Trust in the context of subscription contracts

A case study of interorganizational relationships between a service provider and their customers in Software as a Service contracts

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Abstract

Trust plays an essential role in interorganizational interactions. It reduces uncertainty for parties, ensures long-term relationships, positively influences innovation, product adoption, and serves as a solution to the commitment problem. This work observes trust in the context of a Software as a Service (SaaS) market, where buyers are bound to the supplier by a subscription contract. In a case study of a SaaS service provider and their customers, I apply the Ability, Benevolence, Integrity (ABI) trust framework to illustrate how individual trust dimensions influence the relationship between the customer and the service provider. Empirically, this work contributes to the research on the nuanced effects of trust in interorganizational relationships. First, I use matching and simulation analyses to show that early interactions with customer success teams have an effect on product usage consistent with full mediation by integrity-based trust. Second, I operationalize benevolence-based trust with observational data of customer problems and show that benevolence-based trust increases customer engagement. Third, I use supervised machine learning and explainability methods to illustrate the positive effect of the ABI trust dimensions on customer decisions to extend the contractual relationship – trust being the solution to the commitment problem between a customer and a service provider. Thus, a methodological contribution is achieved with a strategy for machine learning applications in sociological research. Finally, this work derives practical managerial implications for service providers implementing trust-facilitating measures to strengthen their relationships with customers.

Introduction

1.1 Introduction

Interorganizational relationships between suppliers and buyers change as subscription contracts become more and more common (Manu 2017), especially when it comes to software. Such subscription contracts in the software industry are referred to as Software as a Service contracts (Xiao et al. 2020). In these contracts, the software delivery follows an on-demand mode, and the payment is organized as a subscription, i.e., in a pay-as-you-go fashion throughout the contract (Godse and Mulik 2009; Xiao et al. 2020). Software as a Service (SaaS) subscription contracts increase the flexibility for the customers (Xiao et al. 2020). However, they also extend the initial uncertainty regarding product quality that needs to be resolved at the beginning of the contractual relationship to relationship uncertainties when it comes to the reliability of the service provider (supplier) or the assistance to the customer (buyer) in case of issues (Benlian 2009; Marston et al. 2011). From the service provider's perspective, the problem of customer contract termination arises, also referred to as churn (Lariviere and Van den Poel 2005). The uncertainty regarding the consistency of customer actions and future contract continuations presents the commitment problem for the service provider (Venetis and Ghauri 2004; Xiao et al. 2020). These additional uncertainties characteristic of SaaS subscription contracts and the commitment problem are the main focus of this work. I investigate how these uncertainties and the commitment problem can be resolved through different dimensions of trust. Furthermore, I illustrate the representation of individual trust dimensions in the measures taken by a service provider and the role they play when explaining behavioral outcomes in the relationship in a case study of a service provider – SAP SE – and their customers.

The question of uncertainty and its role in market transactions is by no means new in research. Starting with Akerlof (1970), researchers have been studying brand qualities, certifications, and other ways for sellers to assure their prospective buyers of product quality (e.g., Jahn, Schramm, and Spiller 2005; Walker and Johnson 2009). Among suggested solutions to the problem of "the transactions where trust is important" count issuing certifications by institutions, establishing brand names, and providing guarantees (Akerlof 1970:499f).

A common feature of the market transactions discussed in previous research is their one-time character. For instance, the example of buying a car is discussed by Akerlof (1970) as a one-time transaction. In such scenarios, the buyers uncover true information about the quality after the transaction. Regarding the relationship between the seller and the buyer, there is no obligation between the two parties to continue the relationship. For example, after the car is purchased, the buyer is free to use a service center of their choice. At the time of the purchase, the supplier does not rely on future repeated purchases by this customer.

Yet, the markets are in ongoing development, and the recent shift to the subscription economy has changed the format of many transactions (Tzuo and Weisert 2018). Extending the car example, a subscription to a car-sharing service does not make the first experience with the provider matter less. Still, the change in the contract structure establishes a long-term relationship with the service provider and adds uncertainty concerning possible changes in the product (Benlian 2009). Thus, the issue of uncertainty is extended to the entire time frame of the subscription contract. Now, the quality of the product revealed during the first experience with a service provider does not cover all of the uncertainty in the transaction. On the other side of the relationship, the provider of the car-sharing service does not know how long the customer will remain in the contractual relationship.

With the uncertainty remaining a part of the relationship, the customers need a way to estimate what Akerlof refers to as the "trust" component of the transaction (Akerlof 1970:500). The service providers need a way to ensure the repeated actions of customers, i.e., the customer commitment (Becker 1960; Venetis and Ghauri 2004). As various rankings and certifications become standard practice, initial quality uncertainty before the purchase is accounted for (Lansing et al. 2019). This opens a space for research interest in uncertainties at later points in a relationship. Subscription contracts mostly include not only the infrastructure that now belongs to the service provider but also support services, such as providing solutions to customer questions and solving problems (Godse and Mulik 2009). Exactly the uncertainty about such relationship elements becomes important after the initial product quality uncertainty is accounted for.

Investigating the solutions to the uncertainty over the lifecycle of a contract and their relation to the commitment problem is the main interest of this work. I am looking for answers to the following questions: **What behavioral consequences can a service provider's measures targeting uncertainty reduction and formation of individual trust dimensions reach in their customers over the course of the contractual relationship? How does trust affect customer commitment in the renewal phase of the contractual relationship?** I see trust as a mechanism for uncertainty reduction and the solution to the commitment problem and, in particular, look at three dimensions of trust, according to the Ability, Benevolence, Integrity (ABI) trust framework (Mayer, Davis, and Schoorman 1995). I observe integrity-based trust as a mechanism of early-stage uncertainty reduction with respect to the relationship (Pollack, Barr, and Hanson 2017), benevolence-based trust as a mechanism for continuous uncertainty reductions during problem-solving experiences in a subscription contract (McKnight et al. 2011), and all ABI trust dimensions as a mechanism of building customer commitment (Morgan and Hunt 1994).

Thus, I contribute to organizational research with a theoretical extension of the product quality uncertainty and commitment problem concepts to situations when the relationship between the parties turns into part of a product offering (Cusumano 2008). Empirically, I contribute with an evaluation of the effect of the relationship uncertainty prevention measures in explaining customer behavioral outcomes, such as the usage of the product, engagement with the service provider, and terminations of relationships by customers.

Furthermore, a methodological contribution is made in this research through the connection of classical sociological methods and machine learning approaches common in industrial churn research (Hadden et al. 2007; Ullah et al. 2019). With the advanced machine learning methods applied to the question of the commitment problem, this work falls in the category of computational social science. Specifically, in the fourth chapter of this work, I adopt an explainable machine learning method novel for sociology that is gaining importance in industrial data science practice (Slack et al.

2020). In comparing this approach to classical sociological methods, I illustrate how the explainability of machine learning models can be used in sociological studies. Thus, a methodological contribution is made to sociology and the computational social science field, in particular, which opens more space for complex "black box" models in sociological research. In my conclusion, I touch on the necessity of further investigation of the method and contribute to the discussion of how industrial methods can be applied in sociology (McFarland, Lewis, and Goldberg 2016).

Finally, this work presents a case study exemplary for interactions between a seller and buyers in a specific market over a period of several years. Whole population data on interorganizational relationships[1] are seldom available to sociologists[2]. Thus, in addition to the methodological contribution, this work balances the importance of collaboration with the industry suggested by McFarland et al. (2016) and the necessity for sociologists working in computational social science to get closer to industrial practices when analyzing the data available (see McFarland et al. (2016) for an overview of the respective challenges). One further contribution of this work emerges directly from the collaboration with the industry. Namely, I provide the managerial implications and action suggestions to the company, extending their understanding of trust and trust-building mechanisms already present in the setup of the interorganizational relationships. This is an applied contribution showing what elements of the relationship between customers and service providers form intangible relationship value.

I base my work on the Software as a Service market with companies as customers (Business to Business, B2B) as an exemplary market with subscription contracts and multiple interaction points between the customer and the service provider.

[1] All data presented in this work cover the whole population of the interorganizational relationship under the conditions specified in individual chapters. Subsamples are described additionally.

[2] The data availability is also representative of computational social science. This research direction uses datasets that are bigger than the conventional social science data and analytical strategies for such datasets to advance the theoretical development in social sciences (Edelmann et al. 2020). For example, Bail (2014) investigates how culture can be measured with a big data strategy; Salganik (2019) provides an overview of the strategies, including behavioral observation and digital experiments, that are open to social scientists with digital tools. For more information on computational social science and sociology, see Lazer et al. (2020), Edelmann et al. (2020). For more information on machine learning applications in sociology, see Molina and Garip (2019).

1.2 Software as a Service Market

The Software as a Service (SaaS) market of software subscription contracts started to develop in the late 1990s, coming originally from the software outsourcing idea (Benlian and Hess 2011). Before, it was considered too expensive and risky for a company to use software services (Clair 2008; BigCommerce 2021).

In the meanwhile, the market has grown from 5.56 billion US dollars in 2008 to 87 billion US dollars in revenue in 2016 (Forbes and Tata Communications 2021) and 371.4 billion US dollars in 2020 (NCC Group 2021). The SaaS subscription contracts follow the lifecycle of acquisition (signing the contractual agreement), installation and setup (deployment), usage, and renewal (Prabowo, Janssen, and Barjis 2012). I further refer to these parts of the SaaS contract lifecycle as *acquisition phase, deployment phase, usage phase, and renewal phase*. While offering highly standardized products and faster deployment times (KPMG 2016), the SaaS market has opened the doors into software for small and medium enterprises that previously could not afford in-house development teams (Rodrigues, Ruivo, and Oliveira 2014; Haselmann and Vossen 2011). This group of customers is the most interesting one for this research. First, small- and medium-size companies are more likely to implement standard solutions (Haselmann and Vossen 2011), thus, keeping the software part standard when comparing between customers. Second, they are less likely to be bound by other products (e.g., database products) previously purchased from the same provider (Haselmann and Vossen 2011).

Similar to other markets, uncertainties are involved in a Software as a Service purchase. Performance risks and service quality count as the major risks in SaaS purchase (Günther et al. 2001; Marston et al. 2011). One of the major advantages coming with the SaaS purchase is the access to qualified assistance and support personnel (Jayatilaka, Schwarz, and Hirschheim 2003) that is part of the SaaS product offering. This part signals to the customer that a solution will be provided for a quality issue. Thus, the service providers include the promise to minimize the uncertainties with qualified support in the contractual relationship. Nevertheless, until a customer actually faces an issue, the quality of the support services themselves remains unknown. Thus, this additional part of the product is, in fact, a source of further quality uncertainty for the customer over the length of the contractual relationship.

The sellers, in this case, service providers (SPs), are aware of the risks that the buyers take into account when purchasing a SaaS solution (Günther et al. 2001; Haselmann and Vossen 2011). Additional to the customer support offering during the usage phase of the software product, service providers introduce new teams to manage the relationship with the customer from the time of signing the contract (Mehta, Steinman, and Murphy 2016) and before the usage phase of the lifecycle starts, when support teams can react to problems. These teams are frequently called customer success teams (Ulaga 2018; Ulaga, Eggert and Gehring 2020). Their role is to establish a trustful relationship with a customer from the very beginning of the relationship (Mehta et al. 2016). Thus, this is the team that is signaling the reliability of the SP to the customer, especially in the period of time when the uncertainty regarding the product and the reliability of the service provider is the highest.

With customer success teams and customer support service introduced in the discussion, it is necessary to add that there are different customer support and engagement models. Looking at the target group of this work – small and medium companies – makes it possible to refer to standardized engagement programs where the same actions are expected to apply to all customers in the group (Mehta et al. 2016).

The described uncertainties that both customers and service providers face in an interorganizational relationship in the SaaS market and the trust-facilitating measures introduced by the service provider as a solution position trust as an important facilitator of the relationship, central to this work.

1.3 Trust as a Solution to the Commitment Problem

Before starting the discussion of trust within this work, a note on the general concept of trust is necessary. Trust is discussed in many research directions, including psychology (e.g., Rotter 1971), sociology (e.g., Gambetta 1988; Coleman 1994; see Hardin 1992 for an overview), computer sciences (e.g., Huang and Nicol 2013), economics (Zak and Knack 2001), and management (e.g., Williamson 1993). Within these disciplines, multiple perspectives on trust are possible, including but not limited to interpersonal trust (e.g., Wrightsman 1991), institutional trust (North 1990), technical protocol trust (Huang and Nicol 2013), and interorganizational trust (Schoorman, Mayer, and Davis

2007). The latter is discussed in this work. It is certainly possible to accommodate multiple perspectives on trust in the relationship between the customer and the service provider in a SaaS market. However, for conceptual clarity, the interorganizational perspective on trust is in the focus of this work.[3]

As per Akerlof (1970), trust is a necessary condition for a market transaction. Furthermore, Morgan and Hunt (1994) show that trust reduces uncertainty in a relationship and positively influences relationship commitment. Thus, trust is a mediator in explaining the customer's decision to extend or terminate the contract with the service provider in the renewal phase of the SaaS subscription contract lifecycle (Xiao et al. 2020). In the SaaS context, trust creation is the mechanism that an SP attempts to enable with such measures as dedicated customer success and customer support teams (Mehta et al. 2016). Given the complexity of the contractual lifecycle, a more complex concept of trust has to be found for further investigation to distinguish between trust at different stages of the SaaS contract lifecycle.

Namely, such general definitions as "a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another" (Rousseau et al. 1998:395), although established in the literature, do not allow for a precise specification of trust at different points in time in the relationship. Thus, a definition needs to be adopted that covers several dimensions of trust. To achieve such precision, I build my work on the perspective of trust described by Mayer et al. (1995). Their framework provides a breakdown of trust into three dimensions, based on three dimensions of trustworthiness: *ability, integrity, and benevolence*. The corresponding dimensions of trust are *ability-based, benevolence-based, and integrity-based trust*. Researchers adopted these dimensions in organizational (e.g., Baer and Colquitt 2018) and information systems literature, in particular with respect to software products (e.g., Lankton and McKnight 2011; Lansing and Sunyaev 2016), and commonly refer to it as the *ABI framework* (Baer and Colquitt 2018).

Connelly et al. (2018) illustrate the importance of a nuanced perspective of trust with the following example. Suppose trust is seen as a monolithic construct; two suppliers

[3] See Rousseau et al. (1998) for a comparative overview and summary of trust definitions across disciplines.

might seem to have the same level of trustworthiness, but comparing across nuanced dimensions might reveal higher levels in one dimension and lower levels in another. Adopting this approach makes it possible to distinguish between trust at different points in time (Schoorman et al. 2007; Pollack et al. 2017) and also contribute to the research direction that actively uses this framework while maintaining the connection to organizational and software-related trust literature[4].

With the three-dimensional definition of trust and trustworthiness, the distinct role of each of the dimensions in the contractual subscription relationship becomes apparent. My discussion of the three dimensions starts with ability. ***Ability*** is defined as "a group of skills, competencies, and characteristics that enable a party to have influence within some specific domain." (Mayer et al. 1995:717). In software-related trust research, this dimension is described as "the degree to which one anticipates the technology will have the functions or features needed to accomplish one's task(s)" (Lankton and McKnight 2011:35)[5]. Thus, in the context of the relationship between a customer and an SP, ***ability-based trust*** is based on the delivery of technical claims specified in the contract within a time frame specified in a contract (Lin et al. 2011).

In regular one-time market transactions and subscription-based relationships, ability-based trust is the main and necessary condition for a transaction and, therefore, for establishing a relationship with a seller. It solves the initial product quality uncertainty (Lansing and Sunyaev 2016). However, the time dimension of the subscription contracts draws my research focus away from technical ability-based trust – to the trust dimensions that need to be established and maintained during the relationship: integrity-based and benevolence-based trust[6]. Ability-based trust in this context is ensured through a signed contractual relationship between the parties (e.g., Adler 2001; Lui and Ngo 2004). I follow the distinction of ability-based trust as functional and

[4] Another advantage of this definition with respect to trust research in the context of software is that this definition touches on dimensions available in other applied definitions but makes a translation of this work into related trust frameworks possible (McKnight et al. 2011).
[5] This dimension reflects the same qualities as ability, competence, or functionality dimension outlined in software-related trust research (e.g., Muir and Moray 1996; Benbasat and Wang 2005; Eastlick, Lotz, and Warrington 2006; Salo and Karjaluoto 2007).
[6] Ability-based trust, of course, remains a crucial component during the relationship. With it being a necessary condition, a relationship with low ability-based trust will very likely not be initiated in the first place. Thus, assuming that ability-based trust is given when a relationship is initiated, the focus is moving towards the trust dimensions that are open to variation during the relationship.

integrity-based and benevolence-based trust as non-functional (Tams, Thatcher, Craig 2018) and further refer to integrity-based and benevolence-based trust as relationship-based trust dimensions.

Integrity refers to "the set of principles that the trustee finds acceptable" (Mayer et al. 1995:719). Integrity is initially based on an SP's reputation in the absence of own experiences at the beginning of the relationship (Suh and Houston 2010). The process of replacing reputation-based integrity with integrity based on own relationship experiences takes place at the beginning of the relationship. After integrity based on own experiences is formed, its role reduces with meaningful benevolence data being collected (Mayer et al. 1995; Schoorman 2002; Schoorman et al. 2007; Pollack et al. 2017). Within a relationship between a customer and an SP specified in this work, ***integrity-based trust*** relates to the role of the customer success teams responsible for establishing a trustful relationship with a customer before the usage phase of the contractual relationship.

Benevolence is the dimension of trustworthiness based fully on the individual experiences with the trustee (Mayer et al. 1995). In general terms, benevolence describes the expectation that the trustee wants to do good to the customer, independent of the egocentric motives (Mayer et al. 1995:718). This dimension gains importance over time of the relationship (Mayer et al. 1995; Schoorman et al. 2007; Pollack et al. 2017). This distinctive feature of benevolence highlights the contrast between benevolence-based and integrity-based trust, even though both are the dimensions of trust related to the relationship between the parties. In a relationship between SP and the customer, ***benevolence-based trust*** refers to customer support (Alvarez, Vazquez-Casielles, and Diaz Martin 2010) and is based entirely on the customer's experience with the SP.

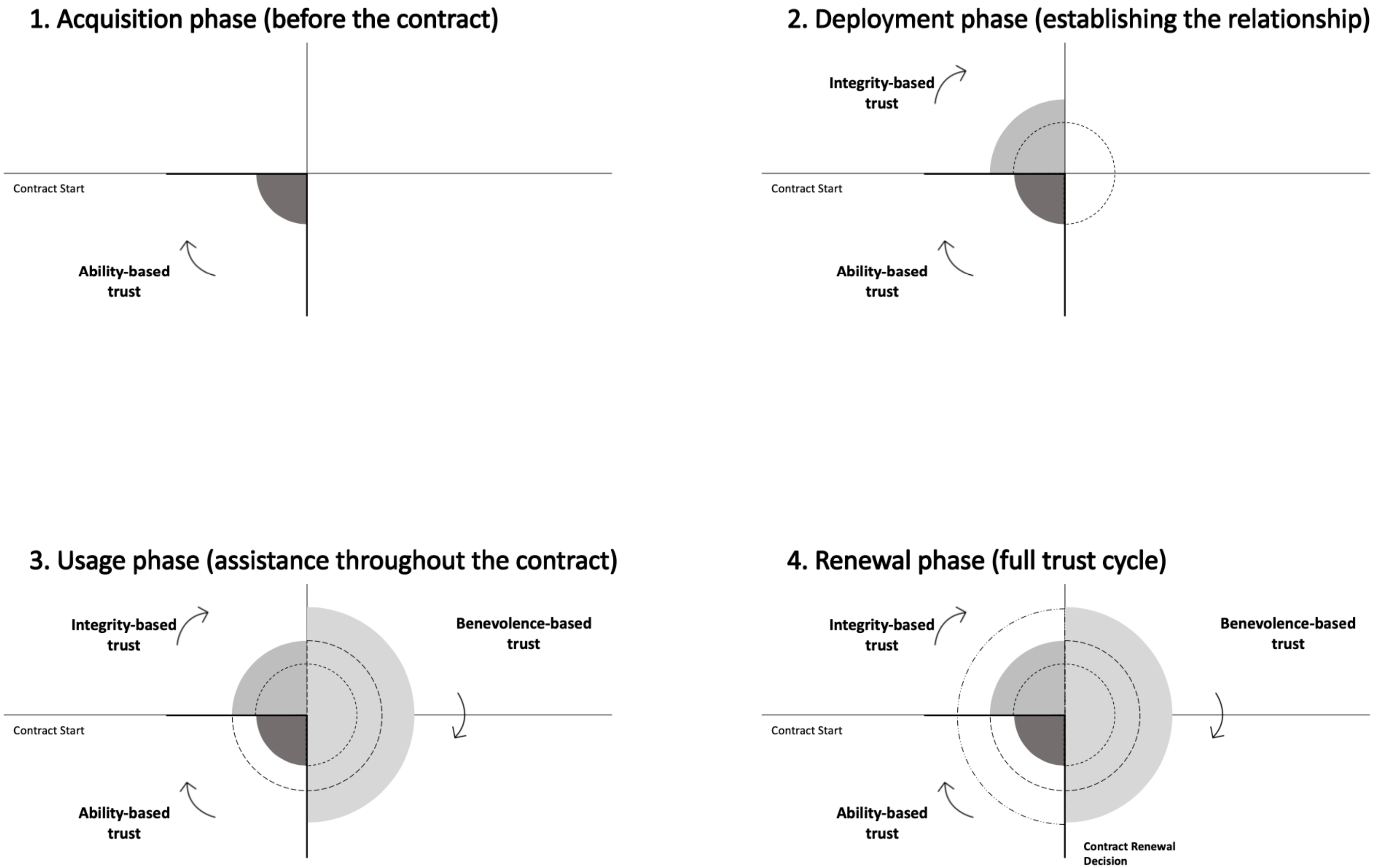
Such a multidimensional view on trust provides detailed insights into the development of trust between two organizations. The multidimensionality of the trust construct allows one to study the dimensions separately, paying more attention to the differences between them. Differences can be found in the way and time when the dimensions are formed (e.g., Pollack et al. 2017) or the independence of their development (e.g., Long and Sitkin 2006; Janowicz-Panjaitan and Krishnan 2009). Shazi, Gillespie, and Steen (2015) illustrate the differences in functions of the three dimensions of trust on the example of interorganizational innovation networks and show the complex relationship between ability-based, benevolence-based, and integrity-based trust and the outcome of trust – tie formation.

Regarding the differences in properties of different trust dimensions, it was shown that integrity-based trust is generalizable across contexts, while ability-based trust is not (Connelly, Miller, and Devers 2012). Not only is the development of the trust dimensions linked to different processes, but the absence of one of the dimensions has been shown to have different effects in different situations. For example, Ferrin et al. (2007) show that perceiving a party as lacking integrity does not negatively affect the evaluation of their ability. Similarly, the importance of the dimensions may vary across relationships. For example, ability-based trust becomes relevant in innovative networks after establishing integrity-based and benevolence-based trust (Shazi et al. 2015). In examples related to contractual relationships, the ability-based trust is the dimension of trust covered by the contract (Adler 2001; Lui and Ngo 2004), while integrity-based and benevolence-based trust are developed later (Pollack et al. 2017). Furthermore, Svare, Gausdal, and Möllering (2020) show that benevolence-based trust is the only trust dimension influencing interorganizational relationships after they were established.

Figure 1.1 illustrates the positions of the three dimensions of trust between an SP and a customer over the lifecycle of the SaaS contractual relationship analyzed in this work, from the acquisition to the renewal phase. The figure is based on the theoretical ABI framework (Mayer et al. 1995; Schoorman et al. 2007) and empirical evidence regarding the individual trust dimensions in interorganizational relationships (e.g., Shazi et al. 2015; Pollack et al. 2017; Svare et al. 2020). It summarizes the theoretical and empirical research on the ABI trust dimensions in interorganizational relationships in general and illustrates the perspective to be analyzed in this work on a case study of a SaaS service provider. The first chart (top left) shows that ability-based trust is necessary even before the relationship is formally established through the contract (acquisition phase). The second chart (top right) shows that integrity-based trust then needs to be established at the beginning of the relationship (deployment phase), while ability-based trust remains a necessary condition for continuing the relationship. In the third chart (bottom left), benevolence-based trust appears starting from the first issue reported to the support service of the SP. Benevolence-based trust plays a vital role over the remaining part of the relationship (usage phase) until the contract is up for renewal (renewal phase). The dotted circles of ability-based and integrity-based trust show that these two dimensions are still necessary for the relationship. However, they are expected to have little variation over the remaining course of the relationship (Schoorman et al. 2007; Pollack et al. 2017). The full trust cycle illustrated in the fourth chart (bottom right) indicates that the dimensions of trust remain important for all following contract cycles, given that the contract was renewed.

As a further general note on trust, it is necessary to discuss its outcomes in interorganizational relationships. Both trust as a holistic concept and its dimensions are reported to have a variety of positive effects on behavioral outcomes (Mayer et al. 1995; Rousseau et al. 1998; Schoorman et al. 2007). For instance, trust positively influences commitment and continuation of relationships (e.g., Morgan and Hunt 1994; Ganesan and Hess 1997; Kumar et al. 2018; Xiao et al. 2020), engagement (e.g., Petzer and van Tonder 2019), loyalty (e.g., Oliver 1999; Kaur and Soch 2018), improves performance in interorganizational collaborations (e.g., Shazi et al. 2015; Svare et al. 2020), and positively influences behavioral outcomes in customers, for example, usage and adoption of software products (e.g., Burton-Jones and Straub 2006; Asadi et al. 2017). This work focuses on the customer behavioral outcomes of individual trust dimensions that can be observed within the contractual lifecycle, i.e., product usage and engagement, and in the renewal phase of the contractual lifecycle, i.e., customer commitment or the termination of the relationship. While both direct and indirect effects of trust-facilitating measures on behavioral outcomes are possible (Lankton and McKnight 2011), this work's focus is limited to the effects under the assumption of full mediation by trust.

Figure 1.1. Trust in a relationship between SaaS Service Provider and a customer, the lifecycle until the first renewal



1.4 Case Study

An essential characteristic of SaaS contracts is the relationship between the customer and the service provider that is maintained over a long period of time (Venetis and Ghauri 2004). This increases the importance of trust when it comes to the extension of the contractual relationship in the renewal phase of the lifecycle – customer commitment. Furthermore, it makes integrity-based trust at the beginning of a relationship and benevolence-based trust during the relationship important from a subscription perspective.

Thus, to analyze the formation and effects of trust in a Software as a Service contractual relationship, I am looking for an organization that, in its contracts, serves as an example of the described scenario of subscription relationships with customers. Furthermore, the organization should fit the two criteria relevant for establishing and maintaining a trustful relationship with the customers: a customer success team and product support services. With many companies fitting this description, an additional requirement is for the company to offer standard products and standardized customer success and support solutions. This is necessary to ensure the comparability of the measures intended to establish and maintain a trustful relationship with the customer.

The data provided for this work come from an organization exactly fitting the description above. SAP SE is a global software producer (SP in the described setting) whose travel and expense management product provides the basis for my case. With over 20000[7] active small and medium customers, the product is widely used in the US market and worldwide. The software product has been sold for over 6 years, which allows building a dataset of an extended timeframe to observe the actions directed at establishing trustful relationships with customers, the support cases over time, and the behavioral outcomes. Furthermore, the customer success teams have been operating for a long enough time to see the effects on behavioral outcomes. Detailed information about the customers is available. Finally, whole population data on customers with various dimensions of the relationship are available.

[7] Due to confidentiality reasons, no exact numbers can be published in this work.

One further advantage of the SaaS market case study is the amount of data the operating model of such companies makes available. It was highlighted by researchers that new data sources make it possible to work on data coming from applications and similar digital sources (Edelmann et al. 2020). This opportunity opens sociological research to amounts of data that were previously only available in rare cases. The new data also open the research to a wide range of methodological solutions, including machine learning techniques that are currently earning their place in the sociological methods toolkit (Molina and Garip 2019).

Summing up, SAP SE represents an SP of the discussed market with implemented measures directed at establishing trust in the relationship with the customer and support for the software being part of its product offering. The company's customers represent the customers from the theoretical market, facing first the initial quality uncertainty and then the relationship quality uncertainty regarding the support services during their contractual relationship with SAP SE. The customers are looking for validation of the SP's reliability and refer to their experiences with the customer success and the support for building integrity-based and benevolence-based trust over the course of the relationship.

From the perspective of an SP, the questions outlined in the theoretical section require a more specific, practical formulation: Does the trust-facilitating measure of customer success teams help to build integrity-based trust and positively affect customer usage behavior at the beginning of the usage phase? What is the effect of benevolence-based trust built through support services on customer engagement? How do measures related to uncertainty reduction help a service provider to preserve a long-term relationship with a customer and ensure customer commitment when it comes to customer contract extensions and terminations? These are the practical questions to be answered in this work, starting with the very beginning of the relationship and moving further towards the behavioral outcomes in the renewal phase. These questions are covered by the managerial implication sections of this dissertation.

1.5 Dissertation Outlook

The structure of this dissertation follows the topics outlined in this chapter. In the first empirical part (second chapter), I look at the beginning of the relationship and how interactions with the service provider help to reduce uncertainty and build integrity-based trust in relationship experiences at the beginning of the contractual relationship. In the second empirical part (third chapter), I look at the problem-solving activities during the usage phase to investigate how benevolence-based trust measured through problem-solving support experiences relates to customer engagement. Finally, in the third empirical part (fourth chapter), I look at how a service provider's solutions to uncertainty reduction solve the commitment problem, i.e., how trust affects behavioral outcomes in the relationship with a customer — customer contract extensions and customer churn. Further in this subsection, I summarize the individual chapters with theoretical assumptions, methodological strategies, and findings.

1.5.1. Integrity-based Trust in Customer Success

After a customer establishes a relationship with the service provider (SP) by signing a contract, the elements of the ability-based trust are covered by the contents of the contract (Lui and Ngo 2004). The next dimension of trust that has to be covered is integrity-based trust. The SP needs to establish a relationship and communicate the organization's principles to the customer (Pollack et al. 2017). This step is accomplished by customer success teams. I refer to integrity-based trust in the second chapter of my dissertation, where the main question is the role of customer success team activities as a service provider's measure in the integrity-based trust formation and resulting behavioral outcomes.

The major theoretical argument of the second chapter draws on the research investigating the antecedents of trust in relationships between customers and service providers (Chen and Dhillon 2003; Doney, Barry, and Abratt 2007). While most of this research focuses on individual consumers, I translate the previously demonstrated mechanism to the Business to Business (B2B) environment. I argue that the initial interactions with the customer success teams are a way of establishing integrity-based trust that leads to positive behavioral outcomes on customer's product usage.

To ensure that all customers have not had previous experiences with the service provider, I focus specifically on new customers in their first months in the contract before the active usage phase. In this scenario, interactions with customer success teams are considered the treatment. I see integrity-based trust as the direct outcome of the treatment and the mediator in the relationship between the treatment and the behavioral outcome (product usage in the first month of the usage phase). In the absence of a dedicated trust survey, I turn to simulation techniques to demonstrate the possible ranges of effects of customer success communication under the theoretical conditions of trust. I apply nearest neighbor matching for effect estimation and compare the simulated effect distributions to the observed effects.

I find a short-term effect of interactions with customer success teams on customer product usage. This effect is visible in the first month of the usage period and then declines. This finding corresponds to the theoretically expected effects in the presence of integrity-based trust as a mediator in the relationship. Thus, I conclude that observing the actions of customer success teams at the beginning of a contractual relationship reveals an effect on customer usage behavior. This effect is consistent with the presence of integrity-based trust.

1.5.2 Benevolence-based Trust in Customer Support

Benevolence-based trust as the helpfulness-related dimension of trust follows ability-based and integrity-based trust in the timeline of trust formation (Schoorman et al. 2007; Pollack et al. 2017). This dimension is at the center of the third chapter. In a relationship between a service provider and a customer, benevolence-based trust can be found in the support offered to the customer by customer support teams (Alvarez et al. 2010). In this chapter, I investigate the effects of benevolence-based trust on engagement with the service provider during the usage phase of the SaaS contract lifecycle and the effects of benevolence-based trust on customer decision to extend or terminate a contractual relationship in the renewal phase of the SaaS contract lifecycle.

The theoretical background of this chapter is constructed, on the one hand, from organizational research on benevolence and benevolence-based trust in interorganizational relationships (Mayer et al. 1995; Schoorman et al. 2007; Svare et al.

2020). On the other hand, I turn to the research on customer support and its impact on the relationship between service providers and customers (Coffelt 2013). I see customer support teams as the source of benevolence-based trust in the relationship with customers through solving customer problems. The benevolence-based trust built this way is expected to have a positive effect on customer engagement with the service provider (Petzer and van Tonder 2019; Chung et al. 2020) and a positive effect on customer contract extensions (Venetis and Ghauri 2004).

I work with observational data of recorded customer support cases to build the measurements of benevolence-based trust based on customer problems. To capture the perception of problems from the individual perspective of each customer (within-customer problem space), I use the measure of modularity, i.e., how concentrated the customer problems are around the same keywords. Looking at the problems in the context of all customer problems (between-customer problem space), I measure benevolence-based trust as the maximal coherence of all customer problems, i.e., the maximal probability of the problems to belong to the same latent topic derived with a Latent Dirichlet Allocation (LDA) topic model. I fit logistic regression models to estimate the effects of benevolence-based trust on participation in Net Promoter Score (NPS) surveys and use two-sided t-tests for the first investigation of the effect of benevolence-based trust on contract extensions.

The findings support the theoretical expectations regarding the effects of both measures on the engagement of customers within the usage phase of the lifecycle and customer decisions on contract extensions during the renewal phase. Thus, benevolence-based trust contributes to the SaaS contractual relationship through increased customer engagement.

1.5.3 Commitment Problem of Customer Contract Terminations

Having discussed the relationship trust dimensions, in the fourth chapter, I investigate the role that ability-based, benevolence-based, and integrity-based trust play in the commitment problem and the behavioral outcome for customers in the renewal phase of the subscription contract. In practical terms, this chapter investigates how the measures applied in the previous chapters can be used to explain if customers extend their contracts or not.

The theoretical background for this chapter comes back to the initial question of trust being a solution to the uncertainty in the relationship and the commitment problem (Morgan and Hunt 1994). Thus, all trust dimensions are expected to influence customer contract extensions positively (e.g., Morgan and Hunt 1994; Ganesan and Hess 1997). According to the ABI framework, ability-based trust is expected to have the strongest effect on the outcomes of trust in the relationship, compared to both integrity-based and benevolence-based trust (Mayer et al. 1995). Among benevolence-based and integrity-based trust, the first is expected to grow in importance over time, while its overall effect is smaller than the effect of integrity-based trust at the beginning (Mayer et al. 1995).

The focus of the work is on the relationship between customers and service providers in the SaaS market. The fourth chapter is closely related to the industrial churn research, studying the predictive possibilities for customer contract terminations (Chen, Fan, and Sun 2012). Given the availability of the data, I turn to the potentials of industrial methods and develop a methodological strategy that combines a classical sociological approach of logistic regressions with machine learning and explainable machine learning methods. This opens the possibility of more detailed modeling of the relationship between trust variables and the outcome.

I use the measures developed in chapters two and three for integrity-based and benevolence-based trust and operationalize ability-based trust through product usage to explain the outcome of interest – customer contract extension or termination. In the first step, I fit multiple logistic regression models and find that all trust dimensions contribute negatively to customer terminations, supporting the theoretical assumption of a positive effect of trust on commitment. I further train multiple machine learning models – logistic regression, decision tree, random forest, and XGBoost – to predict the outcome of interest. To explain the model predictions, I use the SHapley Additive exPlanations (SHAP) to generate the unit-level additive decomposition of the predicted probability. A deep dive into the performance of the models shows that the logistic regression demonstrates a slightly weaker performance in predictions when compared to the random forest and XGBoost models. However, the two best-performing models have differences in modeling the outcome, indicating potentially different ways to interpret the results. A deep dive in the models with feature importances and SHAP values shows that in the best-performing random forest model the importance of ability-based trust is highest among all trust dimensions, followed by benevolence-based and integrity-based trust. This finding supports the theoretically hypothesized relationship. In other models, benevolence-based trust shows higher importance than ability-based trust.

