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Abstract

The shift in enterprise applications to disruptive mobile platforms calls for research to better understand the mechanisms and factors behind success in these new platforms. In this paper, we empirically study the learning dynamics of sales officers and factors associated with business value, measured as account-opening efficiency in a tablet-based banking application at a large private bank in an emerging market. Our model allows us to study individual learning patterns, and our results show that although high performers in the traditional systems continue to maintain their edge in the new mobile platform, the gap between high and low performers is reduced significantly over time. Our results also reveal that customers' awareness of the tablet banking service, their digital literacy, and external environmental factors such as mobile infrastructure and market maturity can affect sales officers' account-opening performance in the tablet-based system.

Keywords: learning under disruption; learning curve; productivity; tablet banking; business value of IT

1. Introduction

Given emerging trends in technology such as ubiquitous connectivity, cloud computing, and the proliferation and adoption of mobile devices, there has been a significant shift in the delivery and interface of enterprise systems that connect firms with organizational stakeholders. The primary device for engagement with these systems has evolved from traditional desktop computers to a variety of mobile devices such as smartphones and tablets. For instance, as part of the IBM MobileFirst for iOS initiative, IBM has created over 100 iOS apps serving 65 professions across 14 industries.[1] More recently, SAP announced a partnership with Apple to revolutionize the mobile work experience of enterprise customers by bringing SAP's deep expertise in business software onto Apple's mobile devices.[2] This shift to mobility is apparent in business processes such as marketing, customer service, sales, field service, finance, procurement, supply chain, and human capital.[3] However, this shift is deeper than mere devices. The embedded digital capabilities in these devices fundamentally alter the backend processes and the nature of engagement with the users of these applications. For instance, when engaging with customers, the activities in the process are shifting from simply recording transactions in texts and numbers on a desktop interface

[1] "Apple and IBM partnership yields 100 iOS enterprise apps" CIO.com, Dec. 18, 2005.
[2] "Apple & SAP Partner to Revolutionize Work on iPhone & iPad", apple.com/pr, May 5, 2016.
[3] In a 2015 survey of 300 North American firms, Frost & Sullivan found wide deployment of mobile apps for enterprise functions: mobile supply chain management (56%), mobile sales force automation (56%), mobile workforce management (49%), and mobile asset tracking (56%). For details, please see http://www.frost.com/sublib/display-report.do?id=9ABE-00-25-00-00.

(Rivers and Dart 1999) to a richer co-creative engagement context that captures information in pictures, digital documents, and videos.

The growth of tablet and smartphone-based applications and their rapid adoption by consumers certainly validates the value of these mobile engagements to customers and their promise to firms (Xu et al. 2016). However, transitioning to these mobile devices has not always been successful from the firm's perspective. For instance, in early 2016, HSBC's mobile banking platform stopped functioning, and customers were locked out of their accounts and unable to complete any transactions. In August 2015, the same organization failed to process 275,000 online payments (Finders 2016). These disruptions have resulted in disgruntled customers taking to social media to express their frustration. The challenges that firms face in delivering a seamless experience for their customers and other stakeholders through these mobile devices are multifold. First, employees of the organization need to adapt to new engagement models and often paperless processes. Second, the quality of the user experience in these systems depends in part on the technology and wireless infrastructure, factors that are often not under a firm's control. Finally, in the case of applications that engage external customers, the readiness and awareness of customers significantly determines the eventual success of these systems. This complex ecosystem of factors requires a deeper understanding of the underlying determinants of success in both adoption and the eventual business value from the transition of enterprise applications to mobile devices.

Prior research provides some general guidance regarding the underlying mechanisms behind technology adoption and the business value of new IT applications. Several papers in the literature on traditional technology acceptance have provided evidence showing that the successful adoption of a technology depends on its acceptance and usage broadly within the organization (Venkatesh et al. 2003, 2000, 2008). In a research stream examining the business value of IT at the application level, researchers link the usage of specific applications to changes in respective business process metrics, such as cost, quality, and cycle time (Barua et al. 1995; Melville et al. 2004; Mukhopadhyay et al. 1995). However, most studies in this research stream assume the effective usage of these applications. As we have noted, the shift in enterprise applications to mobile devices such as tablets presents new challenges that are not specifically addressed in prior literature.

The novelty of the interface and an altered back-end process in these applications require users to learn both the technology and the context of engagement with these devices. Thus, a better understanding of people's learning patterns in these applications can help ensure the successful deployment of these applications. Furthermore, applications delivered on mobile devices depend on technology infrastructure, which is not under the control of the organization (e.g., mobile network, Internet, and electricity). The quality of these mobile networks can vary significantly and influence the effectiveness of these applications. In addition, the success of applications that engage external customers may depend on customer-related factors such as their general awareness and proficiency with these devices as well as their overall digital literacy. In emerging markets, the uncertainty pertaining to some of these factors is especially higher resulting in increased complexity in the interplay between them. With "mobile-first" becoming a dominant paradigm, there is a need to improve our understanding of how human resource readiness, learning dynamics, customer readiness and extra-organizational factors are all associated with the usage and eventual business value from enterprise applications delivered on mobile platforms.

