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The impact of customer ties and industry segment maturity on business model adaptation in an emerging industry

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Abstract

Research Summary: Why do some young firms change their business models while others do not? Why do some firms make small changes, while others make more substantial changes? And does industry context matter? Drawing on organizational learning theory and utilizing a unique database tracking 187 young firms through the first decade of the mobile health industry, we examine the role of customers in young firms' business model adaptation. We find a positive impact of customer portfolio breadth (capturing the number and diversity of customers) on both the likelihood and degree of business model change. Importantly, industry segment maturity moderates this relation: customer effects are strongest in the earliest, most uncertain stages. Our study provides a rare view into how a new industry and its young ventures co-evolve.

Managerial Summary: Customers have been viewed as critical in a start-up venture's search for an initial business model, but their role in young firms' business model adaptation has not been examined. In this study, we show that a young firm's customer portfolio breadth is an important driver of business model change, especially at the earliest, most uncertain stages of an industry. Our results highlight

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the value of customers as sources of knowledge in emerging industries, and suggest that when making decisions about establishing and fostering customer ties, entrepreneurs should consider the number and diversity of those ties in the context of the maturity of the young firm's industry segment.

KEYWORDS

business model adaptation, customers, emerging industry, entrepreneurship, organizational learning

1 | INTRODUCTION

The business model, or the logic by which a firm creates and captures value (Teece, 2010), is increasingly recognized as key to competitiveness and financial performance (Rietveld, 2018; Sohl, Vroom, & McCann, 2020; Zott & Amit, 2007, 2008), and a growing literature spanning strategy, innovation, and entrepreneurship research has explored the creation and adoption of business models (Massa, Tucci, & Afuah, 2017). This literature has recognized the development and change of a business model as an important form of organizational adaptation (Amit & Zott, 2001; McDonald & Eisenhardt, 2020) that drives the survival and growth of young firms (Andries, Debackere, & Van Looy, 2013) and enables incumbent firms to cope with dynamic external conditions (McGrath, 2010; Osiyevskyy & Dewald, 2015).

Only recently have studies begun exploring the processes of business model adaptation to better understand how and when a firm changes its business model. Studies have shown that business model adaptation can be influenced by external factors such as technological innovation, regulatory changes, and financial crises (Osiyevskyy & Dewald, 2015; Saebi, Lien, & Foss, 2017), but also by firm-internal antecedents such as organizational inertia, founding team experience, and founder identity (Gerasymenko, De Clercq, & Sapienza, 2015; Leatherbee & Katila, 2020; Van Boxstael & Denoo, 2021). It is important to distinguish here between business model adaptation in early-stage start-ups, or "nascent firms," and business model adaptation in "young firms" that are active in the marketplace and have stakeholders, such as customers and investors, that they need to take into account. Nascent firms often follow "lean start-up" approaches, whereby they engage in rapid exploration and experimentation in search of an initial viable business model (Blank, 2013; Leatherbee & Katila, 2020; Ries, 2011). For young firms, however, business model change can be more difficult, as it involves modifying existing organizational structures and processes that may involve external stakeholders (Andries et al., 2013; Hampel, Tracey, & Weber, 2020; McDonald & Gao, 2019). The focus in our study is on these young firms and their business model changes.

We specifically investigate the role that customers and industry context may play in triggering business model changes in young firms. Despite the importance of learning from and co-creating with customers in entrepreneurship (Coviello & Joseph, 2012; Yli-Renko, Autio, & Sapienza, 2001) and the lean start-up movement's emphasis on learning from customers for nascent firms (Blank, 2013), no studies have actually investigated the link between customers and young ventures' business models. This is not only a missed opportunity to bring customers back more centrally in the strategic entrepreneurship literature, which has largely focused on value capture rather than value creation (Demil, Lecocq, Ricart, & Zott, 2015), but also leaves us with an important gap in our understanding of how young ventures' business models change over time. Many conventional learning sources, such as successful competitors and past experience (Bruneel, Yli-Renko, & Clarysse, 2010; McDonald & Eisenhardt, 2020) are unavailable to young ventures in an emerging industry, making customers, as early-stage stakeholders, a key potential antecedent to business model change (Amit & Zott, 2015).

Further, business model adaptation is particularly salient in the setting of an emerging industry, where uncertainty is high (Agarwal, Moeen, & Shah, 2017), but we know little about how the dynamics of an emerging industry might impact business model adaptation. As products may be incomplete, customer demands undefined, technological problems unresolved, and industry structures poorly established (Agarwal et al., 2017; McDonald & Eisenhardt, 2020), it is unlikely that the "right" business model will be apparent early on (Andries, Debackere, & Van Looy, 2020; Teece, 2010). Opportunities for business model imitation, or vicarious learning from peers, will be limited. In such a context, we expect interorganizational learning from customers to be particularly impactful. The less established the industry, the more likely young firms should be to change their business models as a result of the assimilation and exploitation of the external knowledge acquired from customers, and the more substantial those changes will likely be.

In this paper, we focus on the likelihood and extent of business model adaptation[1] of young technology firms in an emerging industry. Taking an organizational learning lens, we consider how a firm searches for and acquires knowledge, processes that knowledge, and implements organizational action as a result (Argote, 1999; Crossan, Maurer, & White, 2011). We develop the novel construct of *customer portfolio breadth*, a measure that seeks to capture the knowledge variation stemming from the firm's customer portfolio by weighting the size of a firm's customer portfolio by its diversity. Following Yli-Renko and Janakiraman (2008) and Coviello and Joseph (2012), we define "customers" as the next channel members in the value chain, that is, the parties to which the firm sells to generate revenues. A customer may thus be an end user, distributor, or licensee—any buyer with whom there is a revenue relation. We further theorize that in the young firm's organizational learning process, knowledge acquisition, assimilation, and implementation are influenced by the maturity of the industry segment that the firm operates in. The learning outcomes of interest are the likelihood and degree of business model change. In sum, we address the following research questions: *What is the impact of a young firm's customer portfolio breadth on (1) its business model adaptation likelihood, and (2) the degree of business model adaptation, that is, the extent to which a business model changes?* and *How does industry segment maturity moderate these relationships?*

Our empirical setting is young firms in the mobile health industry. Mobile health, or mHealth, is an industry at the intersection of telecommunications, IT, and health, in which mobile devices are used for health-related services and information. mHealth was originally described as emerging in 2006 (Istepanian, Laxminarayan, & Pattichis, 2006), but a decade later it was still largely unclear how successful customer adoption and the subsequent value capturing could be done in the industry (Denoo & Yli-Renko, 2019; Economist, 2016). Using a broad range of archival and secondary data sources, we created a unique dataset of 187 young firms, corresponding to 961 firm-year observations between 2005 and 2014. The dataset tracks the business models and customer portfolios of young mHealth firms in the US throughout a decade of emergence and growth of the industry. We complement our quantitative dataset with qualitative insights from interviews with entrepreneurs, venture executives, and industry experts.

This study makes multiple contributions. First, we contribute critical new insights to the understanding of business model adaptation—specifically, on the role of customers and industry context. In doing so, we answer recent calls for more research on the antecedents and boundary conditions of business model change, especially in the context of young firms (Bocken & Snihur, 2020; Shepherd & Gruber, 2020). We extend work that has highlighted the importance of stakeholders, such as customers, and environmental factors, such as industry, on initial business model design (Amit & Zott, 2015). Business model adaptation is a phenomenon distinct from both the cognitive processes that nascent entrepreneurs use to develop their initial understanding of a business opportunity and its exploitation strategy (Leatherbee & Katila, 2020; Martins, Rindova, & Greenbaum, 2015) and from the strategic change that incumbent firms undergo to modify established structures and strategies (Rajagopalan & Spreitzer, 1997). Viewing business model adaptation as an organizational learning process and expanding this conceptualization to include learning from customers and the maturity of an industry segment, we add an interorganizational and more granular industry ecosystem level to a literature that has previously focused on firm-internal factors and broader external factors such as technology and regulation. We shed new light on the question of what leads some firms to experiment with their business models while others do not, and why some firms make small changes to their business models while others opt for more substantial ones. Our results show that broader (i.e., larger and more diverse) customer portfolios make business model change both more likely and more substantial. Further, these effects are negatively moderated by industry segment maturity; the positive effects of customer portfolio breadth largely disappear when an industry segment matures. While recent work has highlighted the role of "parallel play," or learning from peers, in business model design (McDonald & Eisenhardt, 2020), the role of customers has been ignored (Demil et al., 2015). Our study shows that customers are an important learning source that influences business model adaptation of young firms, especially in early-stage industry segments.

Second, we contribute to the growing body of literature that focuses on industry birth and emergence (e.g., Agarwal et al., 2017; Moeen, 2017; Moeen & Agarwal, 2017). Our unique data allowed us to track the development of the mHealth industry for the first decade of its existence. Our findings identify industry segment maturity as an important boundary condition that will impact business model adaptation. The importance of industry segments—defined in our study as specific application categories within the industry—and their maturity within a 10-year period in an emerging industry is striking, and suggests that industry studies would benefit from using more fine-grained measures of industry segments and stages.

Third, by shedding light on the role that customers play in shaping the business models of young ventures in emerging industries, our study extends prior work on the importance of learning from and engaging with partners in new technological domains (McDonald & Gao, 2019; Powell, Koput, & Smith-Doerr, 1996; Vasudeva, Alexander, & Jones, 2014) and reintroduces the customer as a central construct in the strategic entrepreneurship literature (Demil et al., 2015). Customers do not only matter for new product development and innovation where the customer will derive direct benefits (Coviello & Joseph, 2012; Yli-Renko & Janakiraman, 2008), but can also profoundly shape a young firm's evolution and the way in which the firm creates and captures value. The unique setting of this study in which we track an emerging industry for its first decade gives a rare view into how an industry and its young ventures co-evolve. Our results indicate that business models are changed more frequently and substantially in less mature industry segments, but only when firms have broad customer portfolios. Both the emerging industry and the young firms in it can thus be seen as a co-constructed outcome of interorganizational learning between the young firms and their customers.

