust and adoption. It compares the effectiveness of communicating a digital benefit—designed to motivate adopters to abandon old technology (Lee and O'Connor, 2003)—with an origin-based benefit—intended to reduce uncertainty (Kuester et al., 2018). The results indicate that emphasizing the origin of the DI in its benefit communication is more effective in boosting initial trust and adoption intention.

The third study consists of two experiments with a combined total of 373 participants. The first experiment compares monetary pricing to a data-based revenue model. Drawing on prior research that suggests adopters often interpret price as a quality signal for unfamiliar products (Voelckner and Hofmann, 2007), and that sharing personal data is viewed as a sacrifice (Bhat, 2015), the findings show that monetary pricing fosters greater trust and higher adoption intention than data-based revenue model. The second experiment incorporates the GDPR context and examines privacy concerns as a mediator between the revenue model communication and initial trust. It confirms that data-based revenue model raises stronger privacy concerns, thereby reducing trust and ultimately hindering adoption.

Paper 3 (**Chapter 4**) builds on these insights by examining how start-ups can ensure a strong differentiation for DIs from their non-digital alternatives by highlighting digital point of difference in their positioning and communications. Paper 3 integrates trust, privacy concerns, and digital nativeness into a broader concept of positioning for DIs, an area previously overlooked in IM research. Using the Porter's Positioning Framework (Porter, 1985), Paper 3 investigates how start-ups can effectively position DIs to differentiate them from non-digital alternatives while still addressing trust and privacy concerns. Three experimental studies (with approximately 200 participants each) conducted with European consumers explore the effectiveness of benefit-based, cost-based, and value-based positioning strategies. The main findings underscore the importance of tailoring positioning strategies to different adopter segments based on digital nativeness.

Benefit-based positioning—emphasizing either technological or motivational advantages—proves effective in building trust. Technology-based benefits are best suited for the general market, whereas motivational benefits are more appropriate for digital immigrants or the late majority. Cost-based positioning, such as free-of-charge or freemium pricing, also helps differentiation from non-digital alternatives of DIs, but must be aligned with adopter privacy concerns. Interestingly, freemium revenue model is found to be more effective than expected, generating lower privacy concerns among both digital natives and immigrants, despite prior studies suggesting otherwise (Engels, 2019; Bordonaba-Juste et al., 2020). Finally, value-based positioning—which combines both benefit and pricing communications—can also effectively differentiate DIs from non-digital alternatives. However, success hinges on pairing benefits with privacy-conscious pricing models, like freemium, and adjusting messaging for different adopter types.

5.2 Theoretical Contributions

The present dissertation offers several theoretical contributions. Overall, it emphasizes the critical role of IM in the commercialization of innovations, while also shedding light on important aspects and specificities of IM in the digital context. More specifically, the findings across the three papers advance current research in the following ways.

Firstly, although IM has been the subject of extensive academic inquiry, most existing studies focus on individual aspects of the tactical marketing program. This narrow scope presents a major limitation, as marketing elements rarely function in isolation in practice (Schuhmacher et al., 2018). This is one of the key findings of the SLR and is addressed more specifically in Papers 2 and 3. Moreover, despite the widespread proliferation of DIs (Huang and Rust, 2013), the SLR reveals a lack of dedicated focus on IM for DIs and highlights the need for further research in this area. In addition, while several reviews of the IM field exist, they often treat IM merely as a sub-component of broader innovation management (e.g., Troy et al., 2008; Evanschitzky et al., 2012; Luchs et al., 2016). Consequently, the field has lacked a comprehensive, holistic understanding of IM and its core themes. By systematically synthesizing the existing body of literature, this dissertation provides a detailed overview of the current research landscape and proposes an integrative framework that captures its central themes. This framework not only maps out the field but also helps to identify critical research gaps and outlines future research opportunities—both for IM as a whole and for each of its elements. As such, the SLR advances current knowledge and serves as a valuable foundation for future studies.

Second, Paper 2 offers initial insights into how a marketing program should be designed specifically for DIs, thereby addressing one of the underexplored areas identified in the Paper 1. In addition, Paper 2 expands the current knowledge on the role of trust in the online environment (Schlosser et al., 2006), which is detrimental for DI adoption, as results show.

Furthermore, Paper 2 considers 3 major elements of IM discussed within the SLR: 1) innovation promotion by investigating specificities of benefit communication for DIs 2) innovation pricing by deriving efficient revenue models 3) physical evidence (one of the least researched elements of IM) by taking a closer look into the impact of customer referrals and ratings. For all those elements Paper 2 considers the impact of digitalisation on their concrete design for DIs. By combining these aspects, Paper 2 provides a significant contribution on how certain elements of IM for DI should be designed to foster DI adoption by positively impacting perceived trustworthiness.

Thirdly, this dissertation takes a deeper dive into the domain of DI adoption and contributes to advancing the understanding of how IM should be applied to DIs to ensure effective differentiation from non-digital alternatives. This is critical, as the lack of clear differentiation has been identified as a key reason for the failure of many DIs in the marketplace (Matthyssens et al., 2009). More specifically, Paper 3 extends the Porter's (1985) positioning framework to the context of DIs, integrating the impact of digitalization. In doing so, it not only contributes to research on effective differentiation strategies for DIs but also addresses key challenges outlined in the SLR and Paper 2, such as trust and privacy concerns—both of which are pivotal mediators for DI adoption (Nienaber and Schewe, 2014).

Furthermore, Paper 3 makes a notable contribution to the emerging, yet underexplored, research area of IM for DIs launched by start-ups (Kuester et al., 2018; Konya-Baumbach et al., 2019). Given that start-ups play a crucial role in the introduction of DIs but frequently face high failure rates (Marmer et al., 2011), this contribution is especially timely and relevant. Finally, Paper 3 introduces the concept of adopter segmentation into the context of IM for DIs—an aspect previously neglected in the literature. Yet, this is essential for the success of marketing strategies, as perceptions of digital technologies differ significantly between adopter groups (Prensky, 2001).

5.3 Managerial Implications

Drawing on the findings and theoretical contributions, this dissertation project provides important practical implications for the design of IM tactics. First, leveraging empirical methods such as text mining and topic modelling, Paper 1 offers a concise and structured overview of the IM field by grouping all studied aspects into a clear and accessible framework. This enables managers to quickly gain a comprehensive understanding of the current state of IM. Furthermore, Paper 1 highlights key IM areas that demand managerial attention in light of digitalisation, offering concrete ideas on how to evolve existing IM approaches.

Second, managers can benefit from numerous insights on IM for DIs presented in this dissertation, particularly in addressing the high market failure rates of DIs. For instance, Paper 2 demonstrates that perceived trustworthiness—both of the start-up and the DI—can act as a significant competitive advantage in online environments. It further shows that appropriately designed IM elements can serve as strong signals to reduce uncertainty for potential adopters. More specifically, managers are encouraged to actively communicate positive customer ratings on platforms such as app stores, websites, or press releases. Importantly, a large volume of reviews is not necessary—the mere presence of positive cues is sufficient to signal trustworthiness. Additionally, while benefit communication is crucial, managers must consider which types of benefits are most effective in enhancing perceived trust and adoption intent. For instance, when aiming for rapid adoption, communicating digital benefits may be more effective. Conversely, for a sustainable, long-term strategy, highlighting category-origin-related benefits may yield better adoption rates. When it comes to pricing, managers should be aware that monetisation strategies involving the commercialisation of users' personal data—although potentially appealing due to the attractiveness of free offerings—can negatively affect trustworthiness perceptions (Niemand et al., 2019). Thus, careful selection of the revenue model is essential.

Finally, managers can draw valuable lessons from the insights on how to position DIs effectively by focusing on the core competitive advantage: their digital nature. Long-term survival of DIs in the marketplace hinges on a clear differentiation from non-digital alternatives (Matthyssens et al., 2009). Paper 3 provides actionable recommendations for effective DI positioning strategies focusing on the digital point of difference.

Specifically, it outlines three main positioning strategies: benefit-based, cost-based, and value-based positioning. However, the choice of strategy and its communication should be informed by the considerations of trust, privacy concerns, and the digital nativeness of the target audience.

Hence, for benefit-based positioning, trust-building is essential. Managers should highlight technological benefits when targeting digital natives (early adopters) and emphasize motivational benefits when addressing digital immigrants (late adopters). Whereas, for cost-based positioning, differentiation from non-digital offerings requires focusing on digitalised revenue models. Nevertheless, privacy concerns must be carefully managed, hence, adopting a freemium model is advisable—regardless of whether the target is a broad market or a specific segment. Finally, for value-based positioning, managers should aim to deliver maximum value through the optimal combination of benefits and pricing. In this case, the chosen strategy should also be aligned with trust and privacy concerns. If targeting digital natives, a mix of technological benefits and a freemium model is recommended. If targeting digital immigrants, the optimal combination would include motivational benefits and a freemium revenue model.

5.4 Strengths, Limitations and Future Research Directions

The present dissertation demonstrates several noteworthy strengths, alongside certain limitations that offer valuable avenues for future research. One of the primary strengths lies in the use of robust data and sophisticated empirical methodologies across all three studies. For

instance, Paper 1 synthesises insights from 163 peer-reviewed articles and applies text mining and topic modelling—methods rarely employed in the marketing literature. These techniques enable a more efficient and comprehensive understanding of the research landscape and facilitate a more precise identification of knowledge gaps.

Paper 2 is based on five experimental studies involving a total of 728 participants and investigates multiple elements of the IM program for DIs, unlike most of existing studies that tend to examine isolated IM elements. In Paper 3, a historical method approach (Eisenhardt, 1989) is initially used to collect evidence from real-world cases of start-up positioning strategies and their communications. This enables the development of a theoretical foundation for the positioning of DIs, linked to the Porter's strategic framework (Porter, 1985)—a significant contribution, given the current lack of a theoretical positioning approach for DIs in marketing literature. Furthermore, Paper 3 includes three experimental studies with a combined sample of 708 participants to derive actionable strategies for a strong differentiation of DIs from their non-digital alternatives.