We attempt to fill this research gap by empirically investigating the business value impact of this shift from the conventional model of opening new accounts in traditional branch locations to a mobile tablet-enabled process that allows customers to open new accounts in their preferred location (e.g., home, the workplace). Furthermore, we have chosen the emerging market of India as our study context.

The process of offering banking services on mobile tablet devices is also referred to as the disruptive Tab Banking initiative. This process is considered disruptive because it overcomes challenges related to crowding and congestion in branch locations, fixed timing of branch offices, and the waiting and turnaround time for document verification. The engagement process with customers is transformed to a time and location of the customer's choosing, and all documents and artifacts are fully digitized. In addition, the tablet allows salespeople to access additional information on the various products offered by the bank. As a result, the tablet becomes an active engagement platform for the customer and the sales officer to co-create the account-opening process more effectively. We worked with a large bank in India to study the performance of the account-opening process before and after the deployment of a Tab Banking initiative. Our unique data set allows us to empirically study the impact of tablet banking technologies on the efficiency of account opening and to better understand the learning dynamics of the sales officers in this new context.

Specifically, we attempt to answer the following research questions: (1) Does the tablet-enabled process significantly alter the efficiency of the account-opening process, measured as total turnaround time? (2) Is there a learning effect in process performance when firms migrate to a disruptive mobile platform? (3) How do these learning effects differ across individual characteristics of employees, such as their prior experience, their performance in the traditional system, and the recency of their experience with the traditional system? We also investigate the effect of customer factors, such as customer awareness and digital literacy, as well as mobile infrastructure factors to control for the differences across various customer locations.

To address these research questions, we propose a hierarchical Bayesian model to simultaneously capture (1) how sales officer-related factors, customer-related factors and extra-organizational factors affect sales officers' account-opening performance after the adoption of the tablet banking technology and (2) sales officers' learning dynamics in the new tablet banking process. Our model allows the sales officers' starting-point performance levels and learning rates in the tablet-based system to be individual-specific and to depend on sales officer characteristics. We estimate the model using data on 994 randomly sampled sales officers' account-opening records over a nine-month period, after the shift to the tablet banking system. We find that sales officers who performed relatively well in the traditional account-opening system are likely to have a head start after switching to the tablet banking technology; however, their learning rate is lower than those who did not do as well prior to the switch. As a result, although the high performers continue to maintain their edge in the new mobile platform, the gap between the high and low performers is reduced significantly. Our results also reveal that customers' awareness of the tablet banking service and their digital literacy, in addition to the quality of the mobile infrastructure and market maturity, affect sales officer's account-opening performance in the tablet-based system.

Our findings provide several insights for managing a technology-enabled change in business processes. First, our results reveal heterogeneity in both the starting performance level and learning rates of newer versus longer-tenured employees. This has implications for hiring as well as personalizing the training of sales force and customer engagement teams in the midst of continuous technological changes. Second, our results show that when firms undertake major changes to customer engagement-linked process, it is important to build awareness about the new technology with customers.

In what follows, we review the literature on both the business value of IT and learning curves in section 2. In section 3, we describe our research context, and in section 4 we develop our theory and propositions. In section 5, we present our research model, estimation, and results. We conclude with a discussion of our findings and highlight some key managerial implications.

2. Literature Review

The literature on the business value of IT has examined the impact of technology in organizations at the firm level (Barua et al. 1995; Brynjolfsson and Hitt 1996; Kriebel and Kauffman 1988), process level (Barua et al. 2004; Mukhopadhyay et al. 1995, 2002; Whitaker et al. 2007), and application level (Banker and Johnson 1995; Banker and Kauffman 1988; Barua and Lee 1997). Across all these levels, the technological interventions studied have focused on automating, informating, and transformating using desktop applications. The advent of mobile enterprise applications creates several new challenges that, to the best of our knowledge, have not been explored in the extant IS literature.

First, in the context of customer-facing IT systems, the focus in the IS literature has been on the implementation (Kim and Mukhopadhyay 2011) and performance implications (Hsieh et al. 2012; Mithas et al. 2005; Zablah et al. 2012) of customer relationship management systems. In these studies, the customer-facing systems are salesperson-centric technologies on the "salesperson–customer interface technology continuum" (Ahearne and Rapp 2010). However, the advent of tablets and mobile technologies is shifting the role of customer-facing technologies from mere sales force automation to allowing salespeople to engage customers in a co-creative experience. In the IS literature, research on the role of technology in personalized selling remains scarce (Ahearne et al., 2008). While the sales and marketing literature has recognized that selling is becoming increasingly personalized (Flaherty et al. 2012) and mediated through IT artifacts and other material devices (Geiger and Turley 2006; Senecal et al. 2007); in general, sales force automation technologies are still viewed as tools for providing timely information and automating tasks for the salesperson (Ahearne and Rapp 2010).