Building trust at the beginning of the relationship

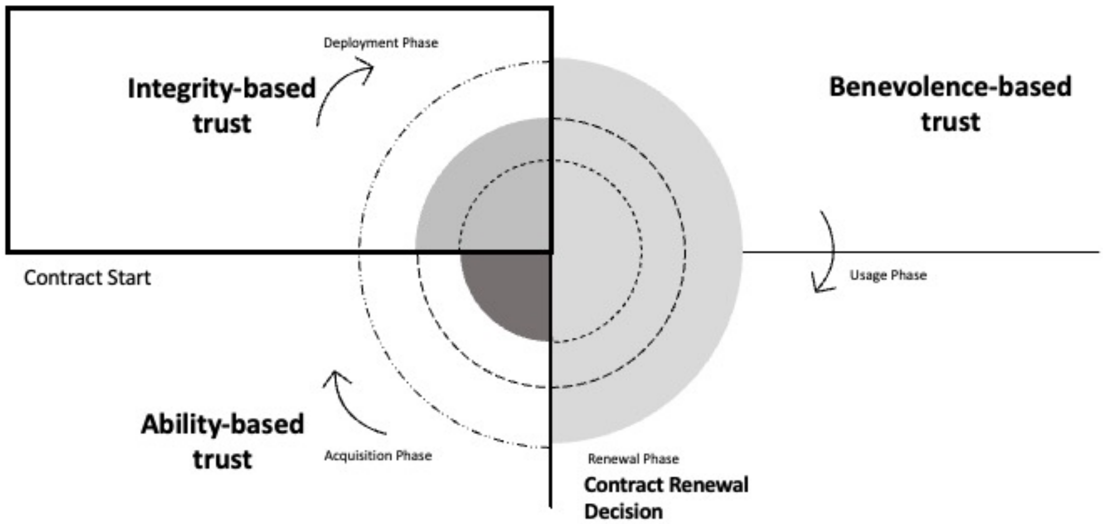
An investigation of how Customer Success Teams influence early trust development

With variations in uncertainty, different forms of trust come to importance at different times in a subscription relationship with a customer (Schoorman et al. 2007). The ABI (Ability, Benevolence, Integrity) trust framework provides a nuanced representation of trust, making it possible to understand how individual dimensions of trust form within a relationship and their roles when explaining behavioral outcomes (Mayer et al. 1995; Schoorman et al. 2007).

Integrity-based trust investigated in this study is formed and has the most substantial effect at the beginning of the Software as a Service (SaaS) contractual relationship with a customer (Mayer et al. 1995; Pollack et al. 2017). Its position in the deployment phase of the SaaS contract lifecycle is illustrated in figure 2.1. By the time the formation of integrity-based trust with own experiences begins, the relationship with the customer is already arranged in a contract, i.e., the acquisition phase is already finished. The ability-based trust, therefore, is secured through contractual obligations (Lui and Ngo 2004). Benevolence-based trust, however, could not be formed yet[8] (Mayer et al. 1995). It is a point in the relationship when relationship-based trust complements the contract-based governance (e.g., Ring and Van de Ven 1992; Puranam and Vanneste 2009).

[8] Figure 2.1 illustrates the periods in the relationship that are most important for the formation of ABI-based trust dimensions. While the figure highlights the differences between the dimensions of trust, the trust dimensions formed earlier need to be present for further trust dimensions to be formed. This fact is indicated by the dashed lines.

Figure 2.1.: Position of integrity-based trust in a relationship between a SP and a customer



Following the suggestion by Baer and Colquitt (2018), the main goal of this study is not to provide a previously unknown conceptualization of trustworthiness but rather place the already described antecedents of integrity-based trust in a very specific concept – this of a Software as a Service contract. I focus on the teams dedicated to establishing the relationship with the customer after the contract has been signed – the customer success teams (CST) (Ulaga et al. 2020). These teams are seen in their job descriptions and the customer success practitioner literature as responsible for forming a trustful customer relationship (Mehta et al. 2016). This study investigates what behavioral consequences a service provider's measures targeting uncertainty reduction reach in their customers when it comes to measures forming integrity-based trust. In practical terms, this study aims to show whether CST help to build integrity-based trust early in the contractual relationship and what effects the CST achieve on customer usage behavior at the beginning of the usage phase.

The interactions of customer success teams with customers in the time before the usage phase of the SaaS contract lifecycle are seen as treatment and no contact with the CST as the control condition. This allows one to understand the effects of their trust-forming activities on behavioral outcomes in customers who were contacted at an early stage in a contract. I test the effects of CST actions at the beginning of a relationship between the customer and the service provider on the customer product usage in the first month and over the first 6 months of the usage phase. I compare the observed effects of CST communication to the simulated effects under conditions previously observed in research (Doney et al. 2007; Casalo, Flavian, and Guinaliu 2007) and find an effect on customer usage behavior in the first month of the usage phase. The customers contacted by CST early in their contracts show higher product utilization rates than the customers who had no early interactions with CST. This effect is visible in the first month of the usage phase and declines over the first six months of the usage phase. This finding corresponds to the theoretical representation of integrity-based trust (Schoorman et al. 2007; Shazi et al. 2015). Thus, I conclude that observing the actions of CST at the beginning of a contractual relationship reveals an effect on customer usage behavior that is consistent with integrity-based trust being generated by CST.

This study contributes to the overall empirical trust research and the ABI trust research in particular. While extending the previous research to the Software as a Service subscription contracts, this study contributes to the emerging field investigating the role of customer success teams in establishing relationships with customers (Ulaga et al. 2020). Finally, a practical contribution regarding the optimization of CST actions is discussed in the managerial implications of the study.

This chapter is structured as follows. I start with the theoretical background on integrity-based trust and derive the expectations for further analysis. Next, the data and the methodological strategy are presented. Then, the results of the analysis are presented, followed by the managerial implications and the discussion.

2.1. Integrity-based trust facilitated by Customer Success Teams

The integrity dimension of trustworthiness is usually defined as the "belief that the trustee adheres to a set of principles that the trustor finds acceptable" (Mayer et al. 1995:719). Integrity-based trust is the trust dimension based on integrity. This definition works in interpersonal and interorganizational settings (McEvily and Zaheer 2006) and is widely accepted by researchers (Baer and Colquitt 2018). When applied to an interorganizational relationship, integrity-based trust is the trust dimension based on a company, for example, a customer, expecting the fulfillment of agreements from another company, for example, a supplier (Schoorman et al. 2007:345).

According to the theoretical description of integrity-based trust (Mayer et al. 1995), this dimension is formed relatively quickly at the beginning of the relationship, before the trustor has enough information to form benevolence-based trust (Mayer et al. 1995: 722; Schoorman et al. 2007: 346). In the setting of this study, a subscription relationship and, consequently, an image of trust at different phases of the SaaS contractual relationship places the three dimensions of trustworthiness, and trust dimensions based on them, at different points in the subscription relationship[9]. As previously mentioned, in the Software as a Service (SaaS) environments, ability-based trust, supported by a contract, is necessary for establishing a relationship in the acquisition phase of the contract lifecycle. A customer will compare multiple service providers (SPs) first, evaluating their ability to provide a functioning product (Bushey, Demoulin, and McLelland 2015; Kanwal et al. 2015; Manuel 2015). In some cases, the contracts also follow standards (European Commission 2014). In one-time transactions, the relationship would end at this point, with ability-based trust being the key trust dimension.

However, in subscription relationships, a part of the relationship is service- (or knowledge-) based (Lansing and Sunyaev 2016). Here, a supplier's usual goal of creating a strong relationship with customers (Cravens 1995; Smith 1998) gains even more importance (Morgan and Hunt 1994, Benlian, Koufaris, and Hess 2011) and turns into a competitive advantage (e.g., Nyaga and Wipple 2011)[10]. This process brings this study's attention to the dimension of trust to be created directly after the ability-based dimension is secured and the contract is signed (Mayer et al. 1995; Schoorman et al. 2007). The basis for integrity-based trust can be found in the perception of the customer that the service provider will hold up to their promises (Lankton and McKnight 2011). Pursuing the goal of creating a solid relationship, a supplier would turn to measures, signaling trustworthiness to the customers – trust-facilitating measures.

[9] A more detailed representation of the placement of the three dimensions of the ABI framework and their effects over time has been discussed in the introduction.
[10] The outcome of competitive advantage can be seen as customer commitment. This point is discussed in more detail in the fourth chapter of this work.

In a broad sense, antecedents of trust often include qualities like fairness, consistency, or discreetness, as researched, e.g., by Butler (1991). In the old world of one-time contracts where the buyer received goods and not services, such actions as certifications (e.g., Anderson et al. 1999; Walker and Johnson 2009; Lansing et al. 2019) and rankings (e.g., Itani et al. 2014) could be considered examples of trust-facilitating measures. However, these measures are directed at the ability-based trust that has already formed with signing the contract (Liu and Ngo 2004). More recent studies pay closer attention to SaaS-specific antecedents of trust, including security of IT artifacts (e.g., Lansing and Sunyaev 2016), as well as relationship-based antecedents, such as interactions with representatives of the supplier (e.g., Doney and Cannon 1997; Chen and Dhillon 2003; Miyamoto and Rexhta 2004), open communication (e.g., Anderson and Narus 1990; Rodriguez and Wilson 2002), customer orientation (e.g., Anderson and Weitz 1989)[11].

Of particular interest to this study are the measures taken by service providers: the introduction of customer success teams. Customer Success is referred to as relationship-focused client management, in which the goals of the service provider and the customers are aligned for mutual benefit (Gainsight 2019; Ulaga et al. 2020:368). The main task of such teams is to establish a trustful relationship with a customer after the customer has purchased the product, as is presented in the customer success practitioner literature (e.g., Mehta et al. 2016; Ulaga et al.2020; Gelb et al. 2020).

After the acquisition phase of the SaaS contract lifecycle is completed[12], the sales department will hand over the details to the customer success team, which will work on establishing a relationship with the customer[13]. While the customer success practitioner literature openly communicates that creating customer success teams leads to forming

[11] There seems to be no consensus on whether the antecedents of trust should be directed at an individual dimension of trust. Thus, many studies that describe the ABI dimensions of trust treat it as an aggregated construct in the empirical analysis (e.g., Doney et al. 2007). The ones that distinguish between different dimensions of trust in path diagrams have all antecedents of trust linked to all dimensions of trust (Chen and Dhillon 2003). Thus, I argue that while antecedents of trust can be directed at all trust dimensions, the isolation of integrity-based trust within the context of this study allows seeing them as antecedents of integrity-based trust.

[12] One might argue that the sales department is the primary connection to the company responsible for establishing the relationship before the customer has signed a contract. However, the compensation structure for Sales employees is partially based on the revenue generated by the employee or an organizational unit (Madhani 2009), not on the longevity of the relationship with a customer. Thus, there is not always an incentive for the Sales employees to establish a relationship with the customer outside of negotiating the purchase details. Ryals and Rogers (2005) emphasize the importance of different sales compensation plans and highlight the downsides of variable pay structures.

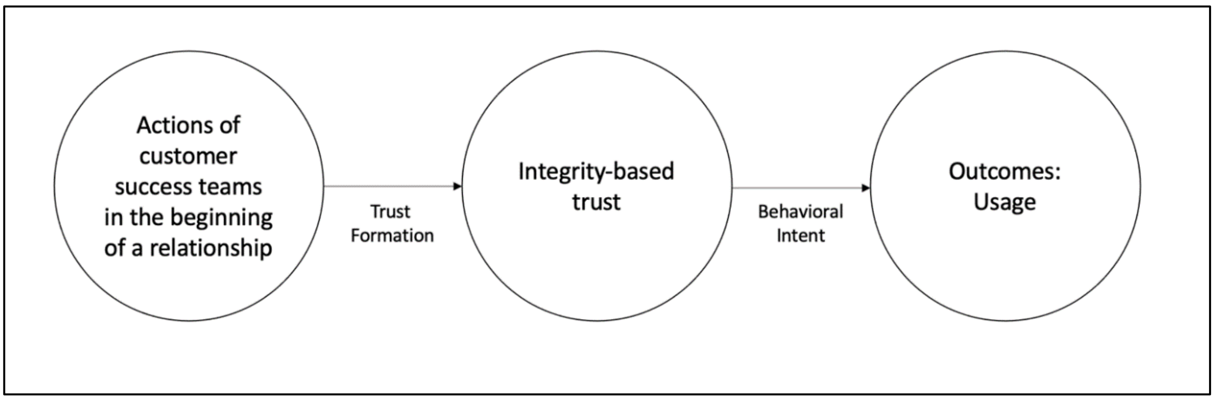
[13] For an example of such a handover document, see Front (2021).

a trustful relationship with the customer (Mehta et al. 2016)[14], there is little specific research dedicated to the effects of these teams (Ulaga et al. 2020). Thus, although contributing primarily to the empirical trust research, this study also contributes to the investigation of the growing role of customer success teams.

While the term customer success team might be new, the word network presented by Ulaga et al. (2020) illustrate a direct connection of customer success job descriptions to the discussed antecedents of trust. For instance, among many general concepts, the network includes words like *on-board*, *contact,* or *meeting* (Ulaga et al. 2020:365), and another Gainsight (2019) description of customer success presented in the paper refers to customer success as "relationship-focused client management" (Ulaga et al. 2020:368). These points come close to the antecedents of trust described above – social interactions with the customers (e.g., Doney and Cannon 1997; Chen and Dhillon 2003; Miyamoto and Rexhta 2004), participation (Casalo et al. 2007).

I place the already studied antecedents of trust in a particular context of a SaaS contract with customer success teams stepping in the relationship at the time of formation of integrity-based trust (Mayer et al. 1995; Schoorman et al. 2007; Pollack et al. 2017) and operating with the measures studied as antecedents of trust. With trust being the function of perceived trustworthiness (Mayer et al. 1995; Möllering 2006), this represents the first link of the mechanism illustrated in figure 2.2.

Figure 2.2.: The mechanism of integrity-based trust formation in the context of a relationship between a SaaS SP and a customer



[14] The practitioner's literature can be extended by the following resources: Bartolacci (2017); Morris (2021).

I already mentioned the assumption of the complementary to contractual agreements role of integrity-based trust applied in this paper. Knowing about the trust-facilitating measures taken by suppliers and, in this case, service providers to create a strong relationship with a customer, the next step is to ask why these measures and overall creating trust beyond the contractual agreement matters in the context of an interorganizational relationship. This question is answered by adding a second link to figure 2.2. This link represents the outcomes of trust. In the following paragraphs, the various meanings of outcomes are discussed.

In their theoretical work on the ABI trust framework, Mayer et al. (1995) put the outcome of trust in a general combined form as risk-taking in a relationship. In the context of a Software as a Service market and subscription contract, risk-taking in the relationship can be interpreted in general as the continuation of the relationship with the software provider[15]. Nevertheless, when breaking the trust concept down into multiple dimensions, the research shows a more detailed picture of possible outcomes of trust, i.e., tie formation (Shazi et al. 2015), increased usage (McKnight 2005), increased likelihood of future deals (Doney and Cannon 1997). These outcomes of trust represent why a strong relationship with a customer is of interest to the supplier (Doney et al. 2007).

Integrity-based trust has been shown to have several positive effects in interorganizational relationships. Integrity-based trust is expected to positively affect tie formation and, in general, is associated with positive performance in innovation networks (e.g., Shazi et al. 2015; Svare et al. 2020). It has also been shown to have positive effects on the success of interorganizational relationships (e.g., Woolthuis, Hillebrand, and Nooteboom 2005; Gulati and Nickerson 2008). In the Software as a Service setting, trust is described as a predictor of usage intentions and usage (McKnight 2005; Lansing and Sunyaev 2016). The term usage can include a broader usage of the product, including, e.g., adoption of more features (Burton-Jones and Straub 2006; McKnight et al. 2011).

[15] This general outcome of trust will be covered in chapter four of this dissertation.

Transferring these findings to the Software as a Service subscription contract, one would expect that integrity is communicated to the customer through the customer success teams. Through this action, integrity-based trust is formed (first link in the theoretical mechanism illustrated in figure 2.2). Integrity-based trust, in turn, positively affects a customer's software product usage (second link in the theoretical mechanism illustrated in figure 2.2). This forms the first expectation of this chapter:

Expectation 1.1: *Early contact actions of customer success teams positively affect the usage behavior of a customer in the first months of the usage phase through trust, i.e., the customers are expected to use more of the purchased product.*

The effect of trust on usage behavior is discussed in research without a restriction on time. On the one hand, when turning to research about the long-term effects of trust, research on repairing trust takes the stage (e.g., Bell, Oppenheimer, and Bastien 2002). This discovery emphasizes the dynamic nature of trust and the need for continuous work from both parties. On the other hand, while looking back at the theory of integrity-based trust, this statement provides insights into the effect behavior over time: "The effect of integrity on trust will be most salient early in the relationship prior to the development of meaningful benevolence data." (Mayer et al. 1995:722). Under the assumption of full mediation through trust, the effect of integrity-based trust is also expected to decline in the usage phase of the relationship when benevolence-based trust is formed. Thus, while a long-term effect of integrity-based trust seems possible, I argue that it will decline over time and eventually disappear with increasing time.

Expectation 1.2: *Early contact actions of customer success teams do not have a long-term effect on customer usage behavior, i.e., there will be no difference between the relative usage of the product of customers, independent of early customer success teams' actions.*

Summing up, integrity-based trust as a trust dimension develops independently of ability-based and benevolence-based trust at the beginning of a relationship with a service provider (Mayer et al. 1995). This dimension focuses on the qualities of the service provider and their predisposition to keep the promise communicated to the customer by customer success teams. Service providers use activities of such teams at the beginning of a relationship to increase a customer's integrity-based trust in a company (Mehta et al. 2016). Integrity-based trust is expected to have positive behavioral outcomes, i.e., a positive effect on customer product usage. In the next section, I cover the data used and the methodological setup of the study.

2.2. Data and Methods

2.2.1. Data

I use the data provided by SAP SE[16], the service provider of a software product, to investigate the mechanisms discussed in the theoretical part. The data used in this study covers information on close to 8000[17] customers over the time period between January 2018 and August 2019[18]. The majority of the accounts in the sample are small and medium businesses (SMB), i.e., enterprises with 1500 employees or less (US Small Business Administration 2019)[19]. All of the customers have started their contracts with the service provider in the time period under observation. In the analysis, I focus on small and medium customers and exclude customers with over 1500 employees. An exception is made for the sample of big customers classified internally as an SMB. These customers are analyzed separately to observe potentially different effects for big enterprises within the same engagement concept.

Speaking of the customer success teams (CST) – their actions are tracked by a system where employees enter their points of contact with the customer. These points of contact range between emails, calls, virtual, and online meetings. On average, a customer is contacted 5 times over the time in the contract. Big customers are contacted 2 times more often than small and medium enterprises. For small and medium customers, calls and emails are a more frequent mode of communication, while calls and meetings are more frequently chosen to communicate with big customers. The outcome measure in this study is the measure of product utilization – the ratio of used licenses out of licenses agreed upon in the contract. For example, if a customer contract

[16] For a detailed overview of the case company and data, see the introduction section.
[17] For confidentiality reasons, no exact numbers can be published in this work.
[18] The end of the time period is defined by the time when the market was affected by covid-19 (Curley et al. 2020). Due to the change in the market, the period of contracts starting after August 2019 will be excluded from the general analysis, as the product usage data there are likely to originate from the early months of the covid-19 pandemic.
[19] With worldwide standards varying on the definition of an SMB (Ayyagari, Beck, and Demirguc-Kunt 2007) and the US standards that range from 250 to 1500 employees based on industry (US Small Business Administration 2019), I consider 1500 employees as a general threshold when combined with the internal classification of the company as SMB by the service provider.

is agreed for 1000 licenses and the customer has utilized 100 licenses in a month, the product utilization measure will be 0.1. If 1000 licenses have been utilized, the product utilization measure will be 1.0. The data is available monthly for the average amount of utilized licenses in a particular month in contract. The data are standardized before the analysis for easier comparability of the results and to include coefficients derived from previous studies in the analysis.

After cleaning the data, the resulting dataset includes over 8000 customers with on average under 500 employees, starting their active utilization in the 3rd month of their contract and having started their contracts in the middle of 2018[20].

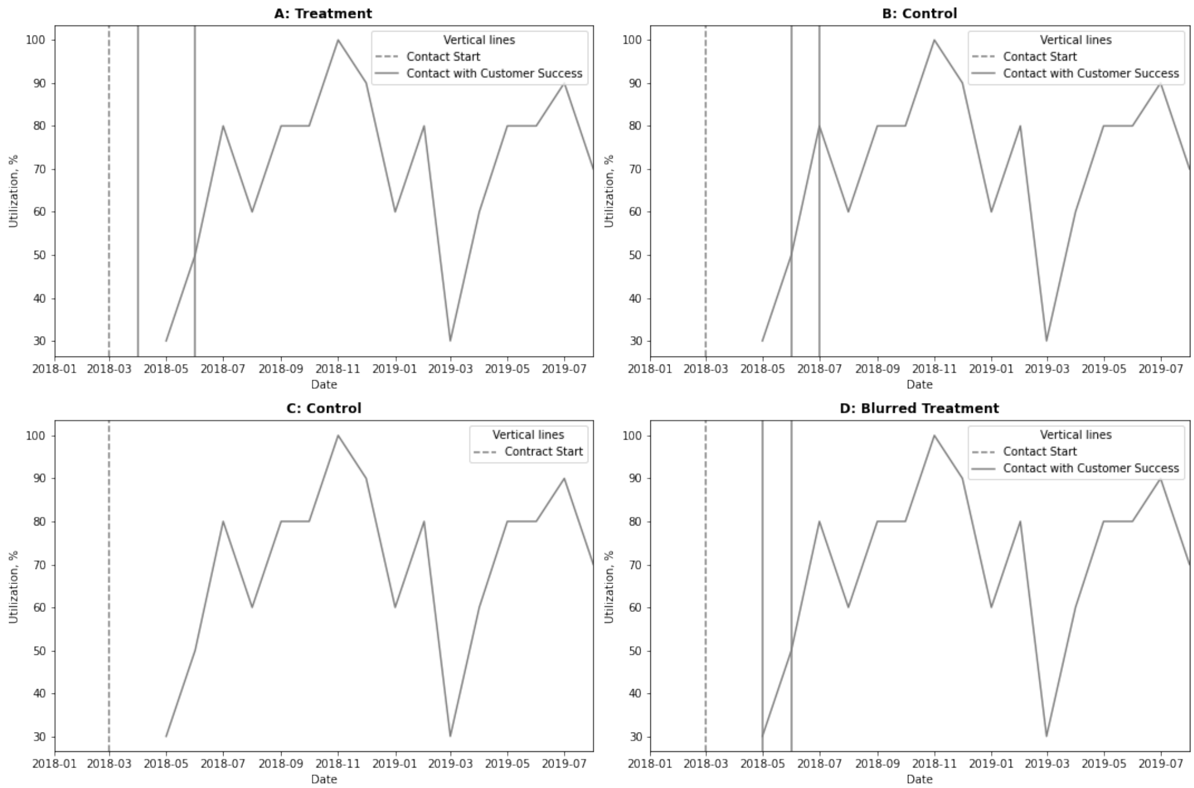
2.2.2. Methods

2.2.2.1 Treatment effect estimation in the observed data

Customer success teams contact the customers at the beginning of the contract, i.e., after the acquisition phase is finalized and the contract is signed. Cases in which this contact happens before the usage phase has started are of interest to this paper as an operationalization of integrity-facilitating activities of a service provider. In the customer base with contacts starting between January 2018 and August 2019[21], there is a total of over 40% of such cases for new customers. I consider cases with up to 3 months of no usage period and the activities within this time period[22]. Figure 2.3 provides four examples of contractual relationships. The graph indicates the utilization levels within the usage phase, the dashed line indicates the beginning of a contractual relationship (the signing of the contract), and the vertical solid lines stand for the timepoints of contact by a customer success team.

[20] For confidentiality reasons, no exact numbers can be published in this work.
[21] I use the data until August 2019, as I use 6 months of usage data after the contract start to evaluate the long-term effects. As for customers with contracts starting after August 2019, 6 months of the usage period overlap with the covid-19 pandemic, they are excluded due to the effect of the pandemic on business travel, as travel expenses are the key business use case of the SaaS product under investigation (Curley et al. 2020).
[22] I use three months as a threshold because the deployment phase for this product on average takes up to 3 months, and usage, on average, starts after 3-4 months from the contract start. The analysis using a threshold of 4 months was conducted and did not indicate any potential differences in the results of this study. While there are cases that take longer for customers to start active utilization, I consider them exceptions, in which case contact by the customer success teams can have other reasons.

Figure 2.3.: Timeline of contract start, interactions with customer success teams and product usage in treatment and control groups



In part A of the figure, a relationship in the ideal treatment case is presented. The contact by the customer success teams takes place before the usage phase starts. Here, the temporal order between the product usage behavior in the next month and the actions of the CST can be established. Part B of the figure presents a case when the contact by the CST happens after the usage phase has started. In this case, as also in part C (no contact by customer success teams), the customer is in the control group – as no contact with the CST happened before the usage phase has started. Part D of figure 2.3 represents a case of "blurred" treatment. In this case, the contact with the CST happens in the same month as the beginning of the usage phase. Since the temporal order between the contact and the usage phase cannot be established in this scenario, I remove such cases (total 9%) from the analysis[23].

[23] Additional analysis conducted when including the cases of blurred treatment in the data shows more pronounced effects than reported in this study. Thus, taking out the "blurred" treatment cases provides more conservative results. The findings for the blurred treatment are in appendix A.2.2.

For the operationalization of product usage, I use the utilization measure – the ratio of utilized licenses to the total number of licenses purchased. Ratios of more than 1.0 are rounded down so that the maximum possible utilization is not exceeded. In the specific setting of this study, the effect of early contact by the customer success teams on product usage will be studied. For short-term outcomes (Expectation 1.1), I use the utilization measure in the first month of the usage phase in the contractual relationship. For long-term outcomes (Expectation 1.2), I use the outcomes in each of the first 6 months after the beginning of the usage phase.

The analysis is conducted in two samples – the general sample, which includes a full sample of accounts of small and medium businesses under normal conditions, and the big accounts sample. This sample includes a total of over 500 customers that do not qualify to be put under the definition of small and medium businesses due to the company size but are classified as SMB engagement model in the data. These companies have more than 1500 employees. It is interesting to observe this sample separately since it allows a bridge to potential effects in big enterprises[24].

For effect estimation, I apply nearest neighbor matching (Rubin 1973) with 1 neighbor to create treated and control pairs and measure the effect between customer success team activities on usage. For pair creation, I use firmographic and transactional information: account size, measured as the number of employees in a company; the monetary value of the contract; earliest active month; the number of committed licenses; month and year of the contract start. The final effect represents the average treatment effect – the difference in product utilization – observed in the matched pairs.

2.2.2.2. Simulation of theoretical effects under different trust conditions

A key difficulty faced when putting the observed treatment effect in the context of the theoretical mechanism presented in figure 2.2 is the absence of a trust measure in the data of the service provider. With only the integrity-facilitating measures of the SP and the outcome of integrity-based trust measured, I turn to simulations to evaluate if the observed effect corresponds to the effect expected theoretically and in previous research under the assumption that the relationship between trust-facilitating measures and the

[24] When included in the general sample, these companies do not affect the results of the analysis.

behavioral outcome is fully mediated by trust. After simulating the dataset of control and treatment variables from the covariance matrix and mean values observed in the data, I build three theoretical conditions: no-effect, weak, and moderate effect of trust-facilitating measures on trust. Each condition uses an effect previously observed in the research. Next, the outcome variable is simulated under the condition of trust directly impacting product usage. Finally, I compute the estimated treatment effects for the simulated samples.

Simulation studies are widely used for method comparisons, especially in papers on matching methods, e.g., comparisons of exact, nearest neighbor, and various kinds of propensity score matching (e.g., as shown in Carpenter 1977; Jacovidis 2017). In these studies, several datasets are created with given relationships between the variables and a given treatment effect. Then, several methods are applied to the dataset, and the closeness of the computed effects to the given effect is evaluated. More broadly, simulation studies are a sociological tool for the analysis of complex systems (Moretti 2002). They are useful in cases when the full complexity of the relationship under investigation cannot be observed (Nicolis and Prigogine 1989; Moretti 2002). In network studies, simulation techniques are applied to reduce the complex formation structures of networks observed in real data (Bergenti, Franchi, and Poggi 2011). Legewie and DiPrete (2012) use simulation studies to evaluate the observed effect in comparison to effects under random assignment conditions in school class assignments.

In this study, I turn to simulations to compare the observed effects of trust-facilitating measures on the behavioral outcomes of trust to the effect distributions observed in simulated datasets under three trust conditions. This strategy addresses the complex problem of measuring trust. It allows one to make conclusions about the presence of trust as the theoretically assumed mediator between the service provider's trust-facilitating activities and the customer usage behavior[25].

The simulation includes several steps. First, I discuss the creation of the simulated datasets for the treatment and control variables. Second, I discuss the creation of the

[25] While the simulation strategy makes it possible to assume the presence of trust based on the similarity of the observed and simulated effects, it still does not illustrate trust as the main mechanism. This limitation is addressed in the discussion.

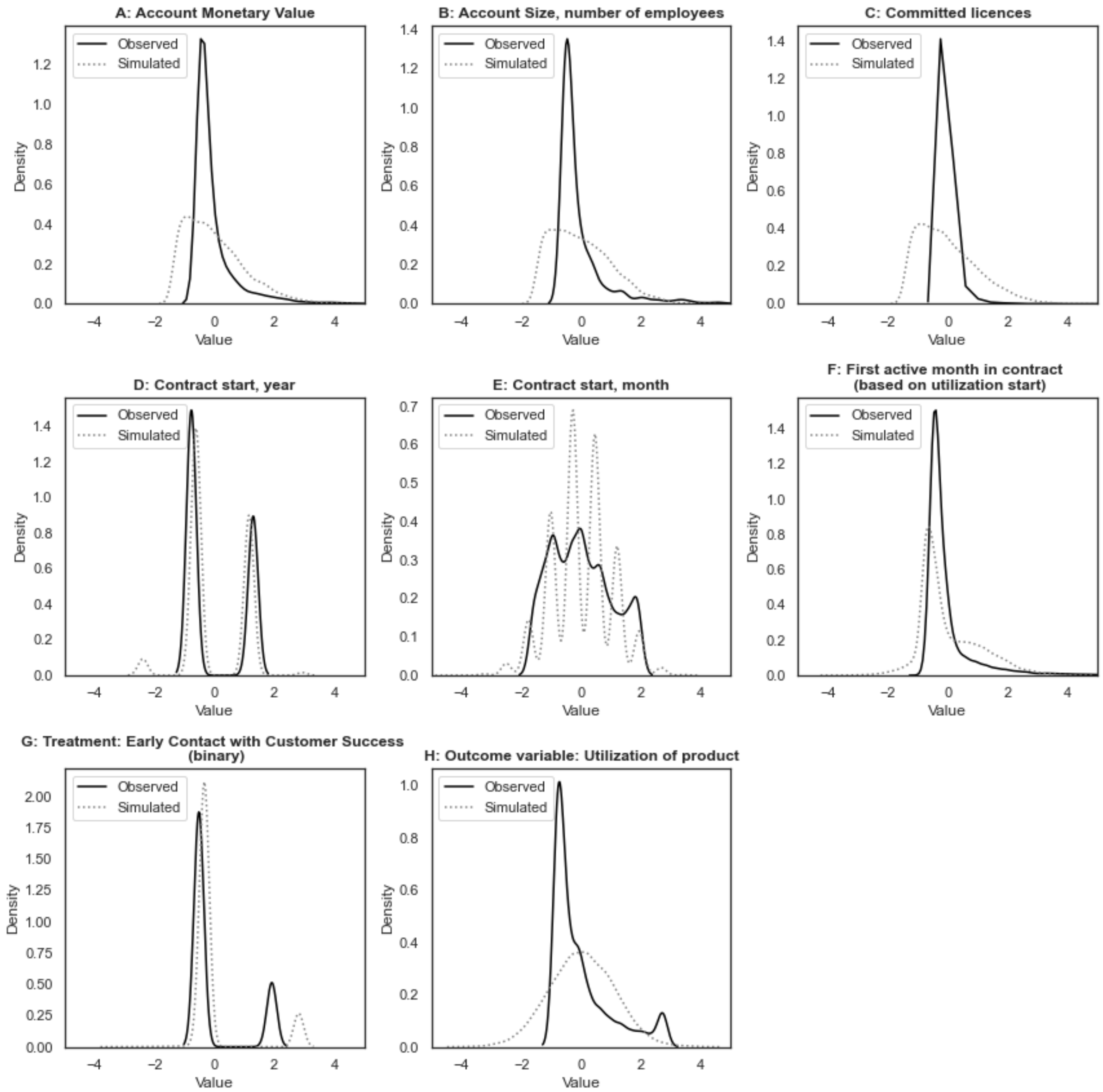
trust variables under three conditions given the coefficients available in previous research. Third, I discuss the creation of the outcome variable under the effect conditions available in previous research.

For the treatment and control variables, I create the correlated simulated datasets following the averages and the covariance structure of the observed dataset. I simulate the datasets with Python 3.9 (Van Rossum and Drake 2000) and the random.multivariate_normal function from the numpy package (Harris et al. 2020). The covariates are account monetary value of the contract, account size (number of employees), licenses purchased (committed), contract start (year), contract start (month), beginning of usage phase (months since contract singed), number of interaction points with customer success before the usage phase. During the simulation, continuous and dichotomous variables are treated equally. After the simulation, I dichotomize the variables given the thresholds derived from a normal distribution. Thus, the simulation results in a data frame that follows the structure of the observed data. Parts A to F in figure 2.4 illustrate the simulated and observed distributions in comparison for the six control variables simulated based on the covariance matrix of observed data.

Next, I derive the treatment variable following the steps described in the previous section. Given the start of the product usage phase, I consider everything before this point, the treatment period. To derive the treatment, I calculate the sum of the activities made by the customer success teams in the treatment period. If the sum equals zero, I consider the customer to be in the control group. For the customers with a sum of activities being above zero, I set the treatment to be one in the binary treatment condition[26]. Part G in figure 2.4 illustrates the distributions of the treatment in observed and simulated data.

[26] An alternative to this approach could be to consider the treatment as continuous. However, this approach requires a deeper understanding of the differences between individual ways of contact and a more detailed assumption about the optimal number of contacts by customer success teams. The possibility of treating the treatment as continuous will be discussed in the conclusion of this chapter.

Figure 2.4.: Density plots of standardized variables in observed (SMB sample) and simulated (one iteration) data



After creating the dataset and the treatment variable, I simulate the trust and the outcome variables. For the simulation of the trust variable, I turn to the theoretical assumption that the presence of integrity through integrity-facilitating actions indicates the presence of integrity-based trust (Mayer et al. 1995). Thus, I argue that the actions of customer success teams communicating integrity are the key predictor of integrity-based trust. For trust estimation, I use three coefficients in three simulated conditions. The no-effect condition corresponds to an effect of customer success teams' activities on the simulated trust variable of 0.0. In the weak effect condition, the coefficient of 0.24 observed by Doney et al. (2007) is used for simulating the trust variable. In the moderate effect condition, the coefficient of 0.316 derived by Casalo et al. (2007) is used for simulating the trust variable. A normally distributed error term is added to the trust simulation equation. Table 2.1 illustrates these coefficients, the backgrounds of the studies where they were derived, and the equations for trust simulation.

Table 2.1.: Relationship-based antecedents of trust and their effects used in the simulation of trust

Condition	Coefficient	Study	Trust simulation equation
Moderate effect	0.316 (standardized)	Casalo et al. 2007	$\mathrm{T} = 0.316 * treat + \epsilon$
Weak effect	0.240 (standardized)	Doney et al. 2007	$\mathrm{T} = 0.240 * treat + \epsilon$
No effect	0.0	-	$\mathrm{T} = 0.0 * treat + \epsilon$

While these studies focus on the effects of social interactions (Doney et al. 2007) and participation (Calaso et al. 2007) on trust, none of the studies turns to the exact same operationalization of the trust antecedents. Such integration of multiple coefficients from the literature allows extending the research to a very specific direction while building upon previous findings. On the technical side, the coefficients are derived from standardized data. As previously mentioned, the data were standardized at the beginning of the analysis, before the simulation takes place.