Despite these strengths, the dissertation has several limitations that should be considered when interpreting its findings. Firstly, while Paper 1 provides a comprehensive overview of IM literature using advanced techniques such as text mining and topic modelling—which enable full-text analysis beyond titles and abstracts—the results are inherently shaped by algorithmic outputs. These results, while data-driven, allow for a broad range of interpretations and are subject to certain methodological constraints. Additionally, these techniques have limited precision in accurately classifying cross-sectional studies under specific topics. As a result, the breadth of the analysis may come at the cost of analytical depth. Future research is therefore encouraged to conduct more focused, in-depth investigations into the specific areas of IM and gaps identified by this study to validate and build on these findings.

Moreover, despite the rigorous theoretical and empirical approaches in Papers 2 and 3, some unexpected and potentially controversial findings emerged. For example, Paper 2 found no significant relationship between the number of positive customer ratings and the perceived trustworthiness of DIs—an unexpected result, which future research should explore more in detail. Additionally, future studies could examine whether similar dynamics exist for negative customer ratings. Paper 3 also yielded surprising insights, particularly regarding the greater effectiveness of technological benefits (specifically mentioning digital technology behind a DI) over motivational ones in building trust and encouraging DI adoption. This contrasts with prior research emphasising user anxiety and resistance towards digital technologies (Huang and Rust, 2013). The findings suggest a potential shift in adopter attitudes over time due to the growing prevalence of digital technologies nowadays. Nonetheless, further studies in different empirical contexts and with various types of DIs are required to substantiate this trend. Another unexpected finding relates to privacy concerns and digital revenue models for digital natives and immigrants. Contrary to earlier studies suggesting that digital natives are more comfortable with data sharing and keen to favour free services (Dingli et al., 2015), Study 3 found no significant difference between the two groups in their privacy concerns about free-of-charge revenue model. In fact, both groups demonstrated a preference for freemium revenue model, indicating a broader shift in user expectations around data privacy. Future research should examine this result further across different contexts and types of DIs.

Finally, as this dissertation represents the first attempt to develop a structured framework for positioning DIs by start-ups, additional research is needed to validate and extend this model. Specifically, future studies should explore other forms of benefits and revenue models to confirm the generalisability and robustness of the proposed framework before drawing definitive conclusions.

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7 Appendices

Appendix A1: Overview of the IM studies during the timeframe of 1990- 2017

Author	Year	Title	Journal	Key words	Topic probability	Topic	Type of innovation	Sector	Type of study
Alexander, Lynch, Wang	2008	As time goes by: Do cold feet follow warm intentions for really new vs. Incrementally new products?	JMR	Really New products, Purchase intentions, New product expectations, Psychological distance, Construal level theory	0,730	Product features	Product	B2C	Survey
Andreassen, Streukens	2009	Service innovation and electronic WoM: is it worth listening to?	MSQ	Digital comms systems, group discussions, internet, service operations, innovation	0,43	Social networks	Service	B2C	Field study
Aral	2010	Identifying social influence: A comment on opinion leadership and social contagion in new Product diffusion	MS	Social networks, peer influence, behavioral contagion	0,96	Social networks	Product	N/a	Conceptual study
Ataman, Mela, Heerde	2008	Building brands	MS	Diffusion, new products, marketing mix, dynamic linear model, empirical generalisation	0,95	Branding	Product	B2C	Field study
Avagyan, Esteban-Bravo, Vidal-Sanz	2011	Riding successive product diffusion waves: Building tsunami via upgrade rebate programs	IJRM	New product diffusion, successive generations, trade in, upgrades, optimal strategies	0,92	Take-off	Product	N/a	Conceptual study
Avlonitis, Indounas	2006	Pricing practices of service organisations	JSM	Pricing policy, Service industries	0,34	Pricing	Service	Both	Interview
Bakshi, Kim, Savva	2015	Signaling new product reliability with after sales service contracts	MS	Signaling games, performance based contracting, after sales services	0,77	Product features	Product	N/a	Conceptual study
Barone, Taylor, Urbany	2005	Advertising signalling effects for new brands: the moderating role of perceived brand differences	JM	N/a	0,73	Branding	Product	B2C	Survey
Barroso, Llobet	2012	Advertising and consumer awareness of new differentiated products	JMR	Advertising, descrete choice models, consumer choice set, awareness process, new products	0,54	Take-off	Product	N/a	Conceptual study

Bayus, Jain, Rao	2000	Truth or consequences: An analysis of vaporware and NP announcements	JMR	N/a	0,74	Preannouncement	Product	B2B	Field study
Besharat	2010	How co-branding vs. Brand extensions drive consumers evaluations of new products	IMM	Co-branding, Brand extension, Brand equity, signaling theory	0,74	Branding	Product	B2C	Lab experiment
Beuk, Malter, Spanjol, Cocco	2014	Financial incentives and salesperson time orientiation in the NP launch	JPIM	New product launch, new product success expectation, sales effort, long term orientation	0,83	Fronline management	Product	B2B	Survey
Bishop, Barber	2013	Putting your money where your mouth is: the value of low purchase intention to product pricing	JPIM	N/a	0,8	Pricing	Product	B2C	Experiment
Boxer, Reketeyye	2011	The relation between perceived service innovation, service value, emotional intelligence, customer committment and loyalty in b2b	JSOM	emotionall intelligence, service innovation, service value, customer committment, customer loyalty, services	0,77	Product features	Service	B2B	Survey
Brakus, Schmitt, Zhang	2014	Experiental product attributes and preferences for new products: the role of processing fluency	JBR	Consumer experiences, experiential marketing, new product design, processing fluency	0,69	Promotion	Product	B2C	Experiment
Bruce, Zhang Foutz, Kolsarici	2012	Dynamic effectiveness of advertising and world of mouth in sequential distribution of new products	JMR	Sequential distribution, new product, aggregate advertising model, world of mounth, Bayesian dynamic linear model	0,83	Social networks	Product	B2C	Conceptual study
Buratto, Grosset, Viscolani	2006	Advertising a new product in a segmented market	EJOR	Control, Marketing, Advertising, market segmentation	0,74	Promotion	Product	B2C	Conceptual study
Burmester, Becker, van Heerde, Clement	2015	The impact of pre-and-post launch publicity and advertising on new product sales	IJRM	Publicity, Advertising, Longitudinal analysis, behavioral data	0,7	Take-off	Product	B2C	Conceptual study
Cadwallader, Jarvis, Bitner, Ostrom	2010	Frontline employee motivation to participate in service innovation implementation	JAMS	Services marketing, employee motivation, service innovation, strategic implementation	0,76	Frontline management	Service	B2C	Interview
Calantone, Chan, Cui	2006	Decomposing product innovativeness and its effects on new product success	JPIM	N/a	0,83	Product features	Product	B2C	Survey

Calantone, Rubera	2011	When should RD&E and marketing collaborate? The moderating role of exploration - exploitation and environmental uncertainty	JPIM	N/a	0,92	Frontline management	Product	B2B	Survey
O'Cass, Song, Yan	2013	Anatomy of service innovation	JBR	Service innovation, service quality, value creation, service branding	0,69	Branding	Service	B2C	Conceptual study
Castano, Sujan, Kacker, Sujan	2008	Managing consumer uncertainty in the adoption of new products: Temporal distance and mental simulation	JMR	New products, temporal distance, mental simulation, postconsumption satisfaction, communication strategies	0,84	Promotion	Product	B2C	Experiment
Chakravarti, Xie	2006	The impact of standards competition on consumers: Effectiveness of product information and advertising formats	JMR	N/a	0,66	Promotion	Product	B2C	Experiment
Corkindale, Belder	2009	Corporate brand reputation and the adoption of innovations	JPBM	Corporate branding, Innovation, Information strategy, Internet shopping, purchasing	0,55	Branding	Product	B2C	Experiment
Cui, Zhao, Ravicharan	2011	Market uncertainty and dynamic new product launch strategies: a system dynamic model	IEEE	new product launch, market uncertainty, system dynamics model	0,62	Launch	Product	B2C	Conceptual study
Danaher, Hardie, Putsis	2001	Marketing mix variables and the diffusion of successive generations of a technolocial innovation	JMR	N/a	0,77	Launch	Product	B2C	Conceptual study
Danaher	2002	Optimal pricing for new subscription services	MS	N/a	0,51	Pricing	Service	B2C	Experiment
Delre, Jager, Bijmont, Janssen	2007	Targeting and timing of promotional activities: An agent-based model for the takeoff of new products	JBR	Diffusion of innovations, Agent-based model, Targeting, Promotions, Take-off, World-of-mouth, Social Influence	0,57	Take-off	Product	B2C	Conceptual study
Dens, Pelsmacker	2010	How advertising strategy affects brands and USP recall for new brands and extensions	IJoA	N/a	0,76	Promotion	Product	B2C	Experiment
di Benedetto	1999	Identifying the key success factors in new product launch	JPIM	N/a	0,87	Launch	Product	B2C	Survey

Du, Kamakura	2011	Measuring contaginon in the diffusion of consumer packaged goods	JMR	Consumer packaged goods, diffusion model, contagion, new product launch, temporal heterogeneity	0,91	Social networks	Product	B2C	Conceptual study
Easingwood	2006	Bringing high technology to market: successful strategies employed in the worldwide software industry	JPIM	N/a	0,76	Launch	Product	B2B	Survey
Feiereisen, Wong, Broderick	2008	Analogies and mental simulations in learning for really new products: the role of visual attention	JPIM	N/a	0,58	Experiential	Product	B2C	Experiment
Fernandez, Del Rio, Varela, Bande	2010	Relationships among functional units and new product performance: the moderating effect of technological turbulence	T	New product performance, Harmony among functional units, physical proximity, product champion, Technological turbulence	0,88	Frontline management	Product	B2B	Survey
Frattini, Dell'Era, Rangone	2013	Launch decisions and the early market survival of innovations: an empirical analysis of Italian mobile added services	JPIM	N/a	0,52	Launch	Service	B2C	Conceptual study
Fruchter, van den Bulte	2011	Why the generalised Bass model leads to odd optimal advertising policies	IJRM	Diffusion models, new products, Advertising, Pricing, Optimal control, variational approach	0,9	Promotion	Product	B2C	Conceptual study
Fu	2009	Effects of salesperson experience, age and goal setting on new product performance trajectory	JMTP	N/a	0,75	Frontline management	Product	B2B	Survey
Fu, Elliott	2013	The moderating effect of perceived product innovativeness and product knowledge on new product adoption	JMTP	N/a	0,59	Product features	Product	B2C	Experiment
Gielens, Steenkamp	2003	Consumer and market drivers of the trial probability of new consumer packaged goods	JCR	N/a	0,37	Take-off	Product	B2C	Conceptual study