2 | THEORY AND HYPOTHESES

2.1 | Business model adaptation

A business model refers to the system of interconnected organizational activities performed by a focal firm to create and capture value (McDonald & Eisenhardt, 2020; Zott, Amit, & Massa, 2011). Of note is that a business model is a broader unit of analysis than just the firm, and explicitly also takes into account a firm's exchanges with partners, meaning that a business model may also encompass activities by firms' partners, suppliers, and customers (Amit & Zott, 2015; Zott & Amit, 2008). The business model literature has debated the distinction between a firm's "strategy" and its business model, with some scholars including competitive strategy as part of the business model construct (e.g., Andries et al., 2013; Morris, Schindehutte, & Allen, 2005), while others have sought to make a clear distinction between the two (e.g., Zott & Amit, 2007, 2008). In this paper, we use the narrower business model conceptualization, which thus excludes competitive strategy, and focus on key elements of value creation and capture: the offering, market, internal capabilities, and economic factors (Gerasymenko et al., 2015; Morris et al., 2005).

Taking an evolutionary perspective, business model adaptation can be understood as an organizational learning process, in which firms experiment with their business models in order to adapt to the environment and deal with uncertainty (Andries et al., 2013; Martins et al., 2015). Of note is that, in our study, business model adaptation may or may not involve business model innovation, that is, the creation of a business model that is novel to the industry (Snihur & Zott, 2020). Business model adaptation in our study refers to changes in any of the items that constitute a firm's business model (see Methods section for details on our operationalization). As business model items are interrelated and consistency across them is required (Demil & Lecocq, 2010; Gerasymenko et al., 2015), the more items are changed at the same time, the more "substantial" the change is. We thus consider the degree of business model change as a continuum ranging from no changes to simultaneous changes in numerous items.

2.2 | Learning from customers and business model adaptation

Interorganizational learning, that is, acquiring knowledge by interacting with others, assimilating the knowledge, and finally exploiting it (Huber, 1991; Lane & Lubatkin, 1998; Larsson, Bengtsson, Henriksson, & Sparks, 1998), has been shown to be important in a broad range of situations, such as when developing new products (Yli-Renko & Janakiraman, 2008), internationalizing (Bruneel et al., 2010), and building future collaborations and communities (Autio, Kanninen, & Gustafsson, 2008). Interorganizational learning is especially important in contexts such as novel technological domains and emerging industries, where internal experience is limited and external knowledge is widespread and fragmented, making external parties, such as users and peers, an important avenue to gain access to knowledge (Chatterji & Fabrizio, 2014; McDonald & Eisenhardt, 2020; Powell et al., 1996).

We argue that—in our setting of an emerging industry in which information is scarce and uncertainty high—a firm's customer portfolio will be an important source of knowledge that will help a firm shape and adapt its business model. Recent research has suggested that external threats and opportunities can result in business model changes, especially when the firm emphasizes market development and engages in an active search for new market opportunities that can then drive change in the firm and industry (Saebi et al., 2017). Customers and the willingness and ability to learn from them will thus likely be a driver of business model adaptation.

We see two main ways in which young ventures will learn from their customers in an emerging industry. First, given the high level of environmental uncertainty and the fact that the ventures themselves are young with limited experiential knowledge bases to draw on, we expect that they will be actively searching and scanning their environment for potential sources of knowledge (Huber, 1991). Firms may thus use their customers and interactions with them as so-called "purposeful interactions" (Bojovic, Genet, & Sabatier, 2018, p. 142), in which they can learn about various aspects related to the business model, such as about how customers make sense of the market, the product and service dimensions that customers care about, and how best to engage with customers (Hsu, Kovács, & Koçak, 2019; Kirtley & O'Mahony, 2020). This can refer to expectations that customers may have for a firm and its business model, such as offering customized vs. standardized products, having a relational rather than a transactional relationship, or questions on who will deliver after-sales services (Andries et al., 2013). The following quote from an interview with the founder of a young mHealth firm illustrates learning from purposeful interactions with customers: "Everything the firm does has been impacted by interactions with customers… Everything is inspired by the market. Customer feedback has changed the focus…the products, how we operate… The firm has used the market to learn."

In addition to these purposeful interactions, firms can also learn from their customers through what is sometimes referred to as "unintentional learning" (Huber, 1991) or "passive learning" (McDonald & Eisenhardt, 2020). Due to uncertainties regarding product features, customer demands, and industry structures (Agarwal et al., 2017), finding a working business model is challenging. Customers themselves may be unsure about the product use or functionality in these early stages of industry emergence (Visnjic, Ringov, & Arts, 2019). It may thus be the case that through waiting, observing, and interacting (the three components of passive learning according to McDonald & Eisenhardt, 2020) with customers, firms discover what it really is that customers want, and may tailor and adapt their business model accordingly. Qualitative insights from a sample firm illustrate this. The firm started out with a tool for parents to keep track of their children's health records. The firm got customer traction, and discovered that the main reason behind the early success was parents who needed proof of immunization for school enrollment. Upon realizing this, the firm changed its name and began directly targeting schools instead of parents. It changed its product from a medical record to a platform that allows schools to keep track of all medical information, and also implemented a new pricing model.

In short, customers are uniquely positioned to provide information regarding the current products and services of the firm, but also about potential value changes that could improve their customer experience, additional target markets that the firm should address, and alternative pricing models that the firm could explore. Given the lack of readily available other learning sources, such as experienced industry executives or successful competitors to imitate, we expect that getting direct information from actual customers will be valuable and will result in learning. Young firms will be likely to adapt their business models as an outcome of this learning.

2.3 | Customer portfolio breadth and business model adaptation

Our work builds on the idea that customers are a source of interorganizational learning. In the innovation literature, some scholars have focused on "lead users", or those users who experience needs before they become general in the marketplace and who inspire suppliers to generate disruptive innovation (Von Hippel, 1986). Other scholars have shown that a firm's existing customers, especially those that a firm is highly dependent on, can drive the direction of innovation. Firms may focus their R&D on incremental improvements that their key customers ask for but that may not necessarily be in the firm's best interest or lead to the most innovative outcomes, thereby potentially even threatening the survival of the firm (Christensen & Bower, 1996; Yli-Renko, Denoo, & Janakiraman, 2020). In the context of an emerging industry, however, young firms will be faced with a multitude of lead-user early customers spanning a wide range of different types of needs and market domains. In order to capture the extent to which a firm can access such fragmented customer knowledge and the scope of that accessible knowledge, we develop the construct of *customer portfolio breadth*. This construct seeks to take into account both the *size* of a firm's customer portfolio, that is, the number of customers the firm has a relationship with, as well as the *diversity* of the portfolio in terms of differences in market domains between the firm and each of its customers. In developing the operationalization of the construct (see Methods section), we draw on approaches by Bruneel et al. (2010) in the context of young firm internationalization and Gruber, MacMillan, and Thompson (2013), who examined young firms' market opportunity portfolios. In short, the customer portfolio breadth construct reflects both the scale and scope of the external knowledge that a young firm can access from its customers.

In emerging industries and markets, customer needs typically do not converge at first (Santos & Eisenhardt, 2009). A large and diverse customer portfolio will thus be important for generating a range of external knowledge that the firm may learn from (Autio et al., 2008; Dahlander, O'Mahony, & Gann, 2016). Consistent with prior research, which has shown that larger and more diverse networks typically provide informational and technological advantages (Shan, Walker, & Kogut, 1994; Sullivan & Marvel, 2011), we expect that firms with ties to many and diverse customers will acquire more knowledge from them than firms with smaller and less diverse customer portfolios. Further, firms will be better able to assimilate and process this knowledge in the context of a broader customer portfolio. Research has also suggested that it is diversity in customers' demands that can help ventures engage in business model and organizational adaptation and overcome potential inherent tendencies to stick to the status quo (Hsu et al., 2019; Shepherd & Gruber, 2020). Customer portfolio breadth can thus not only help increase the range of external knowledge that ventures get access to, but also help them learn, resulting in knowledge assimilation and utilization (i.e., business model change). Our qualitative data provides an example. A young mHealth venture was originally launched to help combat asthma, but in response to various customer requests the firm decided to broaden its business model by adding a second respiratory disease (called COPD): "From a commercial standpoint, there's just so much overlap between what we're doing with asthma and what we need to be doing with COPD that it has just made sense in our customers' eyes, so in part we're reacting to that market demand" (Comstock, 2013). Leading up to the business model change, the young firm had a large and diverse customer portfolio, including public health programs, general hospitals, and insurance companies.

Furthermore, in uncertain settings, the payoff that a venture will derive from a specific customer is unclear. It is difficult, if not impossible, to know upfront what the value of the knowledge imparted by a specific customer will be, as even customers themselves may be unsure about a product's use or functionality in these early stages of industry emergence (Visnjic et al., 2019). As such, the likelihood of obtaining useful feedback from customers will increase with a larger and more diverse customer portfolio, reflecting a "wisdom of crowds" effect (Afuah & Tucci, 2012). Further, in settings in which knowledge is highly fragmented and spread out, such as in an emerging industry, learning can be seen as an interorganizational process. Customers represent isolated packages of knowledge, and the degree to which firms learn about new opportunities will be a function of the extent to which they establish ties (Powell et al., 1996). In sum, we posit that customer portfolio breadth, reflecting the diversity and size of the portfolio, is important in explaining learning from customers. Broader customer portfolios will not only provide access to more knowledge and more diverse knowledge, but will also make learning from it more likely and reliable. We hypothesize:

Hypothesis 1a. *(H1a): The customer portfolio breadth of a young firm in an emerging industry will be positively related with the likelihood of the firm changing its business model.*

In addition to influencing the likelihood of business model change, we also expect the breadth of a young firm's customer portfolio to have an impact on the *degree* of business model change. Given the interrelatedness of a business model's items, a change will be more substantial when more items change at the same time (Gerasymenko et al., 2015). We propose that broader customer portfolios will lead to more substantial business model changes for two reasons.