Summing up, at this stage of the simulation, the control variables and the treatment indicator were simulated based on the covariance structure of the observed data. The trust variable was simulated from the treatment variable under the assumption of full mediation of the effect of integrity-facilitating measures through trust and according to the effects previously observed in research.

Coming to the second theoretical element that must be simulated based on previous research, we turn to the outcome of trust – usage, i.e., the product utilization measure. While usage data is available in the observed data, simply simulating usage based on the covariance matrix does not suffice to illustrate how trust-facilitating activities affect customer behavioral outcomes through trust. Thus, I simulate the usage in three conditions based on the simulated trust variable and the simulated covariates in the simulated datasets.

The usage outcome can be generalized as a (user) behavioral outcome, allowing a wide range of behavioral outcomes and corresponding coefficients for simulations. The coefficient $\boldsymbol{\beta}_t$ used for the simulation of behavioral outcome is 0.151 (standardized), as adapted from Asadi et al. (2017), who derive this effect of trust on behavioral intention for the adoption of cloud technologies in banking with a structural equation model. I use this coefficient as it is associated with behavioral intent and is related to the SaaS market. On the one hand, behavioral intent has shown to not always lead to actual behavior (e.g., Williams et al. 2011), which means that the adopted coefficient stands for a separate construct. On the other hand, behavioral intent can be used as a proxy for actual behavior (Armstrong et al. 2000). The following equation illustrates the simulation procedure for the usage outcome, where $\boldsymbol{T}$ is the trust variable in the simulated dataset, $\boldsymbol{\beta}$ are the coefficients for covariates $\boldsymbol{X}$ presented in table 2.2.[27], and $\boldsymbol{\varepsilon}$ is the error term.

$$Usage = \boldsymbol{\beta_t} * \boldsymbol{T} + \boldsymbol{\beta X} + \boldsymbol{\varepsilon}$$

Summing up, at this stage, the simulation results in a dataset of control variables and a treatment indicator, a trust variable, simulated based on the integrity-facilitating treatment and coefficients from previous literature under the assumption of full mediation by trust, and the usage variable, simulated based on its relationship to the control variables and a coefficient adopted from previous research.

[27] The coefficients in table 2.2 result from a regression model controlling for the activities of CST (β = 0.09) to make sure that full effect of CST activities in the simulation is mediated through the simulated trust variable.

Table 2.2.: Standardized regression coefficients derived for the observed data and used in the simulation of the outcome variable, usage

Regressor, X	Standardized Coefficient, β
Account Monetary Value	-0.1339
Account Size (N employees)	-0.0456
Committed licences	0.0140
Contract start, year	-0.0159
Contract start, month	-0.0535
First active month in contract	-0.2493

Note: With the standardized coefficients used, the intercept is not reported since it is 0.0 by definition and the coefficients remain the same with and without the intercept included (Achen 1977; Bring 1994).

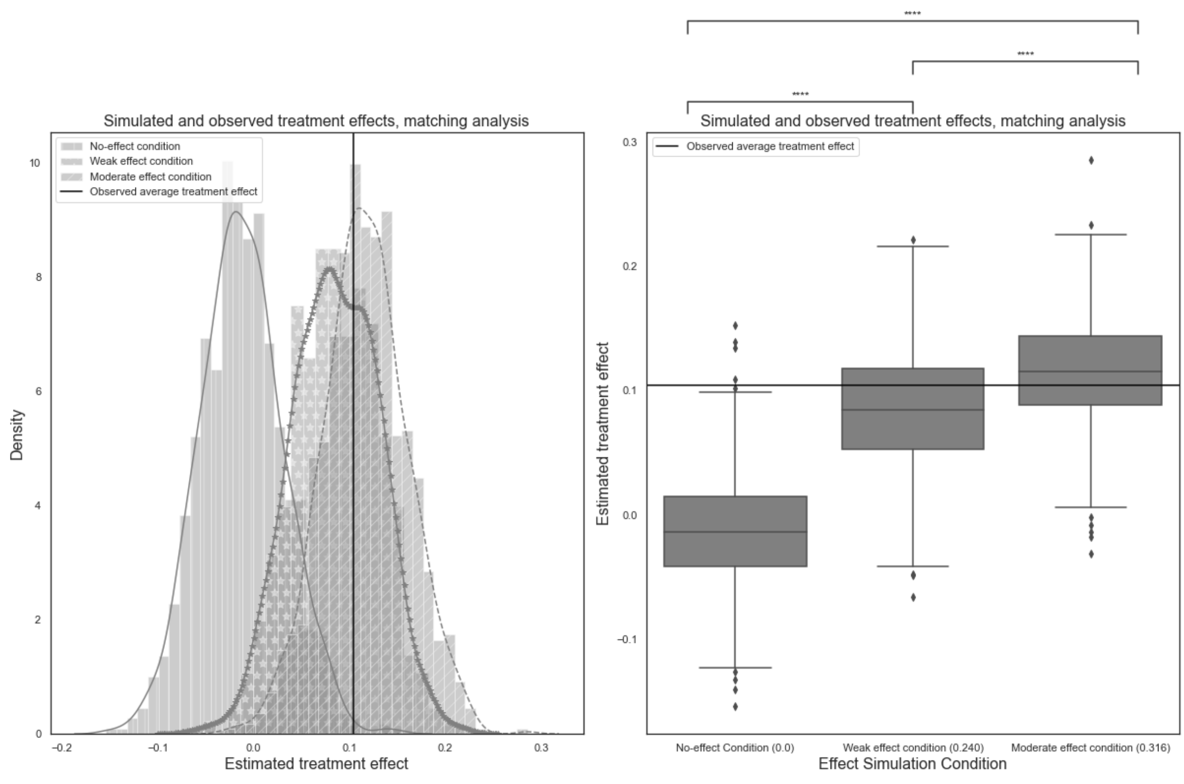
The simulation procedure is repeated 1000 times for 8000 simulated customers. For each simulation, the average treatment effect between matched pairs is calculated with nearest-neighbor matching, in the same strategy as for the effect estimation for the observed data specified above. Thus, the simulations result in distributions of 1000 theoretical average treatment effects under three trust conditions. These distributions are then compared to each other with two-sided t-tests and to the average treatment effect observed in the data. Finally, the similarity of the effect to each of the distributions is evaluated.

For computations, I use python 3.9 (Van Rossum and Drake 2000). A full list of packages and versions used is presented in table A.1.1 in the appendix.

2.3 Results

Figure 2.5 illustrates the distributions of standardized effect coefficients resulting from the simulations under three conditions – no trust effect, weak trust effect, and moderate trust effect[28]. The histograms in the left plot illustrate the overall distributions, while the boxplots in the right plot also include significance tests between the distributions. One of the main conclusions from this plot is that a significant difference between the distributions can be observed. This is true when comparing moderate or weak effects of trust to the no-effect of trust condition. But it is also true when comparing the weak effect of trust and the moderate effect of trust conditions.

Figure 2.5.: Comparison of simulated average treatment effects of CST activities on customer utilization under three trust conditions to the observed effect, full SMB sample



Note: ****: $p < 0.0001$; ***: $p < 0.001$; **: $p < 0.01$; *: $p < 0.05$; ns: $p > 0.05$

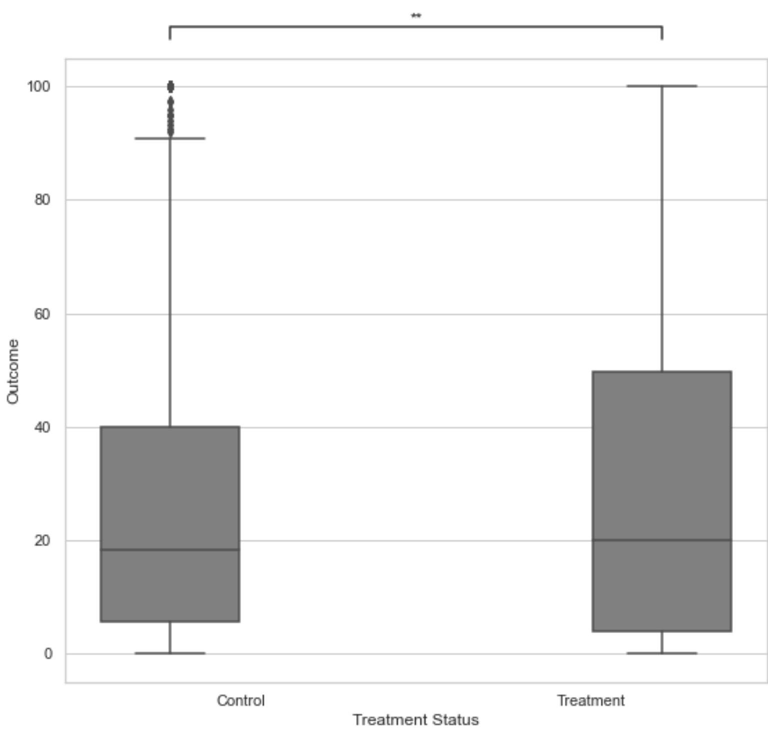
Solid lines in figure 2.5 illustrate the average treatment effect of 0.104 in the observed standardized data. This effect falls outside the no-effect distribution but can be placed in both weak and moderate effect distributions. This confirms that the effect that

[28] Findings observed under the blurred treatment condition are provided for comparison in appendix A.2.2.

customer success teams and their actions have on customers' usage behavior corresponds to a condition when the effect is fully mediated by trust.

Regarding the observed data, this effect corresponds to a difference in usage in the first month of the usage phase of on average 7 percentage points. Customers contacted by the customer success teams after the acquisition phase but before the usage phase has started are utilizing on average 7 percent more of their purchase than those in the control group. A comparison of the non-standardized, not matched outcome distributions with a significance test in figure 2.6 shows that a small difference is visible and statistically significant.

Figure 2.6: Comparison of non-standardized distributions of the utilization between treatment and control groups, first month of the usage phase



Note: ****: $p < 0.0001$; ***: $p < 0.001$; **: $p < 0.01$; *: $p < 0.05$; ns: $p > 0.05$.

From both standardized and non-standardized results, I conclude that expectation 1.1 is confirmed. Activities of customer success teams serve as trust-facilitating measures. They are associated with an effect on usage in the first active usage month that corresponds to the expected effect in the literature under the condition of full mediation by trust.

When looking at the effects of customer success activities on the utilization trend over the 6 months following the beginning of the usage phase, I find that the significant effect visible in the first month disappears in the second month (figure 2.7). From this, the conclusion follows that integrity-based trust only has a short-term effect on customer usage behavior. Thus, expectation 1.2 can be confirmed. The effect of integrity-based trust on behavioral outcomes declines to an insignificant one over time.

Figure 2.7: Comparison of non-standardized distributions of the utilization between treatment and control groups, first 6 months of the usage phase

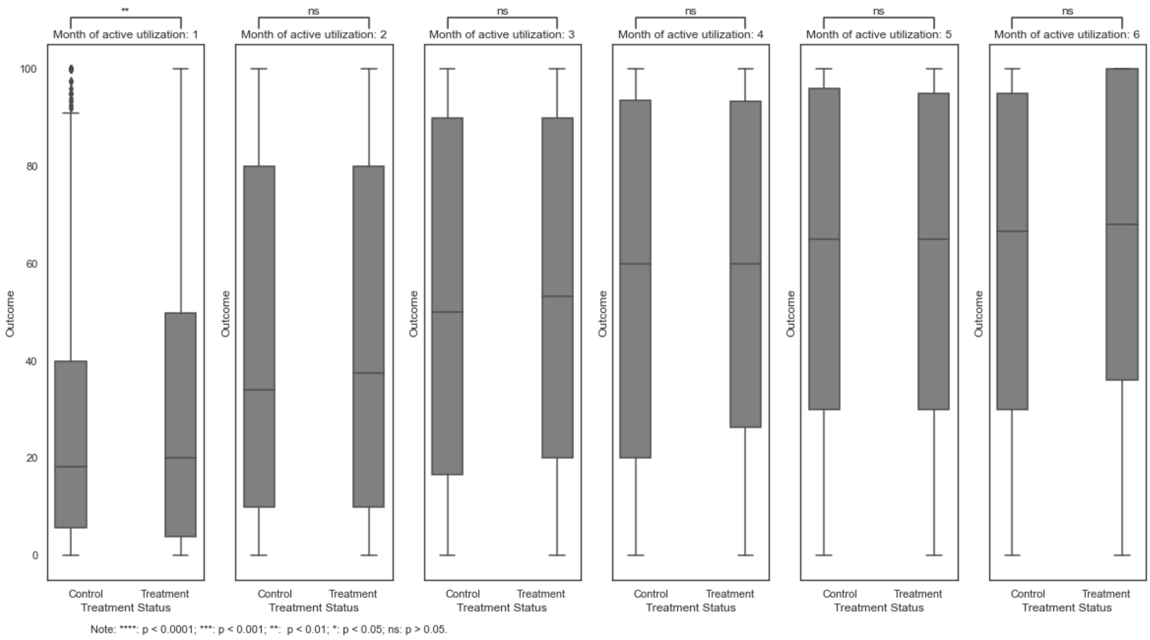
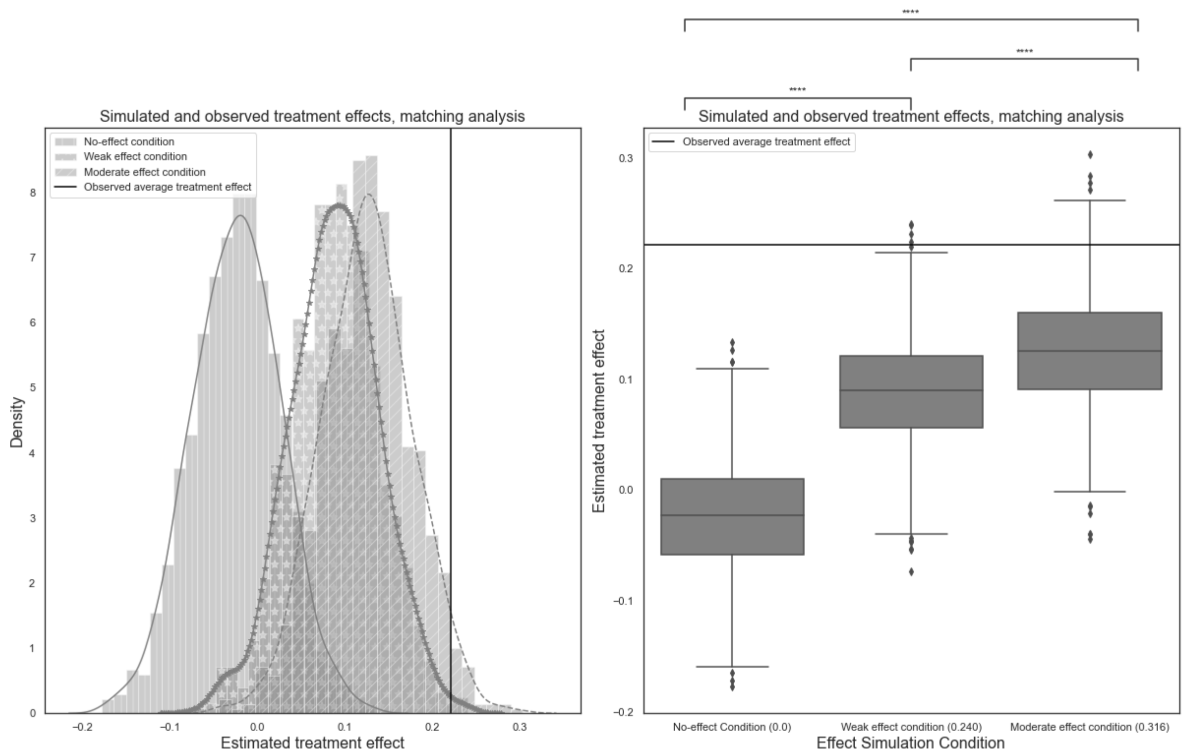


Figure 2.8 illustrates the results for the simulation analysis in the big accounts sample. Overall, the distributions of simulated effects are comparable to the simulated effects from the small and medium enterprises sample. However, the standardized treatment effect of 0.22 in the observed data falls closer to the moderate trust condition of the effect of contact with customer success teams before the usage phase on product usage. Due to the small sample available for big accounts using the same product as the small and medium enterprises, the results cannot be generalized to all big customers. However, the findings provide additional support for the expectations that early interactions with customer success teams positively affect customer usage behavior independent of the customer size. The standardized effect translates to a difference of

5 percentage points in utilization between the treated and the control groups[29]. Customers contacted by customer success teams utilize 5 percent more of the purchased licenses than the control group customers.

Figure 2.8: Comparison of simulated average treatment effects of CST activities on customer utilization under three trust conditions to the observed effect, big accounts sample



Note: ****: p < 0.0001; ***: p < 0.001; **: p < 0.01; *: p < 0.05; ns: p > 0.05.

The presented analysis has shown that the observed effect of early interactions with customer success teams on customer utilization of the product in the first month of the product usage phase is consistent full mediation of this effect through trust, assumed theoretically. The effect is consistent with the weak effect of interactions with customer success teams on trust. Thus, the main expectations investigated in this chapter have been confirmed for SMB customers and big enterprises when the engagement model is SMB.

[29] Again, due to the small sample size of big customers with SMB contracts, the effect sizes observed in this sample should only be considered to indicate a potentially existing effect consistent with the effect for SMB customers, not to evaluate the magnitude of the effect.

2.4. Managerial Implications

This chapter provides an answer to the first research question stated in the introduction from the perspective of the service provider. Does the trust-facilitating measure of customer success teams help to build integrity-based trust and positively affect customer usage behavior at the beginning of the usage phase?

Customer success teams are relatively new units in companies whose goal is vaguely described as "generating a trustful relationship with their customers" (Mehta et al. 2016: Ulaga et al. 2020; Gelb et al. 2020). While there was little previous evidence on the actual effect of customer success teams, this study, first, contributes to the research on customer success, showing that early in the relationship, there is a visible effect of customer success teams' actions. Second, the results can be translated into a practical understanding of intangible value generated by customer success teams at early relationship stages. While the effect of integrity-based trust on a customer's product usage is only present for a short period of time, the development of integrity-based trust can have further effects, not covered in this analysis but mentioned in the trust and integrity-based trust literature. For instance, Connelly et al. (2018) show that integrity-based trust is effective in reducing transaction costs in interorganizational relationships. These transaction costs include, for example, the possibility to ensure future commitments with customers or the monitoring of the partners in an interorganizational relationship (Connelly et al. 2018:922).

Thus, along with empirical confirmation of the value of customer success teams, especially at the beginning of the contractual relationships in a SaaS subscription environment, the findings can be adapted to practical use as action guidelines for customer success teams, targeting more integrity-based trust.

2.5. Discussion

In this study, I focused on the role of customer success teams (CST) in generating trust at the beginning of the relationship between a customer and a service provider and the effect that is achieved through trust on customer usage behavior at the beginning of the usage phase. The proactive communication of the CST at the beginning of the relationship, corresponding to such antecedents of trust as social interactions, participation, and open communication, was evaluated with respect to its effect on behavioral outcomes in customers. I observed a positive effect of CST actions on customer usage behavior in the first month of the usage phase. However, the observed effect does not hold over time. This behavior corresponds to the theoretically expected effect of integrity-based trust. Thus, the first contribution of this paper is the empirical illustration of effects corresponding to integrity-based trust formed through the actions of customer success teams in the early phase of interorganizational relationships in SaaS subscription contracts. This effect is observed in the example of CST and the trust-facilitating effect of their proactive communication.

What does this mean for the overall case of uncertainty? The first step in the relationship is building a foundation of own experiences to build integrity-based trust. This process was not important in one-time relationships between organizations. In SaaS subscription contracts, the relationship uncertainty gains more importance, and, thus, actions are taken by service providers to reduce the relationship uncertainty for customers. This change led to the wide adoption of CST with the goal of forming trust (Mehta et al. 2016). This study shows that CST contribute to forming integrity-based trust in customers while communicating that the service provider will keep their promises – integrity. The results show that such communication leads to a behavioral outcome – a higher product usage - and establishes a foundation for further relationship. Thus, CST present a mechanism for service providers to reduce initial uncertainty for customers in long-term relationships.

The findings result from simulations and illustrate that the observed effect is consistent with the distribution of effects when trust is the mediator in the relationship. Still, as mentioned in the methodological part, this result only allows for initial validation of the CST actions' effect on customer trust. As this study does not measure trust directly, the major limitation is the possibility of alternative explanations present in this relationship. Previous studies investigating trust in the context of relationship investment in buyer-supplier relationships highlight multiple alternative mechanisms, including gratitude (Palmatier et al. 2009), reciprocity (Palmatier, Dant, and Grewal 2007), dependence (Hibbard, Kumar, and Stern 2001). In the SaaS contractual relationship, the product is normally used by a group of individuals not associated with the purchase and the implementation (Tyrväinen and Selin 2011). Thus, a certain level of independence between the actual product usage behavior and the personal predispositions of the company's representatives in the interactions with the SP can be assumed. Nevertheless, the micro-level mechanism for the individuals within the organization can differ and include a broader range than just trust. Additional to this, this study is limited by the necessary assumption of full mediation through trust, while previous research shows that it is not always the case for integrity (Lankton and McKnight 2011). While the observed effect corresponds to full mediation through trust, it is yet to be confirmed that no direct effect of the actions of CST on customer usage behavior can be identified.

Furthermore, while the general dynamic of how social interactions with the CST impact a customer's usage behavior was shown, the variation within the general dynamic remains a subject for further analysis. For instance, future research can indicate whether email communication is as effective as personal meetings, whether groups of customers react differently to the measures and whether some customer groups tend not to react at all. Extending the results of this study with such detailed findings will make it possible to create much more personalized measures to create integrity-based trust in customers. Furthermore, studying the effect of CST actions as a continuous treatment will provide further insights into understanding the marginal effects of additional contact points between customer success teams and the customer.

Integrity-based trust presents the first ABI dimension of trust developed after the contract was signed, and the ability-based trust was guaranteed. After the early relationship uncertainty has been resolved through integrity-based trust, this trust dimension is theoretically assumed to experience little variation over time (Mayer et al. 1995; Pollack et al. 2007). In the next chapter, the focus of this work moves to the next dimension of trust – the benevolence-based trust that is expected to develop later in the relationship.

Maintaining trust during the relationship

An investigation of the role of Customer Support Services for maintaining customer trust

The uncertainty in a relationship between a service provider (SP) and a customer is solved through trust (Kollock 1994). Building trust in the technical performance of the product (*ability-based*) and the reliability of SP (*integrity-based*) allows the SP to solve the initial uncertainty with respect to the Software as a Service (SaaS) product. However, the subscription character of the SaaS products assumes a long-lasting relationship between the SaaS SP and the customer. In a long-lasting relationship, benevolence-based trust is gaining importance (Mayer et al. 1995).

In this chapter, I look at the support service component of the SaaS product to answer the question of what behavioral consequences do an SP's measures targeting uncertainty reduction reach in their customers throughout the contractual relationship. To answer this question, I establish how the benevolence-based trust dimension of support services can be detected and how it is connected to the behavioral outcomes. I compare semantic networks of customer problem profiles and apply topic modeling with Latent Dirichlet Allocation (LDA) and the semantic network analysis of how the problems are described to model the benevolence-based trust of a customer on both within-customer and between-customer problem space. I use participation in satisfaction surveys and continuation of the relationship as outcome variables.

The results indicate a positive effect of benevolence-based trust measures – modularity and latent topic coherence of customer problems – on customer engagement. This finding is more pronounced in the full sample of customers. Thus, it highlights the growing importance of benevolence-based trust over time in the contractual relationship. The analysis of the effects of benevolence-based trust in the renewal phase of the relationship supports this finding – customers with higher levels of benevolence-based trust are less likely to terminate their contracts.

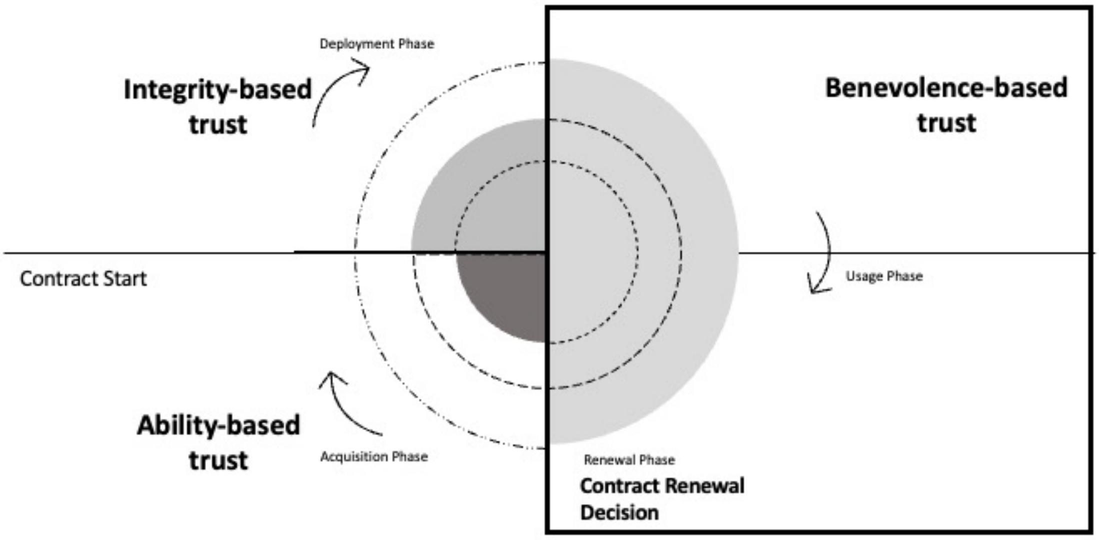
In this chapter, I first turn to the theoretical background on benevolence research and its position in the relationship between service providers and customers. Next, I describe the methodological strategy and the data for the analysis. Finally, I discuss the results and provide the managerial implications.

3.1. Customer Support as the Benevolence-based Trust Unit

According to Mayer et al. (1995:718), the benevolence dimension of trustworthiness is "the extent, to which a trustee is believed to want to do good to the trustor, aside from the egocentric profit motive." The authors suggest that the role of benevolence "will increase over time as the relationship between the parties develops" (Mayer et al. 1995:722). Under the assumption that trust is the function of perceived trustworthiness (Mayer et al. 1995; Möllering 2006), the respective dimension of trust is benevolence-based trust. Figure 3.1 illustrates the position of benevolence-based trust in the relationship between a SaaS service provider and the customer. Schoorman et al. (2007) emphasize the initially suggested by Mayer et al. (1995) importance of the time dimension needed for the trustee to collect benevolence-based data about the trustor's behavior. This time is also required in the relationship between the SaaS service provider and the customer. Benevolence-based trust is being formed with increasing time in the relationship, and its importance grows over time (Mayer et al. 1995; Schoorman et al. 2007). In figure 3.1, benevolence-based trust covers the entire time between the formation of integrity-based trust (the deployment phase) and the extension or cancellation of a relationship (the renewal phase) – the usage phase of the SaaS contractual relationship[30].

[30] While the importance of benevolence-based trust increases in this time, ability-based and integrity-based trust remain essential conditions for continuing the relationship. Thus, the dashed lines in the figure illustrate the remaining importance of ability-based and integrity-based trust, even while these dimensions of trust remain largely constant.

Figure 3.1.: Position of benevolence-based trust in a relationship between a SP and a customer



Organizational research on benevolence-based trust[31] focuses on the already mentioned time dimension, the difference in the position of benevolence-based trust compared to integrity-based and ability-based trust, and the organizational outcomes (Pollack et al. 2017; Svare et al. 2020). For example, Schoorman (2002) and Schoorman et al. (2007) highlight that the longer a relationship lasts, the more information on the benevolence dimension of trustworthiness is available to the trustor, and, following, the better researchers are able to separate it from integrity-based trust. Pollack et al. (2017) discuss the temporal dynamics between ability, benevolence, and integrity dimensions of trustworthiness. They propose a model for benevolence in entrepreneurship, which suggests that it will play a smaller role during the formation of a new venture (Pollack et al. 2017:17). Svare et al. (2020) evaluate the importance of benevolence-based trust in interorganizational innovation networks. According to their findings, benevolence-based trust is the only trust dimension increasing the collaboration after its beginning. Out of all ABI trust dimensions, this is the dimension that facilitates an "open, high-quality communication relationship […] with higher levels of trust corresponding to

[31] For more details on the differentiation between ability-based, benevolence-based, and integrity-based trust, see the introductory chapter for the overview and chapter two for a comparison between integrity-based and benevolence-based trust.

higher performance" (Svare et al. 2020:599). In contrast, certain levels of other trust dimensions are necessary to initiate an interorganizational relationship (Svare et al. 2020). Neergaard and Ulhoi (2006) show that single violations have low importance, while Bell et al. (2002) show that the timing of violation matters. Early violations of benevolence can have significant negative effects on the overall trust and, in turn, on the generalized outcomes of trust (Bell et al. 2002)[32].

While originating from the organizational literature, benevolence-based trust has earned its place in information systems research, especially when it comes to online vendors (Lankton and McKnight 2011). Lankton and McKnight (2011) provide a research overview of trustworthiness dimensions used in organizational and information systems research and find that the dimension of benevolence can best be paired with the information systems dimension of helpfulness. They illustrate in a structural equation model that benevolence and helpfulness dimensions of trustworthiness can be combined in a second-order factor. Combined, they have an effect on the continuance of usage. This effect is fully mediated by trust (Lankton and McKnight 2011). Hence, there is a direct effect of benevolence-based trust on the continuance of the relationship.

The main distinction made between helpfulness and benevolence dimensions of trustworthiness in this context is the assumption that helpfulness of software describes the "feature of technology itself – the help function" (McKnight et al. 2011:5), which is expected to provide "adequate help for users" (McKnight et al. 2011:8), whereas the benevolence dimension relates to human actors (Thatcher et al. 2011). While some authors emphasize the distinction between support provided by the software itself and relationship-based IT support provided by individuals (e.g., Thatcher et al. 2011; Lankton, McKnight, and Trip 2015), others use measurements that do not distinguish between helpfulness-based and benevolence-based trust (Tams et al. 2018).

This work discusses trust in the context of a SaaS service provider and their customer. In SaaS contracts, customer support services turn into part of the product (Godse and Mulik 2009). Thus, the software context of trust in such contracts has to be extended to

[32] While some studies focus on benevolence-based trust specifically, many others analyze violations of integrity-based and ability-based trust and do not investigate benevolence-based trust due to its smaller role in an interorganizational relationship (e.g., Kim et al. 2004, 2006, Janowisz-Panjaitan and Krishnan 2009).

the interorganizational part of the benevolence-helpfulness dimension – benevolence-based trust. This leads to the incorporation of the relationship-based helpfulness aspect of the SaaS software contracts – the customer support provided by the employees of the service provider[33].

Customer support originated in the late 19th century (Sheth, Jain, and Ambika 2020), and associated research covers the elements of personal interactions with support employees, emphasizing the effect of customer support on overall customer experience in offline settings (e.g., Tombs and McColl-Kennedy 2003). In recent years, the topic of online support has been increasingly growing (McLean and Wilson 2016). In SaaS contracts, customer support is usually seen as a reactive unit focusing on customer problems (Hochstein et al. 2020) which practitioners define as a reactive group solving customer issues, often reported as tickets (Client Success 2021). Thus, this unit provides assistance to customer problems and is not a direct part of the software. In the SaaS subscription contracts, I see customer support as the basis for the benevolence dimension of trustworthiness and, following, the benevolence-based trust.

Recent research in customer support is focused on its positive effects on customer satisfaction (Herzig et al. 2016) and loyalty (Murali, Pugazhendhi, and Muralidharan 2016), stronger relationships (Sheth 2011), customer retention (Kumar et al. 2017), and competitive advantage (Lusch, Vargo, and O'brien 2007). Rigopoulou et al. (2008) show that the quality of support leads to higher customer satisfaction and affects the relationship between the company and their customers, leading to behavioral intentions. Lambert and Sharma (1990) show that customer support can lead to repeated purchases. Coffelt (2013) makes similar statements regarding the positive effect of solving customer problems on satisfaction and an increase in customer retention. Sheth et al. (2020) go further and show that customer support has a strategic role in customer service provider relationships and should be placed as a strategically important profit center. Moreover, customer satisfaction with the service provider's solution to the problem reinforces customer trust and commitment (e.g., Kelley and Davis 1994; Tax, Brown, and Chandrashekaran 1998). Alvarez et al. (2010) extend this

[33] With the focus of this work on interorganizational trust, I further use the term benevolence-based trust as a generalization of benevolence-based and helpfulness-based trust dimensions, i.e., the trust dimensions based on the second-order benevolence-helpfulness dimension of trustworthiness.

finding to customer satisfaction with problem-solving experiences of the service provider as a crucial antecedent of benevolence and, following, of benevolence-based trust.

The outcomes of benevolence-based trust observed in research are similar to the discussed outcomes of customer support. In organizational research, Ganesan and Hess (1997) show that benevolence-based trust in an organization is essential for continuing the relationship. The importance of benevolence-based trust for the continuation of use was also studied in the context of social networks (Wu, Huang, and Hsu 2014). Kumar, Adlakaha, and Mukherjee (2018) also show a positive effect of benevolence-based trust on the continuation of relationships on the example of mobile wallet adoption. Nguyen (2016) provides evidence of a positive effect of benevolence-based trust on customer loyalty in a study of service employees' competence in interactions with the customers of a financial service provider. Bell et al. (2002) show that early violations of benevolence can have significant negative effects on the generalized outcomes of trust. In the context of technology, Lankton and McKnight (2011) show that the effect of benevolence and helpfulness on the continuance of the relationship is fully mediated through trust.

When put in the context of the support relationship between a service provider (SP) and the customer, the findings related to the outcomes of customer support and benevolence-based trust suggest that the existence of problems is not evaluated negatively if the problem is solved by the customer support unit of the SP, i.e., the help is provided to the customer problem. Seeing customer support units as the units of benevolence-based trust means that when qualified and timely support is offered for customer problems, the benevolence-based trust is built up and maintained, and the relationship between the parties is continued (Alvarez et al. 2010; Nguyen 2016). When the quality of support does not match the expected or the previous quality, the benevolence-based trust is negatively affected. In the usage phase of the SaaS lifecycle, this can lead to low satisfaction with support services and decreasing customer engagement (Petzer and van Tonder 2019; Chung et al. 2020). In the renewal phase of the SaaS lifecycle, this can even lead to the termination of the relationship (e.g., Venetis and Ghauri 2004). I derive the following expectations for the effects of benevolence-based trust in the usage and renewal phases of the contractual relationship:

Expectation 2.1: Customers with higher benevolence-based trust are more likely to engage in the active feedback process compared to customers with low benevolence-based trust.

Expectation 2.2: Customers with high benevolence-based trust are more likely to extend the relationship with the service provider compared to the customers with low benevolence-based trust.

Summing up, benevolence and benevolence-based trust are dimensions that are sometimes paid less attention to as their effect on the initial formation of the relationship is smaller (Schoorman et al. 2007; Svare et al. 2020). However, this work aims at covering all ABI dimensions of trust in the context of a relationship between the SaaS SP and the customers. I illustrated that customer support research focuses on the outcomes closely related to the general outcomes of trust, and customer support covers the interpersonal part of the benevolence-based trust of a SaaS product. Hence, I focus on customer support units as the benevolence-generating units and, following, the units of benevolence-based trust in the SaaS service provider relationship with customers. In the next section, I discuss the methodological decisions necessary to operationalize benevolence-based trust in the context of customer support.

3.2. Data and Methods

3.2.1. Data Structure and Preprocessing

Before going over the methodological decisions, a detailed description of the data is presented. I am using the case data[34] provided by SAP SE[35] to study customer problems. The data is structured in the following way. Each case has an id and a processing status, a date field of when it was opened, and the date field of when it was closed. This information is used to calculate the time it took to solve the case. Each case has a subject field, in which a brief description of the problem is provided in keywords[36]. This information is used in the text analysis to identify customer problem structures.

[34] Case is the technical term for a filed customer problem in this scenario and will be used further as a synonym to a case of a reported problem by the customer.
[35] For a detailed overview of the case company and data, see the introduction section.
[36] In contrast to other studies of customer support, the detailed information and the content of further communication is not available in this study.

