International Journal of Research in Marketing 36 (2019) 385–399

Contents lists available at ScienceDirect

IJRM
International Journal of Research in Marketing

journal homepage: www.elsevier.com/locate/ijresmar

Full Length Article

# Making a first impression as a start-up: Strategies to overcome low initial trust perceptions in digital innovation adoption

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ARTICLE INFO

*Article history:*
First received on February 7, 2018 and was under review for 4 months
Available online 10 February 2019

*Keywords:*
Start-up
Digital innovation
Digital business model
Initial trust
Privacy concerns
Adoption intention

ABSTRACT

High failure rates of digital innovations 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 digital innovations. 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 digital innovations. The findings demonstrate that initial trust serves as a critical mediator in the relationship between these design strategies and consumers' adoption intentions. Additionally, the chosen revenue model 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 digital innovation launch.



## 1. Introduction

Increasingly, companies focus on developing and launching digital innovations (DIs) (Huang & Rust, 2013). DIs are Internet-enabled service innovations (Dotzel, Shankar, & Berry, 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, Eggers, & Gannamaneni, 2018). As DIs are drivers of future economic success, researchers call for research on consumers' acceptance of DIs (Kannan & Li, 2017; Kuester, Konya-Baumbach, & Schuhmacher, 2018; Kunz & 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, Tellis, & Griffin, 2006). At the same time, achieving a high level of DI acceptance is challenging for companies (Prins, Verhoef, & Franses, 2009). Whether consumers eventually adopt a DI largely depends on their first impression of the DI's trustworthiness. Uncertainty generally surrounds innovations (Meuter, Ostrom, Roundtree, & Bitner, 2000) and this uncertainty is even more pronounced in case of DIs due to their digital na-

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https://doi.org/10.1016/j.ijresmar.2019.01.008
0167-8116/

ture (Coulter & Coulter, 2003; Featherman & Pavlou, 2003). This uncertainty may find expression in privacy concerns, fear of personal data misuse, and in doubts regarding performance of DIs (Featherman & Pavlou, 2003; Meuter et al., 2000). Consumers' unfamiliarity with the launching company further aggravates these conditions (McKnight, Choudhury, & Kacmar, 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 with regard to consumer perceptions (Lemon & 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 & Stoel, 2009; Morrison & Firmstone, 2000; Nienaber & Schewe, 2014). This finding also holds true for services (Coulter & Coulter, 2003) and in the digital environment (Kannan & Li, 2017). In fact, some researchers found evidence for a general positive influence of trust on the use of electronic services (Beldad, De Jong, & Steehouder, 2010) and e-commerce (Ha & Stoel, 2009; McKnight et al., 2002; Morrison & Firmstone, 2000; Nienaber & 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 experience, as initial trust. Initial trust may constitute a valuable piece of information in the otherwise information-poor adoption decision setting. In this setting, start-ups face the challenge to evoke initial trust for their DIs in order to boost consumer adoption. Based on 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, White, & Lloyd, 2006). In the case of a DI by an unknown start-up, consumers have no prior experience and lack comprehensive information. So far, there is no research on the creation of consumers' initial trust in the context of DIs by start-ups. Our research addresses this deficiency by investigating how to overcome low initial trust perceptions to boost adoption of DIs.

Due to the digitalization, we observe 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 personal 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 signals of trustworthiness: customer ratings, benefit communication, and revenue model.

## 2. Adoption of digital innovations

Research on innovation adoption has long been established in the field of marketing (e.g., Taylor & Todd, 1995; for an overview, see Arts, Frambach, & Bijmolt, 2011). However, adoption research has not kept pace with digitalization. Most adoption studies focus on researching product innovations (Feiereisen, Wong, & Broderick, 2013; Müller-Stewens, Schlager, Häubl, & Herrmann, 2017). Other studies are concerned with service innovations (Prins et al., 2009), with very little research pertaining to digital services (Ha & Stoel, 2009) or specifically accounting for the role of trust (Nienaber & 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 & Pavlou, 2003; Hampton-Sosa, 2017). Only a few studies derive recommendations for the commercialization of digital products (Talke & Snelders, 2013) or digital services (Prins & 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 low initial trust perceptions of their DIs. Reviewing relevant literature in these fields, Table 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 use of 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 launch of innovations focuses on