Goedetier, Dawar, Geuens, Weijters	2014	Brand typicallity and distant novel extention acceptance: How risk-reduction counters low category fit	JBR	Brand typicality, Novelty, Perceived risk, Category fit, product innovation	0,77	Branding	Product	B2C	Experiment
Grimpe, Sofka, Bhargava, Chatterjee	2017	R&D, marketing innovation and new product performance: a mixed methods study	JPIM	Marketing innovation, technological innovation, new product performance, mixed methods study	0,53	Frontline management	Product	B2B	Interview
Gruner, Homburg, Lukas	2012	Firm-hosted online brand communities and new product succes	JAMS	Online brand communities, New product success, Product innovativeness, Product introduction timing, Product and brand management	0,38	Social networks	Product	B2C	Interview
Gui, Lui, Guo	2012	The effect of online consumer reviews on new product sales	IJEC	New product sales, online product reviews, panel data analyses, search vs. Experience products, WoM	0,33	Social networks	Product	B2C	Field study
Gupta, di Benedetto	2006	Optimal pricing and advertising strategy for introducing a new business product with threat of competitive entry	IMM	Optimal pricing, optimal advertising, new products, entry timing	0,68	Launch	Product	B2B	Conceptual study
Gupta, Gupta	2014	New product launch through social media and point of sale promotion	AJM	New product launch, WoM, Social Media marketing, PoS promotion, referral marketing	0,54	Social networks	Product	B2C	Lab experiment
Haenlein, Libai	2013	Targeting revenue leaders for a new product	JM	WoM, opinion leaders, associativity, CLV, ABM	0,81	Social networks	Product	B2C	Conceptual study
Halliday, Trott	2010	Relational, interactive service innovation: building brand competence	MT	Branding, new service development, resource-based view of firm, relationships, service innovation	0,6	Branding	Service	B2C	Conceptual study
Handel, Mistra	2015	Robust new product pricing	MS	Non-bayesian learning, ambiguity, pricing, new products	0,75	Pricing	Product	B2C	Conceptual study
Hariharan, Kwon, Talukdar	2015	Optimal targeting of advertising for new products with multiple consumer segments	IJRM	New product diffusion, advertising, targeting, social contagion, dynamic optimisation	0,86	Promotion	Product	B2C	Conceptual study

Heidenreich, Kraemer	2015	Innovations - doomed to fail? Investigating strategies to overcome passive innovation resistance	JPIM	N/a	0,75	Promotion	Product	B2C	Lab Experiment
Hidalgo, Alvano	2015	Service innovation: Inward and outward related activities and cooperation mode	JBR	Innovation, Collaboration, service, network, service innovation process	0,11	Frontline management	Service	B2B	Interview
Hinterhuber, Liozu	2014	Is innovation in pricing your next source of competitive advantage?	BH	Pricing, Innovation, Competitive advantage, Pricing strategy, tactics, Organisation	0,33	Pricing	N/a	B2C	Conceptual study
Hinz, Schulze, Takac	2014	New product adoption in social networks: why direction matters	JBR	Social network analysis, Social contagion, Diffusion, Directed networks	0,52	Social networks	Product	B2C	Survey
Hoegg, Alba	2011	Seeing is believing: The influence of product form perceptions of functional performance	JPIM	N/a	0,74	Promotion	Product	B2C	Survey
Homburg, Bornemann, Totzek	2009	Preannouncing pionerring vs. Follower products: what should message be?	JAMS	Preannouncement, order of entry, new product development, innovation management	0,4	Preannouncement	Product	B2C	Survey
Horsky	1990	A diffusion model incorporating product benefits, price, income, information	MS	Durable products, diffusion of innovations, life cycle pricing	0,31	Take-off	Product	B2C	Conceptual study
Hsu	2011	Design innovation and marketing strategy in successful product competition	JBIM	Product design, innovation, marketing strategy, electronics	0,42	Design	Product	B2C	Conceptual study
Hu, van den Bulte	2014	Nonmonotonic status effects in new product adoption	MS	Hazard model, new product adoption, social contagion, social networks, social status	0,87	Social networks	Product	B2C	Field study
Huang, Zhang, Liu, Liang	2014	The effect of online and offline WoM on new product diffusion	JSM	Product diffusion, communication chanel, WoM, peak adoption time	0,4	Social networks	Product	B2C	Conceptual study
Hultink, Atuahene-Gima	2000	The effect of sales force adoption on new product selling performance	JPIM	N/a	0,87	Fronline management	Product	B2C	Survey

Hultink, Hart, Robben, Griffin	1999	New consumer product launch: strategies and performance	JSM	Consumer product launch, performance outcomes, tactical decision content launches,	0,71	Launch	Product	B2C	Survey
Ingenbleek, Debryne, Frambach, Verhallen	2003	Successful new product pricing strategies	ML	Pricing, new product development, competitive strategy	0,64	Pricing	Product	B2C	Survey
Ingenbleek, Frambach, Verhallen	2010	The role of value-informed pricing in market oriented product innovation management	JPIM	N/a	0,76	Pricing	Product	B2C	Interview
Iyengar, van den Bulte	2015	Social contagion in new product trial and repeat	MS	New product diffusion, social contagion, social networks, social status	0,82	Social networks	Product	B2C	Field study
Iyengar, van den Bulte	2011	Further reflections on studying social influence in new product diffusion	MS	Diffusion of innovations, opinion leadership	0,95	Social networks	Product	B2C	Conceptual study
Jaakkola, Renko	2007	Critical innovation characteristics influencing the acceptability of a new pharmaceutical product format	JMM	Innovation adoption, innovation characteristics, pharmaceuticals	0,41	Product features	Product	B2C	Interview
Jones, Ritz	1991	Incorporating distribution into new product diffusion models	IJRM	N/a	0,35	Launch	Product	B2C	Conceptual study
Jung	2011	Signaling quality with new product preannouncements: Vaporware and the role of reference quality	JBR	New product preannouncements, separating and pooling equilibria, vaporware	0,47	Preannouncement	Product	B2C	Conceptual study
Karlsson, Skalen	2012	Exploring front-line employee contributions to service innovation	EJM	Service innovation, service dominant logic, front line employee involvement, value proposition	0,85	Frontline management	Service	B2C	Field study
Kawakami, Kishiya, Parry	2012	Personal WoM, Virtual VoM and innovation use	JPIM	N/a	0,86	Social networks	Product	B2C	Survey
Kawakami, Parry	2013	The impact of WOM sources and perceived usefulness of innovation	JPIM	N/a	0,87	Social networks	Product	B2C	Survey
Kim, Hanssens	2017	Advertising and WoM effects on pre-launch consumer interest and	JIM	Pre-launch marketing, pre-launch consumer interest, advertising, blogging, online	0,88	Launch	Product	B2C	Field study

		initial sales of experience products		research, new experience products					
Kim, Mazumbar	2016	Product concept demonstrations in trade shows and firm value	JM	Innovation, concept demonsration, product preannouncement, signaling	0,52	Preannouncement	Product	B2C	Conceptual study
Klink, Athaide	2010	Consumer innovativeness and the use of new vs.extended brand names for new products	JPIM	N/a	0,54	Branding	Product	B2C	Survey
Krishnan, Bass, Jain	1999	Optimal pricing strategy for new products	MS	Generalised Bass Model, Optimal strategy, diffusion	0,42	Take-off	Product	B2C	Conceptual study
Krishnan, Jain	2006	Optimal dynamic advertising policy for new products	MS	Dynamic programming, optimal control, new products, advertising	0,93	Promotion	Product	B2C	Conceptual study
Krishnan, Seetharaman, Vakratas	2012	The multiple roles of interpersonal communication in new product growth	IJRM	Interpersonal communication, WoM, New product growth, brand choice	0,65	Social networks	Product	B2C	Field study
Kuester, Feurer, Schuhmacher, Reinhartz	2015	Comparing the incomparable: How consumers judge the price fairness of new products?	IJRM	N/a	0,66	Pricing	Product	B2C	Experiment
Lafferty, Goldsmith, Flynn	2005	Are innovators influenced by endorser expertise in an advertisement when evaluating a high technology product?	JM	N/a	0,6	Promotion	Product	B2C	Experiment
Langerak, Hultink, Robben	2004	The impact of market orientation, product advantage and launch proficiency on new product performance and organisation performance	JPIM	N/a	0,94	Frontline management	Product	B2C	Survey
Langley, Bijmont, Ortt, Pals	2012	Determinants of social contagion during new product adoption	JPIM	N/a	0,37	Social networks	Product	B2C	Field study
Lau, Richard, Yam, Tang	2011	The impact of product modularity on new product performance: Mediation by product innovativeness	JPIM	N/a	0,81	Design	Product	B2C	Survey
Le Nagard-Assayag, Manceau	2001	Modeling the impact of product preannouncements in the context of indirect network externalities	IJRM	New product, preannouncement, network externalities	0,46	Preannouncement	Product	B2C	Conceptual study