First, the broader the customer portfolio, the more novel and abundant the knowledge that can be accessed through it is likely to be. Analogous to crowdsourcing, a broad set of customer ties essentially provides the firm "a distant search" (Afuah & Tucci, 2012; Piezunka & Dahlander, 2015), offering a wide-ranging array of insights related to a venture's products and services, market conditions, and customer needs. Whereas in established industries, having many and diverse customers could be seen as a signal that the firm's current business model is working and that the firm should use the feedback from its customers to fine-tune its business model with small changes, in an emerging industry, customer needs and industry structures have not yet coalesced. Information is widespread and fragmented, meaning that firms will need to establish many and diverse ties to get access to as much information as possible (Chatterji & Fabrizio, 2014; Vasudeva et al., 2014). Simultaneous access to such variety is likely to have implications for multiple items of the business model, requiring interrelated changes, and is thus more likely to result in business model changes that entail more items changing at the same time. The example of the school medical records company described earlier is a clear example of a case in which a firm's learning from its broad customer portfolio was important in helping the firm effectuate a substantial business model change.

Second, we expect that a broader customer portfolio increase a firm's motivation and confidence to engage in more substantial business model changes. Though less constrained than older firms by past activities, routines, and structures (Kirtley & O'Mahony, 2020), young firms nevertheless are likely to exhibit some reluctance to make substantial changes, especially in an emerging industry context where it is difficult to predict the consequences of a business model change. Firms that more actively participate in learning behaviors are more likely to learn about and act upon new opportunities (Levinthal & March, 1993; Powell et al., 1996). Thus, the extent to which a firm attracts customers and builds a diverse customer portfolio reflects the extent to which the firm proactively engages in interorganizational learning. Firms with broader customer portfolios should thus also be more open to taking more substantial action based on the knowledge acquired from their customers. Further, a broader customer portfolio is likely to enhance the assimilation of knowledge acquired from any given customer, providing important context for interpretation and analysis. This is likely to boost a young firm's confidence in the business model changes it is contemplating, helping to overcome resistance to making more substantial business model changes. We hypothesize:

Hypothesis 1b. *(H1b): For young firms that change their business models in an emerging industry, the breadth of their customer portfolio will have a positive impact on their degree of business model change.*

2.4 | Moderating role of industry segment maturity on business model adaptation

Because emerging industries are highly uncertain and knowledge is difficult to come by, external sources of knowledge, such as customers, are critical (Piezunka & Dahlander, 2015; Powell et al., 1996). At the same time, business model adaptation, as a way of learning and aligning the firm's business model to the dynamic environment is more important and challenging in an emerging industry (Martins et al., 2015; Saebi et al., 2017; Teece, 2010). Similar to Uzunca (2018), we account for how different segments within an emerging industry can evolve at different rates. We limit the study to the introductory and growth stages of the industry life cycle (Agarwal, Sarkar, & Echambadi, 2002; Karniouchina, Carson, Short, & Ketchen, 2013). These two stages capture the emergent phase of an industry relevant in our context, and we examine how the maturity of an industry segment can have an impact on a young firm's business model adaptation as a result of learning from its customers.

We posit that the role of customers as learning sources and their impact on business model adaptation will be especially strong in less mature industry segments for two main reasons. First, fewer learning sources are available to firms in earlier stages: there are no dominant designs yet or established business models, firms cannot hire experienced industry executives as the industry itself is new, and industry structures and legislation are lacking. What little information is out there is often widespread with no actors possessing all the necessary information (Powell et al., 1996). Customers, as buyers of the venture's products and services, experience and understand needs for products, services, and innovations early on—before those needs are more widely known by suppliers in an industry. Therefore, learning from customers will not only be more important in early stages of industry emergence, but will likely also be the only way for a firm to know whether it is on the right track or not.

Second, less mature industries, and most notably those in the introductory stages, are characterized by higher levels of uncertainty (Agarwal et al., 2017; Karniouchina et al., 2013), which makes experimentation and adaptation to the environment a necessity for most organizations (Andries et al., 2013; Martins et al., 2015; Rajagopalan & Spreitzer, 1997). Because of this, we expect that firms will be more actively searching for external knowledge that they can learn from. In more mature industry segments, the value of customers as sources of learning may be less because other sources of learning (e.g., business model imitation) may be present, but the uncertainty in the industry itself will also have diminished, making change less necessary and likely. Consequently, we expect that, despite broad customer portfolios that can lead to diverse ideas to learn from, firms in more mature industry stages will be less likely to implement ideas arising from the customers in the form of a business model change. In other words, industry segment maturity will influence the organizational learning process by simultaneously increasing the number of available sources of external knowledge and decreasing the need to cope with uncertainty. As a result, we expect business model change driven by customers to be less likely in more mature industry stages than in earlier stages.

We also see the important influence of industry segment maturity on business model adaptation in our qualitative data. For example, a secure texting app company changed its business model from B2C to B2B in 2011. This change was made in response to customer demands: it became clear that the majority of the firm's customers were healthcare professionals in hospitals and clinics and not "consumers." The change was significantly influenced by the uncertainty in the early-growth stage industry segment at that time: monetization from B2C apps was insufficient (MobiHealthNews, 2013). We hypothesize:

Hypothesis 2a. *(H2a): Industry segment maturity will negatively moderate the relationship between the breadth of a young firm's customer portfolio and the firm's likelihood to change its business model; firms with broader customer portfolios will be more likely to engage in business model change if they operate in less mature industry segments.*

Similarly, we also expect a moderating effect of industry segment maturity on the relationship between the breadth of a firm's customer portfolio and the degree of business model change. At the earliest stages of industry emergence, when uncertainty is highest and knowledge is most fragmented, it is likely that the divergent customer feedback from a broad customer portfolio will lead young firms to make changes that are more substantial to their business models, changing more items at once. As an industry matures, however, information about successful business models will converge and be more widespread and accessible. Consequently, we expect that young ventures will be more likely to make incremental modifications to their business models.

Additionally, it is likely that having a broader customer portfolio in a more mature industry segment is—rather than being driven by exploration and search—more an indication of a young firm successfully executing on a business model, thus attracting and maintaining the broad portfolio of customers. Therefore, changes that firms with many, diverse customers will make to their business models in more mature industry settings will likely be minor changes, whereby the firm fine-tunes its existing business model rather than engaging in more substantial changes. The mHealth segment focused on home monitoring/tracking (of the elderly) targeted at family, was one of the earliest segments in the mHealth industry to reach more mature stages. Despite the presence of firms with broad customer portfolios, we see that more substantial business model changes were no longer undertaken once the industry segment moved beyond early growth. Industry segment maturity can thus be seen as a boundary condition that will impact the extent to which firms will change their business models based on learning from their customers. We hypothesize:

Hypothesis 2b. *(H2b): For young firms that change their business models, industry segment maturity will negatively moderate the relationship between the young firm's customer portfolio breadth and the firm's degree of business model change; firms with broader customer portfolios will make more substantial business model changes if they operate in less mature industry segments*.

3 | METHODS

3.1 | Sample and setting

The research setting for this study is the mHealth industry. mHealth refers to the use of mobile phones for health services and information and contains applications such as wireless secure communication between patients and doctors, home monitoring/tracking targeted at family, fitness and wellness applications, and applications replacing doctors (Denoo & Yli-Renko, 2019). Like other new, technology-based industries, the mHealth industry formed at the intersection of existing industries. mHealth provided a unique setting for our study, as it was emerging during the period 2005–2014 covered in our data collection. We were thus able to capture the evolution of young mHealth firms while the industry itself was unfolding. mHealth was already described as emerging in 2006 (Istepanian et al., 2006), but the first US Food and Drug Administration (FDA) regulation for mHealth was only issued in 2013 (MobiHealthNews, 2014). About a decade after the industry's emergence, it was still largely unclear how firms could capture value from their customers (Economist, 2016). As such, the mHealth industry is a prime example of an emerging industry, in which industry structures and regulation are lagging, customer demands are unclear, and product attributes are poorly defined (Agarwal et al., 2017). Because of the uncertainty in the industry, the high interdependence between value chain partners, and the complexity of products and services, mHealth is a setting in which business models are likely to evolve over time.

3.2 | Data collection and coding

We set out to identify the entire population of young mHealth firms active in the US, using 10 years as the cut-off age (following, e.g., Yli-Renko & Janakiraman, 2008). We used the annual MobiHealthNews reports from 2009 until 2013 as the basis for identifying our sample and complemented these reports with a list of mHealth companies compiled by Rock Health. MobiHealthNews is an organization that focuses on providing news and research on the US mHealth industry. Rock Health provides young mHealth firms with various forms of support, such as funding, access to partners, and office space.[2] Using industry reports to identify firms is appropriate for early-stage industries (Agarwal et al., 2017). We were able to identify an initial sample of 239 young mHealth ventures founded between 2005 and 2013. We removed 52 companies from the sample because not enough information was available on them, the firm turned out to be a subsidiary of an existing firm or older than 10 years. Our final sample consisted of 187 mHealth companies, corresponding with 961 firm-year observations. Most firms were US-based (about 95%) and the average age of a firm was 4.1 years at the end of the data collection period.

We used a wide range of secondary sources to compile the data for our study. These included press releases (downloaded from Factiva), company websites (using the WayBackMachine to access archived versions), the MobiHealthNews and Rock Health industry reports, LinkedIn, ZoomInfo, Crunchbase, Hoovers, US Patent and Trademark Office (PTO) database, and the US FDA database. For each year of each firm's existence (till acquisition, failure, IPO, or the end of the data collection period), two raters independently coded the variables used in the study. The press coverage on our sample firms averaged 470 pages retrieved from Factiva, with a median of 207 pages. If one of the two independent raters felt that insufficient information was available to reliably code a firm's information, the firm was dropped from the sample.