Second, many of the enterprise technological interventions studied in the IS literature have been desktop applications in inter- and intra-organizational contexts. To our knowledge, the IS literature has not empirically explored the performance of mobile enterprise platforms in the context of extra-organizational infrastructural factors such as mobile network quality, internet connectivity, and customer digital literacy.

Third, the introduction of enterprise mobile platforms highlights the role of individual learning on performance in the presence of a disruptive technology. Some IS research has studied the influence of learning on individual performance (Fong Boh et al. 2007; Mukhopadhyay et al. 2011; Singh et al. 2011). The results of these studies indicate that individual productivity improves as people gain experience in performing the same task. However, these studies are in the context of intraorganizational IT systems. To our knowledge, the dynamics of individual learning and its influence on performance in the context of mobile platforms remains unexplored in IS literature.

Finally, the shift of enterprise processes to mobile platforms can be viewed as a disruptive technology in the sense that organizational processes leave the firm's four walls and are executed in real time at the moment of interaction with the customer. This shifts the role of IT from informating, automating, and transformating business processes that support the salesperson to enabling and facilitating salesperson–customer co-creative interplay. Much of the IS literature looks at employee performance in times of stability, after a technology has been introduced, and the marketing literature has examined the determinants of salesperson performance (Brown and Peterson 1993; VandeWalle et al. 2001; Weitz et al. 1986). While these studies shed light on performance during times of stability, little is known about the dynamics of learning and performance when a new technology is introduced.

In this paper, we explore the above-identified gaps by empirically studying these aspects in context of the banking industry. We investigate the impact of a shift from traditional to tablet-enabled personalized account opening (Tab Banking) on the performance of sales officers in a large private bank in an emerging market. Our study sheds light on variations in the learning dynamics of sales officers with different characteristics when transitioning from a paper-based process to a disruptive-mobile-co-creative-customer engagement platform. Second, we explore the role of extra-organizational technology infrastructure on the performance of employees using the mobile platform. Third, we study the role of customer factors, such as their awareness of the new technology and their digital literacy, on the performance of employees using the mobile platform. Finally our study empirically highlights the increasing importance of technology in functions that were hitherto considered “soft skills heavy” and not amenable to technology.

3. Research Context

3.1. The Traditional Account-Opening Process

Our research context is the use of tablet devices in the personalized account-opening process for potential customers of one of India’s largest private banks, with over 52 million customers. The bank had total assets of USD 103 billion on March 31, 2015 and profit after tax of USD 1,788 million for the year ending March 31, 2015. Its presence spans 17 countries, including India. The bank offers a wide range of banking products and financial services to corporate and retail customers through a variety of delivery channels and group companies such as corporate banking, business banking, insurance services, private equity, mutual funds, and personal banking. The bank currently has a network of 4,070 branches and 13,180 ATMs across India.

Despite the extensive banking infrastructure of the Bank and several others, one in five unbanked adults in the world reside in India (Demirguc-Kunt et al. 2015). A survey by the World Bank on reasons for being unbanked reveals that apart from the unavailability of a branch, the unbanked are plagued with perceptions that keep them out of the formal financial system (Demirguc-Kunt et al. 2015). To overcome these perceptual barriers, the Bank engages in extensive outreach involving sales officers visiting customers’ residences in a door-to-door selling mode. Indeed, 30% of the Bank’s workforce is on the move, engaging with customers, explaining product propositions, and creating new relationships.

As part of the account-opening process, sales officers engage potential customers at their residences. The conventional account-opening process involves the collection of a physically completed form along with documents that prove a customer’s identity. This is a regulatory requirement in India because there is no equivalent of a Social Security number to uniquely identify each citizen. This requirement is also known as the “Know Your Customer” (KYC) requirement. Documents that can fulfill the KYC requirement include a passport, a voter ID card, a driver’s license, an electricity or phone bill, among others. Once the sales officer submits these documents in the branch sales office, they are checked for accuracy and validity. These checks sometimes identify that the documents are invalid. This might be the result of expired documents or bills being more than a year old or belonging to an old address. In such situations, the sales officer has to revisit the customer to acquire a document that can serve as a valid form of identification. Incomplete forms can lead to multiple customer visits. These additional trips to the customer can significantly increase the time taken to open an account, causing significant customer inconvenience. This physical movement of paper in the traditional paper-based account-opening process has been associated with delayed account opening and high rejection rates.

To ameliorate such problems and improve customer convenience, the Bank launched a Tab Banking program in August 2012 in an effort to empower its employees by providing information and tools at their fingertips that would help create superior customer engagement. In 2010, 3G mobile bandwidth became available, significantly ameliorating the issue of slow connectivity over mobile networks. In addition, tablet devices began to evolve in sophistication and drop in price, becoming increasingly viable options for enterprise applications. All these factors hastened the scaling up of tablet-based banking for the Bank.