Lhiillery	2015	Marketing and persistent innovation success	EINT	Innovation success, persistence, state dependence, exploration-exploitation	0,52	Take-off	N/a	B2C	Interview
Li, Zhang, Wang	2014	The role of product originality, usefulness, motivated consumer innovativeness in new product adoption intentions	JPIM	N/a	0,56	Product features	Product	B2C	Survey
Libai, Muller, Peres	2012	Decomposing the value of word-of-mouth seeding programmes: Acceleration vs. Expansion	JMR	WoM, customer equity, new product diffusion, seeding, agent-based model, social network	0,73	Social networks	Product	B2C	Conceptual study
Lilly, Walters	1997	Toward a new product preannouncement timing	JPIM	N/a	0,55	Preannouncement	Product	B2C	Interview
Lopez, Sicilia	2012	How WoM Marketing contributes to new product adoption	EJM	WoM Marketing, Advertising, Awareness, Adoption, new products, marketing strategy, communication	0,62	Social networks	Product	B2C	Survey
Lowe, Alpert	2010	Pricing strategy and the formation and evolution of reference price perceptions in new product categories	PM	Reference price, pioneer advantage, pricing strategy	0,65	Pricing	Product	B2C	Experiment
Lowe, Barnes	2012	Consumer perceptions of monetary and non-monetary introductory promotions for new products	JMM	Introductory low price, transation value, perceived innovativeness	0,71	Take-off	Product	B2C	Experiment
Luan, Sudhir	2010	Forecasting marketing-mix responsiveness for new products	JMR	Advertising budgeting, marketing mix modeling, new product introductions, endogeneity	0,72	Launch	Product	B2C	Conceptual study
Manchanda, Xie, Youn	2008	The role of targeted communication and contagion in product adoption	MS	New product adoption, social networks, social interactions, contagion, WoM, hierarchical Bayesian methods, pharmaceutical industry	0,97	Social networks	Product	B2C	Field study
Melton, Hartline	2010	Customer and frontline employee influence on New Service Development performance	JSR	NSD process, customer involvement, frontline employee involvement, success factors	0,34	Frontline management	Service	B2C	Survey

Montaguti, Kuester, Robertson	2002	Entry strategy for radical product innovations: A conceptual model and propositional inventory	IJRM	Takeoff time, radical product innovation, entry strategy, diffusion	0,43	Take-off	Product	B2C	Conceptual study
Moreau, Markman, Lehmann	2001	What is it? Categorization flexibility and consumers responses to really new products	JCR	N/a	0,53	Promotion	Product	B2C	Experiment
Mueller-Stewens, Schlager, Häubl, Herrmann	2017	Gamified information presentation and consumer adoption of product innovations	JM	Consumer adoption of product innovations, information presentation, games, curiosity, relative advantage	0,41	Promotion	Product	B2C	Field study
Mugge, Dahl	2013	Seeking the ideal level of design newness: consumer response to radical and incremental product design	JPIM	N/a	0,53	Design	Product	B2C	Experiment
Nakata, Weidner	2011	Enhancing new product adoption at the base of pyramid: A contextualised model	JPIM	N/a	0,36	Product features	Product	B2C	Conceptual study
Narayan, Manchanda, Chintagunta	2004	Temporal differences in the role of marketing communication in new product categories	JMR	Marketing communication, detailing, learning models, discrete choice, pharmaceutical industry	0,85	Promotion	Product	B2C	Field study
Narayan, Manchanda	2007	Heterogeneous learning and the targeting of marketing communication for new products	MS	Resource allocation, pharmaceutical markets, learning models	0,86	Product features	Product	B2C	Conceptual study
Nienaber, Schewe	2014	Enhancing trust or reducing perceived risk, what matters more when launching new product?	IJIM	Willingness to adopt, launching new products, trust, contact intensity	0,46	Launch	Product	B2C	Field study
Nylen, Holmstroem	2015	Digital innovation strategy: A framework for diagnosing and improving digital products and service innovation	BH	Digital innovation, strategy, Value proposition, user experience, Improvisation	0,42	Product features	Service	B2C	Conceptual study
Ofek, Turut	2013	Vaporware, Suddenware, Trueware: New product preannouncements under market uncertainty	MS	New product preannouncements, market uncertainty, competitive signaling, new product development	0,82	Preannouncement	Product	B2C	Conceptual study

Olson, Walker, Ruekert	1995	Organising for effective new product development: the moderating role of product innovativeness	JM	N/a	0,77	Frontline management	Both	B2C	Interview
Ordanini, Parasuraman, Rubera	2014	When the recipe is more important than the ingredients: A qualitative comparative analysis of service innovation configurations	JSR	New service, configuration, QCA, service adoption	0,55	Product features	Service	B2B	Conceptual study
Park, Love, Maclachlan	2011	New product pricing strategy under customer asymmetric anchoring	IJRM	New product pricing, willingness to pay, anchoring mechanisms, price strategy	0,45	Pricing	Product	B2C	Survey
Parry, Kawakami, Kishiya	2012	The effect of personal and virtual WoM on Technology acceptance	JPIM	N/a	0,87	Social networks	Product	B2C	Survey
Popma, Waarts, Wierenga	2003	New product preannouncements as market signals: A content analysis in the Dram chip industry	IMM	Competition, innovation, new product announcement, market signals, semiconductors	0,57	Preannouncement	Product	B2B	Field study
Ramanan, Bharva	2014	Stimulating early adoption of new products through channel disintegration	PoM	Supply chains, channel disintegration, double marginalisation	0,53	Launch	Product	B2C	Conceptual study
Rangan, Menezes, Maier	1992	Channel selection for new industrial products	JoM	N/a	0,37	Launch	Product	B2B	Interview
Reinders, Frambach, Schoormans	2010	Using product bundling to facilitate the adoption process of radical innovations	JPIM	N/a	0,65	Product features	Product	B2C	Experiment
Roberts, Candi	2014	Leveraging social network sites in new product development: Opportunity or Hype?	JPIM	N/a	0,41	Social networks	Product	B2C	Survey
Rubera	2015	Design innovativeness and product sales evolution	MS	Design innovativeness, technological innovativeness, individual growth analysis, car industry	0,38	Design	Product	B2C	Field study
Samu, Krishnan, Smith	1999	Using advertising alliances for new product introduction: Interactions between product	JM	N/a	0,87	Promotion	Product	B2C	Experiment

		complimentarity and promotional strategies							
Santos-Vijande, Lopez-Sanchez, Rudd	2016	Frontline employee collaboration in industrial service innovation: routes of co-creation effects on new service performance	JAMS	Frontline employees, knowledge intensive business service, new service co-creation, new service development, new service performance	0,19	Frontline management	Service	B2B	Survey
Schatzel, Calantone	2006	Creating market anticipation: An exploratory examination of the effect of preannouncement behaviour on a new product launch	JAMS	Preannouncement, new product development, supply chain management, b2B communications	0,35	Preannouncement	Product	B2B	Survey
Schreier, Oberhauser, Prügl	2007	Lead users and the adoption and diffusion of new product: Insights from two extreme sports communities	MS	Lead users, user innovation, adoption diffusion, new products, opinion leadership	0,55	Social networks	Product	B2C	Survey
Schuhmacher, Kuester, Hultink	2017	Appetizer or Main course: Early market vs. Majority market Go-to-Market strategies for radical innovations	JPIM	N/a	0,62	Take-off	Product	B2C	Experiment
Schweisfurth, Herstatt	2015	Embedded lead users as catalysts to product diffusion	CiM	N/a	0,51	Social networks	Product	B2C	Survey
Sethi, Prasad, He	2008	Optimal advertising and pricing in a new product adoption model	JOTA	Durable goods sales, Advertising, Pricing, Optimal model	0,89	Launch	Product	B2C	Conceptual study
Scheinin, Schmitt	1994	Extending brands with New Product concepts: The role of category attribute congruity, brand effect and brand breath	JBR	N/a	0,88	Branding	Product	B2C	Experiment
Shen, Duenyas, Kapuscinski	2014	Optimal pricing, production and inventory for New Product diffusion under supply constraints	MSOM	OM-marketing interface, retailing, pricing, Bass diffusion model	0,89	Launch	Product	B2C	Conceptual study
Sinapuelas, Wang, Bohlmann	2015	The interplay of innovation, brand, marketing mix variables in line extensions	JAMS	Line extensions, innovation, new product adoption, innovative products, marketing mix variables	0,6	Launch	Product	B2C	Field study

Sok, o'Cass	2015	Achieving service quality through service innovation exploration- exploitation: the critical role of employee empowerment and slack resources	JSM	Service quality, service innovation, employee empowerment, exploration-exploitation, organisational ambidexterity	0,21	Frontline management	Service	B2C	Survey
Song, Parry	2009	Information, Promotion and the adoption of innovative consumer durables	JPIM	N/a	0,66	Promotion	Product	B2C	Experiment
Song, Parry, Kawakami	2009	Incorporating network externalities into the technology acceptance model	JPIM	N/a	0,76	Social networks	Product	B2C	Survey
Souder, Song	1997	Contingent product design and marketing strategies influencing new product success and failure in U.S. and Japanese electronic firms	JPIM	N/a	0,5	Design	Product	B2C	Survey
Spann, Fischer, Tellis	2015	Skimming or Penetration? Strategic dynamic pricing for new products	MS	Price penetration, price skimming, dynamic pricing, product life cycle, consumer durables, brand competition	0,64	Pricing	Product	B2C	Field study
Stanko, Molina-Castillo, Harmancioglu	2014	It wont fit! For innovative products, sometimes thats for the best	JPIM	N/a	0,89	Product features	Product	B2C	Survey
Storey, Easingwood	1998	The augmented service offering: A conceptualisation and study of its impact on New Service success	JPIM	N/a	0,46	Promotion	Service	N/a	Survey
Su, Rao	2010	New product preannouncement as a Signaling strategy: An audience specific review and analysis	JPIM	N/a	0,66	Preannouncement	Product	N/a	Conceptual study
Sussan, Gould, Weisfeld-Spolter	2006	Location, location, location: the relative roles of virtual location, online world of mouth and advertising in the new product adoption process	ACR	N/a	0,51	Social networks	Product	B2C	Experiment
Swami, Dutta	2010	Advertising strategies for new product diffusion in emerging	EJOR	Diffusion, advertising, optimal control, international marketing	0,87	Launch	Product	B2C	Conceptual study