3.3 | Business model coding and measure validation

While business models have received a lot of attention in past years, much debate remains on what is (and what is not) part of a business model (Amit & Zott, 2021; Wirtz, Pistoia, Ullrich, & Göttel, 2016; Zott et al., 2011). How to reliably operationalize a firm's business model is thus an important question. We started from the Andries et al. (2013) adaptation of the comprehensive business model measurement scheme developed by Morris et al. (2005). We chose to use the Andries et al. (2013) scheme because—similar to us—they also investigated business model changes, albeit through qualitative case studies. Table 1's first column contains a list of the 26 items included in the Andries et al. (2013) scheme. Since databases do not typically contain information on firms' business models, we coded each firm's business model based on press releases, company websites (archived versions) and the MobiHealthNews and Rock Health reports. Agreement between the two raters was high: the average deviation (AD) index between the two raters for whether a firm had changed its business model in a given year was 0.23 and 0.27 for the number of items that a firm had changed. Both values are below the suggested thresholds of, respectively, 0.33 (for dichotomous variables) and 4.5 (corresponding to the number of possible categories *c*, divided by 5, as suggested by Burke & Dunlap, 2002).

In developing the original business model measurement scheme, Morris et al. (2005) sought to develop a standard framework for characterizing a business model and stated that "To be useful, such a framework must be reasonably simple, logical, measurable, comprehensive, and operationally meaningful…The challenge is to produce a framework that is applicable to firms in general but which serves the needs of the individual entrepreneur" (Morris et al., 2005, p. 729). They further stated that a business model should address key questions derived from commonalities among the various perspectives in the literature on business models, and identified these as the offering and its value proposition, the market, internal processes and competencies, and how the firm makes money (Morris et al., 2005). After identifying these four "key" elements, Morris et al. (2005) decided to add two more elements: competitive strategy and personal/investor factors. All six elements were included in the Andries et al. (2013) categorization scheme, and thus were captured in our data collection. We carefully considered whether to retain the two additional elements in our operationalization.

First, we decided not to include the competitive strategy element in our business model measurement, in order to maintain a clear distinction between "strategy" and the "business model." Morris et al. (2005) added the competitive strategy element to the four "key" elements in order to account for the need to translate core competencies and the value proposition into a sustainable marketplace position (Morris et al., 2005). However, others have since

TABLE 1 Business model measurement scheme: Andries et al. (2013) scheme, input for factor analysis (including measurement of items and exclusion reasons), and final model (items, standardized loadings, and significance)

Input model	Factor analysis			Final model	
Andries et al. (2013) scheme	**Input variable types for factor analysis**	**Items included in factor analysis**	**Reason for excluding from final model**	**Items, standardized loadings and significance**	
Offering (select one from each set)					
- Product/service	Binary variable	- Product–service		Product–service offering	0.18***,a
- Standardized/some customization/high customization	Ordinal variable	- Standardized–customized		Standardized–customized offering	0.21***
- Internal manufacturing or service delivery/outsourcing/licensing/reselling/value-added reselling	Set of dummy variables	- Internal manufacturing or service delivery		Internal manufacturing/service delivery	0.12**,a
		- Outsourcing		Outsourcing	0.04,a
		- Licensing		Licensing	0.17***
		- Reselling		Reselling	0.08**,a
		- Value-added reselling	Reference category for other dummies		
- Direct distribution/indirect distribution	Binary variable	- Direct–indirect		Direct–indirect distribution	0.31***
Market (select one from each set)					
- Type of customer (b-to-b/b-to-c)	Binary variable	- B-to-B/B-to-C		B-to-B/B-to-C market	0.97***
- Local/regional/international	Ordinal variable	- Local-regional-international		Local-regional-international market	0.31***,a
- Upstream supplier/downstream supplier/government/institutional/wholesaler/retailer/service provider/final consumer	Set of dummy variables	- Upstream supplier	Reference category for other dummies		
		- Downstream supplier		Downstream supplier as customers	0.12
		- Government		Government as customers	0.15***
		- Institutional		Institutional as customers	0.67***

TABLE 1 (Continued)

Input model	Factor analysis			Final model	
Andries et al. (2013) scheme	**Input variable types for factor analysis**	**Items included in factor analysis**	**Reason for excluding from final model**	**Items, standardized loadings and significance**	
		- Wholesaler	No variation in variable in sample		
		- Retailer	No variation in variable in sample		
		- Service provider		Service providers as customers	0.63***
		- Final consumer		Final consumers as customers	0.92***,a
- Broad market/niche market	Binary variable	- Broad–niche		Broad-niche market	0.27***,a
- Transactional/relational	Binary variable	- Transactional–relational		Transactional-relational customer relation	0.40***,a
Internal capabilities (select one or more)					
- Production/operating systems	Binary variables	- Production	Insignificant factor loading		
		- Operating systems		Operating system internal capability	0.12**
- Selling/marketing	Binary variables	- Selling		Selling internal capability	0.09*,a
		- Marketing	Insignificant factor loading		
- Information management/mining/packaging	Binary variables	- Information management		Information management internal capability	0.18***
		- Information mining		Information mining internal capability	0.23***
		- Information packaging		Information packaging internal capability	0.26***
	Binary variables	- Technology		Technology internal capability	0.19***

(Continues)

TABLE 1 (Continued)

Input model	Factor analysis			Final model	
Andries et al. (2013) scheme	**Input variable types for factor analysis**	**Items included in factor analysis**	**Reason for excluding from final model**	**Items, standardized loadings and significance**	
- Technology/R&D/ creative or innovative capability/intellectual		- R&D	Insignificant factor loading		
		- Creative/innovative capability		Creative/innovative internal capability	0.15***
		- Intellectual		Intellectual internal capability	0.13***
- Financial transactions/ arbitrage	Binary variables	- Financial transactions	Insignificant factor loading		
		- Arbitrage	Low standardized factor loading		
- Supply chain management	Binary variable	- Supply chain management		Supply chain management internal capability	0.31***
- Networking/resource leveraging	Binary variables	- Networking	Insignificant factor loading		
		- Resource leveraging	Low standardized factor loading		
Competitive strategy (select one or more)			Not part of "key" elements of BM		
- Image of operational excellence/consistency/ speed	Binary variables	- Image of operational excellence			
		- Image of operational consistency			
		- Image of operational speed			
- Product or service quality/selection/ features/availability	Binary variables	- Product or service quality			
		- Product or service selection			
		- Product or service features			
		- Product or service availability			

TABLE 1 (Continued)

Input model	Factor analysis			Final model	
Andries et al. (2013) scheme	**Input variable types for factor analysis**	**Items included in factor analysis**	**Reason for excluding from final model**	**Items, standardized loadings and significance**	
- Innovation leadership	Binary variable	- Innovation leadership			
- Low cost/efficiency	Binary variables	- Low cost			
		- Efficiency			
- Intimate customer relationship/experience	Binary variables	- Intimate customer relationship			
		- Intimate customer experience			
Economic factors (select one from each set)					
- Fixed/flexible pricing and revenue sources	Binary variable	- Fixed-flexible pricing/ revenue sources		Fixed-flexible pricing and revenue sources	0.36***[,a]
- High/medium/low operating leverage	Ordinal variable	- Low-medium-high operating leverage		Low-medium-high operating leverage	0.11**[,a]
- High/medium/low volumes	Ordinal variable	- Low-medium-high volumes		Low-medium-high volumes	0.27***[,a]
- High/medium/low margins	Ordinal variable	- Low-medium-high margins		Low-medium-high margins	0.51***
Personal/investor factors (select one)			Not part of "key" elements of BM		
- Subsistence/income/ growth/speculative	Binary variables	- Subsistence model			
		- Income model			
		- Growth model			
		- Speculative model			
Total # items: 26	*Total # items: 56*			*Total # items: 29*	

Abbreviation: BM, business model. Standardized generalized least squares parameter estimates.

*$p \leq .10$.

**$p \leq .05$.

***$p \leq .01$.

[a]Reverse-coded items.

argued that product-market strategies, which, although related to the business model, should be viewed as distinctly different because they focus mostly on the "positioning of the firm vis-à-vis its rivals, whereas the business model is a structural construct that centers on the pattern of the firm's economic exchanges in its addressable factor and product markets" (Zott & Amit, 2008, p. 4).

Second, we considered the personal/investor factors, which Morris et al. (2005) added to improve the generalizability of their framework. They argued that a usable framework should apply to all types of ventures and therefore reflect design considerations necessary to accommodate differing levels of growth orientation, time horizons, resource strategies, and exit vehicles. However, our sample is quite homogeneous; for example, over 90% of firm-year observations indicated a growth-oriented ambition, so we chose to leave out the personal/investor factor. Our business model measurement scheme thus focuses on the original four key business model elements: offering, market, internal capabilities, and economic factors.

To empirically validate our business model measure, we relied on Confirmatory Factor Analysis (CFA) using AMOS 24. Given the nature of the items included in Andries et al. (2013)'s scheme—most items are not scales—we had to transform them into variables that could be included in a factor analysis. For categorical items, we created binary variables representing 1/0 for each response option (see Table 1). Similar to when using dummy variables in regression analyses, we always excluded one dummy from our CFA to avoid multicollinearity. Other variables already resembled a scale (e.g., margins: high-medium-low, in the economic factors element); we included one item per variable capturing the ordinal nature of these variables. Table 1 (left and middle sections) provides a full list of the 26 Andries et al. (2013) items and how they were transformed into the 56 items that were the basis for our CFA analysis. We excluded those few items that were never present in our sample and thus had no variation. Table 1 lists the full set of items included in our factor analysis and indicates which items were left out and why.

We then validated our business model operationalization in two steps. First, we empirically validated that our theoretical choice to use the narrower business model view was justified by comparing it with a model that included the two additional factors. The narrower business model scheme had a better fit than the broader business model scheme (see Online Appendix A for more details), thereby justifying our choice for the narrower business model operationalization. In a second step, we loaded the items corresponding to the four remaining elements onto one latent business model construct, and assessed the fit thereof. We again refer to Online Appendix A for more details on this, as well as on how we further simplified our model. In the end, we had a 29-item model capturing the offering, market, internal capabilities, and economic factors, with most items significantly loading onto the latent business model construct and with good fit: $\chi^2/_{df}$ = 5.54, RMSEA = 0.06, GFI = 0.89, and SRMR = 0.08 (Hu & Bentler, 1999). The model's composite reliability and Cronbach Alpha of 0.74 and 0.73, respectively, support its construct validity. Table 1 summarizes the factor loadings of each item onto the latent business model construct.