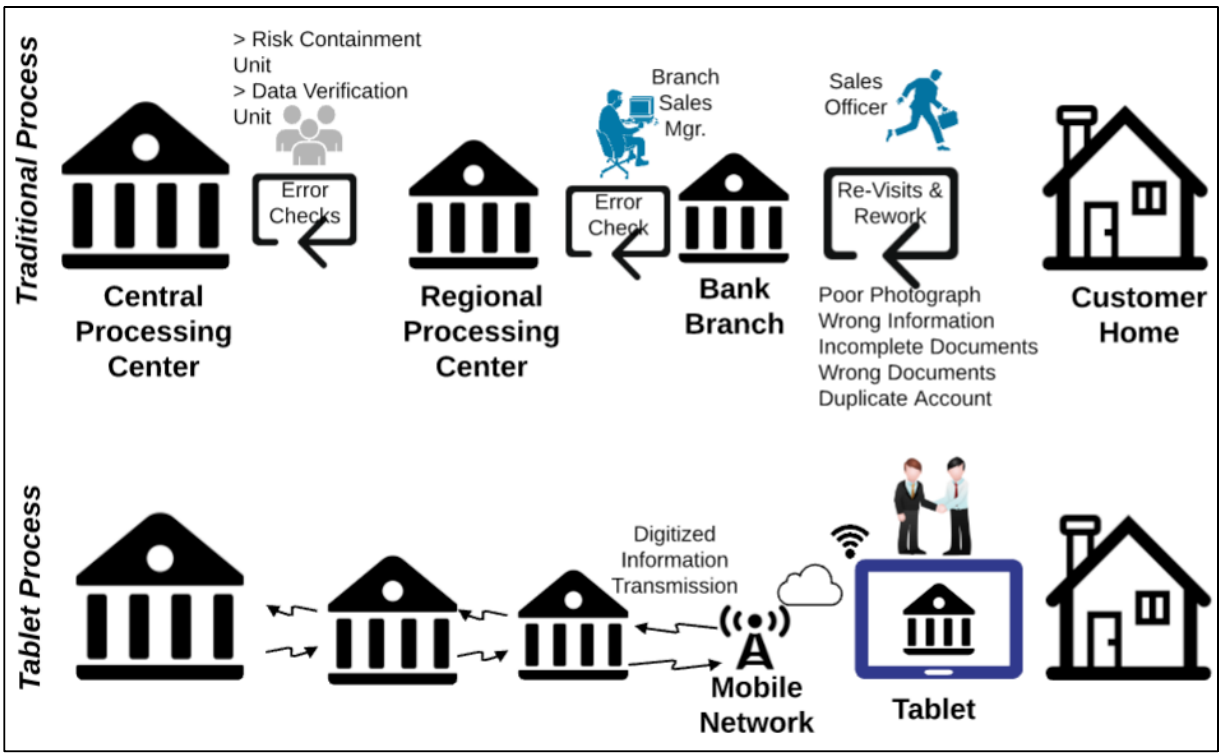
3.2. The Tab Banking Account-Opening Process

The device in Tab Banking is a high-end tablet with advanced processing capabilities, powerful audio and screen resolution, 3G network capabilities, and an efficient autofocus camera (5 MP) (see Figure 1). In addition, various customized applications are installed to provide a suite of quick go-to tools that help sales officers in many ways.

Figure 1: Tab Banking Tablet

The primary reason for introducing the tablet was to improve the account-opening process and enhance customer convenience. The tablet offers tools for capturing account-opening information, with built-in validations and controls for error-free and single-visit account opening. There is an online "Account Opening Form" utility that allows the sales officer to enter customer details along with the customer's photo to minimize errors. In addition, all KYC documents and photographs are now captured through the tablet's camera and uploaded along with customer details. As a result, the problems associated with paperwork, physical photographs, and multiple transfers of physical documents between the sales officer, the bank branch, and regional processing centers are eliminated. Furthermore, the scanned KYC documents are checked for accuracy by automated image-processing software, which provides feedback to the sales officer while he or she is at the customer's location. Any errors are caught immediately, and the sales officer has the opportunity to correct on the spot. This avoids the time-consuming, inefficient routine of multiple customer visits to resolve errors in the old paper-based system. That said, some chances for error remain. For example, the sales officer might make data entry errors when entering the account opening form online, or the photo taken of the customer may not have sufficient lighting, which might render it unfit as a valid photo ID. In such cases, the image-processing software will return an error in real time, allowing the sales officer to retake the picture. Furthermore, while waiting for the online validation of documents, the sales officer has the opportunity to cross-sell additional banking products to the customer. Figure 2 presents a schematic comparison of the old and new processes.

Figure 2: Traditional and Tablet Account-Opening Process



In addition to digitizing and streamlining the account-opening process, the tablet provides a host of additional functionality to facilitate customer engagement through the pre-sale, during-sale, and post-sale stages. With the tablet in hand, the sales officer can potentially carry out all assisted banking transactions (with the exception of cash). Indeed, with Tab Banking, the sales officer is, in effect, bringing the bank branch to the customer. An added indirect advantage of taking the branch to the customer is that there is no need for the customer to visit the branch to open an account. This reduces foot traffic in the bank branches, in turn reducing congestion and improving the customer experience in bank branches. In addition, tablet banking relieves the pressure on the bank to open new physical branches. This is a significant benefit to the bank, as the process of getting approval to open new bank branches from India's central bank (Reserve Bank of India) is laden with onerous regulations and long timelines.