**Table 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, Straub, & Chervany, 1999, MISQ<br>Yu, Lin, & Liao, 2017, CHB | Information systems | Information technology | No | Yes | No | No | No |
| Hoeffler, 2003, JMR<br>Wood & Moreau, 2006, JM<br>Herzenstein, Posavac, & Brakus, 2007, JMR<br>Castaño, Sujan, Kacker, & Sujan, 2008, JMR<br>Alexander, Lynch Jr., & Wang, 2008, JMR<br>Feiereisen et al., 2013, JPIM<br>Kuester, Feurer, Schuhmacher, & Reinartz, 2015, IJRM<br>Müller-Stewens et al., 2017, JM<br>Schuhmacher, Kuester, & Hultink, 2018, JPIM | Marketing | Products | Yes | No | No | No | No |
| Krieger et al., 2003, JSM<br>Prins et al.2009, IJRM | Marketing | Services | Yes | No | No | No | No |
| Nienaber & 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<br>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 & 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*<br>*Revenue model* |

promotion (Fruchter & Van den Bulte, 2011; Hariharan, Talukdar, & Kwon, 2015; Le Nagard-Assayag & Manceau, 2001) or pricing (Kuester et al., 2015; Park, MacLachlan, & Love, 2011).

## 3. Signaling trustworthiness

The present study draws on 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 in a situation of 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 the form of a signal (Connelly, Ireland, & Reutzel, 2011). To be effective, signals need to be observable to outsiders and costly to the effect that obtaining the signal is more expensive for low than for 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 customers. 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 indicate quality (Schuhmacher et al., 2018) or 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 adoption decision. 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 DIs can use design strategies of digital business models to signal trustworthiness. Start-ups can mitigate information asymmetries that exist at the time of a DI's launch, 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 & Coulter, 2003; Featherman & Pavlou, 2003), complexity or (in)compatibility (Boulding & Kirmani, 1993; Rogers, 2003), novelty (Meuter et al., 2000), intangibility (Huang & Rust, 2013), and due to perceived liabilities of start-ups (Baum & Silverman, 2004; Huyghebaert & 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 indicate trustworthiness such as revealing the DI's origin, ensuring personal 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

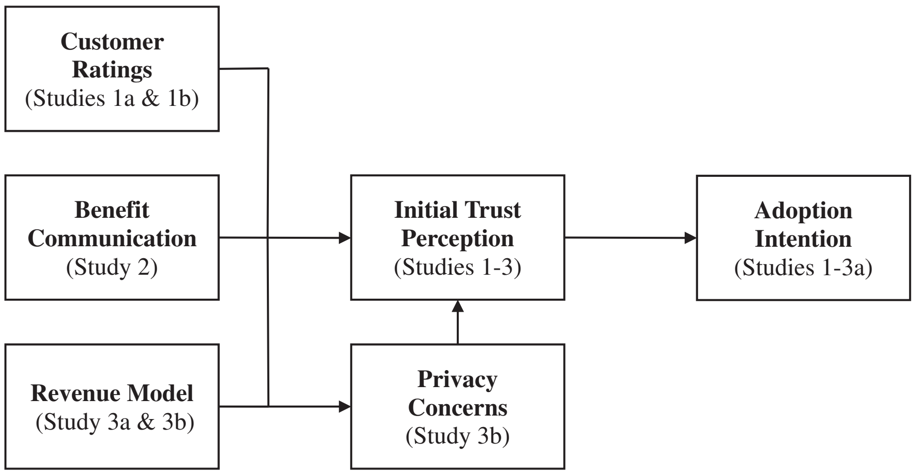


**Fig. 1.** Organizational framework.

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. Fig. 1 provides an overview of the organizational framework of all studies.

## 4. 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 in whether the number of available favorable customer ratings impacts perceived initial trust, and in turn, adoption intention. 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).

### *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, Fernbach, and Lichtenstein (2016) 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' DIs. 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, start-ups offering high quality DIs will automatically receive a high number of positive customer ratings over time. 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 DIs. 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.