3.4 | Measurement: Dependent variables

3.4.1 | Likelihood of business model change

This variable is a firm-level variable that indicates whether or not the firm made a change to its business model in a given year *t* compared to its business model in the previous year. Similar to other studies (e.g., Saebi et al., 2017), we measured business model change by looking at whether any of the individual business model items had changed. Specifically, we coded firms' business models for each year during our period of analysis using our validated, 29-item business model categorization scheme described above and summarized in Table 1. If a firm changed any of the 29 business model items compared to the previous year, we coded this as a business model change. 35% of our firms changed their business models at least once within the period of study, similar to the 34% of video game producers that changed their business models in a study by Rietveld, van Dreunen, and Baden-Fuller (2015).

3.4.2 | Degree of business model change

The degree of business model change measures how many business model items (of the 29 in our scheme) changed at the same time compared to the year before. This reflects the view that business model changes that entail more items are more substantial (Demil & Lecocq, 2010; Gerasymenko et al., 2015). The maximum number of business model items that a firm changed at the same time in our sample was 8.

3.5 | Measurement: Independent variables

3.5.1 | Customer portfolio breadth

This variable measures the size of a firm's customer portfolio in year *t*, weighted by the difference in SIC codes between the focal venture and each of its customers. The values for this variable thus reflect both the scale and scope of the customer portfolio. A similar weighted approach has been used by Bruneel et al. (2010) in the context of young firm internationalization, and Gruber et al. (2013) have used SIC code differences to examine relatedness of young firms' market opportunities. Since young firms and their interorganizational relationships are typically under-represented in databases (Schilling, 2009), we relied on press releases, industry reports, and firm websites to obtain our customer portfolio data. Following Yli-Renko and Janakiraman (2008) and Coviello and Joseph (2012), we considered the next channel members in the value chain, that is, the parties to which the firm sells to generate revenues, as customers. Customers may thus be end users, licensees, or distributors, as long as there appeared to be a revenue relation with the firm. We used Hoovers to identify each customer's SIC code. Drawing on Gruber et al. (2013), we then coded the difference in SIC code between the focal venture and each of its customers: a score of 1 was assigned to customers whose 4-digit SIC code completely overlapped with the focal venture's SIC code, indicating that the activities of the focal venture and its customer were highly related. A score of 2 was given when a customer and focal venture shared the same 3-digit SIC code, a score of 3 when the 2-digit SIC code was the same, and a score of 4 when only the 1-digit SIC code was the same. Finally, a score of 5 was assigned to customers whose 4-digit SIC code was completely different from the focal venture's. We then summed all the values for a firm's customers. A firm's customer portfolio breadth in a given year *t* thus reflects a firm's cumulative number of actual customers, weighted by their difference from the focal venture in SIC code, and captures both the size and the diversity of the firm's customer portfolio.

3.5.2 | Industry segment maturity in year t

Based on the firms' activities, we classified them as belonging to one of nine mHealth industry segments, such as home monitoring/tracking targeted at family, fitness/wellness apps, and monitoring of specific illnesses (see Table OA.2 in Online Appendix B for an overview of all nine industry segments). Two independent researchers separately classified the industry segments based on industry reports and their knowledge of the industry. They both ended up with nine segments and the consensus for the type and classification of segments was high. After the determination of the nine segments, each researcher individually classified each firm into a segment: the high kappa index (κ = 0.83) provides support for the reliable coding of firms into segments. For each industry segment, we then capture its maturity by using the log of the number of firms active per industry segment in a given year *t*. The number of firms active per segment is an important determinant of industry maturity, as the number of firms is typically low in introductory industry stages, but tends to go up in the growth stages of an industry (Gort & Klepper, 1982), which are the two stages of interest within our context of an emerging industry. The measure also aligns with past research, which has used the number of firms active in an industry or entering an industry to capture industry dynamics and the industry life cycle (e.g., Agarwal et al., 2002; Carroll & Hannan, 1989). To validate this measure, we also created an ordinal measure based on qualitative insights, which—in addition to the number of firms per segment—also took into account factors such as acquisition activity and technology maturity (see Online Appendix B for more details). The correlation between the validation measure and the number of firms was 0.57 ($p < .0001$).

3.6 | Measurement: Control variables

We control for the *number of products on the market*, for which information was obtained from company websites and press releases announcing new products/services or withdrawals thereof (e.g., Li, Maggitti, Smith, Tesluk, & Katila, 2013). The variable measures a firm's total number of products on the market in year *t* and reflects both the firm's stage of development and its potential to receive customer feedback on its products. Having more products may thus make business model change more likely and more substantial. *Number of FDA approvals* measures the cumulative number of FDA approvals that a firm held in year *t* and was collected from the US FDA's website. FDA approval demonstrates a shift from R&D to commercialization (Katila, Thatchenkery, Christensen, & Zenios, 2017) and may thus make business model change more likely. We also control for the (cumulative) *number of issued patents* that a firm held in year *t* to control for the potential enabling impact that technological innovation may have on a firm's business model, thereby making change more likely (Calia, Guerrini, & Moura, 2007). Data for this variable was obtained from the US PTO website. We also include the cumulative *number of product awards* that firms received for their products/services as a control variable. Product awards can serve as social cues that assist decision making under uncertainty (Polidoro, 2013), and can contribute to firm legitimacy. As such, we expect that product awards may make business model change more likely and more substantial. Data for this variable came from press releases. We further control for *VC backing*. Previous research has shown that it can be difficult to convince venture capital (VC) investors that a business model change is necessary, as the VC may question whether the initial business model was wrong or may blame the need for a business model change on the venture's poor execution (Andries et al., 2013). At the same time, VCs may assist with business model changes (Gerasymenko et al., 2015). To account for this potential—positive or negative—impact of VCs on the likelihood of business model change, we include a dummy variable that indicates whether a firm was VC-backed in year *t* or not. We relied on press releases and Crunchbase (e.g., Piezunka & Dahlander, 2015) to obtain data for this variable. We further control for *start-up, market, and technology experience* to account for the potential impact of founders' prior experience on the firm's propensity to change (Bruneel et al., 2010; Furr, 2019). We included three variables that capture the proportion of founders who had previous experience in start-ups, the market (i.e., experience in healthcare), and technology (i.e., in IT). All three variables range from 0 to 1, with higher values indicating that more founders had experience in the relevant domain. Similar to past research on change and the identification of market opportunities, we expect start-up experience to have a positive impact, and market and technology experience to have a negative impact on both likelihood and degree of change (Furr, 2019; Gruber, MacMillan, & Thompson, 2012). The data for this variable came from company websites, LinkedIn, and ZoomInfo. We further control for *management team size*, measured as a firm's number of management team members in year *t*. We expect larger teams to be more likely to engage in change because of the greater diversity in knowledge that the firm can act on (Haleblian & Finkelstein, 1993). We further include *firm age* as a control variable because rigidities that develop over time can make it more difficult for firms to undertake change (Soh, 2003). *Number of past business model changes* indicates how many times a firm has changed its business model in the past. It acts as a strong firm-level control that captures firm-specific tendencies to engage in business model adaptation. Given the complexities related to changing a firm's business model, we expect a negative impact on both our dependent variables. We further also control for *alliance portfolio diversity*. This variable measures the diversity of the firm's alliance portfolio, including R&D, outside investor, manufacturing, supply, and marketing ties. This control captures the potential diversity and breadth of knowledge brought forth by these alliance partners; we expect that it will have a positive impact on likelihood and degree of business model change. Alliance portfolio diversity is calculated with a modified Herfindahl index (Hall, 2002; Phelps, 2010): Alliance portfolio diversity$_{it}$ = $\left[1-\Sigma_{j=1}^{J}\left(\frac{N_{jit}}{N_{it}}\right)^2\right]*\frac{N_{it}}{N_{it}-1}$, where N_{it} is the cumulative number of alliances a firm has established and N_{jit} is the total number of alliances of type j that a firm i has. This variable can range from 0 to 1, with 1 reflecting maximum diversity. As the index cannot be calculated if there are less than 2 observations, we set the portfolio diversity of firms with fewer than 2 ties during year t equal to 0. We relied on press releases, company websites, and industry reports to obtain alliance data (Schilling, 2009). We also included *year dummies* to control for potential period effects, such as differences in macroeconomic conditions or industry events that may have had an impact on our sample firms' likelihood of engaging in business model change (e.g., Phelps, 2010), and used standard errors clustered on *industry segment* in most of our analyses.

3.7 | Model specification and estimation

We are interested in analyzing the effect of customer portfolio breadth and industry segment maturity on both the likelihood of engaging in business model change and the degree to which a firm's business model changes. We use the full sample of 187 firms in our panel data probit model with random effects analysis of the likelihood of business model change, and a sample of the 66 firms that changed their business models at least once in our analyses of the degree of business model change, which we analyzed with a random effects panel data negative binomial regression model. We chose to use a random effects rather than a fixed effects model for two reasons. First, our model has a few variables that exhibit relatively little change over time, such as founding team experience and whether the firm is VC-backed. Including these variables in a fixed effects model could lead to incorrect estimates of their coefficients (Clark & Linzer, 2015; Schilling, 2015). Using a random effects model alleviates this problem. Second, when predicting a firm's future business model change behavior, we controlled for the total number of past business model changes. This variable is a strong firm-level control that should capture much of the potential firm-specific time-invariant effects on the likelihood and degree of business model change, thus warranting our choice for a random effects model (Schilling, 2015). To reduce potential reverse causality and confounding effects of the independent and control variables on the dependent variables, we lagged all explanatory variables such that business model change in year t + 1 was predicted by the independent and control variables in year t.