4. Theory & Research Model

4.1. Learning by Doing

Performance gains owing to doing the same task repeatedly have been validated in a wide variety of settings, such as manufacturing (Alchian 1963; Argote and Epple 1990; Benkard 2001; Hatch and Mowery 1998), the food industry (Argote et al. 1990), and surgical procedures (Kelsey et al. 1984; Pisano et al. 2001; Reagans et al. 2005). There have been some studies in the IS literature as well that examine the influence of learning on individual performance (Fong Boh et al. 2007; Mukhopadhyay et al. 2011; Singh et al. 2011). The results from these studies indicate that individual productivity improves as individuals gain experience of performing the same task.

As Figure 2 suggests, learning to use the tablet to open bank accounts requires the sales officer to adapt to the mobile platform and to the new business process. As the sales officer begins to open new accounts in the tablet-based system repeatedly, this repetition helps him or her to learn the menu navigation structure, identify features and capabilities that best serve the transactional needs, and learn to use the tools more effectively. This practice and repetition helps the sales officer navigate the process quickly, avoid potential mistakes, and convince the customer in a more seamless manner to complete all required steps in a single visit.

> *As the sales officer's account-opening experience using tablets increases, we expect his or her average turnaround time to be reduced.*

4.2. Learning Under Disruption

Although the organizational learning curve literature generally shows that learning from experience benefits organizational performance over time (Argote 2012; Dutton and Thomas 1984; Yelle 1979), other research suggests that knowledge accumulated from experience can sometimes create rigidities that disrupt learning and harm performance (Leonard-Barton 1992; Levitt and March 1988; March 1991; Tushman and Romanelli 1985). There are also some studies that examine the effect of experience on performance under disruptions due to employee turnover (Argote 2012) and knowledge obsolescence, which can occur when products and processes change (Leonard-Barton 1992).

At the individual level, the Lewin-Schein theory of change (see Lewin 1947) offers a framework with which to assess the impact of change on performance. It consists of three phases: unfreezing, moving, and refreezing. In the first phase, a disruption is encountered, warranting the need to unlearn old routines

(Schein 1964), a heightened sense of interpersonal risk (Edmondson et al. 2001), and feelings of anxiety (Schein 1964) and uncertainty (Burkhardt and Brass 1990). These processes cause stress and take time away from the normal performance of activities. In the context of the shift to tablet banking, sales officers need to unlearn the traditional account-opening process they are used to and, at the same time, familiarize themselves with the new tablet banking process. As such, the unfreezing phase should be associated with an immediate performance drop.

> *After the introduction of tablets, we expect that there will be an initial increase in the turnaround time to open accounts.*

In the moving phase, after the initial shock, the individual gradually shifts to a semistable state. Sales officers adapt to the change, develop alternative solutions, and choose a course of action (Zand and Sorensen 1975, p. 535)—they go through what can be called "cognitive redefinition" (Schein 1964). Following the initial disturbance caused by the change, a sales officer should begin taking proactive steps toward adaptation by "conceptualizing a problem, acquiring information about relevant forces, locating or developing alternative solutions, and choosing a course of action" (Zand and Sorensen 1975, p. 535). As the sales officer adapts, less time is spent struggling with new processes (Burkhardt and Brass 1990), performance gains are realized, and time allocation shifts from learning to producing. Thus, in the specific context of tablet banking, as the sales officer becomes familiar with the navigation and menu structure, he or she becomes comfortable with the digital platform available on the tablet. As the sales officer begins to learn new features available on the platform, the ability to leverage the capabilities uniquely available on this digital platform increases. Thus, after the initial drop, the sales officer's performance should show evidence of an upward recovery trend.

> *After an initial increase, we expect the turnaround time to decrease.*

In the final refreezing phase, performance stabilizes again, hopefully at a higher level than before the disruption. This stabilization might occur due to diminishing returns on learning after sufficient time has elapsed since the initiation of change. In addition, the sales officer might become more comfortable with postdisruption work when he or she has learned and formed new habits and routines that are "confirmed" as appropriate and effective for the new environment (Schein 1964; Zand and Sorensen 1975). In the specific context of tablet banking, as the sales officer learns the capabilities of the digital platform, he or she makes them a part of the routine of getting customers to open an account. However, with time, the repertoire of leveraged capabilities becomes well defined and any marginal increase in performance becomes more difficult.

> *After a phase of decreasing turnaround times, we expect that it will level off and stabilize at a level lower than the pre-tablet turnaround time.*

4.3. The Effect of Tenure and Recency of Experience Before Disruption on Learning

Organizational routines have been regarded as the primary means through which organizations accomplish their work (Cyert et al. 1963; March and Simon 1958; Nelson and Winter 1982; Thompson 1967). While recognized as an essential aspect of organized work, organizational routines are also a well-known source of inertia (Freeman and Hannan 1983) and inflexibility (Gersick and Hackman 1990).