#### *4.1.1. Method*

*4.1.1.1. 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 design 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) × 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 & Suri, 2012). Excluding 38 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.

*4.1.1.2. 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 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* was the first product by the start-up *CityTour* explaining that the app offered the visualization of city tours using AR. We further instructed the participants to read the app store description of *CityTour AR*. We implemented the customer rating manipulation 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 8786 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 (adapted from Castaño et al., 2008) and rated their initial trust in *CityTour AR* (adapted from Sekhon, Ennew, Kharouf & Devlin 2014; see Appendix A 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.

#### 4.1.2. Results

*4.1.2.1. 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 ($M = 1.29$).

*4.1.2.2. Main result.* An ANOVA shows no significant effect of the number of positive customer ratings on initial trust perceptions ($M_{\text{LowNumber}} = 4.25$; $M_{\text{HighNumber}} = 4.31$; $F\ (1, 172) = 0.072$, $p > .05$). 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, ($F\ (1,172) = 0.154$, $p > .05$). Thus, we do not find support for $H_1$.

Researchers have shown that trust perceptions positively affect purchase intentions in various contexts (Büttner & Göritz, 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 (5000 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 ($b = 0.490$; $p < .001$) (see Table 2). Consistent with our previous results, the overall indirect path from customer ratings to adoption intention through initial trust is not significant ($b = 0.034$) with a 95% confidence interval including zero [−0.147; 0.195]. Holding initial trust constant, the direct path between customer ratings and adoption intention is also not significant ($b = -0.037$; [−0.362; 0.289]; $p > .05$). The number of positive customer ratings has no impact on adoption intention, neither directly nor indirectly via perceived initial trust.

### 4.2. Study 1b: Valence of customer ratings

In light 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 possibly 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.

#### 4.2.1. Method

*4.2.1.1. 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 ratings in the

**Table 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* | 0.069 | 0.392 | 0.696 | 0.034 | −0.147 | 0.195 |
| *PIT* ➔ *AI*[c] | 0.490 | 6.805 | 0.000 | | | |
| *NCR* ➔ *AI* | −0.037 | −0.221 | 0.825 | | | |

[a] Based on 5000 bootstrap resamples.
[b] Dummy-coded (0 = low number of customer ratings, 1 = high number of customer ratings).
[c] $R^2 = 0.638$; we further controlled for perceived usefulness and product category relevance.

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 A 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).

#### 4.2.2. Results

*4.2.2.1. 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 ratings 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 ($M = 5.14$) and that they were not familiar with the app ($M = 1.27$).

*4.2.2.2. 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 ($b = 0.434$) and significant ($p < .001$) in the mediation analysis (Preacher & Hayes, 2004) (see Table 3). The indirect path from customer ratings to adoption intention via initial trust is significant ($b = 0.170$) with a 95% confidence interval excluding zero [0.047; 0.310]. Holding initial trust constant, the direct path between customer ratings and adoption intention is not significant ($b = -0.201$; [−0.500; 0.067], $p > .05$), providing evidence for an indirect only (i.e., full) mediation (Zhao, Lynch, & Chen, 2010).

### 4.3. Discussion

Contrary to both our expectation and prior research (De Langhe et al., 2016), 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., 2016). Thus, showing positive customer ratings, independent of the number of available ratings, turns out to be an effective signal to communicate 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 intentions via initial trust perceptions.

## 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 & Snelders, 2013). Following this notion, we propose that the design of the 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, Yin, Wong, & Calantone, 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 & O'Connor, 2003; Talke & 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 when 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 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 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

**Table 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* | 0.390 | 2.667 | 0.008 | 0.170 | 0.047 | 0.310 |
| *PIT* ➔ *AI*[c] | 0.434 | 6.854 | 0.000 | | | |
| *ECR* ➔ *AI* | −0.201 | −1.328 | 0.185 | | | |

[a] Based on 5000 bootstrap resamples.
[b] Dummy-coded (0 = no customer ratings, 1 = customer ratings).
[c] $R^2 = 0.568$; we further controlled for perceived usefulness and product category relevance.