Furthermore, each case has information on the perceived urgency set by the customer. For the outcome variables, customer Net Promoter Score (NPS) survey results are available to identify customer engagement with the service provider to provide feedback during the usage phase. For the outcome in the renewal phase, data on customers terminating their contracts are available.

When it comes to the customer information, firmographic information, including the size of the customer account, the monetary value of their contract, and the time since the first contract start for the customer (account age), are available. Table 3.1 represents the structure of the dataset[37].

Table 3.1.: Dataset structures for customer data, case data, and outcome data

Customer Information

Customer ID	Account Size, N Employees	Monetary Value	Months Since Contract Start (Age)
XXX1	1200	150	12
XXX2	10	190	7

Case Data

Customer ID	Case ID	Date Opened	Date Closed	Subject	Urgency
XXX1	CSID1	01.01.18	03.01.18	Problem during payment process	high
XXX1	CSID2	10.01.18	11.01.18	Old information reappears	low
XXX2	CSID4	15.01.18	15.01.18	Unable to access account	medium

Outcome data

Customer ID	NPS Cycle	NPS Value	Contract Termination
XXX1	Spring18	8	0
XXX1	Fall18	NA	0
XXX2	Fall18	NA	1

[37] Note that due to the confidentiality of customer data, no real data can be shown in this work. The keywords were replaced by words from the customer complaints dataset published by the US government. This dataset has a similar structure and a similar nature of customer complaints (Consumer Financial Protection Bureau 2021). The data regarding customer ids, dates, and survey results, are simulated.

In my sample, I only include cases of status "closed" opened between January 2018 and December 2019. The full sample contains over 100000[38] cases opened by over 10000 small and medium business (SMB) customers[39]. This sample is further referred to as *the full sample*. An average customer in this sample is an SMB company with under 500 employees and with the service provider for on average 46 months. To make sure that all customer cases since the beginning of their contracts are included in the analyses, I use a partial sample covering SMB customers who started their contracts after January 2018. In this sample, early cases are available for all customers, which allows one to observe potential differences between customer problems occurring early and later in the SaaS contractual relationship. This sample contains over 10000 cases originating from over 3000 customers. I further refer to this sample as *the new customers sample*. The average customer size here is similar to the full sample, while the average time in the contractual relationship is 10 months. In both samples, on average, a customer has opened about 5 cases. 25% of the cases are closed on the same day, and the median case duration is 5 days.

In this analysis, I use Python 3.9 (Van Rossum and Drake 2000) and the following packages for the analysis: pandas (McKinney 2010), numpy (Harris et al. 2020), langdetect (Danilk 2021), scikit-learn (Pedregosa et al. 2011), statsmodels (Seabold and Perktold 2010), statannot (Weber 2021), gensim (Rehurek and Sojka 2011), nltk (Bird, Klein, and Loper 2009), networkx (Hagberg, Swart, and Chult 2008), matplotlib (Hunter 2007), seaborn (Waskom 2021), collections (Van Rossum and Drake 2000). For a detailed list of packages and versions, see table A.1.1 in the appendix.

Before starting the work with the text subject data, I apply several preprocessing steps to the subject lines of customer cases. I remove punctuation, stop words[40], and special characters. I review the language of all cases in the dataset while using the python langdetect package. 68% of the original cases are in English and will be considered for

[38] Again, due to the confidentiality of customer data, no exact numbers can be published in this work.
[39] The SMB customers are businesses with under 1500 employees. While there are industry-level differences in official US definitions (US Small Businesses Administration 2019), same as in chapter two, I use the threshold of 1500 employees and an SMB flag in the firmographic information as the internal SMB definition.
[40] I use the list of stop words available in the gensim package (Rehurek and Sojka 2011). The list can be found in appendix A.3.1. As only data coming from one company is analyzed, I also removed the product and company names from the data.

further analysis[41]. I apply lemmatization to reduce the words to their lemmas[42] and create a text data basis for analysis clean of word forms that can complicate the analysis (e.g., plurals, verb tenses, etc.). Table 3.2 illustrates the process of stop words removal and lemmatization[43].

Table 3.2.: Case subject line preprocessing for further analysis, examples

Example 1

Step	Subject
Raw input text	Was not notified of investigation status or results!
Lowercase	was not notified of investigation status or results!
Removal of special characters	was not notified of investigation status or results
Stop word removal	notified investigation status results
Lemmatization	notified investigation status result

Example 2

Step	Subject
Raw input text	Account status incorrect
Lowercase	account status incorrect
Removal of special characters	account status incorrect
Stop word removal	account status incorrect
Lemmatization	account status incorrect

In this work, I focus on customer-level understanding of the trust dimensions. The case data represents cases opened by multiple users belonging to the same customer. Thus, I combine the case subject line text data for each customer to observe the full problem space of the customer. This space is further evaluated with semantic network and latent topic analysis. Table 3.3 illustrates the representation of all customer problems preprocessed for further analysis.

[41] The descriptive statistics provided above do not include information on non-English cases.
[42] Lemmatization is a preprocessing step in text analysis, when words are reduced to their initial lemmas, e.g., plural forms to singular, past tense of verbs to infinitives. It is different from word stemming since the lemmas are preserved (Plisson, Lavrac, and Mladenic 2004).
[43] This text was simulated based on the financial claims dataset mentioned earlier (Consumer Financial Protection Bureau 2021).

Table 3.3.: Combined case subject lines used for semantic network analysis and latent topic detection, all cases of one customer

Case Data

Customer ID	Case ID	Date Opened	Date Closed	Subject	Urgency
XXX1	CSID1	01.01.18	03.01.18	Problem during payment process	high
XXX1	CSID2	10.01.18	11.01.18	Old account information	low
XXX1	CSID5	15.01.18	15.01.18	Unable to access account	medium
XXX1	CSID7	19.01.18	25.01.18	account status incorrect	medium

Combined Case Subjects Lines
Latent Dirichlet Allocation

Customer ID	Subject Combined
XXX1	problem payment process old account information unable access account account status incorrect

Combined Case Subject Lines
semantic networks, adjacency matrix

	problem	payment	process	old	account	information	unable	access	status	incorrect
problem	-	1	1	0	0	0	0	0	0	0
payment	1	-	1	0	0	0	0	0	0	0
process	1	1	-	0	0	0	0	0	0	0
old	0	0	0	-	1	1	0	0	0	0
account	0	0	0	1	-	1	1	1	1	1
information	0	0	0	1	1	-	0	0	0	0
unable	0	0	0	0	1	0	-	1	0	0
access	0	0	0	0	1	0	1	-	0	0
status	0	0	0	0	1	0	0	0	-	1
incorrect	0	0	0	0	1	0	0	0	1	-

3.2.2. Operationalization of benevolence-based trust

Trust is a complex construct when it comes to measurement (Glaeser et al. 2000). Trust is defined in the ABI theoretical framework as a function of perceived trustworthiness (Mayer et al. 1995; Möllering 2006). Further research positions the ABI dimensions of trustworthiness as parts of trust, e.g., in the e-commerce segment (McKnight and Chervany 2001). Lankton and McKnight (2011) show that the effect of the benevolence dimension of trustworthiness on further outcomes is fully mediated by trust. Furthermore, perceived benevolence is used in research as a proxy for benevolence-based trust (e.g., Shazi et al. 2015; Svare et al. 2020). I follow this approach and develop a measure of perceived benevolence in customer support services as a proxy for benevolence-based trust.

In previous research, benevolence has often been measured with questionnaires. For example, Grayson, Johnson, and Chen (2018) use a three-item measurement of benevolence, containing three questions, including the respondent's belief that "the trusted party will offer support on issues important to the respondent" (Grayson et al. 2018:246). Lankton and McKnight (2011) and Lankton et al. (2015) also use a three-item measurement of benevolence, including, e.g., "[Microsoft Access/MySNW.com] does its best to help me if I need help." (Lankton et al. 2015:916)[44].

In the absence of a dedicated trust questionnaire, I turn to observational data to operationalize benevolence and benevolence-based trust in this work. The advantage of such operationalization is that the benevolence-based trust can be identified through data available on the customer problems reported to customer support units of the service provider (similar to the approach taken by Nguyen (2016) for financial service providers). Thus, while no explicit answer to a benevolence questionnaire is available, the information on customer support services allows to implicitly observe perceived benevolence in the interactions between the customer and the service provider on the customer level. Since the companies are using the same product, there is a common baseline for customer support. The same technical functionality and same help

[44] Their research includes a separate three-item measurement of helpfulness, in which one of the measures is "[Microsoft Access/MySNW.com] provides whatever help I need" (Lankton et al. 2015:915). This illustrates the closeness of previously used measures in studies on benevolence and helpfulness.

functions are available to everyone in the standard solution. With the interest of this work directed at the relationship-based part of the helpfulness-benevolence construct, customer support to customers becomes the main focus of the operationalization.

When it comes to customer support and complaints research, frequently used data sources are Twitter (e.g., Herzig et al. 2016) and industrial collaborations (e.g., Fitzgerald and Doerfel 2004; Symonenko, Rowe, and Liddy 2006). Research is focused on central problem identification (e.g., Fitzgerald and Doerfel 2004), complaint classification (e.g., Symonenko et al. 2006), evaluating the helpfulness of the support agents in conversations (e.g., Packard and Berger 2021), estimating customer sentiments from the customer problem descriptions (e.g., Herzig et al. 2016), and analyzing conversation flow to further predict satisfaction, customer frustration, and problem resolution (e.g., Oraby et al. 2019). Regarding the methodological decisions, Fitzgerald and Doerfel (2004) use a semantic network approach of all customer problems reported to a bank to identify key customer complaints reported to the company. Their analysis does not distinguish between individual customers. Bastani, Namavari, and Shaffer (2019) use an unsupervised Latent Dirichlet Allocation (LDA) model to identify the latent topics of customer complaints reported to the previously mentioned Consumer Financial Protection Bureau.

This study differs from the previous research, as the customer problem descriptions are used to evaluate the perceived benevolence on the organizational level of customer organizations, not on the level of individual users or all customers. This requires an aggregated view of the customer problems. The research on service recovery illustrates that successful problem solving has a range of positive effects on the relationship, whereas failure to solve a problem and, as its outcome, repeatedly reported customer problems influence the relationship negatively (e.g., Michel, Bowen, and Johnston 2009)[45]. Building on this perspective, I derive the measures of benevolence-based trust based on the variation of problems reported by customers. I apply the semantic network and latent topic perspectives to measure customer problem structures. The measures identifying customer problem structures not centered around one problem are

[45] Service recovery research refers to this as a „recovery paradox“. In this case, customer satisfaction is higher after the solution was provided than in the case of service without problems (Michel et al. 2009:257).

interpreted as high perceived benevolence and, following, high benevolence-based trust. In this case, customer problems do not have to be reported repeatedly. Following, the support provided to the customer is providing helpful solutions. Low perceived benevolence and low benevolence-based trust are linked to measures identifying the centering of problems around the repeatedly reported problems. In this case, the support does not provide helpful solutions to customer problems.

I use combined subject lines of customer problems over the time between January 2018 and August 2019 to identify the structures of problems on the customer level. On the within-customer problem level, I look at the semantic networks of customer problems and measure benevolence-based trust as the modularity of the semantic network. On the between-customer problem level, I use a Latent Dirichlet Allocation (LDA) model to model the space of latent problem topics across all customers and measure the benevolence-based trust as the probability of customer problems to belong to the same latent problem – latent topic coherence. I study the effects of benevolence-based trust on customer behavior with the outcomes of customer participation in Net Promoter Score (NPS) surveys as the engagement outcome in the usage phase and customer extensions or terminations as the outcome in the renewal phase.

3.2.2.1 Within-customer problem structures: Customer Semantic Networks

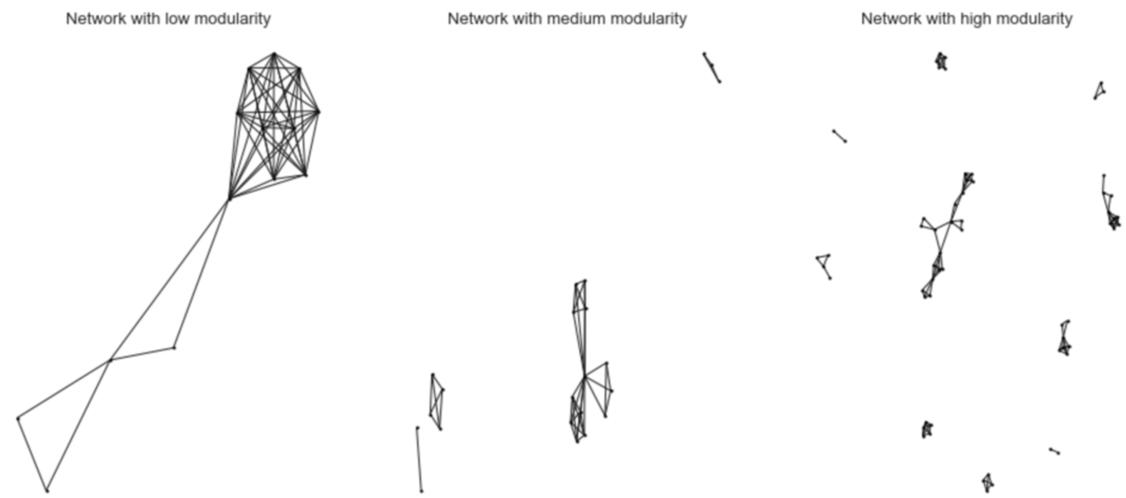
To measure customer problem structures, i.e., the structures of cases a customer files considered independently of the other customers, I form semantic networks of keywords used in all problems filed by a customer[46]. To measure the structure of the network, I use modularity as measured by the greedy modularity algorithm (Newman and Girvan 2004; Clauset, Newman, and Moore 2004; Karrer and Newman 2011). Modularity is a network structure measurement that identifies how a network is distributed into communities (Newman and Girvan 2004). It has, among other applications, been used in social science research for identifying communities within social networks (e.g., Newman 2006; Chen, Zaïane, and Goebel 2009), in semantic

[46] The semantic networks approach is chosen over more complex, e.g., vector embedding approaches, since subject lines analyzed in this work do not offer enough length or context to form meaningful embeddings for the keywords when observing the cases on the within-customer level.

networks (De Deyne et al. 2017; Christensen and Kennett 2019), and in semantic networks of customer complaints (Fitzgerald and Doerfel 2004)[47].

Figure 3.2 illustrates three customer problem networks with different modularity scores. The left network has a low modularity score of 0.22, and it is visible that all nodes in the network form a single component. The middle network has a medium modularity score of 0.59, and while a few separate components are visible, a larger component is still identifiable. The right network illustrates the modularity score of 0.86. Here multiple individual components are identifiable.

Figure 3.2.: Semantic networks of low, medium, and high modularity

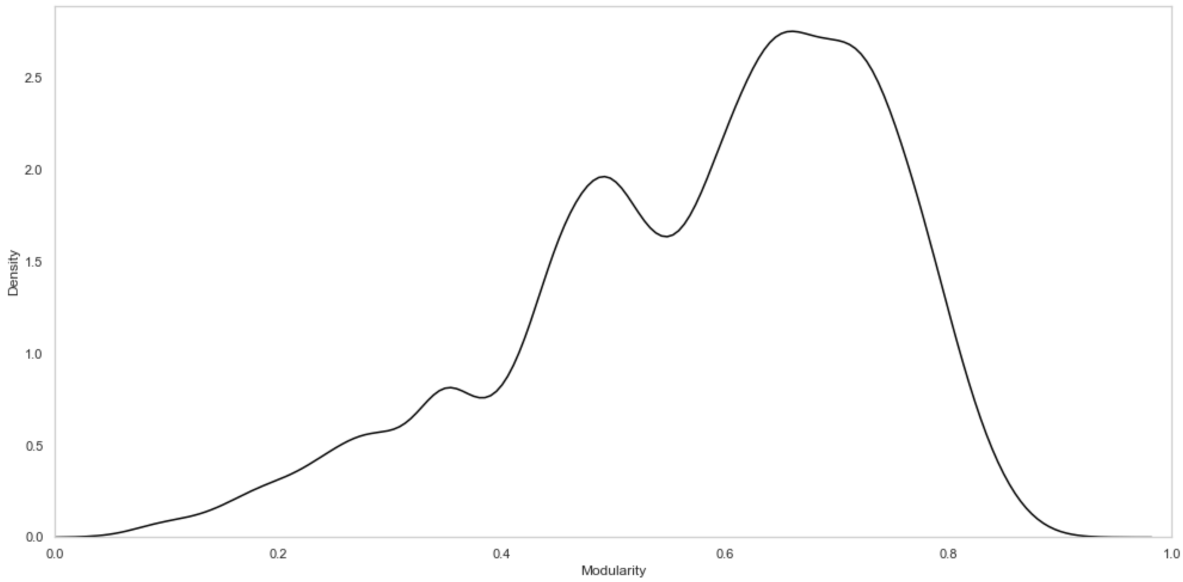


The primary assumption of this analysis is that low modularity is related to the concentration of customer problems around the same keywords. This measure, however, does not directly say that the customer problems are the same. It illustrates that customers describe their problems with the same vocabulary – keywords. Thus, customers having a semantic network of problems where every description is related to previous descriptions have low modularity scores. In contrast, customers with multiple problems not connected semantically have high modularity scores. Thus, this measure identifies the within-customer problem space and the perceived similarity of customer problems on the level of a customer. The modularity score for a customer problem network of a given time period identifies the connectedness of problems around the

[47] For an overview of the semantic network analysis, see Drieger (2013).

same semantic elements – keywords – as reported by the customer. Figure 3.3 presents the modularity distribution of full customer problem spaces for the full sample of customer cases. It shows that there are rather few customers with low modularity scores, while modularity scores between 0.6 and 0.8 have the highest density, indicating a consistent quality of provided support.

Figure 3.3.: Modularity distribution, all cases



Regarding the benevolence-based trust measured with the modularity scores, I argue that low modularity signals connectedness of problems from the customer's perspective. Thus, it illustrates that a problem occurs and is reported in similar terms repeatedly, while the optimal solution from the customer's perspective is not provided. Hence, low modularity represents low benevolence-based trust. In cases of high modularity, the opposite situation is observed. Multiple cases are opened to different topics that correspond to a situation when support is provided, and the problems are not reported repeatedly, i.e., the customer perceives help provided by the service provider to the issues. High modularity represents high benevolence-based trust[48].

[48] While it is natural to assume that no problems are better than solved problems, research shows that positive problem-solving experience can be evaluated better than no problems (McCollough and Bharadwaj 1992; McCollough, Berry, and Yadav 2000). Furthermore, in the data of the service provider, I observe that customers who have never reported a problem case are likely to also not be using the product.

3.2.2.2. Between-customer problem structures: Latent Topic Model

While the within-customer problem space illustrates how the connectedness of the problems is reported by the customers, in the next step, I turn to the between-customer problem space to create a second measure of benevolence-based trust – one based on the problem space of all customers. I follow the latent topic approached used by Bastani et al. (2019).

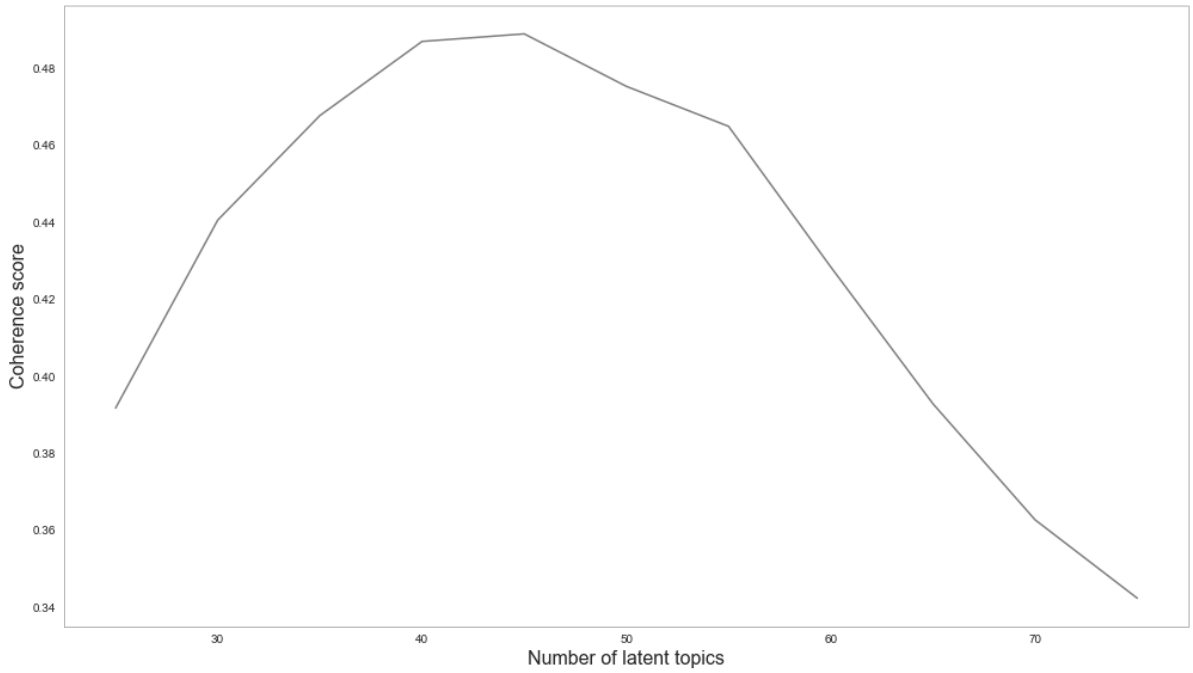
In the first step of the latent topic analysis, I train an unsupervised Latent Dirichlet Allocation machine learning model to identify the latent topics present in individual customer cases. Such models are popular in the domain of text analysis (Molina and Garip 2020). They have computational advantages, e.g., fast processing of high amounts of unstructured text data (Blei, Ng, and Jordan 2003; Wallach et al. 2009), and give the researchers the possibility to use the outcome of the model for further analysis (Molina and Garip 2020). LDA models have been applied to multiple text data sources, e.g., Twitter (Hong and Davidson 2010; Wagner et al. 2012), Science articles (Blei and Lafferty 2007), or political debates (Patwari, Goldwasser, and Bagchi 2017). This approach is similar to the sublanguage model applied to customer "trouble tickets"[49] by Symonenko et al. (2006) and has been applied by Bastani et al. (2019) use an LDA model to study customer complaint data available to the Consumer Financial Protection Bureau (CFPB)[50].

I apply a Latent-Dirichlet-Allocation (LDA) model (Blei et al. 2003) without covariates[51] for topic modeling to the entire data basis of case subjects. The keywords of each case are analyzed with respect to their cooccurrence in other cases. This step results in clusters of keywords corresponding to the latent topics[52]. The coherence score is used to identify the optimal number of topics. Figure 3.4 presents the coherence score plot of multiple LDA models trained on the same basis of case keywords. The coherence

[49] An alternative term to cases.
[50] The CFPB complaints data was used in this study to illustrate the customer case data structure.
[51] Including covariates, e.g., from metadata, is a possibility to improve the models (Wagner, Strohmaier, and He 2011). This approach is not used in this work for two reasons. First, the metadata of cases will be used in the regression analyses together with the topic probabilities. Using it for the topic generation would lead to a correlation between key variables in the following models. Second and more importantly, it is not the goal of this work to build a nuanced topic model but to build a topic model that only represents the underlying connections between customer problems.
[52] In the following, I use the term keyword to refer to the words within a case. I use the term topic to refer to the collection of words that belong to the same latent topic.

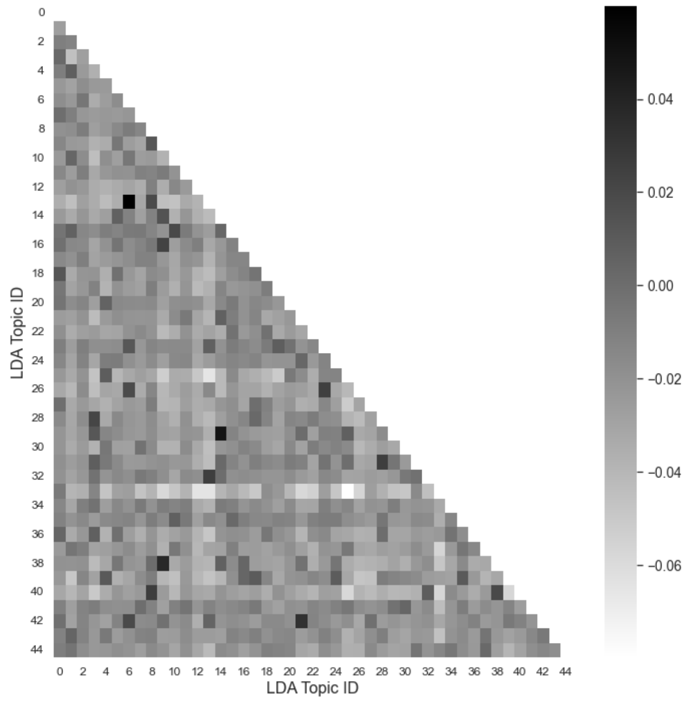
score is maximal at 45 topics. Afterward, a drop in coherence occurs. This number of topics provides maximal within-topic coherence and the maximal distance between topics, thus, reaching the optimal separation of the customer problem space into latent problems.

Figure 3.4.: Latent Dirichlet Allocation Models, coherence score evaluation (N topics between 25 and 80)



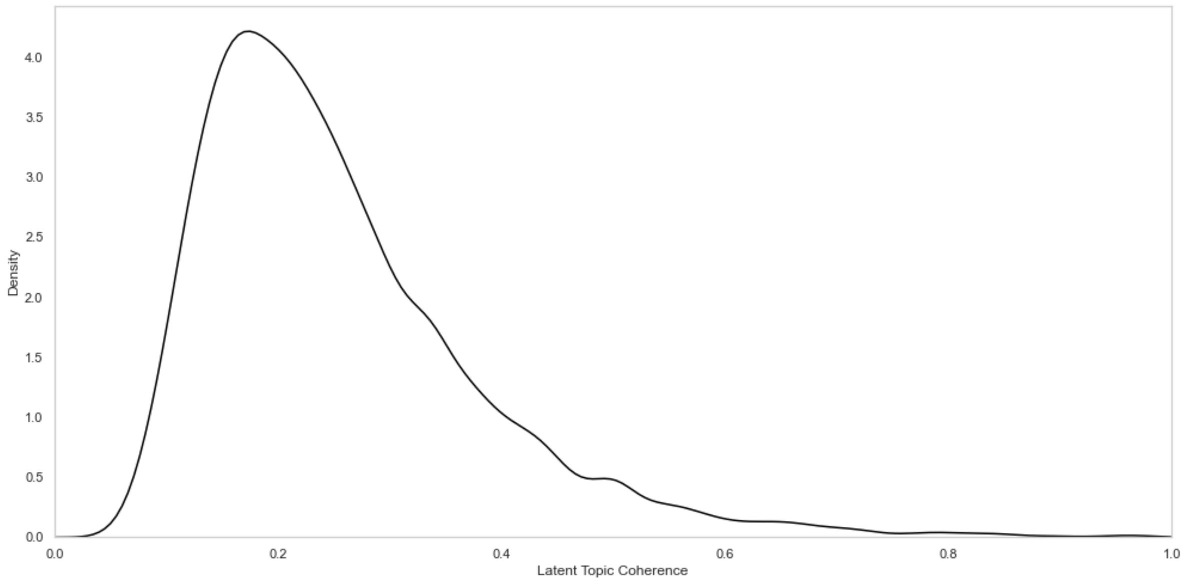
As a robustness check, I check the correlations between the probabilities that a case belongs to a particular topic. For each case, the probability that a text with given keywords belongs to each of the 45 latent topics is calculated. The results are presented in figure 3.5. Strong positive correlation between topics would indicate that with a higher probability of belonging to one topic, the probability of belonging to a different topic would increase as well. Thus, high correlations between topics would contradict the required separation between the topics derived by the LDA model. With the average correlation between topics of 0.0013, I conclude that no correlations between the 45 topics can be observed. The highest positive correlation is visible between topics 6 and 13 (r = 0.0598). The highest negative correlation is observed between topics 33 and 25 (r = -0.0799). Thus, I conclude that the LDA model with 45 topics achieves a representation of customer problem topics and identifies independent customer problems in the form of latent topics. These topics are further used to measure customer problems in the full problem space.

Figure 3.5.: Latent Dirichlet Allocation Model, topic correlations between individual cases



Same as the modularity measure, the latent topic coherence for each customer is calculated based on the combined subject line keywords of all customer cases. Using the combined keywords as input for the pre-trained LDA model with 45 topics, I calculate the probability of combined customer cases to belong to each of the 45 latent topics is calculated. The maximal value of the probabilities is used to identify the probability that all cases opened and closed within the timeframe of interest belong to the same latent problem – the latent topic coherence measure. The maximal theoretically possible latent topic coherence is 1.0, which is not reached in the observed data. The probability of 1.0 identifies that all customer problems are identified by the LDA model as belonging to the same latent problem. The maximal probability value reached in the observed data is 0.976. The minimal theoretically possible probability of 0.022 identifies that the case keywords for the customer have the same probability of belonging to each of the 45 latent topics. This case, however, is not achieved in the observed data. The minimal latent topics coherence for the observed customer cases is 0.055. Figure 3.6 presents the latent topic coherence distribution of full customer problem spaces for the full sample of customer cases. The figure shows that most customers have a probability of all their reported cases to belong to the same latent problem of 0.2. This value is rather low and corresponds to different latent topics being reported by customers.

Figure 3.6.: Latent topic coherence distribution, all cases



Turning to the relationship of this measure to benevolence-based trust, similar to the modularity measure, it relates to the support provided to the customer and the repeated problems reported by the customer. When the probability of all customer cases belonging to the same latent topic, i.e., the same underlying problem, is high, the service provider provides not enough support to the customer. Thus, the issue has to be reported repeatedly. This represents a measure of low benevolence-based trust. A case when the probability of all customer cases to belong to the same latent topic is low signals support provided to different problems. Thus, the low probability of all cases belonging to the same topic represents high benevolence-based trust.

3.2.2.3. Comparison of benevolence-based trust measures

Both proxy measures of benevolence-based trust rely on repeatedly reported problems to customer support. Such repeated reporting of problems is associated with low perceived benevolence of the service provider, i.e., the support and assistance of the support services cannot be evaluated positively due to predominantly recurring problems (e.g., Michel et al. 2009). These operationalizations of benevolence-based trust are derived using state-of-the-art methods to analyze customer problem data. This section discusses the differences between the measures.

The main difference between the measures is the information used to detect recurring problems. The latent topic coherence measure relies on the information provided by all customers to identify the combinations of keywords that form latent topics. In contrast, the modularity measure only relies on the problems reported by one customer. For example, if one customer refers to the same problem with a wide range of keywords, the modularity measure will see them as different problems. However, the topics probability measure will identify them as belonging to the same topic.

A further mentioned difference between the measures is the reverse coding of the latent topic coherence measure compared to modularity. Notably, the distribution of modularity of full customer problem spaces is left-skewed (figure 3.3), while the distribution of maximal latent topic probability is right-skewed (figure 3.6). This observation, together with the observed correlation between the measures of -0.64[53] in the full sample, supports the described expectation of reverse effect directions of the measures.

A major limitation of the proposed measures is that they cannot be fully verified as measuring the perceived benevolence of customer support services within the setting of this study. A dedicated trust survey is not available at the time of analysis. A possible way to evaluate helpfulness as a prerequisite of benevolence-based trust for individual cases is by using the customer satisfaction surveys related to individual problems (Alvarez et al. 2010). The survey response data are not used in further analyses due to low coverage (only 4% of the cases have data on the satisfaction with the resolution of the case and the satisfaction with the support agent). Table 3.4 illustrates the correlations between modularity and latent topic coherence measures and the satisfaction survey results. Overall, no strong correlations to survey responses are

[53] The correlation in further used time-varying samples is slightly lower. However, a variance inflation factor will be calculated to make sure that the correlation is not concerning for the analysis. The measures are treated separately in the analysis of the long-term effects of benevolence-based trust.

observed. Nevertheless, the opposite directions between latent topic coherence and modularity correlations with average survey results for customers are notable.

Table 3.4.: Correlations between latent topic coherence and modularity measures and customer case satisfaction survey results

	Latent Topic Coherence	Modularity
Latent Topic Coherence	1.00	
Modularity	-0.64	1.00
Agent Knowledge Score	-0.06	0.03
Agent Satisfaction Score	-0.05	0.05
Case Resolution Satisfaction	-0.002	0.02

3.2.3. Operationalization of behavioral outcomes

The first outcome variable of interest is the participation in the Net Promoter Score survey. Many enterprises worldwide have adopted the Net Promoter Score Survey (NPS) as a measure of customer satisfaction (Tong et al. 2017; Lewis and Mehmet 2020). Developed initially by Reichheld (2003, 2006), this score is measured with a set of questions regarding the probability that a customer will recommend the service to a friend or a colleague. This score, on the one hand, is a simple and effective measurement of customer satisfaction. On the other hand, researchers find multiple issues related to the interpretation of the score values (Kumar, Petersen, and Leone 2007; Stahlkopf 2019) and the low participation rates, especially in B2B businesses (Grisaffe 2007).

Taking the mentioned issues into account, in this study, I use the participation in the NPS survey along the lines of the exit-voice-loyalty-neglect categorization developed by Hirschman (1970). Following this categorization, customers who have not participated are classified as neglecters. In contrast, customers who participated in the survey, independently of the score value, are classified as either voice or loyalty[54] categories for high and low scores, respectively. Adapting the scores in this way, I am focusing on participation in the NPS survey as a measurement of customer engagement with the

[54] While loyalty is considered passive in the original development of the framework, I argue that positive feedback provided through the established feedback mechanism is, in this case, an illustration of active loyalty (Tong et al. 2017).

company, even if their experience is negative. According to the exit-voice-loyalty-neglect framework, executing the voice option and raising concerns refers to the use of established mechanisms to attempt a positive change (Farrell and Rusbult 1992). Thus, participating in the NPS survey, independent of the survey result, is active and constructive engagement and open communication with the service provider company through an established feedback mechanism of the NPS survey. For the product for which the data are available in this work, there are three NPS cycles – Spring, Summer, and Fall, the average response rate in the time period of the analysis is 5%.

The second behavioral outcome of interest is the extension or termination of the relationship with the service provider. This outcome is important as the general representation of commitment – the continuation of the contractual relationship with the service provider. I measure the extension or termination of a contractual relationship with a dummy variable. The termination rate for this product[55] is close to the termination rate of 5.6% reported for B2B products by Recurly Research (2018).

3.2.3.1 Effect of benevolence-based trust in the usage phase of the contractual relationship

After identifying the measures of within-customer (modularity) and between-customer (latent topic coherence) problem spaces and their relationship to the benevolence-based trust, I turn to the immediate analysis of benevolence-based trust and its effect on customer engagement. I create subsets of customer case data within the months between the NPS survey cycles. The time between NPS cycles amounts to 5 months between Spring and Summer, 4 months between Fall and Spring NPS surveys, the time between Summer and Fall NPS surveys is 3 months. Having only one open case within the timeframe of interest would lead to a fully connected semantic network, which is why I exclude customers with only one case in the subset. As more than three nodes are necessary to create a network, I also exclude customers whose case subjects in the subset only contain stop words or only one keyword. To avoid interactions with integrity-based

[55] Due to the confidentiality of customer data, the exact numbers cannot be published in this work.