In the banking context, the practice of opening accounts with customers is a set of routines enacted by the sales officer. Though these routines are not always standardized processes, they are likely to become an ingrained part of the sales officer's repertoire of bank account opening. The introduction of the tablet requires the sales officer to unlearn old paper-based routines associated with account opening and learn new ones involving a new technology. The confidence a person has in his or her ability to handle a new technology (Compueau and Higgins 1995), as well as the affective reaction to using technology (Davis 1989; Taylor and Todd 1995; Thompson, Higgins and Howard 1991), can exert an important influence on acceptance of a technology (Venkatesh et. al. 2003). When a sales officer has been in the organization for a long time, old routines are likely to become ingrained. Considering that the unfreezing phase involves a disconfirmation of beliefs, behavior, and past routines, the more ingrained those routines are, the more difficult it is to unlearn them and adopt routines built around a new technology.

> *We expect that sales officers with a longer tenure with the bank before the introduction of tablet banking will start out with a longer turnaround time when opening accounts using tablets.*

Furthermore, and for the same reasons, sales officers with a longer tenure will take longer to unlearn their old routines and adapt to the new routine.

> *We expect that sales officers with a longer tenure with the bank before the introduction of tablet banking will learn at a slower rate.*

Another way we define experience is by its recency. We contend that the same mechanisms discussed for the effect of length of experience are at play for the recency of experience. There is evidence that the availability of a routine in organizational (Levitt and March 1988) and individual (Ericsson 2006) memory is associated with the frequency of use of a routine as well as the recency of its use (Levitt and March 1988). Organizations have difficulty retrieving relatively old, unused knowledge or skills (Argote et al. 1990). However, recently used and frequently used routines are more easily evoked than those that have been used infrequently.

Sales officers who have recently been using the traditional process at a higher frequency are more likely to persist with those routines even when presented with a technology-enabled process that offers additional capabilities. This recency of experience is likely to become a hindrance in learning in the new digital platform and is likely to reduce their ability to leverage the capabilities of the new process fully to open accounts faster.

> *We expect that sales officers who opened more accounts before the introduction of tablet banking will start out with a longer turnaround time to open accounts using tablets.*

Several researchers have also found evidence for the presence of organizational momentum that guides patterns of organizational variation (Boyd and Peter 1985) and makes exploration of alternatives difficult (Levitt and March 1988; Starbuck 1983; Wildavsky 1972). Thus, sales officers who opened more accounts right before the tablet banking platform was introduced are likely to have a greater mental barrier to learning the new digital platform-enabled process. This organizational momentum is likely to restrict sales officers from exploring the new technology, thus reducing their learning rate.

> *We expect that sales officers who opened more accounts before the introduction of tablet banking will learn at a slower rate.*

4.4. The Effect of Expertise on Learning Under Disruption

Reckwitz (2002, p. 249) defines a practice as a routinized form of behavior that consists of several interconnected elements. Building on this definition, Shove et al. (2012) identify three building blocks of practices: “competences” (people’s ways of engaging in practices through thinking, talking, and their embodied skills), “meanings” (their understanding of the world and their place within it, their emotions and motivations), and “materials” (things and their use, or the ways in which material objects are incorporated into these practices and, in turn, structure or shape them).

In the context of tablet banking, even though the “material” aspect changes from analog to digital, the “competences” and “meanings” are likely to carry over from the traditional to the new process with the sales officer. Indeed, the sales literature has rigorously examined the elements of selling, such as gifting practices to solidify social ties and to create social obligations (Darr 2006), using finely tuned selling practices such as “nailing” the client by having them handling the object for sale (Darr and Pinch 2013), and on-the-ground segmentation activities of marketing and sales managers (Harrison and Kjellberg 2010). While it is possible to encode some of these practices into digital platforms, much of this remains tacit knowledge acquired over time (Geiger and Turley 2005).

Thus, we expect that the tacit skills acquired by sales officers are transferable from the old process to the new tablet banking process. Even with the introduction of the tablet, sales officers are likely to complement the capabilities of the new technology platform with their earned competencies in the account-opening process.

> *We expect that sales officers who performed better in the traditional account-opening process will start out with a shorter turnaround time in opening accounts using tablets.*

As Figure 2 reveals, tablet banking codifies some tacit aspects of selling such as ice-breaker videos, product demonstration videos, product simulations, and visually appealing and intuitive product comparisons. Thus, with time, sales officers who learn to use these features effectively are likely to make up for any lack in “the art of selling” partly by using technology. This is likely to benefit the sales officers who did not perform as well in the traditional process.

On the contrary, high-performing sales officers may not be as incentivized to exploit the capabilities of the tablet because of a general tendency to draw from an existing repertoire of skills, especially if it has served them well in the past. Another reason individuals rely on prior behaviors to guide future behaviors is that moving away from the known to the unknown is considered risky and evokes fear (Von Krogh et al. 2000). Thus, new behaviors are often avoided when possible and when past behaviors will “satisfice” (March and Simon 1958). Indeed, past routines have been found to be utilized even when more efficient and effective alternatives become available (Cohen and Bacdayan 1994). Thus, sales officers who have performed well in the traditional process may not invest as much effort to learn the new process on the tablet banking digital platform.