		markets: Propositions and analysis							
Tabeau, Gemser, Hultink, Wijnberg	2017	Exploration and exploitation activities for design innovation	JMM	Exploration activities, exploitation activities, design innovativeness, market performance, process performance,	0,7	Design	Product	B2C	Survey
Talke, Heidenreich	2013	How to overcome pro-change bias: Incorporating passive and active innovation resistance in innovation decision models	JPIM	N/a	0,8	Product features	Product	N/a	Conceptual study
Talke, Hultink	2010	Managing diffusion barriers when launching new products	JPIM	N/a	0,89	Launch	Product	B2B	Survey
Talke, o'Connor	2011	Conveying effective message content when launching new industrial products	JPIM	N/a	0,37	Launch	Product	B2B	Survey
Talke, Snelders	2013	Information in launch messages: Stimulating the adoption of high tech consumer products	JPIM	N/a	0,81	Launch	Product	B2C	Experiment
Thamhain	1990	Managing technologically innovative team efforts toward new product success	JPIM	N/a	0,51	Frontline management	Product	N/a	Survey
Thomas	1999	Incumbent firms response to entry: Price, advertising and new product introduction	IJIO	N/a	0,65	Launch	Product	B2C	Field study
Thomke	1998	Managing experimentation in the design of new products	MS	N/a	0,72	Promotion	Product	B2C	Survey
Thorbjornsen, Dahlen, Lee	2015	The effect of new product preannouncements on evaluation of other brand products	JPIM	N/a	0,6	Preannouncement	Product	B2C	Experiment
Tomkovick, Dobie	1995	Applying hedonic pricing models and factorial surveys at Parker pen to enhance new product success	JPIM	N/a	0,45	Pricing	Product	B2C	Field study
Troy, Hirunyawipada, Paswan	2008	Cross-functional integration and new product success: An empirical investigation of the findings	JM	N/a	0,88	Frontline management	Product	B2C	Conceptual study

Urban, Hulland, Weinberg	1993	Premarket forecasting for new consumer durable goods: Modeling, categorisation, elimination and categorisation phenomena	JM	N/a	0,65	Launch	Product	B2C	Field study
van der Borgh, Schepers	2014	Do Retailers really profit from ambidextrous Managers? The impact of frontline mechanisms on new and existing product performance	JPIM	New product selling, autonomy, manager orientation	0,73	Frontline management	Product	B2C	Survey
van Eck, Jager, Leeflang	2011	Opinion leaders' role in innovation diffusion: A simulation study	JPIM	N/a	0,77	Social networks	Product	B2C	Survey
Verniers, Stremersch, Croux	2011	The Global entry of new pharmaceuticals: A joint investigation of launch window and price	IJRM	Entry timing, international new product launch, launch price, window	0,58	Pricing	Product	B2C	Field study
Wood, Hoeffler	2013	Looking innovative: Exploring the role of impression management in high-tech product adoption and use	JPIM	N/a	0,59	Design	Product	B2C	Interview
Wooder, Baker	2011	Extracting key lessons in service innovation	JPIM	N/a	0,57	Launch	Service	B2C	Conceptual study
Wu, Balasubramanian, Mahajan	2004	When is preannounced new product likely to be delayed?	JM	N/a	0,51	Preannouncement	Product	B2C	Survey
Xiong, Bharadwaj	2014	Prerelease buzz evolution patterns and new product performance	MS	Prerelease buzz dynamics, evolution pattern, functional data analysis, forecasting, new product sales	0,76	Launch	Product	B2C	Conceptual study
Yu, Debo, Kapuscinski	2016	Strategic waiting for consumer-generated quality information: Dynamic pricing new experience goods	MS	strategic consumer behavior, price skimming, two-sided learning	0,67	Pricing	Product	B2C	Conceptual study
Yuxing Du, Kamakura	2011	Measuring contaginon in the diffusion of consumer packaged goods	JMR	N/a	0,91	Social networks	Product	B2C	Conceptual study

Zhao, Dahl, Hoeffler	2014	Optimal visualisation aids and temporal framing for new products	JCR	N/a	0,87	Promotion	Product	B2C	Experiment
Zhou, Nakamoto	2007	How do enhanced and unique features affect new product preference? The moderating role of product familiarity	JAMS	Enhanced features, unique features, product familiarity, Incongruity theory	0,25	Product features	Product	B2C	Experiment
Zhu, Chen, Dasgupta	2008	Can trade-ins hurt you? Exploring the effect of a trade-in on consumers' willingness to pay for a new product	JMR	Trade-ins, mental accounting, automobile market	0,53	Pricing	Product	B2C	Experiment
Ziamou	2002	Commercialising new technologies: consumers response to a new interface	JPIM	N/a	0,74	Design	Product	B2C	Experiment
Ziamou, Gould, Venkatesh	2012	Am I getting it or not? The practices involved in trying to consume a new technology	JPIM	N/a	0,83	Product features	Product	B2C	Survey
Ziamou, Veryzer	2005	The influence of temporal distance on consumer preferences for technology-based innovations	JPIM	N/a	0,86	Product features	Product	B2C	Experiment
Zigmond, Stipp	2010	Assessing new advertising effect: measurement of the impact of television commercials on internet search queries	JAR	N/a	0,48	Promotion	Product	B2C	Field study
Zufryden	2007	An integrated virtual store-based approach for price determination before product launch	IJEC	e-Commerce, new product launch, online experimentation, online video games, product pricing, subscription pricing	0,41	Pricing	Product	B2C	Experiment

Appendix A2: Measurements of Core Constructs (Paper 2 Study 1a/Study 1b/Study 2/ Study 3a/Study 3b)

Measurement / Items	Cronbach's alpha	CITC
Adoption intention[a] (adapted from Castaño et al. 2008)	.96/.96/.95/.93/.96	
I would like to try ___.		.91/.95/.87/.84/.91
I would actively seek ___ to download it.		.90/.95/.83/.80/.90
I would like to use ___.		.94/.94/.91/.89/.92
I would buy ___.		.91/.95/.88/.88/.92
Initial trust[a] (adapted from Sekhon et al. 2014)	96/.96/.93/.93/.93	
I perceive ___ to be trustworthy.		.87/.95/.80/.87/.81
I trust ___.		.90/.95/.83/.89/.84
I am certain, that I can trust ___.		.89/.95/.77/.79/.81
___ is interested in my well-being.		.82/.95/.77/.69/.67
I trust ___ to have my best interest at heart.		.83/.95/.78/.74/.74
___ is very reliable.		.84/.95/.81/.80/.82
I trust ___ to do what it says it will do.		.84/.95/.71/.68/.73
Privacy concern[a] (adapted from Liao et al. 2011)	.--/.--/.--/.--/.943	
I am concerned that the data I submit to ___ will be misused.		.--/.--/.--/.--/.86
I am concerned that ___ will sell my personal and usage data to third parties.		.--/.--/.--/.--/.86
I am concerned about submitting personal information to ___ because of what they might do with it.		.--/.--/.--/.--/.90
I am concerned about my data being used by ___ in a way I did not foresee.		.--/.--/.--/.--/.84

Note: [a] 7-point Likert scale with anchors 1 = "disagree strongly" and 7 = "agree strongly".
CITC = corrected item-total-correlation.

Appendix A3: Overview of start-ups' DIs positioning Paper 3

Start-up	Market	Product category	Digital Innovation	Positioning	Key communication claim	Positioning: Benefit/Cost/Value	Cat. origin vs. Digital	Benefit type	Link	Pricing
Modern Health	B2C	Existing	A digital platform for improvement of mental health	Positive proactive solution that anyone can use to improve their mental health.	All in one solution&convenience	Benefit	Category origin focus	Motivational benefit	https://www.joinmodernhealth.com/	Not available
Streem	B2C+B2B	New	An application that makes smartphone camera intelligent by means of spatial mapping, artificial intelligence and machine learning to diagnose and resolve issues remotely	Convenient, fast, secure streaming video connecting to professionals to help resolve issues faster.	Convenient, fast, secure	Benefit	Digital focus	Technological benefit	https://www.streem.pro/	Not available
Feather	B2C	Existing	A digital platform that enables access to high-quality furniture at a low monthly price with an option to add, swap, buy, return.	Easiest, most stress-free way to transform your four walls into a home you love.	Easy, stress free	Benefit	Category origin focus	Motivational benefit	https://www.livefeather.com/	Not available
Urban	B2C	Existing	A digital platform that enables booking of a personal service to be executed at home/at work	Wellness app for busy people: easy way to book trusted massages, beauty, fitness and more - anywhere anytime.	All in one solution& convenience	Benefit	Category origin focus	Traditional benefit: convenience	https://urban.co/en-gb/	Not available
Pana	B2C	Existing	An online travel assistant helping in highs and lows of travel	We combine real humans and purpose built in tech to deliver an all-in-one solution for guest travel, expense and reimbursement	All in one solution & convenience	Benefit	Category origin focus	Traditional benefit: convenience	https://pana.com/	Not available
Voom	B2C	Existing	On demand usage-based insurance for various mobility verticals	Flexible, affordable and personalised insurance at fingertips	Personalised and low cost	Value	Category origin focus	Traditional benefit: personalised, flexibility	https://www.voominsurance.com/	Monetary price
Labster	B2B	New	Online platform that allows students to perform experiments online in a risk-free environment	Radically improving science education	Technology improved process	Benefit	Digital focus	Motivational benefit	https://www.labster.com/	Not available
Neuroflow	B2C	Existing	Digital health application that tracks, assesses and manages mental well-being	A secure mobile app to support and strengthen your mind body connection	Become the better yourself	Benefit	Digital focus	Motivational benefit	https://www.neuroflow.com/for-individuals/	Not available
Dave banking	B2C	Existing	Moblie finanical services that enables to better manage own financial situation	Banking app that puts a financial mind at ease: get paid up two days early, build credit history, get advances	Put mind at ease	Benefit	Digital focus	Motivational benefit	https://www.dave.com/	Not available
Divvy	B2C	Existing	An online solution that makes home ownership accessible	A new kind of a real estate that makes it possible for you to build your wealth while living in your dream home.	Simple	Value	Category origin focus	Motivational benefit	https://www.divvyhomes.com/	Monetary price
Acorns	B2C	Existing	An app that helps better manage own budget, save money	Invest your spare change. Anyone can grow wealth.	Easy and secure	Value	Category origin focus	Motivational benefit	https://www.acorns.com/	Freemium
Superhuman	B2C+B2B	Existing	An innovative email solution	The fastest email experience ever made.	Become the better yourself	Value	Digital focus	Motivational benefit	https://superhuman.com/	Freemium
Wundermobility	B2B	Existing	An online platform for urban mobility	All in one solution for all kinds of transport rentals/sharing	All in one solution & convenience	Benefit	Category origin focus	Traditional benefit: convenience	www.wundermobility.com	Not available
Outfittery	B2C	Existing	An online platform that provides personal shopping for men	Stress-free shopping- receive your personal selection curated by your stylist, tailored to you	Personalised	Value	Category origin focus	Traditional benefit: personalised	https://www.outfittery.com/	Non-monetary price
Anydesk	B2B+ B2C	Existing	Software that enables remote access to computer	Secure and reliable remote desktop connections	Secure and reliable	Value	Category origin focus	Traditional benefit: reliablity	https://anydesk.com/en	Freemium
Echo	B2C	Existing	An app that delivers medicine and helps to keep track of repeated orders	Take the hassle out of managing your NHS repeat prescriptions	Easy and for free	Value	Category origin focus	Traditional benefit: convenience	https://www.echo.co.uk/how-echo-works	Non-monetary price
TransferGo	B2C	Existing	Online money transfer platform	Make faster, low-cost money transfers simply and securely	Fast and low cost	Value	Category origin focus	Traditional benefit: convenience	https://www.transfergo.com/de-de	Non-monetary price