4 | RESULTS

Table 2 displays the variables' descriptive statistics and correlations for the full sample used in the analysis of the likelihood of business model change (panel A) and for the subset of firms that changed their business models at least once that were included in the analysis of degree of change (panel B). Variance Inflation Factors (VIF) are well below the recommended cutoff value of 10 (Ryan, 1997). As such, we do not expect multicollinearity to be a problem in our study.

4.1 | Likelihood of business model change analyses

Table 3 shows the results of the panel data probit model used to test H1a and H2a. H1a predicts that a firm's customer portfolio breadth will have a positive impact on the venture's likelihood of undertaking a business model change. The low p value (p = .03) and the positive coefficient (β = 0.21) associated with this variable in Model 2 indicate support for this hypothesis. To better understand the net effect of a firm's customer portfolio breadth on its likelihood of business model change in this nonlinear model, we also look at its average marginal effect, or the changes in probability of the predicted outcome due to a one-unit change in the independent variable

TABLE 2 Descriptive statistics and correlations

Panel A: First-step descriptive statistics and correlations

	Mean	*SD*	Min	Max	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.
1. Business model change in year t + 1	0.09	0.29	0.00	1.00	1.00														
2. Products on market (log)	0.76	0.61	0.00	3.71	−0.02	1.00													
3. FDA, cumulative (log)	0.05	0.20	0.00	1.39	0.19**	0.05	1.00												
4. Patents, cumulative (log)	0.12	0.43	0.00	3.14	−0.01	0.08	0.20**	1.00											
5. Product awards, cumulative (log)	0.21	0.43	0.00	2.40	0.06	0.13	0.25**	0.16*	1.00										
6. VC-backing (dummy)	0.36	0.48	0.00	1.00	0.08	−0.01	−0.12	−0.06	0.18*	1.00									
7. Start-up experience	0.45	0.42	0.00	1.00	0.03	−0.07	−0.02	0.06	−0.01	0.15*	1.00								
8. Market experience	0.45	0.44	0.00	1.00	0.04	−0.10	0.04	0.13	−0.08	−0.07	0.10	1.00							
9. Technology experience	0.53	0.44	0.00	1.00	−0.01	0.04	0.01	0.13	0.06	0.08	0.14*	−0.09	1.00						
10. Management team size (log)	1.30	0.36	0.69	2.83	0.09	0.08	0.12	0.19**	0.23**	0.26**	0.06	0.12	−0.08	1.00					
11. Firm age	2.49	2.08	0.00	8.00	−0.04	0.21**	0.29**	0.40**	0.26**	−0.05	−0.10	0.03	−0.16*	0.17*	1.00				
12. Number of past business model changes	0.19	0.47	0.00	2.00	0.15*	0.24**	0.10	0.15*	0.25**	0.04	0.05	−0.04	−0.08	0.19**	0.23**	1.00			
13. Alliance portfolio diversity	0.15	0.30	0.00	1.00	−0.01	0.06	0.01	0.03	0.20**	0.02	−0.01	0.01	0.07	0.10	−0.00	0.21**	1.00		
14. Industry segment maturity	2.83	0.55	0.69	3.61	−0.00	0.09	0.00	−0.15*	−0.03	0.02	−0.04	−0.04	−0.12	0.03	0.01	−0.12	−0.01	1.00	
15. Customer portfolio breadth	5.50	11.91	0.00	112.00	0.16*	0.25**	0.18*	0.38**	0.22**	−0.06	0.07	0.08	−0.03	0.23**	0.33**	0.36**	0.09	−0.03	1.00

TABLE 2 (Continued)

Panel B: Second-step descriptive statistics and correlations

	Mean	Std. Dev.	Min	Max	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. Degree of business model change in year $t + 1$	0.50	1.17	0.00	8.00	1.00											
2. Inverse Mills ratio	1.43	0.93	0.00	3.97	0.26*	1.00										
3. Products on market (log)	0.80	0.58	0.00	2.77	−0.29*	−0.24	1.00									
4. Product awards, cumulative (log)	0.30	0.54	0.00	2.40	−0.12	−0.63**	0.21	1.00								
5. Start-up experience	0.49	0.42	0.00	1.00	−0.00	−0.30*	0.04	0.20	1.00							
6. Market experience	0.43	0.44	0.00	1.00	0.02	−0.04	0.11	−0.06	0.19	1.00						
7. Technology experience	0.54	0.43	0.00	1.00	−0.02	0.01	0.06	0.05	0.21	−0.14	1.00					
8. Firm age	2.63	2.08	0.00	8.00	−0.31*	−0.50**	0.26*	0.29*	0.02	0.12	−0.10	1.00				
9. Number of past business model changes	0.50	0.64	0.00	2.00	−0.48**	−0.32**	0.37**	0.24*	0.08	0.03	−0.23	0.37**	1.00			
10. Alliance portfolio diversity	0.20	0.34	0.00	1.00	−0.19	−0.10	0.04	0.02	−0.04	0.04	−0.07	−0.10	0.09	1.00		
11. Industry segment maturity	2.72	0.57	0.69	3.61	−0.02	0.52**	−0.06	−0.14	−0.11	−0.16	−0.22	−0.11	0.02	−0.06	1.00	
12. Customer portfolio breadth	8.68	16.12	0.00	112.00	−0.10	−0.66**	0.23	0.30*	0.10	0.22	−0.10	0.38**	0.24	0.05	−0.16	1.00

Note: Panel A: *n*(companies) = 187, *n*(observations) = 961. Panel B: *n*(companies) = 66, *n*(observations) = 365. Descriptive statistics are based on panel data; correlations are shown for the last available $t - t + 1$ year combination per firm (panel data correlations or other year correlations are available from the authors upon request).

*$p \leq .05$.

**$p \leq .01$.

TABLE 3 Panel data probit model; DV = business model change in year *t* (1/0)

	Model 1		Model 2		Model 3	
	Controls model		Main effects model		Full model	
	Coeff.	*SE*	Coeff.	*SE*	Coeff.	*SE*
Products on market (log)	−0.02	0.13	−0.07	0.11	−0.07	0.11
FDA, cumulative (log)	0.73**	0.36	0.71*	0.38	0.72**	0.36
Patents, cumulative (log)	−0.00	0.25	−0.11	0.22	−0.24	0.24
Product awards, cumulative (log)	0.31	0.19	0.30	0.20	0.31*	0.18
VC-backing (dummy)	0.28	0.28	0.33	0.29	0.32	0.25
Start-up experience	0.14	0.12	0.12	0.12	0.12	0.12
Market experience	−0.17	0.31	−0.18	0.31	−0.19	0.30
Technology experience	−0.14	0.12	−0.13	0.15	−0.12	0.15
Management team size (log)	0.16	0.18	0.11	0.16	0.09	0.17
Firm age	0.00	0.07	−0.01	0.08	−0.02	0.07
Number of past business model changes	−0.21	0.41	−0.34	0.46	−0.26	0.37
Alliance portfolio diversity	0.24	0.25	0.22	0.26	0.18	0.27
Industry segment maturity			0.02	0.09	−0.01	0.09
Customer portfolio breadth			0.21**	0.10	0.19***	0.06
Customer portfolio breadth × industry segment maturity					−0.26***	0.07
Year dummies	Included***		Included***		Included***	
Constant	−2.28***	0.46	−2.15***	0.50	−2.03***	0.42
Log likelihood	−281.87		−279.60		−276.33	
AIC	603.74		603.21		598.65	

Note: n(companies) = 187, *n*(observations) = 961; DV was measured in year $t + 1$, independent and control variables in year *t*. Two-tailed significance tests reported. All standard errors are robust standard errors clustered on industry segment. AIC, Akaike information criterion. Models with lower values of AIC are preferred. Significance of year dummies is based on the most significant year dummy.
*$p \leq .10$.
**$p \leq .05$.
***$p \leq .01$.

(Hoetker, 2007; Norton, Wang, & Ai, 2004). The average marginal effect of customer portfolio breadth is significant and positive (β = 0.03, p = .07), indicating that a one-unit increase in (standardized) customer portfolio breadth will increase the likelihood of undertaking a business model change by about 3 percentage points. Given that about 8% of our sample's firm-year observations have a business model change, this is substantial. We thus find support for H1a.

The third model includes the interaction effect between customer portfolio breadth and industry segment maturity. The significant, negative coefficient (β = −0.26, p < .01) indicates support for H2a. The interaction effect's marginal effects are also significant and negative. We graphed this interaction effect (based on a logit model; our results are similar when using this model specification) keeping all other variables constant at their mean in Figure 1a. The figure shows that the breadth of a firm's customer portfolio has a positive impact on the venture's likelihood of business model change for firms active in industry segments with a low maturity, but that this effect becomes (slightly) negative for firms in more mature industry segments. Specifically, an increase in the firm's customer portfolio breadth from 2 to 3 brings about an 18 percentage point higher likelihood of engaging in business model change, compared to a decrease of 0.5 percentage points for firms in mature segments. Our results thus provide support for H2a.