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 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 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 initial trust perceptions. In contrast, 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 communication of an origin-based benefit is more effective in overcoming low initial trust perceptions than that of 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.

### 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. 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.

#### 5.1.1. 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* being 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.

#### 5.1.2. Participants and design

For the online experiment we used a 2 (benefit: personal vs. transparent) × 1 factorial between-subjects design 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 yielding a final sample of 91 individuals. We randomly assigned the participants to one of the two groups resulting in nearly equal cell sizes.

#### 5.1.3. 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 when 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 and play store. The remainder of the questionnaire comprised the same questions as in Study 1 (see Appendix A for measurements).

### 5.2. Results

#### 5.2.1. Manipulation check

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

**Table 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 | 0.000 | 0.477 | 0.142 | 0.835 |
| *PIT* ➔ *AI*[c] | 0.470 | 3.516 | 0.001 | | | |
| *BC* ➔ *AI* | −0.685 | −2.431 | 0.017 | | | |

[a] Based on 5000 bootstrap resamples.
[b] Dummy-coded (0 = digital benefit, 1 = origin-based benefit).
[c] $R^2 = 0.476$; we further controlled for perceived usefulness and product category relevance.

### 5.2.2. 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* $\eta2 = 0.268$). Thus, we find support for $H_2$. To check the robustness of our findings, we again conducted an ANCOVA including the two covariates product category relevance and perceived usefulness, supporting the results of the ANOVA.

Furthermore, we expect that origin-based 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 (5000 resamples) (Preacher & Hayes, 2004) (see Table 4). We find a positive (b = 0.470) 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 and positive (b = 0.477) with a 95% confidence interval excluding zero [0.142; 0.835]. Holding initial trust constant, the direct path between benefit communication and adoption intention is significant and negative (b = −0.685; [−1.245; −0.125]), 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).

### 5.3. Discussion

Signaling 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 effect adoption intentions. Hence, in order 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 a slightly higher adoption intention compared to 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 advertising campaigns. Accounting for the strong impact of initial trust perceptions on adoption intentions, 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 initial trust perceptions of DIs by start-ups, which then drives consumers' adoption intentions.

## 6. 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, Frankberger, & Csik, 2014). We refer to the former 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 intention. 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.

### 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 indicator for both a monetary sacrifice and quality (Kardes, Cronley, Kellaris, & Posavac, 2004; Suri, Kohli, & Monroe, 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 & 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 & Smith, 2005; Ram & 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, ultimately resulting in higher adoption intentions.

### 6.1.1. Method

*6.1.1.1. 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; $M_{\text{age}} = 33.10$). Participants were randomly assigned to a 2 (revenue model: monetary vs. data-based) × 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.

*6.1.1.2. 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 A for measurements) with adjusted manipulation checks.

### 6.1.2. Results

*6.1.2.1. 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”, $M_{\text{Price}} = 1.07$, $M_{\text{Data}} = 5.52$, $F\,(1, 171) = 313.741$, $p < .001$). Further, participants rated the data safety to be 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 not to be familiar with *CityTour AR* ($M = 1.05$).

*6.1.2.2. Main effect.* In line with $H_3$, an ANOVA of participants' initial trust perceptions showed a main effect of monetary price as compared to 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* $\eta 2 = 0.124$). Again, an ANCOVA with the two covariates product category relevance and perceived usefulness yielded similar results.

Furthermore, we expect that the monetary 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 & Hayes, 2004) revealed a positive significant impact of initial trust on adoption intention (see Table 5). In support of our prediction, the overall indirect path from the revenue model signal to adoption intention through initial trust is significant and positive (b = 0.505) with a 95% confidence interval excluding zero [0.310; 0.799]. Holding initial trust constant, the direct path between the revenue model signal and adoption intention is not significant (b = −0.229; [−0.612; 0.155]), providing evidence for an indirect only (“full”) mediation (Zhao et al., 2010).