Chip	B2C	Existing	Smart money saving app	Automatic savings app that uses AI to save up money and get better returns	AI driven simplicity and security	Value	Digital focus	Technological benefit	https://getchip.uk/	Freemium
Tractable	B2C	Existing	AI solution for accident or disaster recovery	AI to assess damage and to estimate repair costs in real time. For claims to be faster and livelihoods restored.	AI driven processing speed & simplicity	Benefit	Digital focus	Technological benefit	https://tractable.ai/	Not available
Moneyfarm	B2C	Existing	An online solution for smarter money investments	An intelligent simple way to invest with the help of digital technologies and experience of the biggest asset manager.	Intelligence through DT	Benefit	Digital focus	Technological benefit	https://www.moneyfarm.com/de/	Not available
Capacity	B2B	New	An online solution that helps businesses to automatize helpdesk, processes, decisions in real time	A new kind of a helpdesk powered by artificial intelligence that automates support for customers and employees	AI driven processing speed	Value	Digital focus	Technological benefit	https://capacity.com/	Freemium
CoachHub	B2B	Existing	A mobile coaching cloud platform that provides personalised coaching to employees at all career levels	A turnkey solution to transform your managers into highly effective, inspiring leaders	Personalised	Benefit	Category origin focus	Traditional benefit: personalised	https://coachhub.io/	Not available
Nuovo	B2B	New	A device leasing solution	Simplified mobile leasing, reduced EMI defaults, assured payment requisition	Simple	Value	Category origin focus	Traditional benefit: simple	https://nuovopay.com/	Freemium
ButtonWallet	B2C	New	A solution for cryptocurrency trade	Buy, sell, trade cryprocurrency with a telegram app. Fast and secure.	Fast, simple and secure	Benefit	Category origin focus	Traditional benefit: simplicity	www.buttonwallet.com	Not available
Hastee	B2B	New	An App that features employee benefits allowing employers to take a portion of their earned pay, on-demand	Revolutionizing the way people are paid for the better.	Fast, convenience	Benefit	Category origin focus	Motivational benefit	www.hastee.com	Not available
Imfraspeak	B2B	Existing	An application to report issues and get them resolved at any time	Service providers use infraspeak to achieve super performance in one single platform.	DT driven processing speed	Benefit	Digital focus	Technological benefit	www.infraspeak.com	Not available
Nodle	B2B	New	A solution to connect hardware	The largest ecosystem of connected devices, providing infrastructure, software and access to for the IoT.	Security	Benefit	Category origin focus	Traditional benefit: security	www.nodle.io	Not available
Soundsuit	B2B+ B2C	Existing	An application to create a playlist for a restaurant, gym, events	Your tailored business playlist in seconds	Easy and personalised	Value	Category origin focus	Traditional benefit: personalised	www.soundsuit.fm	Monetary price
Grab	B2C	Existing	An application to bundle services to fulfil essential daily needs	In many different ways we serve your daily needs.	All in one solution	Benefit	Category origin focus	Traditional benefit: convenience	www.grab.com	Not available
Porch	B2C	Existing	An application for an easy booking of home maintenance services	Now calling a local plumber, electrician, maid or carpenter is as simple as clicking a button.	Easy	Benefit	Category origin focus	Traditional benefit: convenience	www.services.porch.com	Not available
HotSpot Shield	B2C	New	A software that encrypts a user's online activity	Protect yourself with military-grade encryption and access sites and streaming content around the world.	Secure	Value	Category origin focus	Traditional benefit: security	www.hotspotshield.com	Freemium
Onfido	B2B+B2C	New	A software that helps to verify identity the digital world	Onfido helps companies see real identity using world leading AI and identity experts	AI driven processing speed	Benefit	Digital focus	Technological benefit	www.onfido.com	Not available
Sonder	B2C	Existing	Hotel chain that operates like AirBnB	Modern design, contact free service and exceptional comfort with more space to live, work, play.	All in one solution	Value	Category origin focus	Traditional benefit: comfort	www.sonder.com	Non-monetary price
Airgarage	B2B	Existing	An automated parking operator	Solutions for all parking owners-enforcement, payment collection, visitor registration, customer support and more	All in one solution	Benefit	Category origin focus	Traditional benefit: convenience	www.airgara.ge	Not available
Better	B2C	Existing	Quick and efficient mortgage application solution	Our efficiency not only makes it easier to buy a home, it translates into best rates possible.	Simple and low cost	Value	Category origin focus	Traditional benefit: easiness	www.better.com	Non-monetary price
Afresh	B2B	New	Food waste reduction solution	Afresh empowers grocers with technology to boost fresh sales, eliminate waste and multiply profitability.	All in one solution	Benefit	Digital focus	Motivational benefit	www.afresh.com	Not available
Cazoo	B2C	Existing	An online platform for used car purchase	With Cazoo you can buy or finance your car entirely online and complete your purchase from the comfort of your sofa.	Easy and fast	Value	Category origin focus	Traditional benefit: convenience	www.cazoo.co.uk	Non-monetary price
Gett	B2B	New	A digital solution to manage employee/business travel	A simple end to end SaaS solution for stress free business ground travel that works anywhere in the world.	Simple	Benefit	Category origin focus	Traditional benefit: convenience	www.gett.com	Not available

Picnic	B2C	Existing	Grocery delivery service	Online supermarket that delivers all your groceries to your home for free.	Low cost & convenience	Value	Category origin focus	Traditional benefit: convenience	www.picnic.app.de	Non-monetary price
Patch	B2C	Existing	Plants delivery service	Helps you discover the best plants for your space, delivers them to your door and helps you look after them.	Convenience	Value	Category origin focus	Traditional benefit: convenience	www.patchplants.com	Non-monetary price
Wolt	B2C	Existing	Food delivery	Wolt makes it incredibly easy for you to discover and get what you want. Delivered to you- quickly, reliably and affordably.	Quickly, easily and low cost	Value	Category origin focus	Traditional benefit: convenience	www.wolt.com	Non-monetary price
Helpling	B2C	Existing	Online booking platform for on demand home services	Hauptpflichtversichert, zuverlässiger Kundenservice, transparente Preise.	Trusted and transparent	Value	Category origin focus	Traditional benefit: transparency	www.helping.de	Non-monetary price
Tiquets	B2C	Existing	Online ticketing platform for attractions around the world	Most trusted platform: From iconic attractions to amazing experiences.	Trusted	Value	Category origin focus	Traditional benefit: convenience	www.tiquets.com	Non-monetary price
Deezer	B2C	Existing	Dynamic personal music streaming company.	A world of music in your pocket. Made for you.	Easy and pesonalised	Value	Category origin focus	Traditional benefit: personalised	www.deezer.com	Freemium
Badi	B2C	Existing	Powered by AI an online booking platform that offers users room rental service.	All payments are safe and protected. Badi guarantee. Support team is always there for you.	Security and trust	Benefit	Digital focus	Technological benefit	www.badi.com	Not available
Zeenly	B2C	Existing	Smartphone app that allows friends and families follow each others's tracks.	It is a most fun way to meet up or just see whats up- so you can feel together even if you are apart.	Easy	Value	Category origin focus	Traditional benefit: easiness	www.zen.ly	Non-monetary price
Cleo	B2C	Existing	Artificial intelligence solution that offers an intelligent assistant to help manage finances.	Personalised budget and spending breakdowns, budgeting tips and help with bills.	AI driven efficiency	Value	Digital focus	Technological benefit	www.meetcleo.com	Non-monetary price
Spotahome	B2C	Existing	An easy way to find and book residental rentals 100% online	Save time, energy and money- find and book your new home 100% online.	Easy, convenient	Benefit	Category origin focus	Traditional benefit: convenience	www.spotahome.com	Not available
Signal AI	B2B	New	Artifical intelligence company that transforms the world's information into accessible, actionable business knowledge	AI that understands your unique data horison at scale and surfaces key insight to augment your decisions.	AI driven processing speed	Benefit	Digital focus	Technological benefit	www.signal-ai.com	Not available
Circ	B2C	Existing	Highest quality rides with custom-made light electric vehicles.	Responsible rides to enhance our cities and build a cleaner, safer and more connected world	Convenience, sustainability	Value	Category origin focus	Motivational benefit	www.circ.com	Non-monetary price
Brainly	B2C	Existing	An Edtech and social learning network platform	Your 24/ 7 homework helper	AI driven service	Value	Digital focus	Technological benefit	www.brainly.com	Non-monetary price
Bung	B2C	Existing	A totally independent bank that makes life easy.	Helps you save time, money and Co2. All with safety and security of a true bank.	Convenience	Value	Category origin focus	Motivational benefit	https://www.bunq.com/	Non-monetary price
Naturebasics	B2C	Existing	A digital health solution providing personalised high-quality vitamins and nutrition consultation	Impowers you with the right information to make smarter choices.	Smart, convenient	Value	Category origin focus	Motivational benefit	www.joinhundred.com	Non-monetary price
Blacklane	B2C	Existing	An online chauffeur service	Easily book, change, cancel rides on the go. Peace of mind in the palm of your hand.	Easy	Benefit	Category origin focus	Traditional benefit: easiness	www.blacklane.com	Not available
Taxfix	B2C	Existing	An app that simplifies tax filling	With our customer friendly app and smart technology, we have made it possible for everyone to claim their tax refund.	Easy	Value	Category origin focus	Traditional benefit: convenience	www.taxfix.de	Non-monetary price
Coya	B2C	Existing	Digitalised insurance	Versicherung so digital wie dein Lifestyle.	Convenience	Value	Category origin focus	Traditional benefit: convenience	www.coya.com	Non-monetary price
Twenty Billion Neurons	B2B+B2C	New	AI company that builds intelligent avatars that can interact with people	A human centric AI technology that brings seeing and sociable digital assistants to life.	AI driven process improvement	Benefit	Digital focus	Technological benefit	www.20bn.com	Not available
8fit	B2C	Existing	An app that helps to develop healthy habits	Transforming the concept of fitness from the pursuit of perfection to a liberating journey of healthy, body positive and lasting changes.	Simple	Value	Category origin focus	Motivational benefit	www.8fit.com	Non-monetary price
Building radar	B2B	New	Digital consultant on construction projects across the world	Automate your worldwide construction project research and free up time to focus on your sales success.	DT driven process improvement	Benefit	Digital focus	Technological benefit	www.buildingradar.com	Not available