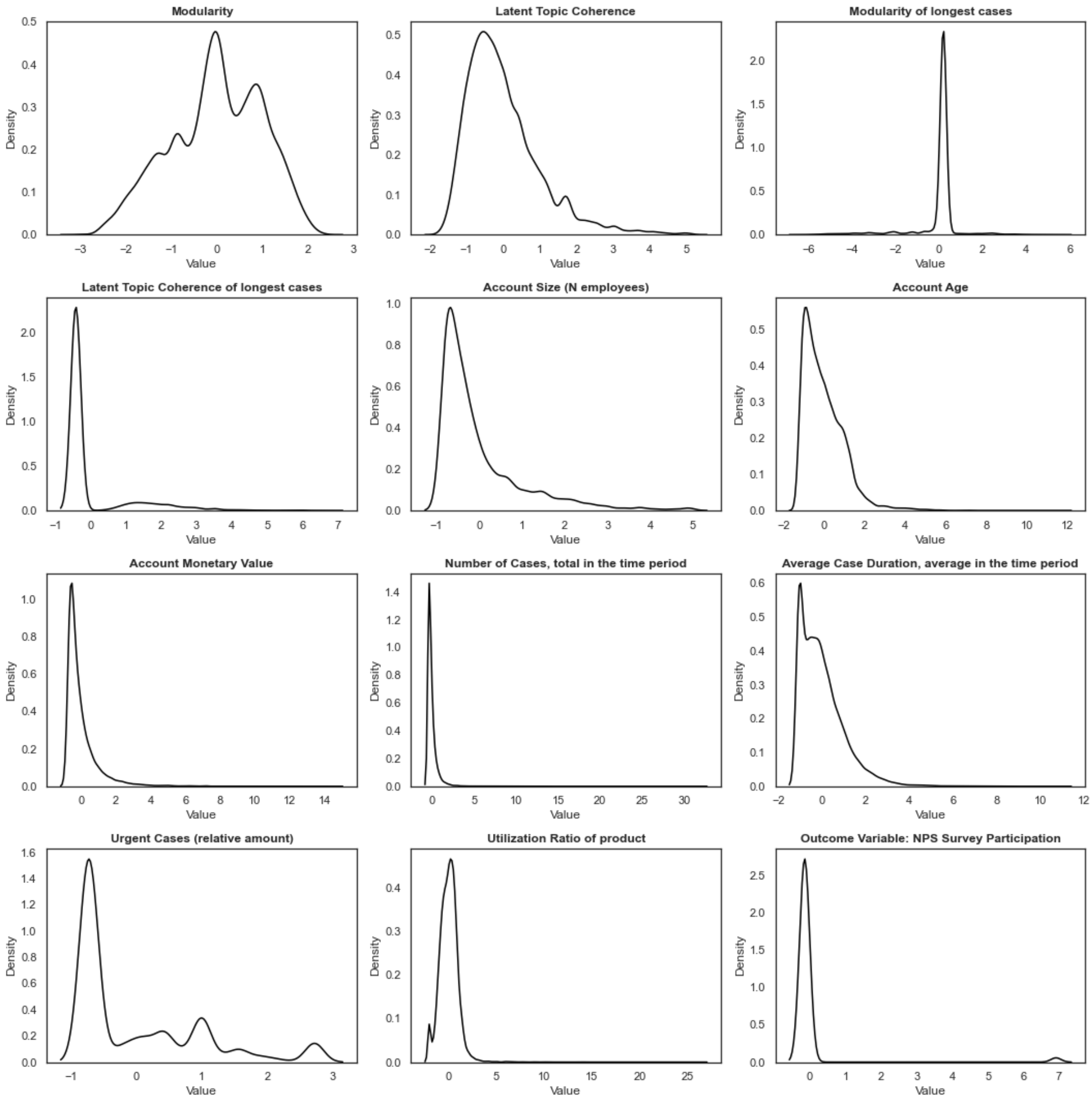
trust forming at the beginning of the relationship, I exclude customers under 2 months of age[56]. In total, 2% of the customers are excluded.

The resulting case subsets include all cases opened within the timeframe before an NPS survey cycle for each customer. I calculate the modularity score of the semantic network as the first and the latent topic coherence as the second benevolence-based trust measure. Additionally, I extract the cases taking more than 3 times the median time to solve as the longest problems[57] and measure the modularity and latent topic coherence of these cases to belong to the same topic. This is done to investigate potential differences in the most severe customer problems compared to all customer problems.

In the next step, I use a logistic regression model to investigate the effects of benevolence-based trust on participation in the NPS survey during the usage phase of the contractual relationships. The dependent variable is the participation in the NPS survey at one of the specified points in the NPS cycles of years 2018 and 2019. The independent variables of interest are two benevolence-based trust measures – modularity and latent topic coherence – for the full subset and for the most severe (longest to solve) cases in the subset. The control variables include firmographic controls (account age (time in contact), account size measured with the number of employees, and the monetary value of the contract), as well as control variables for cases (total number of cases, number of cases of high urgency, and average case duration in the timeframe of interest) and the ability-based control variable (utilization of the product in the timeframe of interest, in percent)[58]. All variables are standardized before the analysis. Figure 3.7 illustrates the distributions of the standardized independent and control variables[59].

[56] This finding is based on the measurement of integrity-based trust developed in the second chapter. An average customer starts the product usage after about 3 months, and integrity-based trust was shown to be developed earlier.
[57] Again, only customers having more than one case that lasted 3 times longer than the median time to solve with more than three keywords in the description have measures for these values. In other cases, the missing values for the maximal probability of longest cases to belong to the same topic are replaced with a 0, and the modularity of longest case networks for these customers is set to 0.5.
[58] While the data structure described here looks suitable for a multilevel regression model, the only variable available on the higher level is the number of employees in a company. Thus, a classical approach is chosen.
[59] A corresponding figure for the new customers sample can be found in the appendix.

Figure 3.7.: Density plots of standardized variables, full sample



As many independent and control variables originate from the measurements of cases in the timeframe before the NPS survey cycle, some of them are correlated. For instance, the correlation between the number of cases and the modularity is 0.5. Thus, I calculate the variance inflation factors (VIFs) for the independent and control variables in the full regression model to investigate potential problems with multicollinearity. Table 3.5 illustrates a higher VIF for the variables number of cases and modularity, while for other variables, the VIF is close to 1 and can be considered unproblematic. A VIF of over 10 is considered high in literature, while the conservative threshold for a problematic VIF is 3.3 (see Kock and Lynn (2012) for a detailed analysis). With the VIF values for the number of cases and modularity below both thresholds, I consider the multicollinearity not concerning for the planned analysis.

Table 3.5.: Variance Inflation Factor (VIF) of independent and control variables, by sample

	Variance Inflation Factor	
Variable Name	Full Sample	New Customers Sample
Benevolence: Modularity	1.584	1.605
Benevolence: Latent Topic Coherence	1.531	1.456
Benevolence: Modularity of longest cases	1.535	1.532
Benevolence: Latent Topic Coherence of longest cases	1.951	1.946
Firmographic: Account Age	1.071	1.058
Firmographic: Account Size (N employees)	1.083	1.111
Firmographic: Account Monetary Value	1.114	1.146
Number of Cases	1.187	1.649
Urgent Cases (relative amount)	1.057	1.066
Average Case Duration	1.369	1.366
Utilization Ratio	1.002	1.012

I follow a nested regression approach and calculate the following models. First, separate models are fitted for the modularity measure of benevolence-based trust (Model 1) and the latent topic coherence measure of benevolence-based trust (Model 2). In the following models, I include both benevolence-based trust measures, add firmographic control variables (Model 3), benevolence-based trust measures for the longest cases in the sample (Model 4), and finally, the remaining control variables for case-related measures and the utilization control (Model 5). All models are fitted for the full sample and the new customers sample. Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) are used for model evaluation.

3.2.3.2 Effect of benevolence-based trust in the renewal phase of the contractual relationship

The expected outcome of trust in the renewal phase of the contractual relationship is the customer contract renewal. To investigate the general effect of benevolence-based trust on the customer contract extensions and terminations, I compare the distributions of modularity and latent topic coherence of customers' full problem space (all cases) and longest problems (cases taking more than 3 times the median time to solve). I run two-sided t-tests between the distributions to evaluate if there is a significant difference in benevolence-based trust measures between customers with different long-term outcomes. I repeat the analysis for both full and new customers samples[60].

[60] Long-term consequences of benevolence-based trust and its effect on customer terminations deserve much more attention than this chapter offers it. A more specific analysis is part of my fourth chapter, where I evaluate the effect of all three trust dimensions on the extensions and terminations of the relationship between the customer and the service provider with regression and supervised machine learning methods.

3.3. Results

To investigate the effect of benevolence-based trust on customer engagement in the usage phase of the SaaS contractual lifecycle, I analyze customer problem structures originating from customer support interactions between the customer and the service provider. I focus on the customer problem structures in the within-customer (modularity) and between-customer (latent topic coherence) problem spaces. In my analysis of the effects of benevolence-based trust, measured as modularity and latent topic coherence of customer cases, I fit logistic regressions to observe how benevolence-based trust relates to further customer engagement. Figure 3.8[61] illustrates the observed standardized coefficients from the fitted models in two samples.

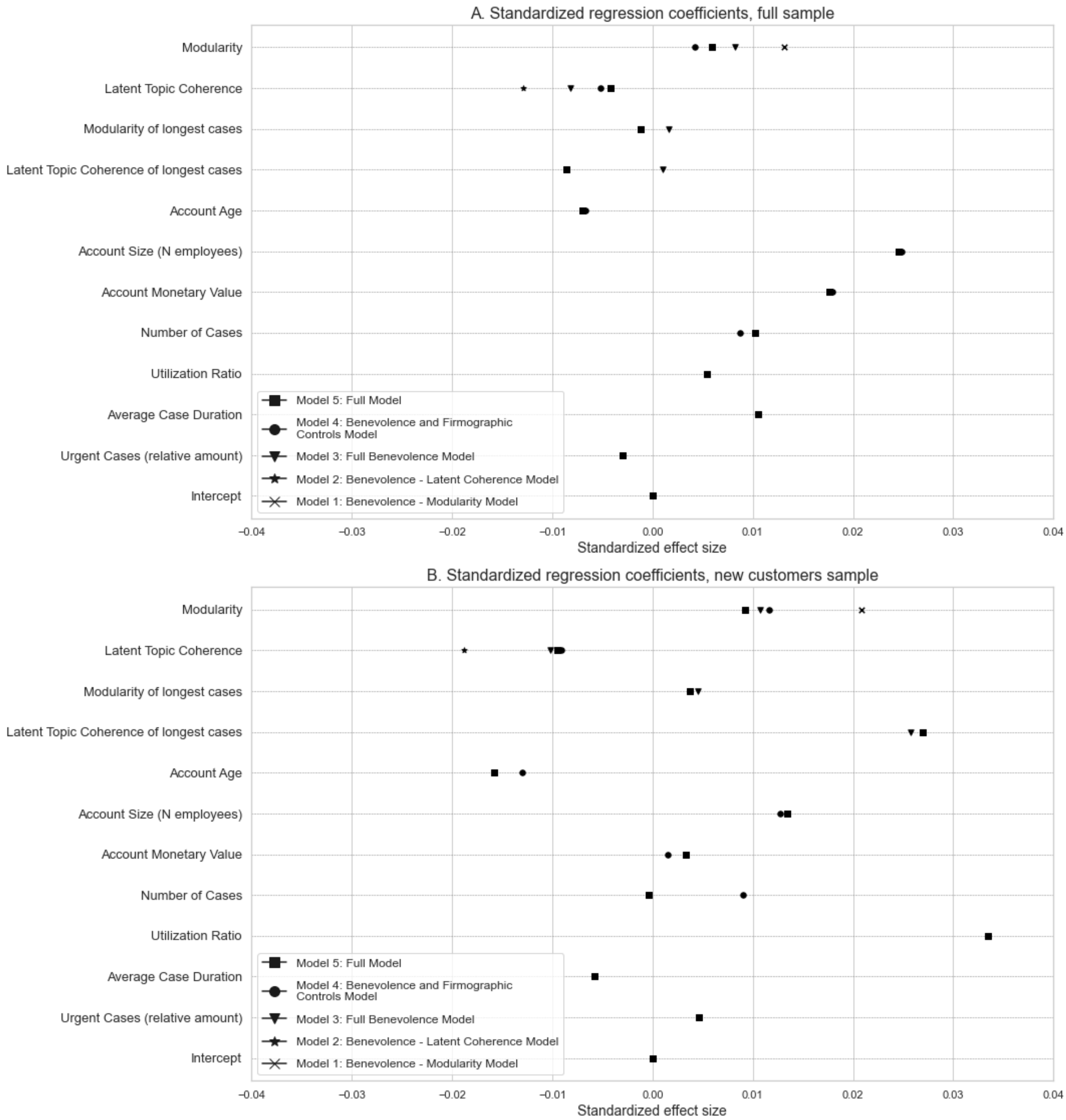
Overall, the models show a clear positive effect of modularity in customer problems on active participation in the feedback loop from the customer and a clear negative effect of latent topic coherence on participation in the next NPS survey cycle. Thus, the reoccurrence of one problem signaling lower benevolence-based trust of a customer has a negative effect on customer engagement in the usage phase of the contractual relationship and supports expectation 2.1 of this analysis. The effects are similar in the full and new customers samples.

Turning to the problem structures of the longest (most severe) problems (taking 3 times longer than the median time to solve), both the modularity and the latent topic coherence measures show negative effects on engagement in model 5 with control variables in the full sample. In the full benevolence model, these variables show a positive effect on engagement. When looking at the new customers sample with younger customers in general, the effects of the structures of longest problems are positive across all models. With the effect of account age being negative in both samples, this finding speaks to younger customers having a different reaction to violations of benevolence-based trust represented by longest to solve problems. Younger customers are also more likely to voice their feedback in an NPS survey. This finding corresponds to the previously detected differences when it comes to early

[61] The coefficients are presented without confidence intervals. With this analysis being based on a full sample, not the inference but the actual effects are of interest for interpretation. Regression tables with standardized coefficients and standard errors are presented in appendix A.3.2 (full sample) and A.3.3 (new customers sample).

benevolence-based trust violations in contracts (Bell et al. 2002) and shall be investigated in further research.

Figure 3.8.: Standardized regression coefficients for the effect of benevolence-based trust on customer engagement, full and new customers samples



Note: Standard errors of the standardized coefficients are not reported in the figure, since both samples are full samples given the specified conditions. Detailed regression tables can be found in appendix A.3.2 and A.3.3.

For both samples, it is notable that the effects of benevolence-based trust on engagement with the service provider decrease in magnitude in models when the firmographic control variables are added to the model. While first having a higher magnitude, the effect of within-customer benevolence-based trust measured by modularity is, in the end, smaller than the effect of the number of customer problems, which is a control variable representing ability-based trust.

The firmographic control variables, apart from the already mentioned difference in the effect of age, have similar effects in both samples. Bigger customers are more likely to engage in feedback loops with the service provider through the NPS survey. Regarding the case-related control variables, the effects differ between the samples. For instance, new customers are more likely to participate in the feedback loop when the relative amount of high urgency cases is high, while the opposite effect is observed in the full sample.

Table 3.6.: AIC and BIC of fitted models, by sample

	Full Sample		New Customers Sample	
Model	AIC	BIC	AIC	BIC
Benevolence - Modularity Model	22725.584	-136343.673	3312.193	-15256.398
Benevolence - Latent Topic Coherence Model	22725.458	-136343.8	3312.260	-15256.330
Full Benevolence Model	22731.332	-136314.812	3317.823	-15233.434
Benevolence and Firmographic Controls Model	22730.611	-136300.124	3321.936	-15217.764
Full Model	22740.134	-136252.078	3330.963	-15179.846

Table 3.6 illustrates the performance of the models for both samples. The full model shows the lowest BIC and highest AIC in both samples. Thus, the full model is the best option to model the relationship between benevolence-based trust and customer engagement.

Summing up, I could confirm expectation 2.1 with the modularity- and latent-topic-coherence-based benevolence-based trust measures between the customer and the service provider. Customers whose problems concentrate around similar topics are less likely to engage with the service provider to give feedback. This effect, however, is not observed for the most severe (longest) customer problems.

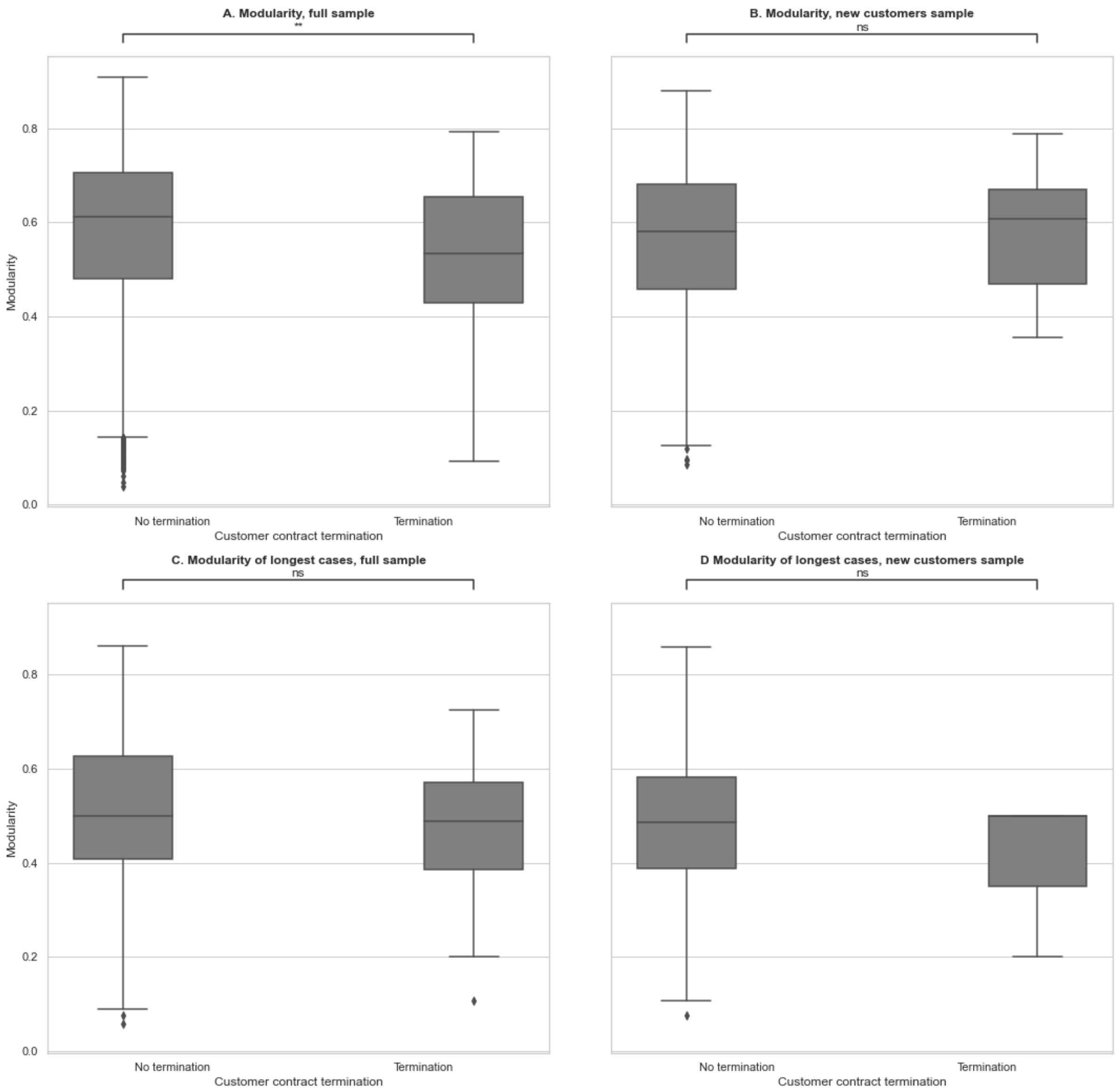
Turning to the effects of benevolence-based trust in the renewal phase of the contractual relationship – its effect on customer decisions to terminate their relationship with the service provider is similar to the observed effects on customer engagement. The findings are illustrated in figures 3.9 and 3.10. Modularity (as shown in figure 3.9, A, top left) is significantly higher, and latent topic coherence of all customer problems over their lifetime (as shown in figure 3.10, A, top left) is significantly lower in the group of customers who extended their contractual relationships when the full sample is considered. This finding provides support for expectation 2.2 stated in the theoretical part.

The distributions differ significantly for both benevolence-based trust measures when the full sample is considered. No significant difference is observed in the new customers sample, as also no significant difference is observed between the measures based on only the most severe (longest) problems. Although this difference in effects cannot be studied entirely in this work, it, first, emphasizes the importance of considering benevolence-based measures as aggregated measures of full customer problem spaces, not just subsets. Second, it emphasizes the time dimension. Namely, the effect of benevolence-based trust is expected to increase with the age of the relationship (Schoorman et al. 2007; Svare et al. 2020). The observed effect in the full sample with average customer age of 46 months (vs. 10 months in the new customers sample) indicates that the importance of benevolence-based trust is accumulating.

Although not significant for the longest problem measures, the effects seem to be more pronounced in the new sample. This can relate to the theoretical statement on early violations of benevolence-based trust being important (Bell et al. 2002).

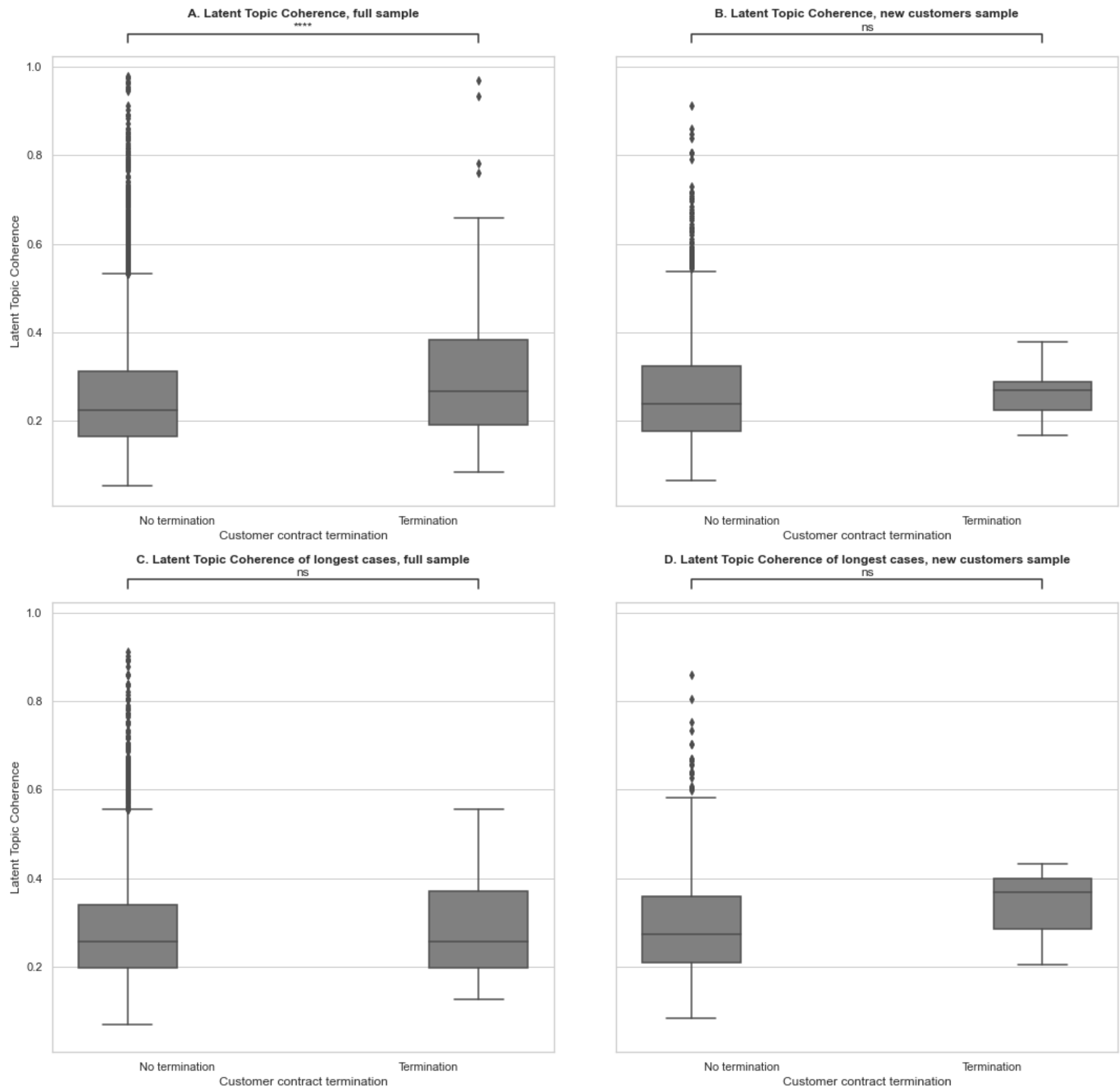
Summing up, the analysis presents evidence of benevolence-based trust and its outcomes observed through within-customer and between-customer problem structure measures – modularity and latent topic coherence. The findings support the expectations that customers with higher benevolence-based trust are more likely to engage with the service provider, provide both positive and negative feedback, and are less likely to terminate the relationship.

Figure 3.9: Modularity distributions by customer behavioral outcome in the renewal phase (contract extension or termination), full and new customers samples



Note: ****: p < 0.0001; ***: p < 0.001; **: p < 0.01; *: p < 0.05; ns: p > 0.05.

Figure 3.10: Latent topic coherence distributions by customer behavioral outcome in the renewal phase (contract extension or termination), full and new customers samples



Note: ****: p < 0.0001; ***: p < 0.001; **: p < 0.01; *: p < 0.05; ns: p > 0.05.

3.4. Managerial Implications

This chapter provides an answer to the second research question stated in the introduction from the service provider's perspective. Do the support teams achieve a positive effect on customer engagement when providing solutions to customer problems?

Customer support is an essential way of communicating issues between a service provider and their customers (Jabr et al. 2014; Hochstein et al. 2020). Recent studies highlight the importance of customer support as a value-generating unit (Sheth et al. 2020). This study contributes to this research while illustrating the effects of benevolence-based trust measured through customer problem cases on customer engagement in the form of NPS surveys and customer contract extensions and terminations.

Thus, this study provides additional support to the previous findings on the value that can be generated through customer support activities that can be directly interpreted in measures of customer engagement in feedback loops and customer contract extensions and terminations. Furthermore, the measures proposed in this study allow one to understand the problems of customers and provide targeted solutions to customers having problem structures with high problem concentration in the within-customer problem space (low modularity of problems) or in the between-customer problem space (high latent topic coherence). Thus, the proposed measures can be leveraged to improve customer support offerings and strengthen the relationship with the customers through benevolence-based trust. Furthermore, these measures can be included in the applied models to detect customers with termination risk (Slof, Frasincar, and Matsiiako 2021).

3.5. Discussion

This chapter focuses on the dimension of trust expected to gain importance over time in a relationship but to have a smaller effect on customer behavioral outcomes (Mayer et al. 1995) – benevolence-based trust. While looking at this dimension of trust, I investigated the behavioral outcomes that a service provider's support measures can reach in customers. The findings show a clear positive effect of benevolence-based trust on customer engagement with the service provider in the usage phase of the product and provide the first evidence of a positive effect of benevolence-based trust on customers' commitment in the relationship, in this case, on contract extensions. In other words, customers whose problem structures indicate higher benevolence-based trust are more likely to respond to the survey coming from the service provider and are less likely to terminate their contracts.

The first contribution achieved with this work is to the organizational research focusing on trust and benevolence-based trust in particular. First, I extend this research to the SaaS market and confirm the suggested theoretical effects of benevolence-based trust in long-term relationships. Second, I propose two observational measurements of benevolence-based trust specific to the SaaS market, where benevolence-based trust can be found in the interactions with customer support. However, further investigations of the measurement will be needed to ensure the external validity of the findings.

An extended theoretical contribution of this work can be observed when the uncertainty in the relationship between a service provider and a customer over a long period of time is considered. Support provided to customers corresponds to the relationship element of uncertainty that is more pronounced in an established relationship (Benlian 2009; Marston et al. 2011). This uncertainty extended over the duration of the relationship is a key difference between Software as a Service subscription contracts and one-time contracts, frequently discussed in uncertainty research. Thus, this work further emphasizes the importance of differentiating between the different trust dimensions when looking at trust as a solution to the uncertainty in a relationship.

The second contribution of this work is practical and refers to the trust-generating value of customer support that I discussed in the managerial implications of this work. It opens possibilities for service providers to better understand their customers and the relationships formed between the organizations when studying the customer's problem spaces with the proposed measures of benevolence-based trust.

Next to the advantages of the proposed measures stand the limitations of this study. The applied measures are based on the relationship between solving customer problems and trust (Gounaris 2005) and on the state-of-the-art methods to analyze customer problems and derive the underlying topics and structures (Firzgerald and Doerfel 2004; Bastani et al. 2019). Nevertheless, these measures have not been used previously to measure trust and trustworthiness. Thus, the main limitation of this study remains the validity of the measures. The correlation analysis for the measures with the problem solution satisfaction survey only allows for limited validation of the measures. Before applying the measures in future research, a detailed study of the relationship between customer problem profiles must follow.

Multiple extensions of the proposed research agenda are possible that lie outside of this work's scope. The aforementioned in-depth study of measuring benevolence-based trust with a combination of observational and survey data is the first possible extension to this work. Moreover, the understanding of benevolence-based trust had to be isolated from the cultural aspects for the purpose of this analysis. As only English-speaking customers were considered for this analysis, the cultural aspect of benevolence-based trust (Sheppard and Sherman 1998) was deliberately excluded from this study. Extending the benevolence-based trust measurements to other countries and especially to other languages, as well as to service providers with different customer bases, provides an opportunity to observe intercultural differences in benevolence-based trust illustrated in previous research (e.g., Wasti and Tan 2010).

Finally, a further natural extension of this and the previous chapter is an in-depth investigation of the combined effects of different trust dimensions in an interorganizational setting on customer commitment. This extension is in the scope of this work and will be covered in the next chapter.

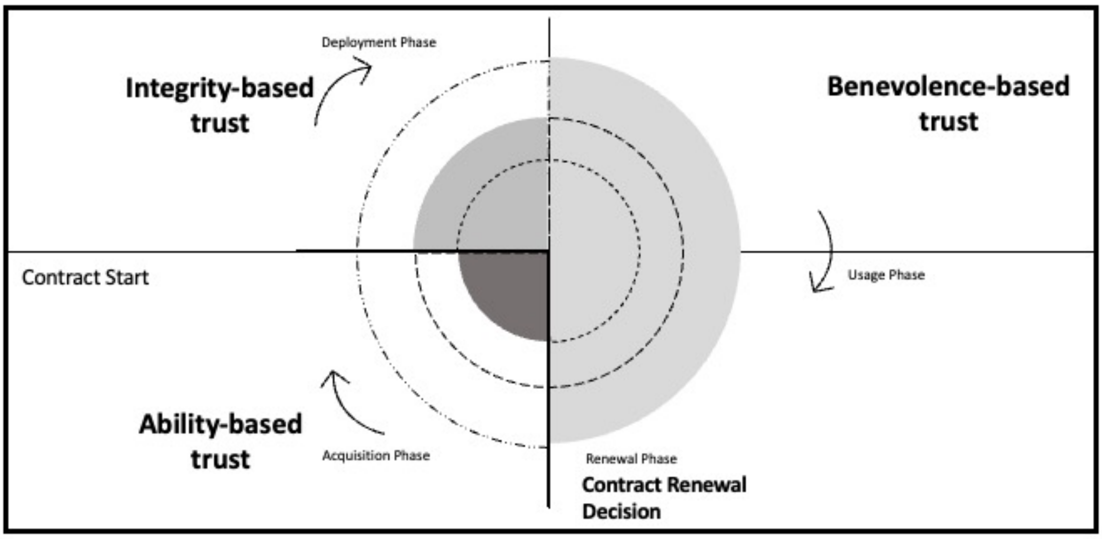
Effects of trust dimensions on customer commitment in the relationship

Linking the ABI trust dimensions to customer decisions to extend or terminate their contractual relationship with the service provider

Relationships between the customers and the service providers (SP) in Software as a Service (SaaS) contracts exist under a necessary condition of trust (McKnight et al. 2011). In the previous two chapters of this work, on an example of a company and its customers, I illustrated how the dimensions of trust are developed in the customer success and support units of a service provider. Integrity-based trust is based on the experiences of interactions in the earliest stage of a relationship with the customer and, according to theory, reduces over time (Mayer et al. 1995; Pollack et al. 2017). Benevolence-based trust is created over time through the interactions with customer support and can vary over time (Mayer et al. 1995; Alvarez et al. 2010). This study investigates the different effects of dimensions of trust according to the Ability, Benevolence, Integrity (ABI) framework on behavioral outcomes of customer commitment, i.e., a customer's decision to extend or terminate the contractual relationship. The effect of ability-based trust is expected to be the strongest, the effects of benevolence-based and integrity-based trust to be of lower magnitude (Mayer et al. 1995; Schoorman 2002; Schoorman et al. 2007).

Figure 4.1 illustrates the position of the effects under investigation in this chapter. While the previous chapters focused on individual parts of the contractual relationship, now the contractual relationship as a whole is observed, and the trust dimensions formed during the relationship are studied with respect to their effect on customer continuation of a contractual relationship. This represents the commitment problem investigated in this work.

Figure 4.1.: Contract renewal decision and trust dimensions in a relationship between a SP and a customer



Commitment, simply put, is understood as consistent behavior (Becker 1960). Recent studies emphasize the importance of commitment in contractual relationships (Venetis and Ghauri 2004). Multiple interpretations of commitment in business relationships are possible, from repeated purchases and continuation of the contractual relationship, therefore, building a long-term relationship between the parties (e.g., Moorman, Zaltman, and Deshpande 1992; Xiao et al. 2020), to a perception of commitment as covering an aspect of loyalty to the service provider (e.g., Morgan and Hunt 1994). Still, it is possible to generalize the perception of commitment in business transactions to the continuation of the relationship (Venetis and Ghauri 2004). Thus, in the case of service providers and their customers, the commitment is presented through the action of the contract extension. In this study, I see customer commitment as the outcome of trust (Morgan and Hunt 1994) and analyze how different dimensions of trust, according to the ABI framework, influence commitment in the relationship, namely, the contract extension or termination. This is the primary research question and the main empirical contribution of this study.

This research question comes close to the industrial churn research – computational studies of customer data with the aim of predicting customer contract extensions and terminations (Neslin et al. 2006). This research area is characterized by frequent applications of machine learning methods (e.g., Huang, Kechadi, and Buckley 2012; Huang and Kechadi 2013). The data for this case study are provided by a service provider, which introduces a practical research question. How do SP's measures related to uncertainty reduction help a service provider to preserve a long-term relationship with a customer and ensure customer commitment when it comes to contract extensions?

In this chapter, I use the operationalizations of integrity-based and benevolence-based trust discussed in previous chapters to investigate how these trust dimensions relate to customer decisions on terminating their contracts. The analytical structure of this chapter consists of two parts. First, I follow a logistic regression approach and fit nested models to evaluate how different trust dimensions influence customer decisions. Second, I train several supervised machine learning (SML) models (logistic regression, decision tree, random forest, and XGBoost) to evaluate how the trust dimensions can be used in predictive models. While evaluating the models, I focus on the measures of accuracy, precision, recall, F1-score, and area under the precision-recall curve. Furthermore, I observe the feature importance values of the input variables in each machine learning model. Subsequently, I use the SHapley Additive exPlanations (SHAP) approach to calculate the individual variable contributions to the predicted outcome. While doing so, I show the overall importance of trust and its dimensions for explaining and predicting contract terminations and show the range of trust contributions to the outcomes for individual customers.

With this collection of methods and industrial data, this study combines the theoretical approach for solving a sociological question of a commitment problem and industrial machine learning practices from churn research. It leverages the novel data collection practices of a service provider. This positions this study in the area of computational social science, where industrial practices and methods are frequently adopted to sociological questions (Lazer et al. 2009). The application of machine learning methods and the availability of industrial data allow for more nuanced research (McFarland et al. 2016), while the availability of full population data, further referred to as the full sample, allows one to build a complete picture of the studied environment (McFarland et al.

2016)[62]. In this work, apart from the empirical contribution to organizational research, I contribute to the computational social science research and propose a sociological application of industrial methods that assist with making machine learning models explainable – the explainability framework of SHapley Additive exPlanations (SHAP).

In the logistic regression analysis, I show a negative effect of all trust dimensions on contract terminations of contractual relationships. Thus, as expected in theory, trust has a positive effect on customers extending the relationship and serves as the solution to the commitment problem. In the supervised machine learning analysis, I show that the differences in the importance of trust dimensions vary across models. A random forest model, reaching the highest performance across all models, supports the expected effects of ability-based trust being most important, benevolence-based trust, and integrity-based trust following. In the logistic regression and the XGBoost models, benevolence-based trust is the main contributor to predicting the outcome of contract extensions and terminations. In the investigation of the individual SHAP value distributions, the assumed relationships between the trust variables and the outcome of contract extensions and terminations are studied in more detail and confirm the effects observed in the logistic relationship analysis.