> *We expect that sales officers who performed better in the traditional account-opening process will have a lower learning rate in the tablet banking process.*

4.5. The Effect of Mobile Infrastructure on Sales Officer Performance

For mobile digital platforms, the mobile network is an essential enabling technology. In emerging markets such as India, the growth of the mobile network infrastructure has not kept pace with the meteoric rise in mobile phone adoption and use. As the density of mobile devices in a location increases, network congestion increases, leading to a drop in the quality of service (QoS) available to mobile devices in that location. This manifests as a reduction in the connection speed over mobile devices and, more distressingly, dropped calls. For example, a study by the Telecom Regulatory Authority of India (TRAI) found that in the April–June quarter of 2015, call drop rates stood at a staggering 24.59%.[4]

Deteriorated QoS in the mobile network is likely to be associated with lower connection speeds available on the tablet, resulting in high latency. Poor connectivity, in turn, might lead to an increase in time taken to open accounts. In the context of tablet banking, the QoS is a function of not only the data transfer rate but also the bit error rate, which is important for providing high-quality image and video services. Thus, high mobile density might result in a deterioration in the functionality available on the tablet, which is likely to lead to a reduction in the perceived ease of use by the sales officer, limited adoption (Venkatesh 2003), and reduced learning and performance.

[4] PTI, “Call drop rates at 25% in April-June: TRAI”, Times of India, November 25, 2015.

We expect that locations with higher mobile phone density will be associated with lower sales officer performance.

4.6. The Effect of Customer Digital Literacy on Sales Officer Performance

When individuals are exposed to a new technology, they may perceive it as complex and feel anxious (Taylor and Todd 1995). This is likely to influence the judgement of their ability to use a technology to accomplish particular jobs or tasks (Compueau and Higgins 1995). Customers who have low perceived self-efficacy are likely to be instruments of delay in the account-opening process. In addition, customers who are not adept at using the Internet are likely to be uncomfortable with sharing their personal information, as is required for opening a bank account. Thus, customers who have used digital and mobile technologies in the past are likely to work more effectively with sales officers using tablet banking to open accounts.

We expect that locations with higher internet penetration will be associated with higher sales officer performance.

4.7. The Effect of Customer Awareness of Service on Sales Officer Performance

Forming trust or perceived credibility before service subscription has a significant impact on customer acceptance because customers generally stay away from a service provider they do not trust (Gefen and Silver 1999; Reichheld and Schefter 2000). Perceived credibility is "the belief that the promise of another can be relied upon even under unforeseen circumstances" (Suh and Han 2002). Distrust (low perceived credibility) of service providers makes consumers afraid to provide sensitive information such as financial details on the internet (Suh and Han 2002).

A common practice in India for firms to establish credibility with customers is by using brand ambassadors in print and television advertising. Companies typically choose highly regarded sports or movie celebrities as brand ambassadors. These advertisements generate awareness of the product and help allay concerns about the quality and safety of a product. Thus, priming customers with awareness of a service is likely to make the job of convincing the customer to adopt the service much easier for the sales officer, which is likely to reduce latency in converting leads into customers.

Because television advertising can only reach households that own a television, we expect that locations with higher television penetration will be associated with higher sales officer performance.

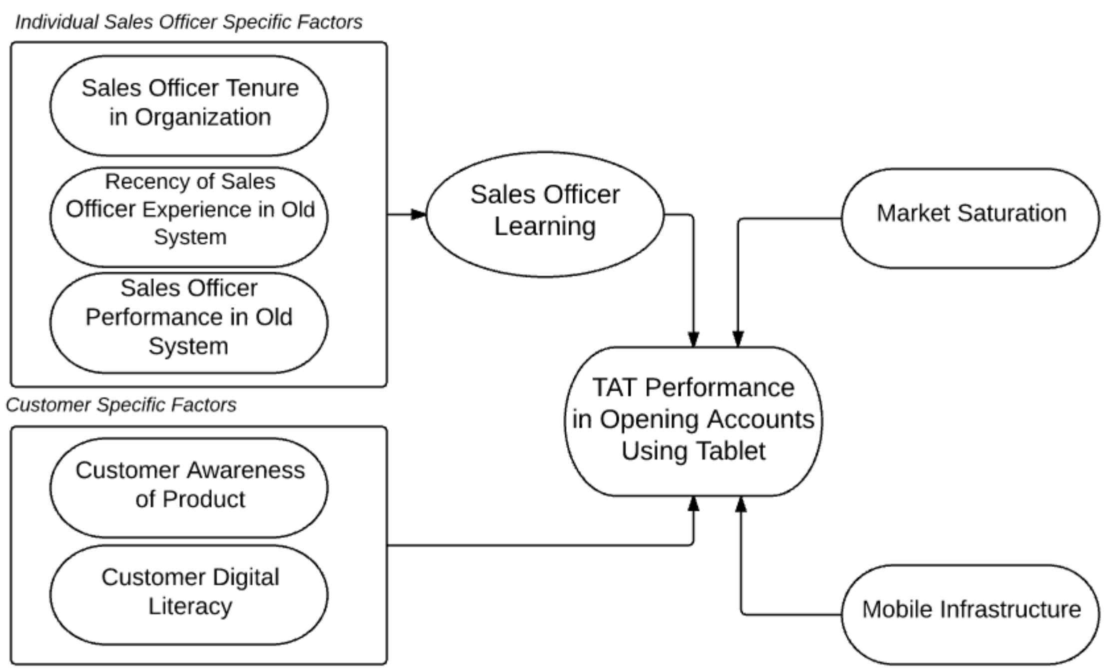
4.8. The Effect of Market Saturation on Sales Officer Performance