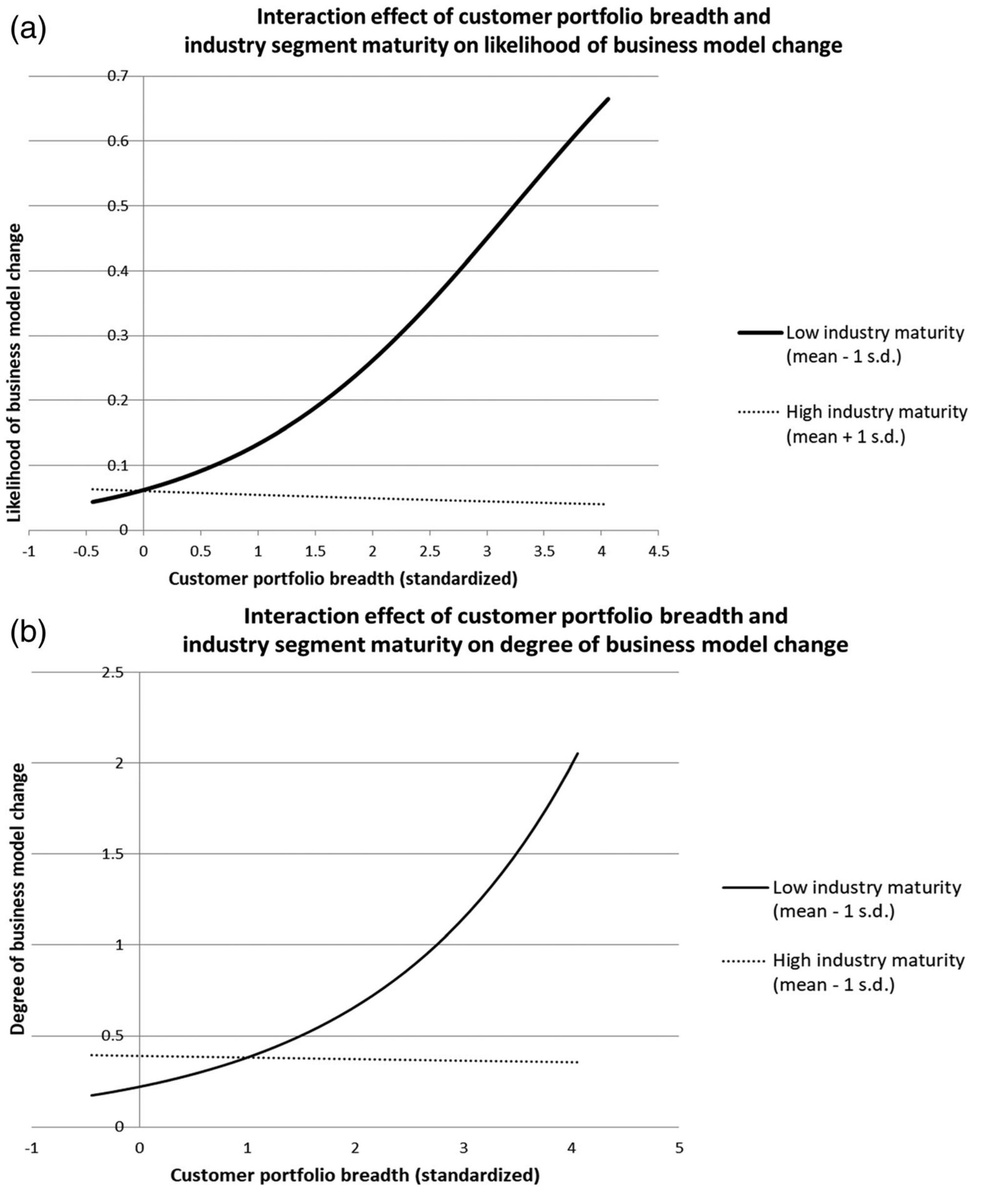

FIGURE 1 Interaction effect between customer portfolio breadth and industry segment maturity on (a) likelihood and (b) degree of business model change

4.2 | Degree of business model change analyses

To test our degree of business model change Hypotheses 1b and 2b, we only used the subset of firms that have changed their business models at least once. It is possible that firms that changed their business models at least once are different from firms that never changed their business models, and that the factors explaining whether a firm changed its business model also influence the degree by which a firm changes its business model. To alleviate this potential issue, we first ran a Heckman selection model, which was based on an additional probit regression model in which the dependent variable was whether the firm engaged in business model change at least once during the period of study or not. Based on this Heckman selection model (the results of which are available in Online Appendix C), we then calculated the inverse Mills ratio which we included in our second step, degree of business model change analysis (Heckman, 1979). We included the same variables in the Heckman selection model as in our first step analysis of the likelihood of engaging in business model change (except for the number of past business model changes, as this variable perfectly predicts the selection model's dependent variable of whether the firm's business model ever changed). The instrumental variables in the Heckman model, that is, the variables that were included to calculate the inverse Mills ratio and that were excluded from the subsequent analysis of the degree of business model change, are the firm's patent stock, its VC backing, management team size, FDA approvals and the year dummies. We chose these variables as instruments based on theoretical (they were all thought to affect a firm's likelihood of business model change; see Section 3.6 for more details on each variable's expected impact on the likelihood of business model change), and empirical reasons, as they all had stronger correlations with the likelihood of business model change than with the degree of business model change. In fact, of all these variables, only 1 year dummy had a significant ($p < .10$) correlation with the degree of business model change dependent variable.

Table 4 shows the results of our negative binomial panel data regression model of the degree of business model change (used to test H1b and H2b) which includes the inverse Mills ratio calculated based on the Heckman selection model. The second model shows the results for our hypothesized positive relationship between a firm's customer portfolio breadth and its degree of business model change (H1b). Its coefficient and marginal effect (both significant at $p < .05$) indicate that every 1-unit increase in customer portfolio breadth increases the number of business model items that change by 0.37, or, in other words, a 2.5-unit difference in (standardized) customer portfolio breadth brings about one additional changed item in the firm's business model, supporting H1b.[3] The full model in Table 4 shows a significant, negative coefficient for the interaction effect between customer portfolio breadth and industry segment maturity. Figure 1b (again setting the other variables to their mean values) provides further support for H2b by showing that the effect of customer portfolio breadth on the degree of business model change is indeed dependent on industry segment maturity. For firms in more mature segments, customer portfolio breadth has a negligible impact on the degree of change. For firms in less mature segments, however, the degree of business model change grows substantially as the firm's customer portfolio breadth increases: an increase in customer portfolio breadth from 3 to 4 increases the degree of business model change by about 0.8 items. Given the average degree of change of 2 for firm-year observations with a business model change, this effect is substantial and offers support for H2b.

4.3 | Robustness checks and post-hoc analyses

In our main analyses, we used the number of business model items that a firm had changed at the same time as the degree of business model change. We also tested our model using two alternative specifications of the degree of change. The first one is by counting the number of key elements (i.e., offering, marketing, internal capabilities, and economic factors) of the Andries et al. (2013) scale that changed at the same time. The other one is by counting the overall number of business model items from the full Andries et al. (2013) business model operationalization rather than our narrower construct. Our results are robust to both alternative specifications. Our results also hold when using linear regression (using the log of the number of items that were changed at the same time) and ordered logit specifications. While less significant, our results also remained consistent when analyzing the degree of change based on the full sample of firms (thus including the firms that did not change their business models and not using a two-step approach).

We also tested our results using an alternative measure for customer portfolio breadth, whereby—instead of using our measure based on SIC distance between focal firm and customers—we counted the number of different 4-digit SIC codes that firms have customers in. While somewhat less significant, our results remain the same. We further tested the robustness of our results when using the ordinal, qualitative-based measure for industry segment maturity (see Online Appendix B for more details) as this variable is less affected by potential confounding effects with industry segment size than our main industry segment maturity variable. Our results remained similar. Per Hoetker (2007)'s

TABLE 4 Panel data negative binomial regression; DV = degree of business model change in year *t*

	Model 1		Model 2		Model 3	
	Controls model		Main effects model		Full model	
	Coeff.	*SE*	Coeff.	*SE*	Coeff.	*SE*
Inverse Mills ratio	0.63***	0.15	0.60*	0.31	0.36	0.33
Products on market (log)	0.34	0.24	0.31	0.24	0.27	0.23
Product awards, cumulative (log)	0.72***	0.26	0.55*	0.29	0.53*	0.28
Start-up experience	0.60*	0.33	0.65*	0.34	0.51	0.34
Market experience	−0.49	0.31	−0.52	0.34	−0.41	0.33
Technology experience	−0.29	0.33	−0.24	0.34	−0.09	0.33
Firm age	0.17*	0.09	0.10	0.09	0.04	0.09
Number of past business model changes	−1.55***	0.34	−1.68***	0.34	−1.49***	0.34
Alliance portfolio diversity	0.57*	0.34	0.46	0.37	0.34	0.37
Industry segment maturity			0.14	0.25	0.27	0.27
Customer portfolio breadth			0.37**	0.16	0.21	0.17
Customer portfolio breadth × industry segment maturity					−0.27*	0.15
Constant	−2.14***	0.51	−1.88***	0.72	−1.52**	0.72
Wald χ^2	33.78***		37.85***		43.49***	
Log likelihood	−305.00		−301.42		−299.67	
AIC	634.01		630.83		629.33	

Note: n(companies) = 66, *n*(observations) = 365; DV was measured in year *t* + 1, independent and control variables in year *t*. Two-tailed significance tests reported. AIC, Akaike information criterion. Models with lower values of AIC are preferred.
*$p \le .10$.
**$p \le .05$.
***$p \le .01$.

suggestion, we also graphed our interaction effects at other values than the mean to assess their robustness. Online Appendix D shows these graphs (graphing each interaction for the mean ± one standard deviation).

Finally, to test for endogeneity in our main independent variable, customer portfolio breadth, we ran an analysis using number of FDA approvals, products on the market, and product awards as instrument variables—these three variables are likely to influence the number and diversity of customers a firm attracts, and thus its customer portfolio breadth. Durbin and Wu–Hausman endogeneity tests indicate that endogeneity is not present ($p > .05$; Durbin, 1954; Hausman, 1978; Wu, 1974). Even so, we ran a two-step instrumental variable procedure using these instruments: our results remained the same and endogeneity is not likely driving our results.

5 | DISCUSSION

5.1 | Contributions to business model research

In recent years, management research has seen the business model concept become established as a new unit of analysis that represents a company's value creation and capturing activities (Massa et al., 2017). Increasingly, scholars have understood the importance of looking at business models as dynamic concepts, whereby questions such as how, why, and when firms' business models change are central. In doing so, prior research has focused on incumbent firms reacting to changes in established industries as a result of external shocks, such as financial crises and changing regulation (Osiyevskyy & Dewald, 2015; Saebi et al., 2017), and on firm-internal factors, such as board member and CEO experience (Gerasymenko et al., 2015). Largely overlooked by existing research, however, is when and how young firms, active in uncertain settings such as emerging industries, change their business models. Given that a business model is a concept that is nested between the firm and the network level and that emphasizes value creation as both a supply- and demand-side phenomenon (Amit & Zott, 2021; Massa et al., 2017), a more interorganizational view of business model adaptation is warranted. While recent work has highlighted the role of learning from peers (McDonald & Eisenhardt, 2020), the role of customers in business model adaptation has been ignored. Our study is the first quantitative study to show that customers and industry context play critical roles in determining whether or not a young firm adapts its business model, and if it does, to what extent. Specifically, we argued that broad customer portfolios can provide young firms with access to a range of external knowledge and that industry segment maturity will influence the need for and processing of the information acquired from customers. We found support for our hypotheses that developing a large and diverse portfolio of customers earlier in the industry life cycle is more likely to lead to changes in the business model and that those changes are likely to be more substantial changes. Even though industry segment maturity did not have a direct impact on business model change in our study, its moderating impact on the role of customers is quite striking. This finding confirms the importance of examining the effects of stakeholders and environmental conditions jointly to uncover interactive effects on business model design.