This chapter is structured as follows. I start with the theoretical presentation of the role that the ABI trust dimensions play when explaining customer commitment. Next, I describe the methodological strategy and the data. Finally, I turn to the discussion of the results.

4.1. ABI Trust Dimensions Solving the Commitment Problem

In interorganizational subscription relationships, the question of the buyer's (customer's) commitment to the supplier is of crucial importance for the supplier (Van den Poel and Lariviere 2004). Commitment in the form of repeated purchases is expected to enhance the value of the relationship for both parties (Sirdeshmukh, Singh, and Sabol 2002; Ryssel, Ritter, and Gemünden 2004; Alejandro et al. 2011). This work aims at illustrating how the commitment problem is solved by trust in relationships

[62] While the novelty and the positive sides of industrial methods outweigh the concerns in this study, there are arguments more critical to such applications (Lazer et al. 2009). While comparing a classical sociological approach to the industrial methods, this study is looking for a compromise between the two sides.

between service providers (SPs) and their customers. Using the multidimensional Ability, Benevolence, Integrity (ABI) trust framework allows to differentiate between the effects of individual trust dimensions and illustrate the theoretically assumed differences between the importance of different trust dimensions for explaining the continuation of a contractual relationship.

In the ABI framework, ability-based trust is based on the general competencies of the party providing a service, in this case, the trustee, integrity stands for the reliability and the set of principles of the trustee, and benevolence refers to the helpfulness of the trustee and their willingness to do good for the trustor (Mayer et al. 1995). In the relationship between the service provider and their customers, ability-based trust translates into the technical competencies and the technical functioning of the product (Lin et al. 2011; McKnight et al. 2011). Integrity-based trust refers to the SP's reliability and is built through communication with customer success (Doney et al. 2007; Pollack et al. 2017; Ulaga et al. 2020). In contrast, benevolence-based trust refers to helpfulness and is covered on the relationship level by the support services offered to the trustor (Alvarez et al. 2010; McKnight et al. 2011)[63].

In the earlier parts of this work, I presented the integrity-based trust operationalized through the contact activities by the customer success teams in the first months of a contract (chapter two). For benevolence-based trust, I have argued that this dimension of trust in its relationship-based part can be found in a support service setting that embodies the helpfulness of the service provider (SP). This is illustrated by the effect of customer problem structures measured in the within-customer and the between-customer problem space on participation in Net Promoter Score (customer satisfaction) surveys and the effect of benevolence-based trust measures for the customer on contract extensions and terminations (chapter three).

So far in this work, I have mainly considered the effects of integrity-based and benevolence-based trust in the usage phase of the SaaS contractual relationship with the goal to show how these elements can be detected in a setting where a relationship between a service provider and their customers is considered. Less attention has been

[63] For a more detailed description of the individual dimensions, see the introduction of this work. For a detailed study of integrity-based trust, see chapter two. For a detailed study of benevolence-based trust, see chapter three.

paid to the outcomes of the trust dimensions in the renewal phase of the contractual relationship. But the primary objective of this work has always been to investigate how these trust dimensions relate to the commitment problem under investigation – the question of whether the customer renews a contract with the service provider or not.

Early studies of commitment problems between organizations include, for example, Becker (1960) discussing commitment and its presence in sociological research as "consistent behavior" (Becker 1960:33). In a later study of relationship commitment, Morgan and Hunt (1994) point out that commitment is more than the repeated transactions and set trust as the mediator in the relationship between such concepts as communication, shared values, commitment, and propensity to leave as a separate construct. Their empirical analysis shows a positive relationship between customer trust and commitment and, following, a negative relationship between customer trust and customer propensity to leave (Morgan and Hunt 1994:30).

Mayer et al. (1995) refer to all outcomes of trust as risk-taking in the relationship. Customer commitment, as theorized by Morgan and Hunt as mediated by trust (Morgan and Hunt 1994:21) and discussed in previous studies in such interpretations of consistent behavior as repeated purchases (Doney and Cannon 1997), relationship terminations (Doney et al. 2007), duration of collaboration and expectation of continuity (Delbufalo 2012). In this work, I use the ABI trust framework to show how the different dimensions of trust in an interorganizational relationship influence the key behavioral outcome of commitment – customer decision of terminating or not terminating the relationship. Thus, trust is the theoretical mechanism in place to solve the commitment problem between the SP and their customers. The ABI framework provides a multidimensional perspective on how trust is mediating the relationship between the activities of SPs and the customer decisions to extend their contracts.

Empirical studies of long-term interorganizational relationships and the role that trust plays in maintaining such relationships are frequently found in supply chain research (e.g., see Delbufalo 2012 for an overview), which, until recently, was the main area of continuous interorganizational relationships. Recently, this research direction has received scholarly attention in consumer research. This attention is connected to the shift to relationship marketing (Morgan and Hunt 1994) and subscription contracts

(Coussement and Van den Poel 2008). For example, studies cover customer trust as a mechanism leading to customer loyalty (e.g., Oliver 1999; Chiou and Droge 2006; Kaur and Soch 2018), purchase intentions in e-commerce platforms (e.g., Chen and Dhillon 2003; Oliveira et al. 2017), and continuing the usage of platforms and services (e.g., Hsu et al. 2006; Wu et al. 2014).

This research direction comes very close to the so-called customer churn research that is growing in the computer science and information systems literature, as the problem of keeping the customers is gaining importance in the industry (Van den Poel and Lariviere 2004). Such studies often focus on increasing the performance of machine learning models (Mena et al. 2019) and creating new models targeting the problem of predicting customer contract terminations (De Caigny, Coussement, and De Bock 2018). Classical studies focus on the telecommunication industry (e.g., Huang and Kechadi 2013), while more methodological studies focus on handling the imbalanced data problem (e.g., Burez and Van den Poel 2009; Zhu, Baesens, and van den Broucke 2017) or the application of new models, such as LSTM networks (Mena et al. 2019). This research, however, is primarily concentrated around the computational problems, while the theoretical problem of the underlying mechanism remains on the sidelines.

In the relationship between a service provider and their customers discussed in this work, the commitment problem and the main risk-taking in the relationship are focused on the customer's decision to terminate a SaaS subscription contract. The resulting length of the relationships and the uncertainties related to customer support and future maintenance of the purchased products, on the one hand, make the question of customer trust in the SaaS service provider more important (Benlian et al. 2011). On the other hand, these points open the possibility to study this relationship not from the generalized perspective of trust that is used by Morgan and Hunt (1994) but from the detailed trust framework proposed by Mayer et al. (1995) and further extended for the lifecycle of the subscription relationships between organizations by Schoorman et al. (2007).

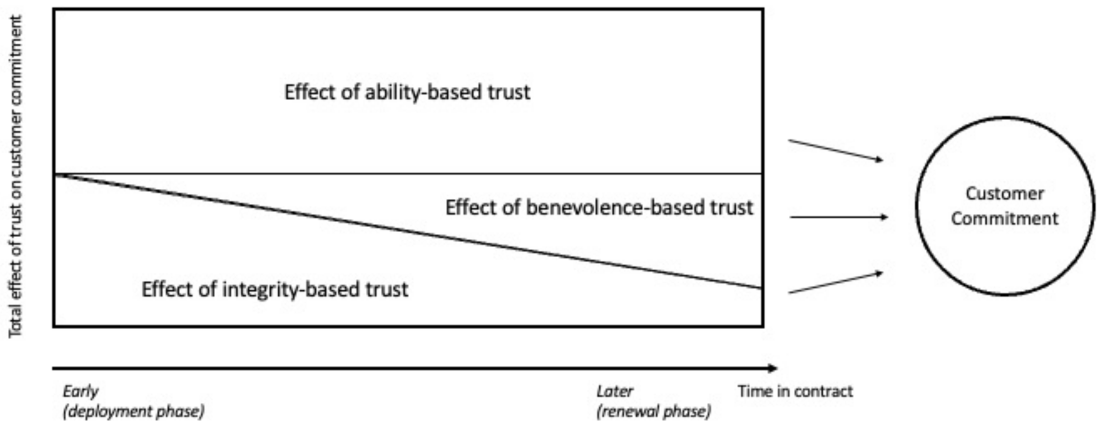
The main practical question of this work remains similar to the churn studies and the existing research. Is the customer going to extend the relationship? However, while most of the previous organizational studies rely on holistic measurements of trust (e.g., Morgan and Hunt 1994; Doney et al. 2007) and the computational research often undervalues theory (Radford and Joseph 2020), I use the ABI trust framework to provide a multidimensional perspective on the role of trust in the relationship between a service provider and their customers.

Starting with the similarities between the dimensions of trust, all dimensions of trust are expected to have a positive effect on commitment in a relationship (contract continuation) (Morgan and Hunt 1994; Ganesan and Hess 1997; Doney et al. 2007; Aurier and N'Goala 2010), which translates into a negative effect on contract terminations (Aurier and N'Goala 2010). Thus, the first expectation applies to all of the trust dimensions and is specified as follows:

Expectation 3.1: *All trust dimensions are expected to have a negative effect on the customer's decision to terminate the contract and a positive effect on customers extending the relationship.*

While the presence of trust as a solution to the commitment problem for explaining the continuation of the relationship has a long presence in research (Morgan and Hunt 1994; Ganesan and Hess 1997), it is the investigation of the individual dimensions of trust that is of interest for this work. Coming to the differences between the dimensions of trust, figure 4.2 illustrates the summary of the theoretical expectations related to ability-based, integrity-based, and benevolence-based trust that is tested in this analysis. At the beginning of the relationship, no benevolence data has yet been collected to form benevolence-based trust (Mayer et al. 1995, Schoorman et al. 2007). Thus, the effect of this dimension is the smallest out of all the three trust dimensions. As time passes and benevolence-based data is collected, the importance of this dimension grows (Mayer et al. 1995; Schoorman et al. 2007). On the contrary, the importance of integrity-based trust decreases (Mayer et al. 1995). With this study focusing on the renewal phase of the relationship between the service provider and the customers, the following expectations relate to the effect of individual dimensions at a later stage in the relationship.

Figure 4.2.: Expected effects of individual trust dimensions on customer commitment in the renewal phase (contract extension or termination), summary



This figure corresponds to the representation of the importance of trust over time by Rousseau et al. (1998:401)

According to the theoretical representation of the effects of the ABI dimensions on their outcomes in business relationships between companies, ability-based trust will be the highest contributor to the continuation of the contract (Mayer et al. 1995; Schoorman et al. 2007). The importance of ability-based trust can be explained through the nature of the business relationship between the customer and the service provider (Sako 1992; Jap 2001; Dowell, Heffernan, and Morrisson 2013). The ability of the service provider and the SaaS product to address the business use case of the customer and provide value will remain the main driver of the relationship (Zhu and Kraemer 2005). For example, Dadzie, Dadzie, and Williams (2018) analyze the role of trust dimensions for maintaining a long-term buyer-supplier relationship. Their findings support the thesis that, out of all trust dimensions, ability-based trust is the most important driving force for a relationship. This constant importance of the ability-based trust in the relationship is illustrated in figure 4.2 through the continuous effect size at any chosen time points, independent of the stage in the relationship. When compared to ability-based trust, integrity-based, and benevolence-based trust dimensions that are in focus in this dissertation are assumed to have a lower importance than ability-based trust by theory (Mayer et al. 1995; Schoorman et al. 2007; Svare et al. 2020).

Expectation 3.2: *Ability-based trust is expected to have the strongest effect of all trust dimensions on customer decisions to stay in contract.*

Integrity-based trust is expected to lose importance over time of the duration of the relationship (Mayer et al. 1995; Schoorman et al. 2007; Pollack et al. 2017). In the first chapter, I have shown that the differences in the behavioral outcome are most visible in the first month of usage and are not held over time (Svare et al. 2020). I expect a lower effect of integrity-based trust on the long-term behavioral consequences.

Expectation 3.3: *Integrity-based trust is expected to have an effect not bigger in magnitude than the effect of benevolence-based trust.*

The importance of benevolence-based trust increases over time (Mayer et al. 1995; Schoorman 2002; Schoorman et al. 2007). A positive effect of organizational benevolence-based trust on customer commitment is observed by Ganesan and Hesss (1997), for the organizations in the financial sector (Nguyen 2016), and in the context of technology (Lankton and McKnight 2011). Svare et al. (2020) illustrate on the example of innovation networks that benevolence-based trust gains importance and facilitates collaboration between the parties during the relationship, while integrity-based and ability-based trust do not have this effect. Thus, the effect of benevolence-based trust is expected to be of no smaller magnitude when compared to the effect of integrity-based trust.

Expectation 3.4: *Benevolence-based trust is expected to have an effect of not smaller magnitude than the effect of integrity-based trust.*

4.2. Data and Methods

The data used comes from the main data source in my dissertation – SAP SE[64], the service provider. I am focusing on small and medium customers[65] who have started their contracts since the beginning of 2018 and have purchased the same standard product from the service provider. As I need to estimate behaviors in the product usage phase for such variables as customer problems and utilization, I only include customers after their 6th month in the contract. Customers who have not yet reached the 6th month in the contract are excluded. To exclude the effects of the covid-19 pandemic on the product usage and, thus, on the models, I am only considering the data from before December 2019[66]. The resulting sample has account and behavioral information of 6135 SMB customers with, on average, under 500 employees, an average account age since contract start of 13 months[67].

4.2.1. Dependent Variable

I measure the customer behavioral outcome as a binary response to either continuing or terminating the relationship[68]. Relationship continuation is coded as 0.0 and relationship termination is coded as 1.0. In the context of SaaS, while customers are more flexible in their options to switch between service providers (Benlian and Hess 2011), the decision to terminate is associated with potential costs, data migration, and learning (Whitten, Chakrabarty, and Wakefield 2010). This decision is taken by the customer before it is communicated to the service provider. The usage of the product and the customer's engagement declines in the immediate time before the decision is communicated. Thus, to avoid reverse causality coming from the data collected immediately before the communicated termination decision, I am removing all data from the last three months before the decision regarding the termination of the relationship is communicated. This number is based on the usage decrease observed in customers for the product under investigation after their termination decision and up

64 For a detailed overview of the case company and data, see the introduction section.
65 As in previous chapters, the small and medium customers are defined by the number of employees under 1500 (US Small Business Administration 2019) and an internal flag set to Small and Medium Business.
66 For an overview of the effects of the covid-19 pandemic on the travel industry, see Curley et al. (2020).
67 Due to the confidentiality of the data, no exact values can be stated for further variables.
68 As the contracts are extended automatically in case a termination was not requested, I cannot run the analysis by cohort.

to 3 months until the actual termination. With the data after December 2019 excluded, the latest termination point in the data is December 1, 2019, and the latest data point for all other variables is August 31, 2019. To remove the same amount of data before the renewal decision for the customers with no termination point, I chose to also remove all data from the three last months before the prediction point for customers with outcomes of non-termination.

4.2.2. Independent and Control Variables

The key interest of this work is in the investigation of the trust effects on the customer commitment in a relationship, i.e., customer decisions about extending or canceling the contracts. I follow the operationalization of trust as integrity-based, benevolence-based, and ability-based trust (Mayer et al. 1995).

Integrity-based trust is operationalized, as shown in chapter two. It is defined in proxy by the service provider's measure, i.e., the presence of customer contact by the success teams at the beginning of the relationship. Chapter two illustrates that this measure has an effect on customer product usage that is consistent with a weak level of mediation through trust. In the absence of a direct measure of trust, I use the findings of chapter two to adopt this measure as a proxy for integrity-based trust. This variable is binary, with 1.0 standing for at least one touchpoint with the customer success teams before the start of the customer's utilization period of the product.

Benevolence-based trust is operationalized through benevolence, i.e., perceived helpfulness of provided support, as shown in chapter three. I evaluate the total history of customer problems and, first, use the modularity (Newman and Girvan 2004) measure to identify how focused the customer phrasing of the problem statements is around the same keywords. High modularity stands for customer problems being raised to multiple topics, thus, showing high benevolence-based trust. Modularity measures the within-customer perspective on benevolence-based trust[69]. Second, I use the latent topic coherence of the subject lines of problem cases measured as the maximal probability that the cases belong to the same latent problem topic. High latent topic

[69] Within-customer problem space perspective assumes that only the problems reported by one customer are analyzed. A more detailed perspective can be found in chapter 3.

coherence signals that all customer problems belong to the same problem and stand for low benevolence-based trust. The latent topic coherence measure is based on the Latent Dirichlet Allocation model trained in chapter 3[70] based on the entire basis of customer problem cases since 2018. Latent topic coherence, i.e., the probability of the cases to belong to the same latent topic, represents the between-customer measurement of benevolence-based trust[71].

While the focus of the previous chapters lies primarily on the relationship-based trust dimensions, i.e., integrity-based and benevolence-based trust, including ability-based trust is necessary to evaluate the relative importance of the other trust dimensions and control for the performance effect of the software. When it comes to ability-based trust, the technical functionality of the software in a standardized product has little variation across customers (Haselmann and Vossen 2011). Ability-based trust is supported by the existence of the contractual relationship between the customer and the service provider (e.g., Adler 2001; Lui and Ngo 2004). Nevertheless, several reasons speak for adopting an additional measure of ability-based trust to capture potential breaches of ability-based trust, resulting in differences between customers. I use the product usage measure as a proxy for differences in ability-based trust between customers. This measure is calculated as the average percentage of the utilized product in the last 3 months before the prediction over the average utilization of the customer over the entire utilization timeframe[72].

On the business side, continuous usage of the product is closely related to the value that the company can derive from using the purchased SaaS product (Zhu and Kraemer 2005). This corresponds to the understanding of ability-based trust being based on the ability to deliver the promised service and business functions of the software (McKnight et al. 2011; Lin et al. 2011; Lankton et al. 2015). On the technological side, significant outages and issues on the side of the service provider are linked to breaches of trust through the expectation of service availability (Marston et al. 2011; Benlian and Hess

[70] The preprocessing of the subject lines follows the preprocessing used in chapter 3.
[71] Between-customer problem space perspective assumes that the problems reported by all customers are analyzed. A more detailed perspective can be found in chapter 3.
[72] This operationalization is chosen because utilization is shown in the churn literature to be one of the main predictors of churn (Kisioglu and Topku 2011).

2011) which serves as a basis for ability-based trust[73] (Lankton et al. 2015). Thus, while most customers reach stable product usage rates over time for the studied product, a relative measure of product usage captures changes that can be caused by technical outages (a breach in expected ability as availability) or low business value (breach of expected ability as functionality). Thus, although the product usage measure is not measuring ability-based trust directly, it captures potential variation in ability-based trust alongside the formal ability-based trust established through contracts. This measure captures the value aspect of the purchased SaaS product and the technical service stability of the service provider[74].

As an additional indicator of ability related to the argument of outages and service availability in previous research (e.g., Lin et al. 2011), I use the number of medium priority cases as an indicator of customer raising problems. While the solutions to problems correspond to the benevolence-based trust, customer problem reports can be linked to the ability-based trust of the service providers as they state problems with the functionality of the software product (Pan and Mitchell 2015). Moreover, the number of customer problems must also be included as a controlling mechanism for the benevolence-based trust variables, as the measurements of modularity and latent topic coherence are correlated with the number of customer problems. To further control for the severity of the issues, I also include the number of problem cases of high urgency.

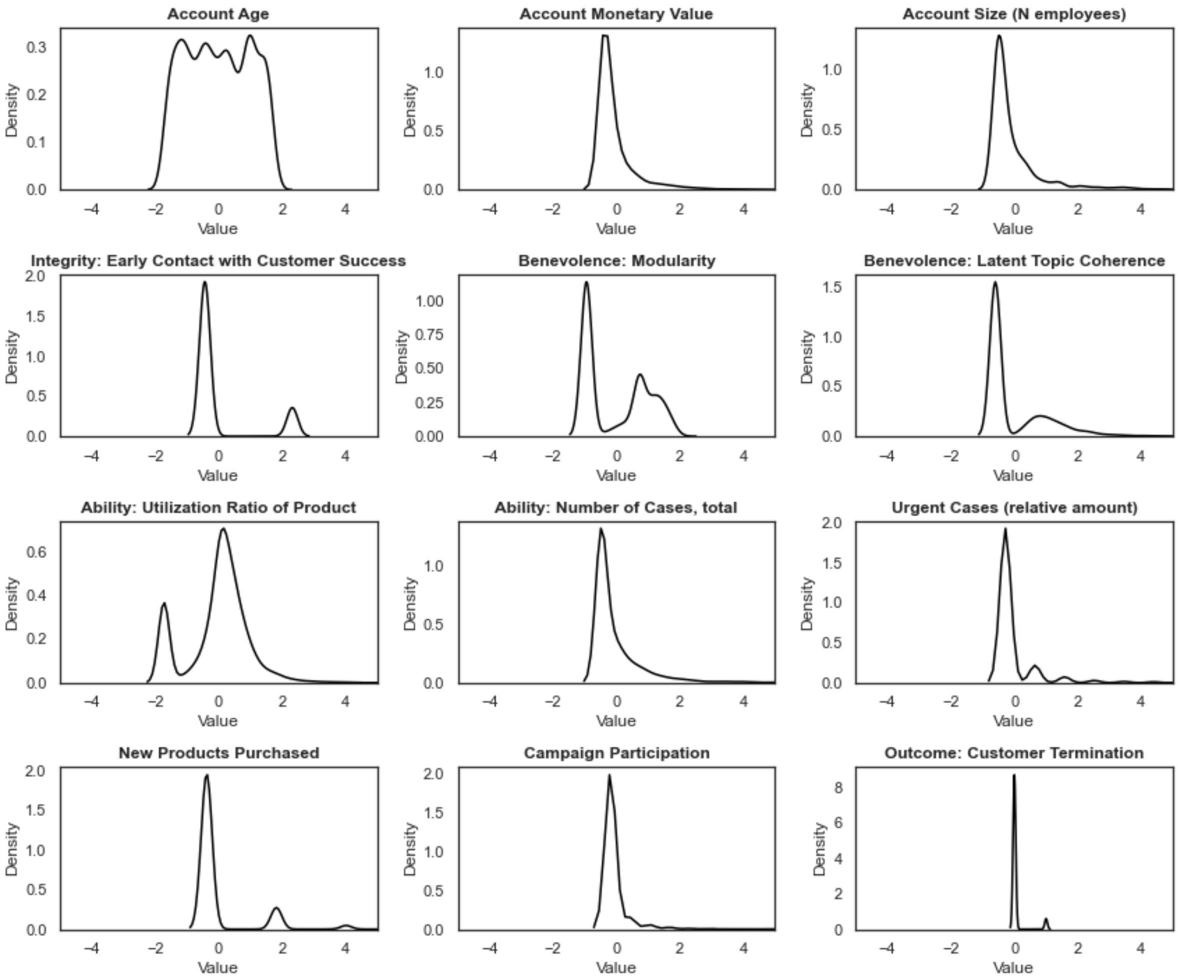
For the control variables going outside of the trust measures, I rely on the customer firmographic information – account age, the monetary value of the contract, account size measured as the number of employees. To control for the outcomes of trust that can further reinforce the development of trust (Mayer et al. 1995), I use the number of customer reactions to marketing campaigns as a proxy of customer engagement. Furthermore, I include the number of recently purchased additional products.

[73] Similar to the combined dimension of benevolence-helpfulness-based trust, I see ability-based trust as the extended dimension of ability-competence-functionality-based trust in the context of technology.
[74] It is notable that usage of SaaS products is frequently discussed as the outcome of trust in SaaS subscription contracts, as it is framed in chapter two of this work. Using this measure as a proxy for ability-based trust, however, does not contradict it being a possible outcome of trust. According to the ABI trust model, the reinforcement of the trust dimensions by previous outcomes of trust is part of the process (Mayer et al. 1995). Similarly, during the renewal phase of the contractual relationship, all experiences with the service provider will be evaluated.

I stated earlier that this research combines the theoretical approach of trust operationalization and conceptualization with the applied practice of churn research. The usage of the control variables follows the variable set used by Mena et al. (2019), divided into customer demographic, customer behavior, and customer contact variables. In the business-to-business setting, the customer firmographic variables reflect the demographic variables, customer utilization, and support cases reflect the customer behavior variables, while contact with support teams reflects the customer contact dimension. Another known approach in churn research is the division of variables in frequency, recency, and monetary (e.g., Buckinx and van den Poel 2005; Cao 2010). Finally, Chen et al. (2012) discuss the distinction between time-varying and constant variables to be considered in churn research. They suggest that time-varying variables must be included to evaluate the changes in customer behavior. This concern is addressed by the ratio of recent to overall utilization used in this study. Thus, this study connects the two approaches through the application of practically established variables common in churn research with theoretically derived trust measures from previous chapters.

The data are standardized before the analyses are performed to achieve better comparability of the results for regressions and in the machine learning models. Descriptive statistics of independent and dependent variables are presented in figure 4.3.

Figure 4.3.: Density plots of standardized variables



4.2.3. Methods

Conventionally, logistic regressions are one of the most common methods to investigate explanatory effects of variables in sociology when the outcome variable is binary (e.g., Wright 1995; Kleinbaum, Klein, and Pryor 2002; Molina and Garip 2020). As a timeless classic, logistic regression is the first method I use in this analysis. However, as already suggested at the beginning of the paper and given the closeness to the approaches applied in the industry, it will not be the only method I use.

Recent developments in sociology and computational social sciences, in particular, show that the attention of sociologists is increasingly directed towards the machine learning toolkit (Edelmann et al. 2020; McFarland et al. 2016; Molina and Garip 2020). Several papers on this topic highlight the positive sides of machine learning methods, such as supervised learning being able to fit models more complex than linear (Athey and Imbens 2016; Molina and Garip 2020). For instance, machine learning methods are already being used for propensity estimation in propensity score matching applications (e.g., Diamond and Sekhon 2013; Molina and Garip 2020), dimensionality reduction (for example, principal component analysis, LDA models for topic modeling of the text data (Molina and Garip 2020)). Machine learning ensemble models are adapted to focus specifically on causal inference and heterogeneous treatment effects (Grimmer, Messing, and Westwood 2017; Athey, Tibshirani, and Wager 2019). Furthermore, predictive language is finding its way in social science research. Kleinberg et al. (2015) provide a general overview of the differences in the predictive and causal approaches when an OLS regression model is used in both cases. Similarly, Askin and Mauskapf (2017) use a regression model to predict song positions in the charts.

Overall, machine learning as a term does not contradict the classical approach of using logistic regression. On the contrary, the logistic regression can be seen as one of the simplest and most intuitive machine learning models (e.g., Dreiseitl and Ohno-Machado 2002). A growing body of research compares the effectiveness of classical regression models and the non-linear methods originating in the machine learning research in their predictive performance. For example, Di Franco and Santurro (2021) compare logistic regression models to artificial neural networks (ANN) in a classification problem and show that the ANN outperforms the logistic regression if the dataset is representative (Di Franco and Santurro 2021). Also, in churn research, logistic regressions are frequently compared with more complex models, such as decision trees, artificial neural networks, and support vector machines (Chen, Hu, and Hsieh 2015), with Naive Bayes, decision trees, multilayer perceptron neural networks (Huang et al. 2012). Depending on the variable set and the context of the study, the logistic regression shows predictive performance comparable to other machine learning methods (e.g., Ge et al. 2017 for churn prediction in SaaS context; Lalwani et al. 2021 for churn prediction in telecom).

Researchers point to the predictive advantages of advanced machine learning methods and higher predictive accuracy (e.g., Muchlinski et al. 2016; Couronné, Probst, and Boulesteix 2018). But the downside of the high accuracy is pointed out too – the “black box” nature of the models (Breiman 2001a; Breiman 2001b; McFarland et al. 2016;

Ribeiro, Singh, and Guestrin 2016; Lundberg and Lee 2017). For this reason, in social sciences, the researchers interested in the explanatory functions of statistical methods have created additional models that extend the predictive nature of machine learning models to possibilities of statistical inference and effect estimations (e.g., Wager and Athey 2018)[75].

Summing up, while there are advantages of applying the machine learning methods in sociological research, such as high precision in the modeling of the outcome variable, the complexity of the model and the impossibility of the interpretation that is growing with the improvement of predictions are highlighted as the main difficulties in the application. Even the researchers focusing on the causal tree development still refer to the random forest model in their research as a black box (e.g., Breiman 2001b, Wager and Athey 2018).

I approach this problem from the perspective of explainability frameworks discussed more and more often recently (Ribeiro et al. 2016; Molnar, Gasalicchio, and Bischl 2020). Following the additive explanation framework (Lundberg and Lee 2017), I show how SHapley Additive exPlanations (SHAP) values can be used for understanding machine learning models in sociology.

The SHAP method originates from the game-theoretical approach of allocating contributions to model predictions (Lipovetsky and Conklin 2001, Lundberg and Lee 2017). Based on the paper published by Lundberg and Lee (2017), this approach has been used frequently to explain the individual-level performance of machine learning models, ranging from tree-based to more complex deep learning methods (Slack et al. 2020). The main advantage of this approach is the additive form of variable contributions that is shown to be model-agnostic (Lundberg and Lee 2017)[76]. This form of the outcome is argued to be intuitive to the users (Lundberg and Lee 2017[77]) and

[75] For an overview of the causal tree research, see Wager and Athey (2018); Athey et al. (2019). See Athey and Imbens (2017) for limitations of random forests in their statistical properties; Athey and Imbens (2016) on causal tree group-level effect estimation.
[76] Lundberg and Lee (2017) show the model-agnostic performance of the SHAP values and define the class of additive values as having such properties as local accuracy, consistency, and missingness (Lundberg and Lee 2017:4) and provide the mathematical background for this statement. There are currently computational improvements suggested for faster calculation of the results (e.g., Lundberg et al. 2019 for tree-based ensembles) and research showing potential sources of bias present in the SHAP values calculation (Slack et al. 2020; Kumar et al. 2020).
[77] Mittelstadt, Russell, and Watcher (2019) present a perspective of why providing an explanation to a model is itself a tradeoff.

opens the possibilities to better understand how machine learning models generate predictions. While not common to sociological research, the SHAP method can already be found in computer science applications (e.g., Mokhtari, Higdon, and Basar 2019), bioinformatics (Rodriguez-Perez and Bajorath 2020), and business research (Meng et al. 2021; Zhang and Luo 2021). For example, Zhang and Luo (2021) use SHAP values to predict and explain the drivers of restaurant survival derived from consumer-posted images in reviews.

In other words, SHAP explanation values allow for a regression-like additive approach to interpreting the individual-level predictions for complex models and are more and more frequently used in research applying machine learning techniques. This approach allows the investigation of local behaviors of independent variables and, thus, a better understanding of the evaluated mechanism. Therefore, along with a theoretical contribution, I present a new methodological strategy for sociological analysis that combines a precise model on the macro level with micro-level explanations provided for a deeper investigation of the results. However, I must note that the investigation of this new method is possible in this work because the full sample data are available, and the inference is not part of the analysis in both the logistic regression approach and the supervised machine learning approach. Naturally, the validation of such models should continue in the future, as also the inference research for SHAP values[78].

From the perspective of my practical research question, the practical advantage of using machine learning methods for this chapter is the wide adoption of these methods in the industrial setting I am investigating. Thus, while showing the performance of the trust variables in the machine learning framework, I am illustrating how the results of this work can be used in an industrial application[79].

[78] See Williamson and Feng (2020) for a research overview on inference in the context of SHAP values.

[79] This connection to the industrial work, on the one hand, embeds this study in the discussion of the practical applications of social science research discussed, e.g., by Watts (2017). On the other hand, it opens space for questions regarding the "colonization" of social science research by industrial methods (McFarland et al. 2016). In the scope of this work is the illustration of how sociological methods can be enriched by industrial models in the future. However, the theoretical part of this work highlights the importance for industrial practitioners to pay attention to sociological theory when social processes, e.g., in this case, interorganizational relationships, are modeled.

4.2.3.1. Logistic Regression

In the logistic regression approach, I build several nested models and investigate the direction of effects and the changes in Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values across models. I calculate a total of nine models. The first four models focus on integrity-based and benevolence-based trust indicators individually. Models five and six are fitted for the two dimensions of trust and include control variables. In model seven, only control variables are included. Model eight includes all trust variables in the dataset and the control variables. Model nine includes additional variables, such as customer engagement, and can be considered the full model. The calculations for the logistic regression are based on the full dataset.

4.2.3.2. Supervised Machine Learning

For the supervised machine learning (SML) approach, I first split the data into train and test data. I follow the 70% train – 30% test set approach[80]. The train data are used to fit the model, and the test data are used to evaluate the model performance. I fit a logistic regression model (to compare with the logistic regression from the logistic regression approach), a decision tree model (Breiman et al. 1984), a random forest model (Breiman 2001a), and an XGBoost model (Chen and Guestrin 2016). The main difference in the logistic regression approach compared to the decision tree approach is the absence of assumptions about the underlying model (Worth and Cronin 2003). In the decision tree approach, the dataset is split into parts of similar qualities, and the predictions are made for these parts, while the splits do not have to follow any assumptions about the relationship between the independent and dependent variables (Breiman et al. 1984). The tree-based ensemble approaches – random forest and XGBoost – are similar in the mechanism to the simple decision tree approach. The difference is that multiple trees are created to generate predictions (Breiman 2001a)[81].

[80] See Singh et al. (2021) for a detailed review of this strategy and the alternatives.
[81] This is precisely what makes these models interesting for heterogeneity predictions but also difficult in explainability. While the explaining of a single tree is easily accessible with, for example, decision plots, it turns into an explainability problem with the growing number of trees involved in the model. For a comprehensive overview of machine learning methods mentioned in this paragraph in econometrics discussion, see Athey and Imbens (2019).

For model evaluation, I use precision and recall measures, F1-scores, and area under precision-recall curve scores (ROC AUC) calculated from the test data to compare between the models[82]. Furthermore, I compare the predictions across models to understand differences in model performance. To evaluate how the models use the independent variables, I will first calculate the feature importance values for all models. These calculations are based on the information gain criteria for the models (Quinlan 1986; Deng, Runger, and Tuv 2011) and provide insights into how important the individual input variables are for model performance[83]. Next, I calculate the SHAP values (Lundberg and Lee 2017) for each of the models and observe how the variables of interest influence the prediction outcomes for individual customers. Furthermore, I calculate the feature importances based on the SHAP values to investigate which variables have the highest impact on the magnitude of the model outcome (Lundberg et al. 2018). Finally, I plot the results and provide a visual analysis of the distributions of SHAP values. The SHAP variable contributions to the probability outcome of the models are calculated with the KernelSHAP (Lundberg and Lee 2017) approach for the logistic regression model and the TreeSHAP (Lundberg et al. 2019) approach for random forest and XGBoost models[84].

While machine learning is associated with the term big data (Molina and Garip 2019), the methods used in this study do not require big datasets. For instance, the studies applying them often cover only several thousands of observations (Kisioglu and Topcu 2011), and applications of the methods are possible for even very small samples with only tens of observations (e.g., Airola et al. 2009). Furthermore, the churn studies applying the methods can use as few as 10 variables (e.g., Chen et al. 2012). Thus, while having a smaller than usual sample size and feature set for the industrial machine learning models, this study still fits into the framework of machine learning studies.

[82] See formulas and explanations of the measures in appendix table A.4.1.
[83] For more about the methods of feature importance calculations for tree-based models, please follow Saarela and Jauhiainen (2021).
[84] The calculations with KernelSHAP are also possible for the tree-based models, but this approach is much more computationally expensive (Lundberg and Lee 2017; Lundberg et al. 2019). For the logistic regression, the LinearSHAP approach can be used to reduce the computational time. However, this approach is resulting in log-odds contributions. Thus, KernelSHAP for the logistic regression and TreeSHAP for tree-based ensemble models are chosen to achieve comparable results.

I use python 3.9 (Van Bossen and Drake 2000) for calculations. A list of packages and versions is presented in appendix table A.1.1.

4.3. Results

4.3.1. Logistic Regression Approach

The results of the regression analysis are presented in figure 4.4[85]. The standardized coefficients visualize the effects of integrity-based, benevolence-based, and ability-based trust on customer decisions to terminate the relationship support. The findings support expectation 3.1 of this study. The effects of integrity-based, benevolence-based (modularity), and ability-based (utilization ratio) trust are negative and support the expected negative effect of all ABI trust dimensions on the behavioral outcome of contract extensions or terminations. While the measure of latent topic coherence is reverse-coded and higher values signal lower benevolence-based trust, the positive effect of this measure also supports expectation 3.1 of this study. Finally, the second measure of ability-based trust – the total number of customer problems – also has a positive effect on customer terminations. The positive effect of the number of customer problems on customer contract terminations can be explained through reverse-coding of the variable[86].