Mylivn	B2C	Existing	A lifestyle platform that simplifies social life by letting people create their own micro networks	Mylivn is where millions can connect, organise and create together	Convenience	Value	Category origin focus	Traditional benefit: convenience	www.mylivn.com	Non-monetary price
Fineway	B2C	Existing	Online trip planner	Free instant trip planner for everyone.	Simple and free	Value	Category origin focus	Traditional benefit: convenience	www.fineway.ai	Non-monetary price
MessengerPro	B2B+B2C	Existing	Professional messaging services	Your partner for successful messenger communication.	Simple, convenient	Value	Category origin focus	Traditional benefit: convenience	www.messengerpeople.com	Freemium
Smashdocs	B2C	New	Web based word processing application for writing and reviewing documents	Dokumente schreiben, überarbeiten und produzieren jetzt ganz entspannt und 10x schneller als bisher.	DT driven processing speed	Benefit	Digital focus	Technological benefit	www.smashdocs.net	Not available
Airgreets	B2C	Existing	Professional and complete management of AirBnB rentals	Kurzzeitvermietung war noch nie so einfach und unkompliziert.	Simple	Benefit	Category origin focus	Traditional benefit: convenience	www.airgreets.com	Not available
Sofarsounds	B2C	Existing	An online community hosting live performances	Supporting artists around the world through live shows and performances.	Simple	Benefit	Category origin focus	Traditional benefit: simplicity	www.sofarsounds.com	Not available
Everledger	B2C	Existing	Digital ledger for diamond and other asset ownership and related supply chain history.	We create a secure and permanent digital record of an asset origin, characteristics and ownerhsip	Smart and secure	Benefit	Category origin focus	Traditional benefit: smartness	www.everledger.io	Not available
Keyless	B2B	New	Data privacy and security solutions for enterprises	Zero trust authentification to protect remote workforce and enable strong customer authentification with just a look.	Secure	Benefit	Category origin focus	Traditional benefit: security	www.keyless.io	Not available
Koyo	B2C	Existing	A solution that provides loans for people with short credit histories	Personal loans that consider more than your credit score.	Trusted and personalised	Value	Category origin focus	Traditional benefit: fair	www.koyoloans.com	Non-monetary price
MishiPay	B2B	Existing	A solution that allows making payments from everywhere in a store.	Offer the experience of mobile self-checkout.	Fast and secure	Benefit	Category origin focus	Traditional benefit: convenience	www.mishipay.com	Not available
HowNow	B2C	Existing	EdTech solution that connects experts and learners via interactive digital lessons	Everything you need to organise, capture, share and sell knowledge.	Convenience	Value	Category origin focus	Traditional benefit: convenience	www.learnhownow.com	Freemium
Luko	B2C	Existing	Digital home ensurance	Insured in 2 minutes, reminbursed 2 times faster, a craftsman at home in 2 days	Simple and fast	Benefit	Category origin focus	Traditional benefit: convenience	www.luko.eu	Not available
Foodvisor	B2C	Existing	An app that helps eat smarter and healthier by analysing nutrients in the food.	Foodvisor is more than just a calorie counter, it is an app that will help you eat healthier	Achievement of life goals and values	Value	Digital focus	Motivational benefit	www.foodvisor.io	Non-monetary price
BackMarket	B2C	Existing	Online marketplace for refurbished products	Restore trust and desire for refurbished devices.	Good quality and low price	Value	Category origin focus	Traditional benefit: quality	www.backmarket.com	Monetary price
Sendinblue	B2B	New	All in one digital platform for growing strong customer relationships	All the tools you need to be everywhere your customers are.	Convenience	Value	Category origin focus	Traditional benefit: convenience	www.sendinlblue.com	Freemium
Dental Monitoring	B2B	Existing	Web and mobile application for self-monitored dental treatment	The most cutting-edge solution to help you provide a high level of care to patients remotely.	Smart and convenient	Value	Category origin focus	Traditional benefit: convenience	www.dental-monitoring com	Non-monetary price
Iziwork	B2C	Existing	Temporary jobs online platform	Radically improving access and work experience thanks to technology.	Trust	Benefit	Digital focus	Technological benefit	www.iziwork.com	Not available
Ornikar	B2C	Existing	Online driving school	The online driving school that revolutionized driving licences	Easy and fast	Benefit	Category origin focus	Traditional benefit: convenience	www.ornikar.com	Not available
Proprioo	B2C	Existing	An online real estate trade solution	Consultants to support you from A to Z and digital at service of transparency	Personalised	Value	Category origin focus	Traditional benefit: personal	www.proprio.fr	Non-monetary price
Linktree	B2B	New	A platform that makes users' social content more discoverable and easy to manage	Connect audiences to all of your content with just one link.	Easy	Value	Category origin focus	Traditional benefit: convenience	www.linktr.ee	Freemium
Esports	B2C+B2B	New	A provider of esports media with offerings such as tournaments, content and marketing.	The esports total solution provider.	Convenience	Benefit	Category origin focus	Traditional benefit: convenience	www.vspn.com	Non info
Once water	B2C	Existing	A solution that provides drinking water and tracks daily water consumption.	Once water makes healthy habits easier by doing the math for you.	Smart and easy	Benefit	Category origin focus	Motivational benefit	www.getounced.com	Not available
Livestorm	B2B	Existing	A browser-based video communication platform to promote, host, analyse online events.	Simple yet powerful communication tool for companies of all sizes.	Convenience and trust	Value	Category origin focus	Traditional benefit: convenience	www.livestorm.co	Non-monetary price

Locker	B2C	Existing	A single centralised platform for sports fans to consume their favourite sports media and bet.	The best of the world's sports media personalised for you.	Convenience and trust	Value	Category origin focus	Traditional benefit: personalised	www.getlocker.com	Non-monetary price
News guard	B2C	New	Online ratings and write-ups for news and information websites	We tell you if a site is reliable as you browse online news.	Security	Benefit	Category origin focus	Traditional benefit: reliability	www.newsguardtech.com	Not available
Homeday	B2C	Existing	Online real estate brocker.	Full service. Local brockers. Low provisions.	Convenience and low cost	Value	Category origin focus	Traditional benefit: convenience	www.homeday.de	Monetary price
Hyperscience	B2B	Existing	Offline data automation solution	Build and run mission critical processes with ease and speed.	AI driven process optimisation	Benefit	Digital focus	Technological benefit	www.hyperscience.com	Not available
Moon Hub	B2B	Existing	VR based training solution for enterprises	Immersive VR Training.	DT driven process improvement	Benefit	Digital focus	Technological benefit	www.themoonhub.com	Not available
Tibber	B2C	NEw	An app monitoring individual's electricity consumption	Make energy consumption smarter using digital technology.	Smart	Value	Category origin focus	Traditional benefit	www.tibber.com	Non-monetary price
Peltarion	B2B	New	AI driven process efficiency improvement solution	Peltarion platform empowers anyone to design and deploy AI without a single line of code.	AI driven process improvement	Value	Digital focus	Technological benefit	www.peltarion.com	Non-monetary price
Lexolve	B2B	Existing	Digital assisstant for legal matters for enterprises	A Digital colleague who solves legal needs easily and efficiently	Achievement of goals and values	Value	Digital focus	Motivational benefit	www.lexolve.com	Freemium
Hygglo	B2B+B2C	Existing	A rental platform for sharing economy.	Your vicinity at times that suit you.	Convenience	Value	Category origin focus	Traditional benefit: personalised	www.hygglo.no	Non-monetary price
Unloc	B2C	Existing	An app for digitalising keys	Save time by opening doors with your phone. No more hassle looking for keys.	Easy	Benefit	Category origin focus	Traditional benefit: convenience	www.unloc.app	Not available
Ayfie	B2B	New	A smart data management solution to process, analyse large amounts of data.	Turning your data into an asset and managing risk at the same time.	DT driven process improvement	Benefit	Digital focus	Technological benefit	www.ayfie.com	Not available
Choose	B2B+B2C	New	An App that helps to live and act more sustainably	Choose digital tools make climate action part of everyday life.	Smart	Benefit	Category origin focus	Motivational benefit	https://chooose.today/	Not available
Spond	B2C	Existing	An app for organisation of sport and group activities	Smooth communication between team leaders, coaches, members and guardians in one platform.	Easy	Benefit	Category origin focus	Traditional benefit: convenience	www.spond.com	Not available
Testo	B2B	Existing	A digital solution that helps make better and informed decisions by knowing how users experience product or service.	Remote, unmoderated user testing. Results from users anywhere anytime.	Easy and convenient	Benefit	Category origin focus	Traditional benefit: convenience	www.teston.io	Not available
Hold	B2C	New	Individual's performance improvement platform	Measure and maximise your productivity through a cross plattform solution.	Achievement of life goals and values	Value	Digital focus	Motivational benefit	www.hold.app	Non-monetary price
Hjemmelegene	B2C	Existing	An app for doctor remote appointments	Hand-picked doctors to trust.	Convenience, easy	Benefit	Category origin focus	Traditional benefit: convenience	www.hjemmelegene.no	Not available
Moodie	B2C+B2B	Existing	Mobile application that combines services for urban experiences.	The new hotspot for entertainment.	Convenience	Benefit	Category origin focus	Traditional benefit: convenience	www.moodie.no	Not available
Yousician	B2C	Existing	A digital music educator.	Everything you need to master your instrument. Tailored to your needs and updated regularly.	Personalised	Value	Category origin focus	Traditional benefit: personalised	www.yousician.com	Non-monetary price
Vizor	B2C	New	Online platform for sharing VR experience	The quickest, simplest way to create and share immersive VR experiences.	Simple	Benefit	Category origin focus	Traditional benefit: convenience	www.site.vizor.io	Not available
Sayduck	B2B	New	3D and AI visualization platform.	Helping world leading design brands to drive product engagement with 3D and AI	AI driven process improvement	Benefit	Digital focus	Technological benefit	www.sayduck.com	Not available
Singa	B2C	Existing	Spotify of karaoke	Sing karaoke anytime, anywhere.	Convenience	Value	Category origin focus	Traditional benefit: convenience	www.singa.com	Non-monetary price