Consistent with recent research that has argued that pivots are not fundamentally different in nature from incremental business model changes (Kirtley & O'Mahony, 2020), our results also suggest that business model changes have the same drivers (such as customer portfolio breadth) irrespective of the magnitude of the change, and that industry segment maturity will influence to what extent a business model change is more or less substantial. Broad customer portfolios in early industry stages tend to be associated with pivots, whereas broad customer portfolios in more mature stages tend to be associated with smaller changes, or "tweaks." In showing this, our study is one of the few papers in the entrepreneurial strategy literature that does not only focus on change in young firms, but also on the degree thereof (e.g., Furr, Cavarretta, & Garg, 2012).

Finally, as an important empirical contribution, we validated an existing business model measurement scheme in our paper. Validated business model schemes are rare (Saebi et al., 2017), which is perhaps why business model studies are primarily qualitative. We hope that our empirical validation of the Morris et al. (2005) and Andries et al. (2013) business model scheme will spur more quantitative research on business models, as—to the best of our knowledge—our paper is the first large-sample, quantitative study on business model adaptation in young firms, thereby responding to calls for more research on business model change, its antecedents, and boundary conditions (Bocken & Snihur, 2020; Shepherd & Gruber, 2020; Wirtz et al., 2016).

5.2 | Contributions to industry emergence research

Our unique, longitudinal dataset on the first decade of the emerging mHealth industry allowed us to track the birth of the industry on a granular level. This detailed tracking of the industry and its firms on a yearly basis allowed us to examine the important moderating impact of industry segment maturity. Despite the relatively short period of analysis of 10 years, industry segment maturity significantly moderates the relation between a firm's customer portfolio breadth and its business model adaptation. Our study's findings demonstrate the importance of focusing on narrower industry segments and using more fine-grained measures of industry segment maturity. The importance of industry segment maturity in our study further shows that—contrary to what was suggested in the context of some more technology-driven emerging industries, for example, in the agricultural biotechnology industry (Moeen, 2017; Moeen & Agarwal, 2017)—the point of commercialization in an emerging industry is not always clear-cut. In the mHealth industry, firms managed to attract customers in the earliest industry stages, but this did not necessarily imply a resolution of demand uncertainty, as the attraction of customers typically led to subsequent business model changes. The different segments in the emerging industry evolved at different rates, with some maturing more quickly than others. Our focus on a digital emerging industry, where customer involvement can come at a much earlier point than in highly regulated industries such as biotech, allowed us to show that customer involvement does not automatically imply a reduction in demand uncertainty in emerging industries, and that business models will still be prone to change as a result of learning. Our study thus contributes to a growing literature on the resolution of demand uncertainty and, relatedly, value appropriation in emerging industries (e.g., Agarwal et al., 2017; Hsu et al., 2019; Snihur, Zott, & Amit, 2020).

5.3 | Contributions to organizational learning and strategic entrepreneurship research

Entrepreneurship research has increasingly emphasized discovery-based approaches, such as effectuation, experimentation, and fast learning from customers, proposing that they play a critical role in the start-up process (e.g., McGrath, 2010; Sarasvathy, 2001). These approaches that suggest exploration and frequent business model changes focus on nascent firms, that is, firms still in the start-up process. Much less is known about how and why young firms, that is, firms that are already active in the market and have gathered some stakeholders (e.g., venture capitalists, customers) change their business models. Our study has shown that customers play a central role in explaining when—and to what extent—young firms change their business models. In doing so, our study's findings extend the importance of learning from customers (a central tenet of the popular lean start-up approach, e.g., Blank, 2013; Ries, 2011) beyond the nascent stage of venture evolution to business model adaptation in young firms. Our study also addresses calls for research that reintroduces customers as central constructs in the strategic entrepreneurship literature (Demil et al., 2015). Moreover, by demonstrating the importance of customers as drivers of business model adaptation in young firms in an emerging industry, our study complements past research that showed that firms could learn and borrow from peers in designing their business models (McDonald & Eisenhardt, 2020). We have provided unique quantitative evidence to this growing stream of literature on how young firms learn, which until now had largely consisted of conceptual or qualitative work (e.g., Andries et al., 2013; Sapienza, Autio, George, & Zahra, 2006).

5.4 | Practical implications

While our study did not focus on the performance outcomes of business model adaptation, recent studies suggest that business model changes are driven by opportunity and have a beneficial impact on firm performance (Kirtley & O'Mahony, 2020; Pillai, Goldfarb, & Kirsch, 2020). Thus, our results imply that young firms in an emerging industry should try to attract as many and as diverse customers as possible in early-stage industry segments. Not only will these customers generate revenue for the young ventures, but they will also impart the firm with useful external knowledge. This is vital in a setting in which customer demands and product requirements are unclear and value chains not yet established. In more mature industry segments, customer ties largely lose these learning effects and firms may be better off focusing their efforts on particular types of customers to realize efficiencies in sales and operations. Since business model changes are more likely to be undertaken by firms with many and diverse customers, business model adaptation should not be considered an indication of having a business model that does not work, but instead as a way to create a better fit with an evolving market. This is especially important in light of recent work that has highlighted the difficulties that young firms can have with keeping their stakeholders satisfied after having engaged in a strategic change (e.g., Hampel et al., 2020; McDonald & Gao, 2019). This may be less of a hurdle when implementing business model changes based on learning from customers. Moreover, stakeholders, such as investors, should realize that even young firms that have been active in the market for a few years and that have attracted resources may change their business models. In fact, firms that attracted many and diverse customers will be especially likely to do so. Stakeholders should thus support firms in this change. Together, these insights illustrate the complexity of issues involved in the management of a young firm and its business model, and suggest that when making decisions about establishing and fostering customer ties, entrepreneurs should consider the number and diversity of customer ties they have in the context of the maturity of the industry segment in which they are active.

5.5 | Limitations and future research directions

The results of this study should be considered in light of their limitations. First, even though we adopted a lagged formulation in our empirical model to reduce potential reverse causality, our results cannot prove the causality between customer portfolio breadth, industry segment maturity, and likelihood and degree of business model adaptation. We did undertake interviews with founders and executives of young mHealth firms, who provided anecdotal support for our key premise that customer ties serve as an important source of organizational learning and have an impact on the business model adaptation of a venture. Second, our study was conducted in the unique setting of the emerging mHealth industry, potentially limiting the generalizability of our findings. However, the evolution of the mHealth industry at the intersection of telecom, IT, and healthcare mirrors the development of many other new industries that have similarly emerged at the intersections of existing industries (e.g., the rideshare industry combines a digital platform with transportation). As such, we expect our findings of customers as drivers of business model adaptation to be applicable in other emerging, technology-based industry settings. Nevertheless, future studies could benefit from replicating our research in other industries. Future studies could also extend our research to later stages of the industry life cycle and examine how customers and other interorganizational ties might play a role in business model adaptation of young ventures active in mature or declining industry segments. Third, it is possible that we have missed some business model changes, despite taking great care in collecting and analyzing our data. Consistent with prior work (Rietveld et al., 2015), we found that 35% of young firms in our sample changed their business models during the 10-year study period. While this could perhaps be considered low in nascent start-ups, which often follow discovery-based approaches, this is not the case in our sample of young firms. Contrary to such nascent firms, our sample firms were active participants in the market—as evidenced by them being listed in industry reports, having websites, VC backing (more than 60% of our sample firms) and customers. Business model changes should thus be less prevalent, especially in light of recent research indicating that stakeholders may not appreciate business model changes in young firms (Hampel et al., 2020; McDonald & Gao, 2019). Future research could nevertheless attempt to collect business model (change) data directly from sample firms. Fourth, we used the cumulative number of customers as the basis of our customer portfolio breadth measure as we did not have data on customer contract dissolutions. This choice was justified, as customer relationships tend to be multi-year, and their learning effects are likely to persist long-term, even if a customer is no longer active. Our data collection, relying on secondary sources, may also have missed some customer relationships. Future research could collect more fine-grained primary data on firms' customers. Finally, future research could improve our understanding of the performance implications of business model adaptation, and investigate whether the effectiveness of business model adaptation depends on the triggers of the adaptation (e.g., learning from customers versus as a result of external shocks).

6 | CONCLUSION

In conclusion, this study sought to shed new light on the antecedents of business model adaptation and to provide novel insights into how young firms learn and evolve in emerging industries. Our findings highlight the importance of interorganizational and industry segment contextual influences in studying business model adaptation and contribute to a more fine-grained understanding of the emergence and growth of an industry and the young firms active in it.

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ENDNOTES

[1] We will use the term business model *adaptation* to refer to the overall firm behavior of adapting the firm's business model, that is, making changes to it, and the term business model *change* to refer to a specific instance of a change to the firm's business model.

[2] Firms identified through Rock Health did not necessarily receive (financial) support from Rock Health. These firms also did not significantly differ from firms identified from the MobiHealthNews reports in terms of customer portfolio breadth or business model change.

[3] While the coefficient of customer portfolio breadth is no longer significant in the full model (Model 3), its coefficient and marginal effect are significant in Model 2. Moreover, the coefficient of customer portfolio breadth was significant ($p < .10$) in the full model in at least one of the robustness checks. We therefore accept H1b.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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