When observing the control variables, the negative effect of account age on the customer decision of contract termination is most prominent, alongside the negative effects of other firmographic variables – account size measured in the number of employees and the monetary value of the contract.

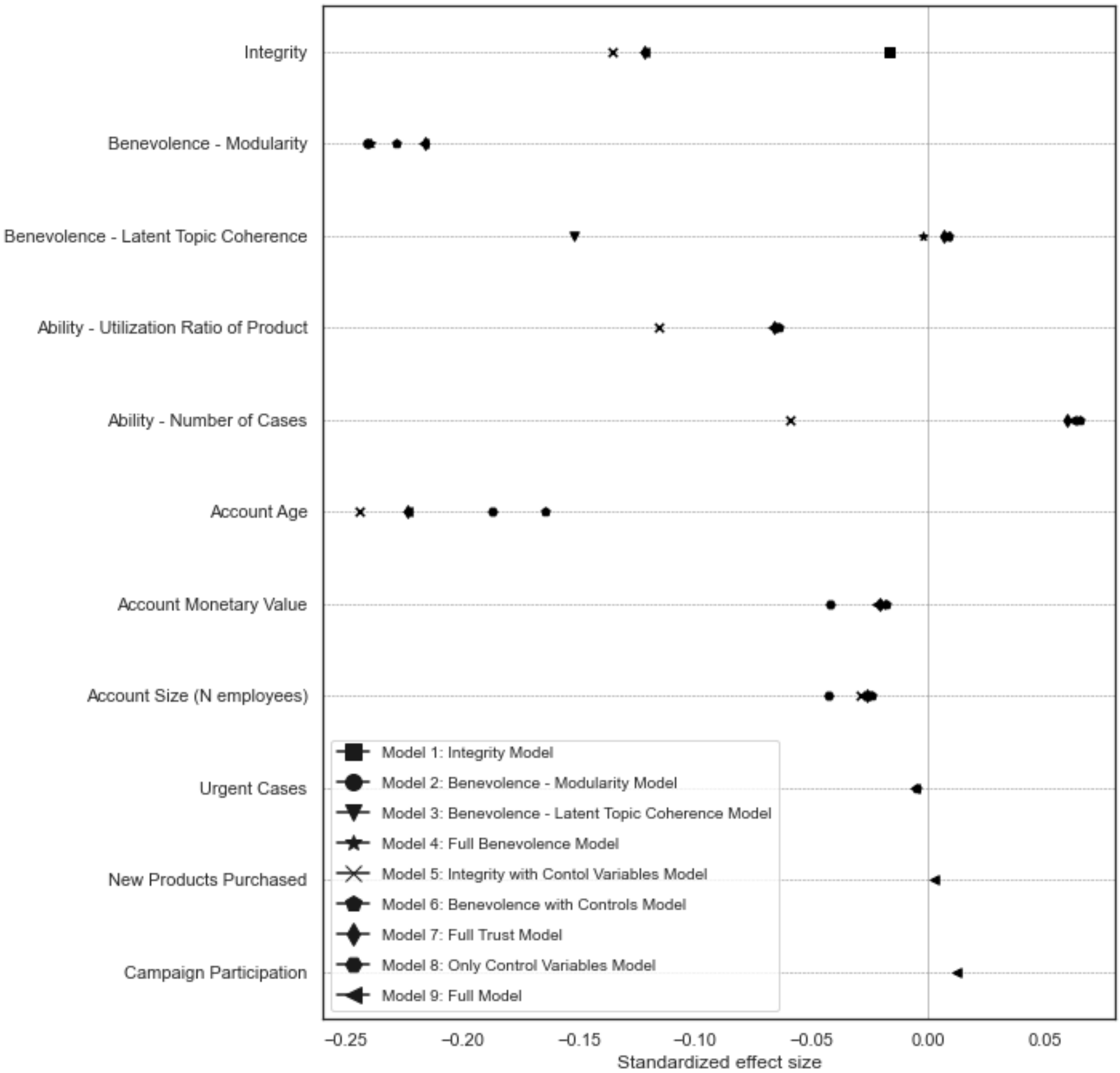
The effects are consistent across all models, apart from the benevolence-based trust measure of latent topic coherence. This measure is very close to 0 and only turns positive when other trust variables and control variables are included. Table 4.1 illustrates the performance metrics of the logistic regression models. Both measures are

[85] The coefficients are presented without confidence intervals. With this analysis being based on a full sample, not the inference but the actual effects are of interest for interpretation. Regression tables with standardized coefficients and standard errors are presented in appendix A.4.2.

[86] While the reverse coding sounds plausible, a certain amount of customer problems can signal higher customer satisfaction (McCollough and Bharadwaj 1992; McCollough et al. 2000) and healthy adoptions of SaaS products involves a number of open support cases (Avgar, Tambe, and Hitt 2013). Thus, further investigation is needed to fully understand this variable, which is not the focus of this study.

lowest for the full trust model, which includes the firmographic control variables alongside the key trust dimensions, and the full model, which includes further control variables. Thus, the logistic regression analysis results in a finding that the ABI trust dimensions and the firmographic variables provide the best explanatory evidence when explaining customer decisions to terminate or extend the relationships with a service provider. Further control variables, such as new products purchased and campaign participation, have a smaller contribution to explaining additional variance in the outcome variable.

Figure 4.4.: Standardized regression coefficients for the effect of ABI trust dimensions on customer commitment in the renewal phase (contract extension or termination)



Note: Standard errors of the standardized coefficients are not reported in the figure, since the sample represents the full sample (whole population) given the specified conditions.
Detailed regression table can be found in appendix A.4.2.

Table 4.1.: AIC and BIC of fitted models

Model Name	AIC	BIC
Integrity	8506.50686	-44994.80184
Benevolence - Modularity	8419.15096	-45082.15774
Benevolence - Latent Topic Coherence	8472.20436	-45029.10434
Benevolence combined	8421.14659	-45073.44034
Integrity with controls	8408.45646	-45059.24341
Benevolence with controls	8388.05340	-45066.20294
Full Trust Model	8370.96357	-45083.29278
Controls	8448.68632	-45039.17885
Full Model	8376.71160	-45057.37945

When it comes to expectations 3.2, 3.3, and 3.4, not only the effect directions but also the effect sizes must be evaluated. As all models use standardized values, the effect estimates presented in figure 4.4 can be compared. Out of all trust dimensions, ability-based trust is expected to have the highest magnitude (expectation 3.2). This, however, is not observed in the results of the analysis. The effect of utilization ratio is not stronger in magnitude than the effects of benevolence-based and integrity-based trust measures. Thus, expectation 3.2 cannot be confirmed.

For expectations 3.3 and 3.4 to be confirmed, the standardized effect sizes of integrity-based and benevolence-based trust are compared. Integrity-based trust has a negative effect on customer decisions to terminate their contract (β = -0.121, std. error = 0.029). This effect, however, is smaller in magnitude than the effect of the benevolence-based trust measure of modularity (β = 0.216, std. error = 0.039). Yet, this effect is bigger in magnitude than the effect of the second benevolence-based trust measure – latent topic coherence (β = 0.007, std. error = 0.033)[87]. Thus, expectation 3.3 can be confirmed for benevolence-based trust in one of the two applied measures. Expectation 3.4 – of benevolence-based trust effect being not smaller in magnitude than the effect of integrity-based trust – can also only be confirmed by comparing the integrity-based trust measure and the measure of benevolence-based trust through modularity.

[87] The coefficients presented are from the full model, the full results are presented in appendix A.4.2.

In the first step of the analysis, a logistic regression approach was used to understand the relationships between ability-based, benevolence-based, and integrity-based trust and customer decisions to terminate their contracts with the service provider. While the general negative effects of ability-based, benevolence-based, and integrity-based trust on customer contract terminations could be confirmed, the expectations related to the comparison of the effect magnitudes between trust dimensions could not be answered fully. In the next step, I extend the logistic regression model with further supervised machine learning models to illustrate how these methods can be used to address these questions.

4.3.2. Supervised Machine Learning Approach

Different from the logistic regression approach, in which all data was used for estimation, for the supervised machine learning approach, I follow the strategy described in the methods part and fit four models on the 70% split of the preprocessed data (e.g., Singh et al. 2021). The included variables follow the full model used in the logistic regression approach. After the models are fitted, I test the predictive performance of the models on the remaining 30% split of the data. The results and the predictions made on the full dataset are then used to calculate individual SHAP values.

Table 4.2 represents the performance values of the trained models when testing on the 30% test set of the data. The decision tree model performed worse than other models across such metrics as accuracy, ROC AUC, and precision and, thus, will not be considered in the further evaluation. All other models show high levels of accuracy, while the logistic regression model shows lower ROC AUC scores than the other models, and the XGBoost model is best in a ROC AUC-based comparison. When evaluating the model's sensitivity to customer terminations – class 1 for customers who have terminated their relationships – I look at the measure of recall to understand which model can provide better predictions for the customers who are going to terminate their relationships. When comparing the results of recall for class 1, the logistic regression performs worse than other trained models, while the random forest model performs best[88].

Table 4.2.: Performance measures of SML models on the test data

	Accuracy	ROC AUC Score	Precision (class 1)	Recall (class 1)	F-1 Score (class 1)
Logistic Regression	0.94	0.85	0.50	0.03	0.05
Decision Tree	0.89	0.58	0.19	0.22	0.20
Random Forest	0.93	0.84	0.36	0.10	0.16
XGBoost	0.93	0.87	0.38	0.05	0.09

Summing up, it is visible that the logistic regression model, although showing lower performance when predicting which customers are going to terminate the relationship with the service provider if we consider recall of class 1, shows acceptable overall predictive power when such measures as accuracy and ROC AUC are considered. Thus, in this specific application, the predictive power of an approach classical for social sciences is comparable with the predictive power of the more complex supervised machine learning models. Considering all measures identifies the random forest model as the best performer, as for this model, an increase in recall is not associated with a substantial decrease in precision[89].

As noted by McFarland et al. (2016), an interesting distinction is that even when social scientists have good predictions, their focus is directed on the explanatory side of things rather than the predictive side. In the next steps, I evaluate the predictive power of the models in more detail and propose a strategy on how a combination of explanatory and predictive research can be achieved when SHAP values are computed for input datasets in each of the models.

The first exploratory analysis of how machine learning models predict the outcomes and which variables are used in the modeling process is available with the analysis of feature

[88] Notably, the previously excluded decision tree model performs best of all models in the recall. This, however, does not compensate for its poor performance in other measures. The model was included in all further stages of the analysis and did not provide results changing the general outcome of the study.
[89] It must be noted that the performance of the models is still far from the performance that can be achieved in supervised machine learning when optimization techniques for the data (e.g., under- and oversampling, see Yap et al. (2015)) or the model (e.g., hyperparameter tuning, see Tran et al. (2020)) are applied. Since this work does not follow a goal of high predictive performance on new data, the results are acceptable.

importances of different models. Table 4.3 illustrates the feature importances of the previously trained models. The feature importance values can be read as the relative contribution of each variable to modeling the outcome. Thus, the importance values of each model sum to 1.0[90].

The importance values in table 4.3 show that all models use the information in the data differently. The worst-performing decision tree model (DT) does not use the benevolence-based trust measures when making predictions. There are also visible differences in the way how the trained ensemble models make their predictions. While the random forest model (RF) takes 47% of the information from two control variables, account age and account recurring revenue, the XGBoost model (XGB) takes 45% of information from the benevolence-based variables in the model. Regarding the indicators of ability-based trust, the XGBoost model takes a total of 8% of its predictive power from utilization ratio and customer case problems, while for the random forest model, it is 24%. Integrity-based trust and benevolence-based trust measurements are also more important for predictions in the XGBoost model[91].

[90] As the concept of feature importances does not exist in the world of regression models, the information-gain-based importances are not available for the logistic regression model. Thus, the coefficients are shown for the logistic regression model. These values cannot be compared with the other values. A possibility of comparison between the effects of the logistic regression and the treatment effects estimated in a random forest model can be approximated when training a Causal Forest model with the same parameters as in the random forest model used in the SML part of the analysis. For more information on the Causal Forest model and its practical implementation, see Battocchi et al. (2019) for the econml package in Python and Athey (2020) for the causalTree package in R.

[91] It must be highlighted that the importance calculation is based on information gain. Thus, the earlier a variable is used by a decision tree, the more importance will be attributed to it (Deng et al. 2011).

Table 4.3.: Relative feature importance values of variables in SML models

	LR	DT	RF	XGB
Integrity	-0.122	0.03	0.02	0.17
Benevolence - Modularity	-0.217	0.00	0.06	0.44
Benevolence - Latent Topic Coherence	0.007	0.00	0.03	0.01
Ability - Utilization Ratio of Product	-0.067	0.19	0.15	0.07
Ability - Number of Cases	0.062	0.07	0.09	0.01
Urgent Cases	-0.005	0.00	0.01	0.00
Account Age	-0.223	0.29	0.27	0.11
Account Monetary Value	-0.022	0.22	0.20	0.07
Account Size (N employees)	-0.027	0.14	0.15	0.04
New Products Purchased	0.002	0.03	0.02	0.03
Campaign Participation	0.012	0.01	0.02	0.05

Note: As specified earlier, for the logistic regression model, the coefficients and not the feature importance values are displayed. These values cannot be compared to the other values in this table.

Connecting these findings to the theoretical expectations for the importance of ability-based, benevolence-based, and integrity-based trust for explaining customer terminations shows that different machine learning models leverage the information differently. However, across all models, ability-based and benevolence-based variables show the strongest predictive importance, while the integrity-based trust variable is less important. The random forest way of modeling the outcome variable corresponds to expectations 3.2, 3.3, and 3.4. In this model, ability-based trust is the most important among all trust dimensions, followed by benevolence-based trust and integrity-based trust, with a small difference between the importance values of the two trust dimensions. The RF model is also the strongest when all performance measures are considered. This provides evidence to confirm expectations 3.2, 3.3, and 3.4. However, the overall results achieved in this analysis do not allow to confirm the expectations fully.

Thus, while the predictive performance of the machine learning methods is comparable to the predictive performance of the logistic regression, the tree-based models and their relative importance measures of variables are advantageous when the formulation of a hypothesis requires a comparison of the effects of multiple variables.

The correlations in table 4.4 illustrate the model prediction comparisons and show that random forest and XGBoost models provide very similar predictions. The correlation between the predicted probabilities of customer contract terminations is 0.89. A similar observation is made for logistic regression and XGBoost (the correlation of 0.87) and for random forest and logistic regression (0.75). From the values observed for the decision tree model is visible that this model differs from the others in predictions[92].

Table 4.4.: Correlations of predicted probabilities across trained SML models, full dataset

	Prediction LR	Prediction DT	Prediction RF	Prediction XGB
Prediction LR	1.00	0.39	0.75	0.87
Prediction DT	0.39	1.00	0.58	0.47
Prediction RF	0.75	0.58	1.00	0.89
Prediction XGB	0.87	0.47	0.89	1.00

So far, this analysis has presented a comparison of multiple supervised machine learning methods, including the classical for sociology logistic regression, as well as multiple tree-based models. The findings highlight the differences in how models use the input variables to model the outcomes, while very similar levels of performance are reached across multiple models. However, the performance and the feature importance values for individual variables do not provide insights into the direction and magnitude of the effects of individual variables.

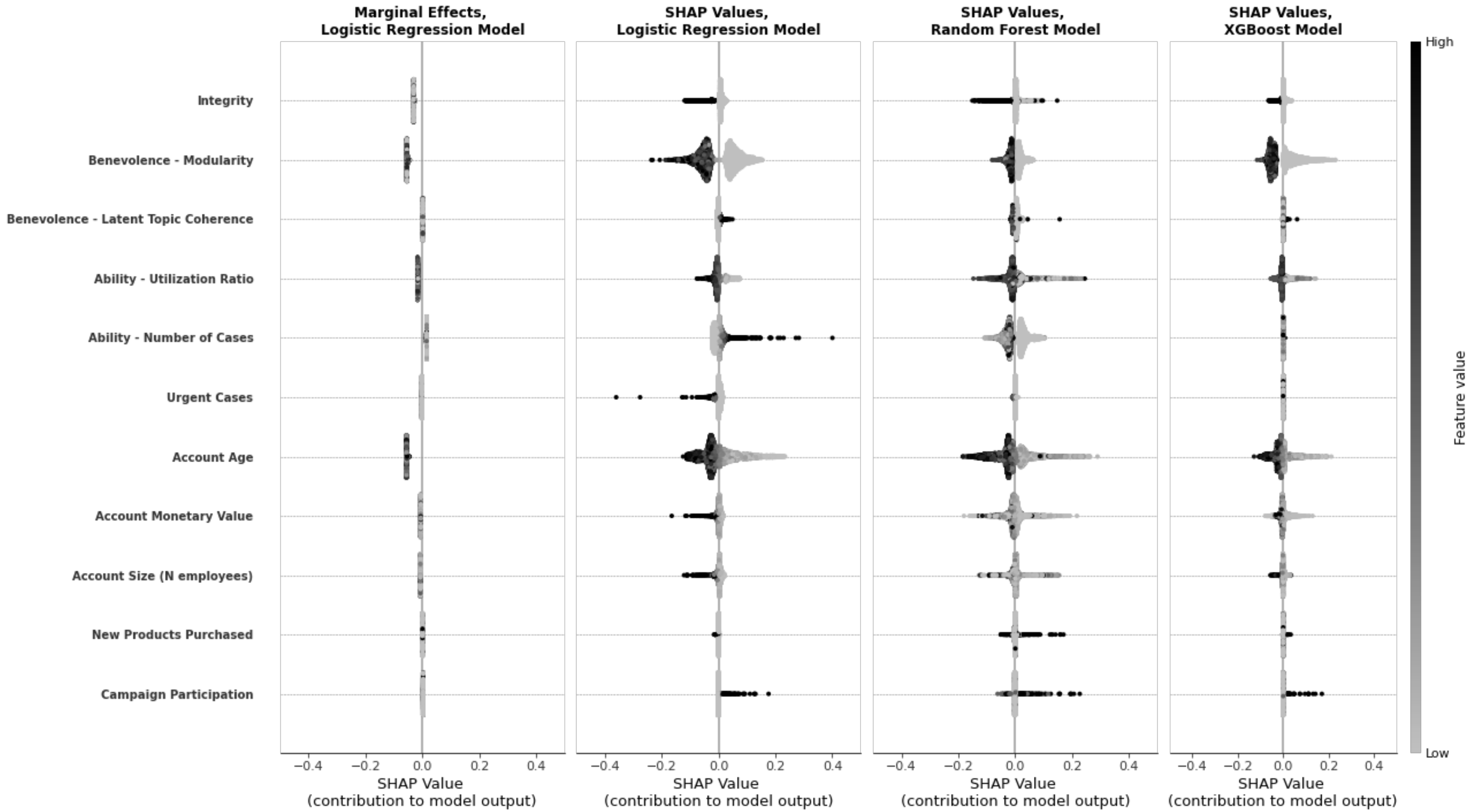
In the next step of the supervised machine learning approach, I use the individual variable contributions using the SHAP values approach (Lundberg and Lee 2017; Lundberg et al. 2019). The resulting plots in figure 4.5 illustrate how the individual contributions of variables are distributed, depending on the value of the variable. The x-axis shows the value of the probability contributions of each of the variables to the outcome of the model relative to the base expected value for class 1 (customer terminating the relationship). The y-axis represents the list of variables used in the model. The individual plots are similar to violin plots and illustrate the density of how

[92] The outcome variable is not measured in probabilities and, thus, is not presented in the table. Overall, random forest and XGBoost predicted probabilities have the highest correlation with the outcome in the test dataset (0.37 and 0.34 vs. 0.14 for decision tree).

many individual customers share the same contribution value of this variable. The individual dots are colored depending on the value of the variable for the specific customer, with darker dots indicating higher and lighter dots indicating lower values.

Exemplary, the plot for the variable utilization ratio in the random forest model can be interpreted the following way. The contribution of this variable to the outcome probability ranges between -0.17 and +0.23. The lower SHAP contribution values generally correspond to higher values of the variable. Thus, for customers with high utilization ratio, the contribution of the utilization ratio variable to the outcome probability of customer terminations is negative. The widest point of the plot is located in the negative area of the chart. This means that the most common contribution of product utilization ratio to the outcome probability of customer termination is negative. In the positive area of the contributions, customers with predominantly lower values of the product utilization variable are situated. Thus, for the customers with low product utilization ratios, the variable has a positive contribution to the outcome probability of contract termination. When comparing this plot to the representation of this variable in other models, it is visible that the contributions in the logistic regression model have a similar linear relationship. The same effect is observed in the XGBoost model.

Figure 4.5.: Summary plots of SHapley Additive exPlanation values in trained SML models and marginal effects in the fitted logistic regression model, full dataset



The overall comparison of the plots shows a clear difference between the functioning of the models. For instance, the SHAP contributions in the logistic regression plots follow a linear relationship concerning the variable values. High and low values of the variables are always located at the opposite sides of the x-axis. This is different for the tree-based models, where the contributions can result from tree splits in subgroups that follow non-linear relationships (Breiman 2001a). For example, the contribution values of campaigns a customer participated in (in the random forest model) are negative for the customers with moderate values of the variable. There is no effect if the customer has not participated in any campaigns and the values are low. However, there is also a group of customers who participated in many campaigns, and for whom the contribution of the variable is positive. This, on the one hand, speaks to the possible conditional effect in the relationship between the independent and the outcome variable. On the other hand, this opens the possibility to investigate the subgroup of customers with positive contributions of customer engagement to the probability of contract termination.

Turning to the key variables in the model, the integrity-based trust variable – early contact with the customer success team – has a negative contribution to the probability of termination across all models. This effect corresponds to the effect observed in the logistic regression analysis in the earlier step of the analysis and confirms the theoretical expectation that the effect of integrity-based trust on contract termination is expected to be negative. However, for a small group of customers in the random forest model, the effect of integrity-based trust on the probability of contract termination is positive.

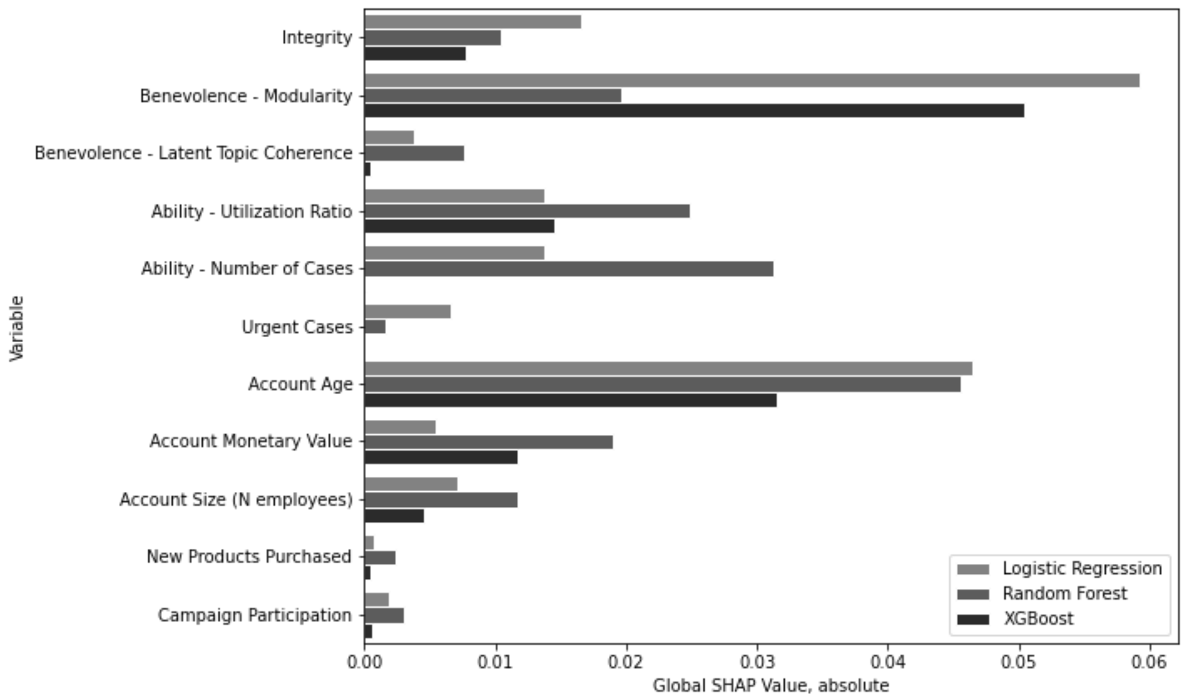
The SHAP contribution values of benevolence-based trust variables – modularity and topic coherence – vary across models. For modularity, the contribution to the probability outcome is consistently negative for higher modularity values, while it is neutral to positive for lower modularity values. For the latent topic coherence variable, however, the contribution values in the logistic regression model match the earlier findings from the logistic regression analyses and support the theoretical expectations that high latent topic coherence of customer problems, interpreted as low benevolence-based trust, contributes positively to the probability of customer termination. The same effect is observed for the high values of the topic coherence variable in the XGBoost model, while moderate values correspond to no effect. For the random forest model, however, the effect is divided into two groups: for some customers with high latent topic coherence, the variable contribution is negative, while for another group the contributions to the probability of terminating the contract are positive.

The left chart in figure 4.5 illustrates the marginal effect of the variables, which in the classical sociological approach can be considered individual-level contributions comparable to the SHAP values. The main mathematical difference between the SHAP values and the marginal effects is that the marginal effects are not additive (Williams 2012; Norton, Dowd, and Maciejewski 2019) and can be best applied to categorical variables (Williams 2012). And, as part A of figure 4.5 illustrates, the values are mainly centered around the effect coefficients of the logistic regression with only small deviations from the overall effects.

The findings illustrated by the SHAP values support the expectations of the effect directions in most of the models and support the conclusions reached in the logistic regression approach earlier, while the resulting distributions highlight the variance in the effects that the classical approach of logistic regression cannot cover.

Apart from the individual contributions, aggregated absolute SHAP values can be studied to compare feature contributions based on the magnitude of the SHAP values (Lundberg et al. 2018). The feature importances plot based on the absolute average magnitude of the calculated SHAP values illustrated in figure 4.6 shows clear differences between how the probability outcome is attributed to variables by models. The magnitude-based SHAP importance values presented in this analysis can be used for comparisons of the logistic regression to the non-linear machine learning models. The results show that while there are differences between the models, the general tendency of higher contributions of benevolence-based (modularity) and ability-based trust measures and lower contributions of integrity-based and benevolence-based (latent topic coherence) trust measures are consistent across all models. Furthermore, the importance of the control variables is emphasized, which corresponds to the high importance of the account age variable in the feature importance values analyzed earlier.

Figure 4.6.: Global absolute SHapley Additive exPlanation values across trained SML models, full dataset



Summing up, the SHAP values measuring individual contributions of input variables to the predicted outcome of the model provide individual-level insights about how the predictions are made based on the information of individual variables. They also provide aggregated information explaining how the final probabilities are predicted on average. In this analysis, the findings from the SML approach are largely consistent with the results achieved with a logistic regression model. Furthermore, the SHAP approach allows to compare between the models, illustrate observed nonlinearities and gain a better understanding of how different models are sensitive to varying structures in the underlying data.

4.4. Managerial Implications

This chapter provides the answer to the third practical research question of the overall study – how the trust-facilitating measures of the service provider relate to customer behavioral outcomes when it comes to preserving a long-term relationship with a customer and customer commitment – contract extensions. The apparent negative effect of the main ability-based, benevolence-based, and integrity-based trust measurements on the contract terminations highlights the importance of both functional and relationship-based trust between the customer and the service provider (McKnight et al. 2011; Tams et al. 2018). A customer contacted early in the relationship, before the active usage period started, is less likely to terminate the relationship. Similarly, a customer who experiences helpful support services and does not have to repeatedly open problem cases on related topics is less likely to terminate the relationship. Finally, a customer who uses the product actively and does not have to open many problem cases is less likely to terminate the relationship.

On the one hand, these findings support previous churn research showing that product utilization is one of the key predictors of churn, measuring the value delivered to the customer (similar to the findings of Kisioglu and Topcu 2011; Li et al. 2021). On the other hand, the findings explicitly show the importance of the relationship elements when explaining and predicting customer terminations.

Thus, this study provides evidence of the crucial role that the relationship-based elements of trust play in preventing customer terminations. This calls for an investigation of a variety of measures directed at termination prevention (Gelb et al. 2020; Xiao et al. 2020). Moreover, benevolence-based and ability-based trust measures used in this study can be adopted to identify customers at risk and prevent customer churn early (Slof et al. 2021). Early interactions cannot be added later in the relationship when it comes to the integrity-based trust measurement. However, the findings highlighting the importance of early communication need to be further extended by investigating the interventions through customer success teams and their role in churn prevention.

4.5. Discussion

In this study, I use an example of a service provider and their customers to illustrate how different trust dimensions throughout time in contract influence customer commitment – their decision to terminate the relationship or extend the contract. All dimensions of trust, defined according to the Ability, Benevolence, Integrity (ABI) trust framework in the theoretical section, have a negative effect on customer contract terminations and confirm the expectation of the general positive effect of trust on customer commitment in a relationship. In contrast, the differences in the effect magnitude do not provide results consistent with the theoretical expectation of ability-based trust playing the main role in explaining the behavioral outcome. With multiple models fitted, only the results from the best performing model in the supervised machine learning approach support the expectation of ability-based trust being most important, followed by benevolence-based and integrity-based trust. Furthermore, multiple models highlight the importance of benevolence-based trust. These findings provide an extensive answer to the primary empirical question of this chapter and contribute to the research on the effects of trust in interorganizational relationships.

The second question, answered in the managerial implication section, provides insights into the practical functioning of the relationship between a service provider and their customers. The empirical results provide evidence and offer practical implications of how customers with termination risk can be identified and what relationship-based elements can be used to prevent the terminations.

Finally, this chapter attempts a methodological contribution while implementing a methodological strategy that uses supervised machine learning and an explainable machine learning approach to examine the effects of variables on the individual level. In this work, the availability of a full sample of the data for a given timeframe is leveraged to investigate how the results received with a classical logistic regression approach can be deepened when looking at non-linear models of the data.

While the logistic regression proves to be a tool of high predictive accuracy, I use tree-based ensemble models (random forest and XGBoost) to show their potential for sociological applications, especially in studying non-linear effects. When considered individually, these methods allow a comparison of the relative importance of the input variables for modeling the outcome variable. These methods alone do not allow to achieve an explanatory representation of the problem. However, their combination with an explainability framework (SHAP) extends the possibilities of individual effect estimation in sociology.

This study shows how the SHAP values, on the one hand, can be used for individual-level effect investigation. This side of the SHAP values is especially interesting to test the linear effect assumed in the logistic regression with the distribution of individual effects in different models. In this study, linearity could be observed for the main variables. At the same time, some models introduce a non-linear understanding of the input variables in relation to the outcome.

On the other hand, applying SHAP values to both non-linear and regression models offers an approach where classical sociological models can be compared to supervised machine learning models. This methodological strategy is extended with the SHAP feature importances that not only provide more reliable feature importance values (Lundberg et al. 2018) but also offer a strategy of comparing the contribution to the outcome variables from otherwise not comparable models, e.g., logistic regression and tree-based ensemble models.

Alongside an empirical contribution and a novel methodological approach, this study opens several research directions for future research. First, when it comes to the trust aspect, this study offers new insights into the differences between the effects that individual trust dimensions have on the customer contract terminations as an outcome of the commitment problem. These findings, however, are based on a case study of a single product and a single service provider. Thus, replicating the findings in a study of multiple companies is the first future research direction. Second, the observed differences in the trust effects vary across methods. A more detailed investigation of the findings in different settings and a more detailed analysis of how the effects change over time is a further research direction. Third, the results illustrated with the SHAP value approach highlight potential differences in the effects of individual trust dimensions. Further research can focus on investigating the heterogeneity in the effects of trust, i.e., whether the effect of integrity-based trust for some customers is stronger than others or has an opposite direction.

Regarding the methodological part, this study, first, does not aim at building best-performing models. Many strategies can be applied to improve the performance of the supervised machine learning (SML) models, to achieve better model performance. With this work aiming at a comparison of a classical regression approach to the SML ones, the possibility of applying such practices as oversampling (e.g., Yap et al. 2015) to sociological data remains a separate research direction[93].

Applying multiple models to investigate the relationship between the variables has many already described positive sides. However, given the growing methodological complexity, researchers should be aware of possible contradicting results for the same question when different models are applied. To my knowledge, there exists no guideline on how to address such differences in the findings when translating the results back into the theoretical part, especially when machine learning models are used. This presents the second crucial question for sociological methods that requires further investigation.

With the strong focus on the methodological part of this study, its main limitation comes from the applied measures. Previous chapters discuss the difficulty of trust measurement (Glaeser et al. 2000) that is faced by researchers in general and in the present work. The proposed measures of ability-based, benevolence-based, and integrity-based trust are an attempt to derive trust measures from observational data in connection to research on customer success, customer support, and churn. While highly useful in an industrial context, these measures come with the previously discussed validity problems. Subsequently, while trust is the mechanism discussed in this study, the applied measures open the discussion of potential alternative mechanisms explaining customer contract terminations in the analyzed case study, such as, for example, service quality and satisfaction (e.g., Venetis and Ghauri 2004; Chou and Chiang 2013), or general relationship quality (Rauyruen and Miller 2007). A further limitation resulting from the applied measures is the necessity to assume full mediation

[93] For examples of exiting research regarding oversampling in social sciences, see Kalton (2009); Ghosh et al. (2019).

of the relationship by trust and the impossibility to study indirect effects combined with the direct ones. The importance of the indirect effects on customer behavioral outcomes is emphasized by, e.g., Lankton and McKnight (2011) and provides a crucial future extension to validate the presented findings.

Summing up, this chapter supports the theoretical expectations of trust dimensions having a positive effect on the outcome of the commitment problem in the relationship with a service provider. The study illustrates the differences between the individual trust dimensions and their effects. For instance, ability-based and benevolence-based trust are more important for predicting the outcome of relationship terminations with supervised machine learning models than integrity-based trust. This research question and the case study of a service provider position this study at the intersection of churn research and sociological research and open the possibility of applying a combination of classical sociological methods and industrially applied supervised machine learning models and explainability methods. Finally, this chapter offers a methodological combination of how these methods can be adopted for answering sociological research questions.

Discussion

Several contributions are achieved with this work. First, I extend the empirical findings on ability-based, benevolence-based, and integrity-based trust and their effects in interorganizational subscription relationships. With the SaaS market chosen for the analysis and the availability of the data, this work also creates a bridge between the organizational trust research on the ABI framework and the information systems trust research. It further provides managerial recommendations regarding trust-facilitating actions of the service providers. The analytical strategy chosen for three chapters and the explainability methods applied in the third chapter, in particular, place this study in the area of computational social science. The combination of industrial data and industrial machine learning practices provides a methodological contribution to the application of explainable machine learning methods in sociology.

5.1. Summary of the findings

This dissertation discusses the growing importance of solving the commitment problem, which is increasingly important in the changing structure of software contracts to Software as a Service (SaaS) (Godse and Mulik 2009; Xiao et al. 2020). In SaaS contracts, which are subscription-based (Xiao et al. 2020), trust is a solution to the commitment problem and the question of contract extensions (Ganesan 1994; Benlian et al. 2011; Xiao et al. 2020). The role of trust is recognized not only in sociological and organizational research (e.g., Schoorman et al. 2007; Baer and Colquitt 2018). A growing body of literature, e.g., in information systems research (e.g., Lankton and McKnight 2011; Lansing and Sunyaev 2016), also covers trust in general and individual trust dimensions as contributors to solving the commitment problem (e.g., Xiao et al. 2020). In this dissertation, the widely adopted Ability, Benevolence, and Integrity (ABI) trust framework (Mayer et al. 1995) is used to provide a multidimensional perspective of the role of trust in a relationship between a service provider and its customers.

In the introduction, I state two research questions that are further translated into empirical questions in the individual chapters of the dissertation. The question of **the behavioral consequences which a service provider's measures targeting uncertainty reduction and formation of individual trust dimensions reach in**

their customers over the course of the contractual relationship is referred to in the second and the third chapter, focusing on the integrity-based and the benevolence-based dimensions of trust.