### 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 about whether and how they use individuals' usage data. For example,

**Table 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*[b] | 0.911 | 5.440 | 0.000 | 0.505 | 0.310 | 0.799 |
| *PIT* ➔ *AI*[c] | 0.554 | 6.734 | 0.000 | | | |
| *RM* ➔ *AI* | −0.229 | −1.179 | 0.240 | | | |

[a] Based on 5000 bootstrap resamples.
[b] Dummy-coded (0 = data price, 1 = monetary price).
[c] $R^2 = 0.599$; we further controlled for perceived usefulness and product category relevance.

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, when employing a data-based revenue model and indicating that usage data is collected and used, privacy concerns will be higher, impacting initial trust negatively.

#### 6.2.1. Method

*6.2.1.1. 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 directly order selected furniture. 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) × 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; $M_{age} = 42.72$) equally allocated to the two groups.

*6.2.1.2. 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 use tools neither 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, based on the declaration 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, Liu, and Chen (2011), while the remainder of the questionnaire was the same as in Study 3a (see Appendix A for measurements).

#### 6.2.2. Results

*6.2.2.1. 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", $M_{Price} = 1.63$, $M_{Data} = 6.10$, $F\,(1, 198) = 427.949$, $p < .001$). Finally, the scenarios were perceived as realistic ($M = 5.31$) and participants indicated to not be familiar with *mydesign3D* ($M = 1.34$).

*6.2.2.2. Main effect.* An ANOVA of participants' privacy concerns showed a main effect of monetary price as compared to 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* $\eta 2 = 0.089$). Again, an ANCOVA with the two covariates product category relevance and perceived usefulness yielded similar results.

Further, we again ran a mediation analysis (Preacher & Hayes, 2004) that supported our prediction by disclosing a negative significant impact of both the monetary revenue model signal on privacy concerns and of privacy concerns on initial trust perceptions (see Table 6). In fact, the overall indirect path from the revenue model signal to initial trust perceptions through privacy concerns is significant and positive (b = 0.345) with a 95% confidence interval excluding zero [0.175; 0.548]. Holding privacy

**Table 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*[b] | −1.265 | −5.632 | 0.000 | 0.345 | 0.175 | 0.548 |
| *PC* ➔ *PIT*[c] | −0.273 | −6.238 | 0.000 | | | |
| *RM* ➔ *PIT* | −0.084 | −0.564 | 0.574 | | | |

[a] Based on 5000 bootstrap resamples.
[b] Dummy-coded (0 = data price, 1 = monetary price).
[c] $R^2$ = 0.436; we further controlled for perceived usefulness and product category relevance.

concerns constant, the direct path between the revenue model signal and initial trust perceptions is not significant (b = −0.084; [−0.376; 0.209]), providing evidence for an indirect only ("full") mediation (Zhao et al., 2010).

### 6.3. Discussion

The findings demonstrate 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 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.

## 7. Overall discussion and research contribution

Although trust has been an important topic in both information systems and e-commerce research (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 doubts regarding performance (Featherman & 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 & 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 how to evoke initial trust because effective trust-building strategies, such as using well-established brand names, are not readily available. 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 is 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 information poor situations such as when 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. 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., 2016) 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 the message content on adoption intention (Lee & O'Connor, 2003). Even though studies highlight the importance of benefit-based communication for innovations (Talke & Snelders, 2013), research has not explored the differential effectiveness of various 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 towards 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 low initial trust perceptions of their DIs. By taking the perspective of the consumer adoption process (Arts et al., 2011), we hone our understanding of consumer decision making with regard to DI adoption.

## 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, Becker, von Wangenheim, & Schumann, 2016; Lemon & 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 releases 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 address 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 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 target 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 one 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 clearly state 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.

## 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 negative 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, Jahn, & Boztug, 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.

## Appendix A

**Table A.1**
Measurements of Core Constructs (Study 1a/Study 1b/Study 2/ Study 3a/Study 3b).

| Measurement / Items | Cronbach's alpha | CITC |
|---|---|---|
| *Adoption intention*[a] | .96/.96/.95/.93/.96 | |
| (adapted from Castaño et al., 2008) | | |
| 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] | 96/.96/.93/.93/.93 | |
| (adapted from Sekhon et al., 2014) | | |
| 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] | .--/.--/.--/.--/.943 | |
| (adapted from Liao et al., 2011) | | |
| 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.

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