Klarna	B2C	New	Flexible payment options in e-commerce.	Experience smooth shopping mit Klarna App.	Convenient, flexible	Value	Category origin focus	Traditional benefit: convenience	www.klarna.com	Non-monetary price

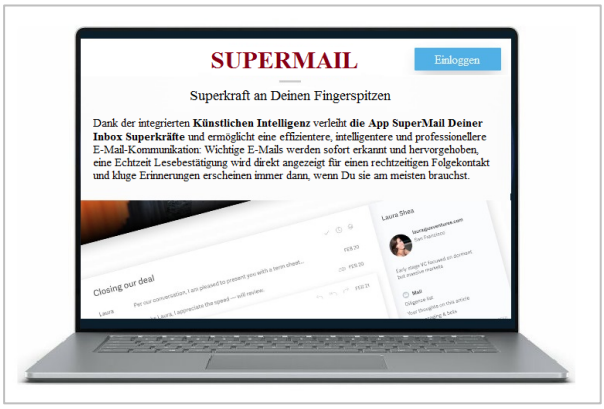
Appendix A4: Measurements of core constructs (Paper 3 Study 1/ Study 2 / Study 3)

Measurement / Items	Cronbach's alpha (Study 1/2/3)	CITC (Study 1/2/3)
Adoption intention[a] (adapted from Castaño et al. 2008)	.920/.935/.950	
I would like to try ___.		.850/.862/.889
I would actively seek ___ to learn more it.		.768/.814/.879
I am generally interested in using the ___.		.891/.883/.907
I like the idea of ___.		.766/.832/.836
Initial trust[a] (adapted from McAllister 1995, Sekhon et al. 2014)	.953/.952/.959	
I perceive ___ to be trustworthy.		.910/.918/.914
I am certain that I can trust ___.		.878/.911/.898
The ___ appears very trustworthy.		.906/.856/.908
I trust ___ to do what it says it will do.		.853/.854/.877
Privacy Concerns (adapted from Liao et al. 2011)	.946/.964/.968	
I am concerned that my personal data will be misused by ___.		.863/.899/.915
I am afraid, that the Start-up ___ my personal and usage data will be sold to third parties.		.865/.895/.920
I am hesitating to provide my data to the Start-up ___ because I am not certain what the start-up does with that data.		.863/.935/.919
I am concerned that my personal data will be used by the Start-up ___ in a way that I cannot foresee.		.887/.918/.925
Digital Nativeness (adapted from Keaveney& Madhavan 2001, McKnight et al. 2002;)	.869/.911/.865	
I always keep myself up-to-date regarding newest developments in Digital Media (e.g. Computer, Mobile, Internet)		.651/.745/.656
I consider myself an expert in Digital Media.		.582/.712/.625
My good knowledge about Digital Media helps me to understand all technical information about such media.		.653/.691/.649
I regularly use one communication services (e.g. Chats, Blogs, Internet forums)		.596/.604/.672
I regularly use online information services (e.g. Wikipedia)		.502/.388/.581
I regularly use mobile internet.		.618/.505/.560
I regularly check my emails on my smartphone.		.470/.517/.542
I regularly use digital functions of my smartphone (e.g. Location services, activities, Siri/Google assistant)		.650/.655/.675

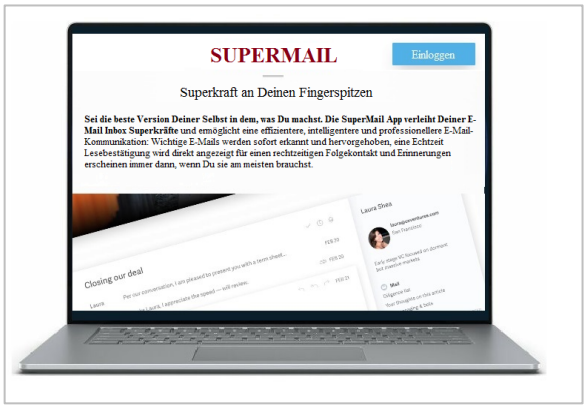
Note: [a]7-point Likert scale with anchors 1 = "disagree strongly" and 7 = "agree strongly".
CITC = corrected item-total-correlation.

Appendix A5: Visualisations of experimental manipulations (Paper 3 Study 1/ Study 2/ Study 3)

Appendix A5.a: Study 1: Benefit-based positioning manipulation



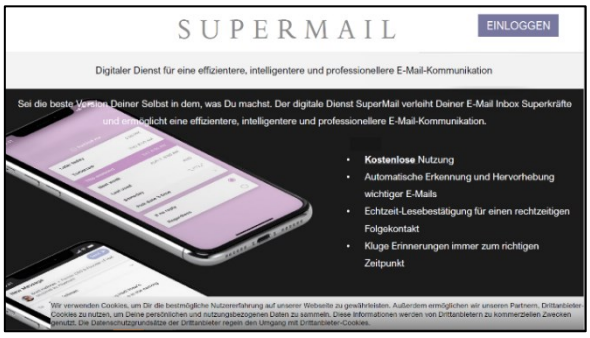
a) Technological benefit



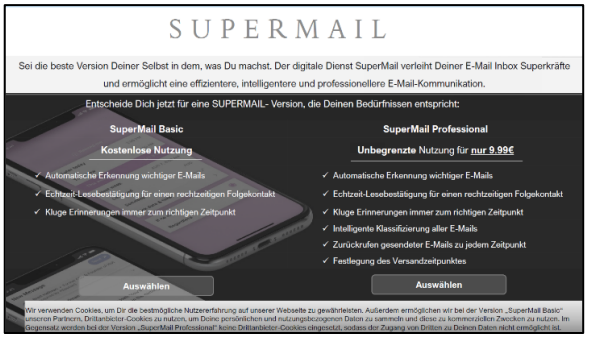
b) Motivational benefit

Appendix A5.b: Study 2: Cost-based positioning manipulation

a) Technological benefit & Free-of-charge



b) Motivational benefit & Free-of-charge



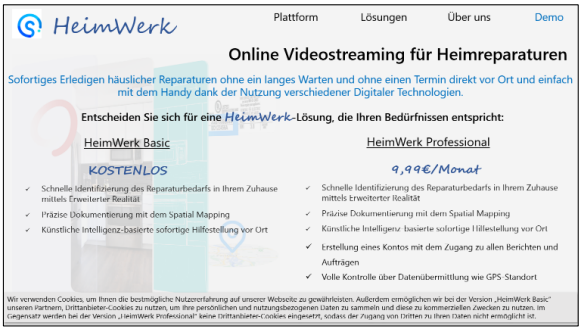
c) Technological benefit & Freemium

d) Motivational benefit & Freemium

Appendix A5.c: Study 3: Value-Based positioning manipulation

a) Technological benefit & Free-of-charge

b) Motivational benefit & Free-of-charge



c) Technological benefit & Freemium

d) Motivational benefit & Freemium

Affidavit

Ich erkläre hiermit, dass ich die vorgelegten und nachfolgend aufgelisteten Aufsätze selbstständig und nur mit den Hilfen angefertigt habe, die im jeweiligen Aufsatz angegeben oder zusätzlich in der nachfolgenden Liste aufgeführt sind. In der Zusammenarbeit mit den angeführten Koautoren war ich mindestens anteilig beteiligt. Bei den von mir durchgeführten und in den Aufsätzen erwähnten Untersuchungen habe ich die Grundsätze guter wissenschaftlicher Praxis, wie sie in der Satzung der Justus-Liebig-Universität Gießen zur Sicherung guter wissenschaftlicher Praxis niedergelegt sind, eingehalten.

Kuharev, V., and M. C. Schuhmacher (2018). Research on innovation marketing: A text-mining approach to systematic literature review and future research directions. Working Paper.

Konya-Baumbach, E., Schuhmacher, M. C., Kuester, S., and Kuharev, V. (2019). Making a first impression as a start-up: Strategies to overcome low initial trust perceptions in digital innovation adoption. *International Journal of Research in Marketing*, *36*(3), 385-399.

Kuharev, V., and M. C. Schuhmacher (2025). Choosing the right positioning when launching digital innovations by start-ups. Working Paper.

Gießen, 1. September 2025

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Victoria Kuharev