I show that the trust-facilitating measure of early contact with the customer by the customer success teams corresponds to the expected effect of a measure when integrity-based trust is the mediator in the mechanism. Early interactions with the customers, initiated by SP's customer success teams, contribute to trust formation in the relationship and lead to a short-term increase in customer utilization of the purchased product as the outcome. This effect corresponds to the short-term effect expected in the theoretical understanding of integrity-based trust (Mayer et al. 1995; Schoorman et al. 2007).

Benevolence-based trust is expected to evolve over time in the contractual relationship (Mayer et al. 1995; Schoorman et al. 2007; Svare et al. 2020). In the SaaS subscription contracts, this dimension relates to the relationship-based support services provided by the customer support units of the service provider (Alvarez et al. 2010). I see customer support as benevolence-based trust units of the service provider and show that support provided to customers positively affects customer engagement and is associated with fewer customer terminations. On the contrary, customers whose problems are related semantically or based on the same latent topic are less likely to give feedback to the service provider and more likely to terminate the contractual relationship.

The question of **how trust affects customer commitment in the renewal phase of the SaaS contractual lifecycle** is reflected in the fourth chapter of the dissertation. In the fourth chapter, the relationship between the trust dimensions and the behavioral outcome of relationship termination is studied. I operationalize ability-based trust through the proxies of product utilization and the number of reported problems, benevolence-based trust through the proxy of customer problem profiles (modularity and latent topic coherence), and integrity-based trust through the proxy of early contact with the customers, corresponding to the operationalization in the previous chapters. I show that all trust dimensions have a negative effect on customer contract terminations and, following, a positive effect on customer contract extensions in the renewal phase of the contractual relationship. Ability-based and benevolence-based trust have a more pronounced effect than integrity-based trust across all models of the relationship. This finding corresponds to the theoretically expected temporal dynamics of trust formation and importance (Schoorman et al. 2007; Pollack et al. 2017).

The findings of this dissertation show that trust in all its dimensions serves as a solution to the commitment problem in an interorganizational relationship between the SP and their customers. As theoretically suggested, integrity-based trust is more pronounced in its effect on product utilization at the beginning of the relationship. Benevolence-based trust impacts customer engagement and is associated with a lower probability of customer contract terminations. Ability-based trust in the form of usage has a negative effect on customers leaving the contractual relationship with the service provider.

5.2. Methodological Contribution

A service provider SAP SE provided the data foundation for this dissertation. With the availability of full population data together with the thematical closeness of this dissertation to the industrial churn research, the fourth chapter of this dissertation opens an important methodological contribution to sociological research in the area of computational social science.

First, the fourth chapter considers a wide range of supervised machine learning models to illustrate the differences in modeling available with non-linear models of the outcome variable. Second, this approach opens a possibility to compare the feature importance values – relative contributions of the individual trust variables to modeling the outcome, which is more difficult to achieve in regression analysis. This approach allows one to investigate the relative importance of trust variables across multiple models and suggests that similar predictive performance can be achieved, even if the input variables are considered differently by the models.

Machine learning methods used in the industry are well-known for their accurate predictive performance (e.g., Di Franco and Santurro 2021). However, the adoption of such methods to sociological studies is often limited by the "black box" nature of the methods, i.e., the impossibility of understanding the contributing factors to predictions (McFarland et al. 2016). As a second methodological contribution, SHapley Additive exPlanation (SHAP) values (Lundberg and Lee 2017) applied in the fourth chapter as an extension of the machine learning methods allow for a deeper look at the contributions to the probability values predicted by machine learning models. By estimating the local variable contributions, the SHAP approach represents the predicted outcome probability in a regression-like additive form. This allows the researchers to investigate the full range of individual variable contributions in the sample and compare the absolute SHAP values for a wide range of models, including the logistic regression, the random forest, and the XGBoost models.

Summing up, the unconventional for social science methods applied in this work emphasize the potential of machine learning models and explainability extensions of such models for sociological research. The models allow one to confirm the linearity of relationships, identify and investigate the outliers when it comes to observed effects, and compare the relative importance of the independent variables. Thus, in future research, machine learning models can be applied together with regression approaches to validate and enrich the findings.

5.3. Managerial Implications

Alongside the goal to illustrate the theoretical position of trust in solving the commitment problem between the SP and their customers, this work follows the agenda of answering the practical research questions related to the managerial implications of the findings. When looking at the ABI trust dimensions from a Service Provider (SP) perspective, the ability-based trust dimension refers to the technical ability of the service provider to deliver a product that provides all promised functions (McKnight et al. 2011; Lankton 2015) and can be used according to the value expected by the customer (Zhu and Kraemer 2005). The integrity-based trust dimension results from the early interactions with customer success teams. Customer support activities and problem-solving reflect the benevolence-based trust dimension. I stated three practical questions, interesting from the side of the SP in the introductory chapter.

The question of **whether the customer success teams help to build integrity-based trust and positively affect customer usage behavior at the beginning of the usage phase** – is covered in the second chapter of the dissertation. The presented detailed investigation of the integrity-based dimension of trust shows that early-on interactions with customer success teams in their effect on customer product usage correspond to the theoretical effect under the condition that integrity-based trust is facilitated through these activities. Early contact activities initiated by customer success teams are found to achieve higher adoption rates of a product at the beginning of the usage period. This finding underlines the importance of early interactions with customers. Adoption is an important indicator for successful implementation of products (Kim and Son 2009) and is expected to have a range of further positive effects, including, for example, perceived and actual efficiency gains (as shown by Wu, Zsidisin, and Ross (2007) for e-procurement products). Consistent with the theoretical expectations on integrity-based trust, this effect decreases over the first 6 months of the usage phase.

Thus, this dissertation contributes to the research investigating the effect of customer success teams and emphasizes the importance of customer success plans for customers, which are frequently highlighted by the customer success practitioners (Mehta et al. 2016; Vaidyanathan and Rabago 2020). Practically, this highlights the high value of customer success teams and their actions at the beginning of the relationship and the need for efficient handover mechanisms between sales and customer success teams (Hochstein et al. 2020; Vaidyanathan and Rabago 2020).

The third chapter answers the question of **whether the problem solving activities of support teams, building benevolence-based trust, positively influence customer engagement**. The presented analysis of benevolence-based trust – also referred to as helpfulness – in the context of SaaS contracts (Lankton and McKnight 2011) is reflected by customer support service. While looking at the structures of customer support cases and relating these structures to the outcomes of customer engagement in the usage phase (participation in NPS) and the outcomes of contract extensions in the renewal phase, I show that high helpfulness of customer support leads to an increase in engagement and is associated with a decrease in customer terminations.

Customer support does not enjoy a reputation of providing essential services to the customers (Sterling and Lambert 1989; Sheth et al. 2020). Recently, it has attracted more attention (Sheth et al. 2020), as more and more companies turn to the Software as a Service business model. My findings emphasize the importance of customer support in the context of trust between the SP and the customer and the value of customer support offering that goes beyond solving customer problems in a timely fashion. Thus, this study advocates repositioning customer support as a value-driving unit (Sheth et al. 2020) due to the value of the customer support services in building trust. The measures of customer problem subject lines analysis further underline the importance of understanding and in-depth analysis of customer problems by the SP (Sheth et al. 2020; Slof et al. 2021). This opens the possibility of intervening and providing better and more helpful support to customers with related problems, which further impacts benevolence-based trust between the parties.

All chapters cover the question of **the effect that the measures targeting uncertainty reduction have on behavioral outcomes during the renewal phase of the SaaS contractual relationship.** The fourth chapter provides a detailed investigation of the outcomes of all trust dimensions in the renewal phase, including ability-based trust. The crucial outcome of trust in the commitment problem scenario is the customer's decision to extend or terminate their contracts. The findings of the fourth chapter correspond to the theoretical propositions regarding the effects of trust

(Mayer et al. 1995; Schoorman et al. 2007; Pollack et al. 2017). All trust dimensions have a negative effect on customer decisions to terminate their contracts. Compared to other trust dimensions, the lower importance of integrity-based trust supports the temporal differences in the effects between the dimensions. The best-performing machine learning model provides evidence that ability-based trust is the most important dimension of all when explaining customer contract extensions and termination in the SaaS contract context.

With customer terminations being a highly relevant problem for SaaS companies (Van den Poel and Lariviere 2004; Xiao et al. 2020), this work provides scientific evidence of the importance of relationship quality and relationship trust dimensions between the customers and their SP. Thus, this dissertation shows how adding new indicators to the customer churn models helps to improve the predictive performance of churn models and covers a theoretically valuable dimension of trust that is not usually part of industrially applied models (Lariviere and Van den Poel 2005). The methods applied in the fourth chapter and already discussed in the methodological contributions of this dissertation emphasize the importance of the explainability of churn models. This is crucial since the relationship dimensions of trust, such as benevolence-based and integrity-based trust, can be directly influenced by the employees of the companies, thus, creating a valuable mechanism for churn prevention.

5.4. Limitations and Future Research

With many contributions discussed, this dissertation has limitations and opens space for future extensions of the research agenda. Starting with the limitations, the main points discussed in the individual chapters relate to the difficulties of measuring relationship-based trust dimensions with observational data. Both measures used in chapters 2 and 3 can only be referred to as partial measures of the respective trust dimensions. For integrity-based trust, as the quality of interactions between the customer success teams and the customer cannot be observed, the measure of interaction allows for only limited conclusions when it comes to actual trust. It was also mentioned that the initial integrity-based trust is based on the service provider’s reputation (Suh and Houston 2010). The assumed mechanism requires the replacement of reputation-based integrity at the beginning of the relationship (Mayer et al. 1995). Nevertheless, it is plausible that a part of the not measured integrity-based trust is based on the service provider's reputation for some customers.

Similarly, benevolence-based trust is theorized to be based fully on the trustee's goodwill (Mayer et al. 1995), which in practical survey implementations covers consideration of customers before action-taking and the customers' welfare (e.g., Grayson et al. 2008). Further nuances of this dimension, e.g., altruistic benevolence (e.g., Nguyen 2016) and the intercultural differences (e.g., Wasti and Tan 2010) also lie outside of the scope of this work. The helpfulness element of this dimension, covered in this work, is argued to be more prominent in relationships involving technology (McKnight et al. 2011). Still, this study only allows for a limited representation of benevolence-based trust.

Concerning the theoretical model, the main limitation can be derived from the complexity of the analyzed concepts and the relationships between them. While the perspective of the trust research on the trust dimensions is clear (Baer and Colquitt 2018), the connection of trust research to such concepts as commitment, loyalty, satisfaction is very broad. Due to this complexity, Rauyruen and Miller (2007) go as far as summarizing these concepts in the combined concept of relationship quality. With the goal of a detailed investigation of trust dimensions, the detailed representation of all relationship-based concepts in interorganizational relationships was not the scope of this research. For this reason, it is even more important to highlight the recurring connections between the studied concepts. With trust affecting engagement (Brodie et al. 2013) and commitment (Morgan and Hunt 1994), engagement affecting loyalty (Hollebeek 2011), and both trust and commitment affecting loyalty (e.g., Singh and Sirdesmukh 2000; Zins 2001; Delbufalo 2012), the investigation of the direct effects of trust is always limited by the theoretical framework and the closeness of the concepts. With the strong focus on trust and on the measures implemented by the service provider, this work could pay very limited attention to competitive explanations of customer contract extensions.

Another limitation of the theoretical scope of this work comes from the framing of the commitment problem from the perspective of a customer's commitment to the service provider. This is partially determined by the case study analyzed and the data for one service provider available for the analysis. Still, as outlined in the introduction, the commitment problem can be presented from both sides in the context of the SaaS contractual relationship (Benlian 2009; Buckinx and van den Poel 2005; Xiao et al. 2020). On the one side is the commitment of the customers to the service provider, represented by contract extensions, which was thoroughly discussed in this work. On the other side is the commitment of the service provider to the customer, i.e., their continuous delivery of products and consistency of product quality (Benlian et al. 2009). An investigation of this side of the commitment problem remains open.

Coming to the future research directions, the first point relates to specifics of the business relationship between the parties. While there are competitors to the studied product on the market, the question of individual customer decisions to turn to the competitors can only be studied thoroughly if a customer survey related to extended termination reasons is included in the research design. Thus, the first future extension of this study is to combine the presented design with a detailed survey of perceived problems in a relationship and customer termination reasons.

The second future extension of this study relates to the external validity of the findings. The case study setting of this study allows for full sample analysis of a service provider and their customers. Such analysis provides valuable results to extend the empirical findings of trust research in organizational and information systems research. However, the differences in customer bases between service providers may result in significant differences in the importance of trust across service providers.

The third extension is related to the assumptions that customer success teams and customer support act with the goal of trust creation. For customer success teams, this perspective is emphasized by the customer success practitioner literature (Mehta et al. 2016). For customer support, it is derived from the close link between the support offering and the benevolence-helpfulness trust dimension (McKnight et al. 2011). Yet, many additional elements in the relationship can influence trust. With careful isolation of the sample groups, I argue that the factors accounted for in this study allow for the conclusions made. Nevertheless, a future research extension in the direction of marketing communication with the customer, customer participation in webinars and learning activities provided by the service provider, customer's involvement in the practitioners' community of the software can be further studied as additional trust-facilitating mechanisms in a relationship between the service provider and the customers.

The next two extensions of the study are related to the machine learning approach applied in the fourth chapter. The application of multiple machine learning models extends the methods usually available to social scientists (Molina and Garip 2019). The SHapley Additive exPlanations framework allows the researchers to discover the non-linearities in the data that are leveraged by machine learning models to accurately model the outcome variable (Lundberg and Lee 2017). However, even if the resulting model performance is similar across multiple models, the ways these models use the input variables may differ. Thus, the fourth extension is a detailed study comparing and evaluating machine learning model performance in an explainability context. Furthermore, the advantages of such a novel method as SHAP come with limitations related to the inference possibility (Williamson and Feng 2020). Thus, in the fifth extension, a method of applying SHAP values to sample studies should be investigated.

Finally, when it comes to the complete relationship between an SP and their customers, the time aspect is an important force influencing the relationship (Schoorman et al. 2007; Pollack et al. 2017). Thus, the final extension relates to investigating customer behavior and the actions of the trust-related units in the SP organization over a longer period of time than was possible in this study. With this, a more detailed picture of customer behavior during extreme conditions (e.g., the covid-19 pandemic) can provide valuable insights into the study of trust between the SP and their customers.

Conclusion

This study describes the relationship between customers and a service provider in a SaaS subscription market from the perspective of trust between the parties. With ability-based trust enabled by the contract (Liu and Ngo 2004), integrity-based trust formed by customer success teams and their actions (Mehta et al. 2016; Pollack et al. 2017), benevolence-based trust formed through interactions with customer support (Alvarez et al. 2010; McKnight et al. 2011), this study illustrates how a classical concept of trust is applicable to the Software as a Service market. This market is uniquely positioned to allow for innovation through trust operationalization with observational data and a combination of classical sociological and industrial methods. Furthermore, this dissertation's combination of industrial and sociological predictive and explanatory design offers a methodological practice that combines predictive machine learning models and their explainability in sociological research designs. With a service provider supporting this research, this study further emphasizes the deep importance that thorough study of interorganizational relationships in their directly and indirectly tangible aspects contributes to successful relationships between the service providers and their customers.

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Appendix

Table A.1.1.: Python 3.9 packages used for computations

Package Name	Version	Citation
gensim	4.1.2	Rehurek and Sojka (2011)
langdetect	1.0.8.	Danilk (2021)
matplotlib	3.5.0.dev2510+g3af610c2aa.d20211111	Hunter (2007)
networkx	2.6.3	Hagberg, Swart, and Chult (2008)
nltk	3.4.5	Bird, Klein, and Loper (2009)
numpy	1.20.3	Harris et al. (2020)
pandas	1.3.4	McKinney (2010)
pickleshare	0.7.5	Vainio (2018)
regex	2021.11.10	Barnett (2021)
scikit-learn	1.0.1	Pedregosa et al. (2011)
scipy	1.7.2	Virtanen et al. (2020)
seaborn	0.11.2	Waskom (2021)
shap	0.39.0	Lundberg and Lee (2017)
statannot	0.2.3	Weber (2021)
statsmodels	0.10.2	Seabold and Perktold (2010)

Figure A.2.1.: Density plots of standardized variables in matched treated and control groups

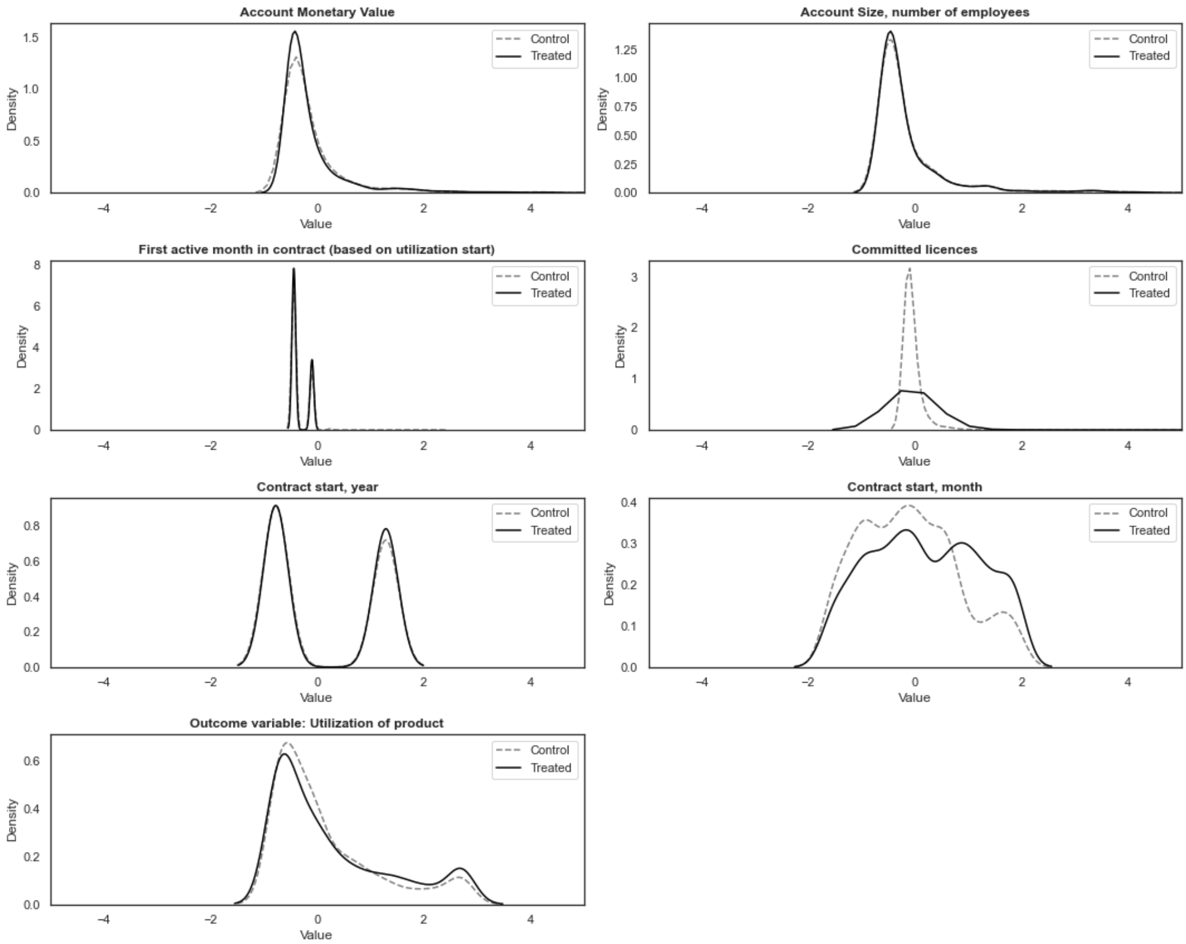
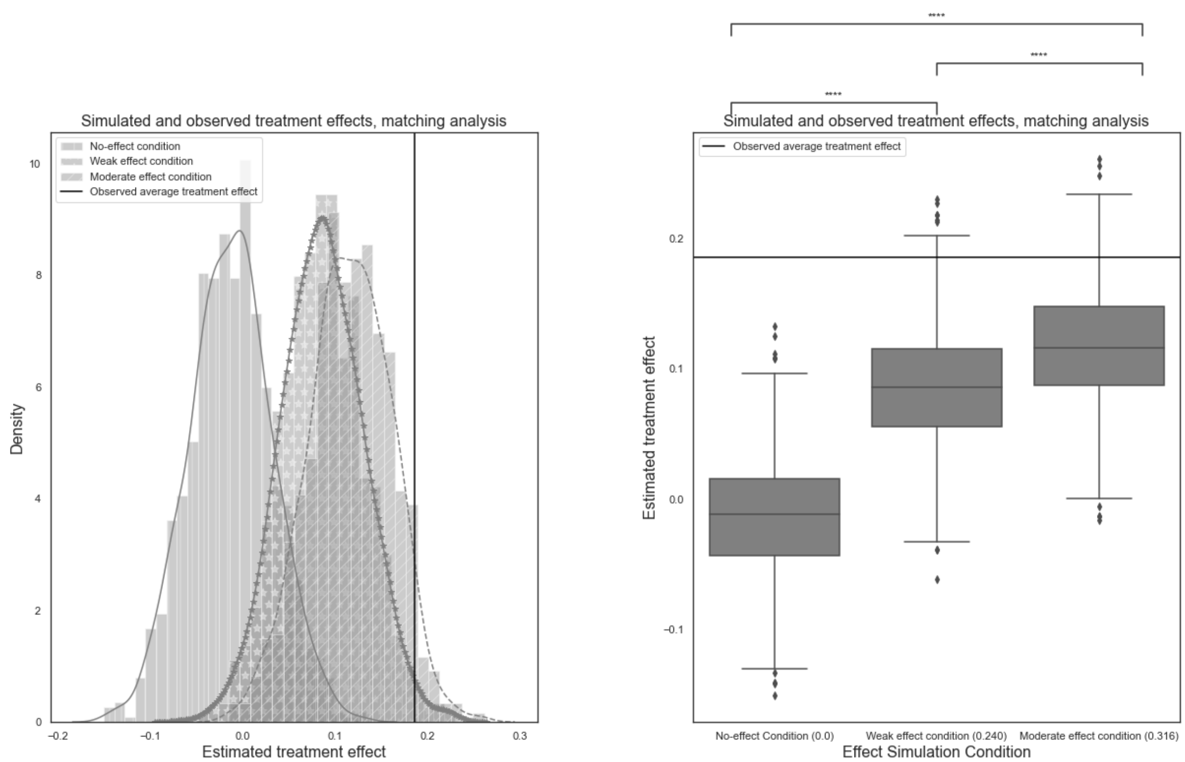


Figure A.2.2.: Comparison of simulated average treatment effects of CST activities on customer utilization under three trust conditions to the observed effect, full SMB sample, blurred treatment condition



Note: ****: p < 0.0001; ***: p < 0.001; **: p < 0.01; *: p < 0.05; ns: p > 0.05.

Standardized effect under the condition of blurred treatment: 0.185.
Unscaled effect under the condition of blurred treatment: 9 percentage points of utilization.

Figure A.3.1.: List of stop words for text preprocessing

```
['whether', 'that', 'other', 'only', 'seem', 'she', 'who', 'sometimes',
'them', 'less', 'it', 'almost', 'nor', 'afterwards', 'ever', 'un', 'whe
reas', 'while', 'indeed', 'have', 'then', 'such', 'nothing', 'than', 'm
e', 'seems', 'until', 'forty', 'interest', 'nobody', 'anywhere', 'keep'
, 'etc', 'nevertheless', 'upon', 'didn', 'yet', 'those', 'formerly', 'n
ever', 'ten', 'himself', 'ltd', 'former', 'been', 'get', 'perhaps', 'ou
t', 'via', 'seeming', 'further', 'side', 'once', 'doesn', 'latter', 'be
comes', 'whereupon', 'themselves', 'show', 'system', 'any', 'three', 'n
amely', 'everything', 'or', 'thereupon', 'for', 'quite', 'cry', 'by', '
an', 'fill', 'whereafter', 'towards', 'ourselves', 'along', 'her', 're'
, 'might', 'hereupon', 'already', 'same', 'otherwise', 'latterly', 'co'
, 'herself', 'when', 'don', 'six', 'front', 'rather', 'was', 'ie', 'eve
ry', 'before', 'using', 'mine', 'since', 'own', 'yourselves', 'from', '
kg', 'whom', 'always', 'with', 'even', 'amount', 'due', 'its', 'were',
'doing', 'no', 'say', 'now', 'itself', 'behind', 'without', 'cannot', '
hereafter', 'your', 'thru', 'these', 'we', 'over', 'wherein', 'their',
'can', 'cant', 'more', 'enough', 'four', 'just', 'the', 'some', 'being'
, 'do', 'across', 'well', 'my', 'hers', 'con', 'regarding', 'make', 'th
rough', 'after', 'couldnt', 'within', 'thick', 'used', 'serious', 'beco
me', 'fifty', 'but', 'under', 'neither', 'call', 'beside', 'none', 'twe
lve', 'onto', 'least', 'full', 'describe', 'are', 'a', 'whose', 'of', '
would', 'fifteen', 'hundred', 'this', 'computer', 'move', 'too', 'he',
'us', 'all', 'sometime', 'several', 'whoever', 'what', 'find', 'de', 'y
ou', 'is', 'herein', 'found', 'unless', 'on', 'which', 'another', 'anyh
ow', 'about', 'therein', 'his', 'hereby', 'third', 'they', 'beforehand'
, 'anyone', 'also', 'where', 'because', 'amongst', 'thin', 'between', '
last', 'ours', 'whole', 'someone', 'either', 'in', 'although', 'name',
'wherever', 'alone', 'part', 'amoungst', 'bill', 'eight', 'back', 'may'
, 'does', 'mostly', 'yourself', 'detail', 'myself', 'five', 'how', 'any
thing', 'below', 'except', 'again', 'down', 'will', 'and', 'among', 'bo
th', 'so', 'others', 'seemed', 'whenever', 'made', 'various', 'thereby'
, 'had', 'inc', 'fire', 'whereby', 'thereafter', 'sincere', 'meanwhile'
, 'could', 'please', 'take', 'nine', 'yours', 'up', 'against', 'give',
'km', 'everywhere', 'many', 'throughout', 'am', 'hence', 'two', 'each',
'eg', 'not', 'thus', 'our', 'therefore', 'often', 'something', 'beyond'
, 'anyway', 'top', 'why', 'moreover', 'became', 'twenty', 'be', 'if', '
sixty', 'still', 'somehow', 'i', 'very', 'above', 'most', 'really', 'ho
wever', 'whither', 'one', 'though', 'did', 'as', 'go', 'hasnt', 'put',
'to', 'see', 'should', 'whatever', 'thence', 'next', 'nowhere', 'bottom
', 'done', 'elsewhere', 'off', 'into', 'there', 'has', 'whence', 'at',
'much', 'around', 'must', 'somewhere', 'eleven', 'else', 'together', 'f
irst', 'mill', 'per', 'here', 'noone', 'him', 'empty', 'during', 'few',
'becoming', 'toward', 'besides', 'everyone']
```

Figure A.3.2.: Density plots of standardized variables, new customers sample

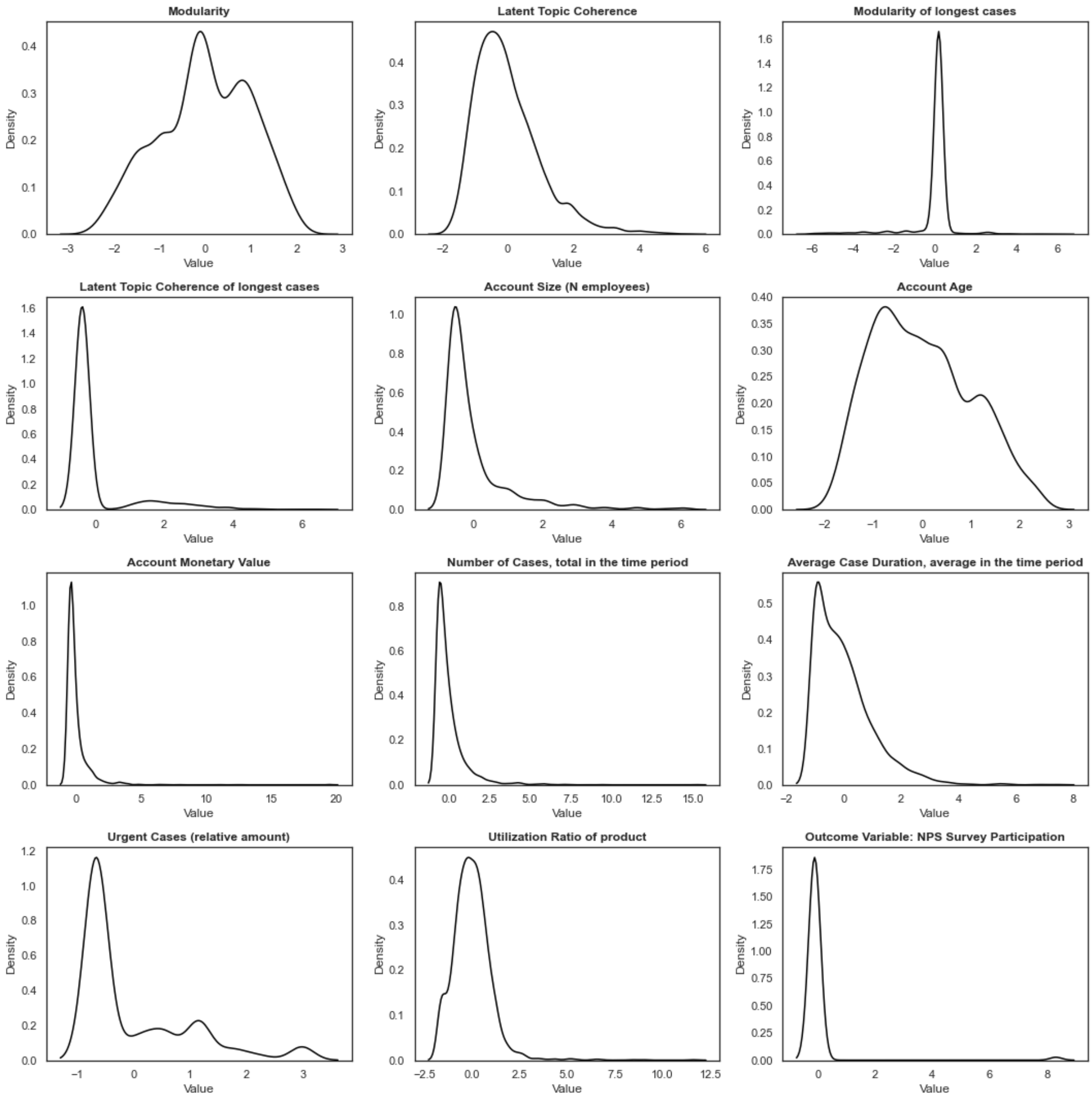


Table A.3.3.: Standardized regression coefficients for the effect of benevolence-based trust on customer engagement, full sample

	Full Sample				
	Model I	Model II	Model III	Model IV	Model V
Modularity	0.0131 (0.041)		0.0083 (0.019)	0.004 (0.019)	0.006 (0.019)
Latent Topic Coherence		−0.0128 (0.0156)	−0.008 (0.0187)	−0.005 (0.019)	−0.004 (0.019)
Modularity of longest cases			0.002 (0.019)		−0.001 (0.019)
Latent Topic Coherence of longest cases			0.001 (0.019)		−0.009 (.022)
Account Age				−0.007 (0.016)	−0.007 (0.016)
Account Size (N employees)				0.025 (0.016)	0.025 (0.016)
Account Monetary Value				0.018 (0.016)	0.018 (0.017)
Number of Cases				0.009 (0.017)	0.010 (0.017)
Utilization Ratio					0.005 (0.016)
Average Case Duration					0.011 (0.018)
Urgent Cases (relative)					−0.003 (0.016)
Intercept	0.0	0.0	0.0	0.0	0.0
AIC	22725.584	22725.458	22731.332	22730.611	22740.134
BIC	-136343.673	-136343.8	-136314.812	-136300.124	-136252.078
N	16392	16392	16392	16392	16392

Note 1: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Note 2: Since the full sample (whole population) of customer data is available, the standard errors cannot be interpreted according to their definition (Ziliak and McCloskey 2004). They are reported for information purposes only.

Table A.3.4.: Standardized regression coefficients for the effect of benevolence-based trust on customer engagement, new customers sample

	New Customers Sample				
	Model I	Model II	Model III	Model IV	Model V
Modularity	0.021 (0.041)		0.011 (0.05)	0.012 (0.05)	0.009 (0.05)
Latent Topic Coherence		−0.019 (0.041)	−0.011 (0.05)	−0.009 (0.04)	−0.009 (0.05)
Modularity of longest cases			0.005 (0.05)		0.004 (0.05)
Latent Topic Coherence of longest cases			0.026 (0.05)		0.027 (0.06)
Account Age				−0.013 (0.04)	−0.016 (0.04)
Account Size (N employees)				0.012 (0.04)	0.013 (0.04)
Account Monetary Value				0.002 (0.04)	0.003 (0.04)
Number of Cases				0.009 (0.05)	−0.0003 (0.05)
Utilization Ratio					0.033 (0.04)
Average Case Duration					−0.006 (0.05)
Urgent Cases (relative)					0.0045 (0.04)
Intercept	0.0	0.0	0.0	0.0	0.0
AIC	3312.193	3312.260	3317.823	3321.936	3330.963
BIC	-15256.398	-15256.330	-15233.434	-15217.764	-15179.846
N	2388	2388	2388	2388	2388

Note 1: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Note 2: Since the full sample (whole population) of customer data is available, the standard errors cannot be interpreted according to their definition (Ziliak and McCloskey 2004). They are reported for information purposes only.

Table A.4.1.: Formulas for performance measures of supervised machine learning models

Measure	Formula
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FN}$
Recall	$\frac{TP}{TP+FN}$
F1-Score	$\frac{2*TP}{2*TP+FP+FN}$
Area under Precision-Recall Curve (AUC)	$\int_0^1 TPR(t)dFPR(t)$

TP: True Positives
TN: True Negatives
FP: False Positives
FN: False Negatives
TPR: True Positive Rate
FPR: False Positive Rate

Table A.4.2.: Standardized regression coefficients for the effect of ABI trust dimensions on customer commitment in the renewal phase (contract extension or termination)

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX
Integrity	-0.016				-0.135		-0.121		-0.122
	(0.026)				(0.029)		(0.029)		(0.029)
Benevolence - Modularity		-0.240		-0.239		-0.228	-0.216		-0.217
		(0.026)		(0.033)		(0.039)	(0.039)		(0.039)
Benevolence - Latent Topic Coherence			-0.152	-0.002		0.009	0.007		0.007
			(0.026)	(0.033)		(0.033)	(0.033)		(0.033)
Ability - Utilization Ratio					-0.116	-0.064	-0.066		-0.067
					(0.027)	(0.028)	(0.028)		(0.028)
Ability - Total N cases					-0.059	0.065	0.060		0.062
					(0.029)	(0.041)	(0.034)		(0.041)
Account Age					-0.244	-0.164	-0.224	-0.187	-0.223
					(0.030)	(0.027)	(0.030)	(0.026)	(0.030)
Account Monetary Value					-0.020	-0.018	-0.020	-0.042	-0.022
					(0.028)	(0.028)	(0.028)	(0.028)	(0.029)
Account Size (N employees)					-0.029	-0.024	-0.026	-0.043	-0.027
					(0.027)	(0.027)	(0.028)	(0.027)	(0.028)
Urgent Cases						-0.005			-0.005
						(0.034)			(0.034)
New Products Purchased									0.002
									(0.027)
Campaign Participation									0.012
									(0.026)
AIC	8506.507	8419.151	8472.204	8421.147	8408.456	8388.053	8370.964	8448.686	8376.717
BIC	-44994.802	-45082.158	-45029.104	-45073.440	-45059.243	-45066.203	-45083.293	-45039.179	-45057.379
N	6135	6135	6135	6135	6135	6135	6135	6135	6135

Note 1: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Note 2: Since the full sample (whole population) of customer data is available, the standard errors cannot be interpreted according to their definition (Ziliak and McCloskey 2004). They are reported for information purposes only.