A 2014 World Bank study on financial inclusion across the world found that half the world's adult population (2.5 billion people) is unbanked. Only 20% of the unbanked do not bank for lack of money. For the rest, the reasons span from lack of trust to lack of documentation to the physical distance of banks to religious reasons (Demirguc-Kunt et al. 2015). Some of these barriers are easier to resolve than others. Locations that already have a high density of banking are likely to have people who are unbanked due to more deep-rooted reasons. As the market for banking becomes saturated, acquiring the next customer becomes increasingly difficult. The sales officer will likely need to exert more effort and skill in coming up with creative workarounds to resolve the roadblocks preventing an individual from opening an account, resulting in increased delays.

> *We expect that locations with higher banking penetration will be associated with lower sales officer performance.*

We depict our research model in Figure 3.

Figure 3: Research Model



5. Data and Empirical Analysis

5.1. Data Summary

As we mentioned previously, the data set used for the empirical analysis is drawn from the Bank's tablet banking initiative. This initiative was launched in August 2012 and was rolled out all over India in stages. The data set we have is related to the wave of rollouts starting in September 2013, involving the cities of Agra, Amritsar, Bhopal, Coimbatore, Kota, Ludhiyana, Meerut, Patna, and Udaipur. The data were acquired following a visit to and discussions with managers at the bank headquarters in Mumbai, India. This ensured that there was a clear understanding between the researchers and the bank employees who would be providing the data.

This data set contains detailed information about the account-opening activities of 994[5] randomly sampled branch sales officers from the cities involved in this wave of rollouts for a nine-month period since launch (September 2013 – May 2014). For each account opened using the tablet banking technology, we observe account type, location on the account profile, the sales officer who handled the account-opening process, the date and time when the process was initiated, and the account-opening total turnaround time (TAT). The TAT is defined as the time difference, in hours, between the account activation time (time when account is activated and customer can start doing banking transactions) and the case initiation time (time when the sales officer logs first interaction with the customer). These 994 sales officers opened 67,613 accounts using the tablet banking technology during the time interval spanned by the data. Among all account types, household savings accounts (HSAs) and salary savings account (SSAs) are the most common in the data. Other less common account types include youngster accounts. SSAs are typically opened in batches for employees from the same company; therefore, we treat SSAs opened within an hour by the same sales officer as one record and use the average TAT across those accounts as the TAT in that record. The number of account-level records in our data is then 36,993, and among these records, 39.29% are HSAs and 14.76% are SSAs. For the 994 individuals in the sample, we observe their job tenure (in months) and academic degree. We also have their aggregate account-opening data in the old system, including the number of accounts opened using the traditional process (N_i^{old}) and the average TAT of opening these accounts ($AvgTAT_i^{old}$), for three months prior to the launch of tablet banking initiative (June–August 2013). We report the summary statistics of individual sales officer-level variables in Table 1.

Table 1. Summary Statistics for Sales Office Specific Characteristics (n=994)

Variables	Mean	Std. dev	Min	Max
$Tenure_i$	3.364	2.055	1	35
N_i^{old}	135.9	171.1	1	583
$AvgTAT_i^{old}$	108.5	48.58	2.117	479.9
$Degree_i$	Science & Technology (0.349)		Other (0.651)	

The data on customer and environmental factors were collected based on the 2011 Indian census data. We use the percentage of households that have mobile phones in the location[6] where the account was opened to measure the mobile infrastructure ($PercMphone_{ik}$). We use the percentage of households having bank accounts in the account-opening location to measure market saturation ($PercBank_{ik}$).

[5] We exclude individuals who opened fewer than three accounts using the tablet technology because there are too few data points to either examine their learning process or identify the individual-specific parameters.
[6] "Location" refers to the neighborhood in which the sales officer operates.

The launch of tablet banking by the Bank was accompanied by a very popular television commercial featuring Amitabh Bachchan, one of India's top movie celebrities. Because this commercial was played on television, it reached only households that have a television. Thus, we measure customer awareness of the tablet banking service based on the percentage of households that have a television in the account-opening location ($PercTV_{ik}$). Finally, we use the percentage of households that have an Internet connected computer in the account-opening location ($PercNet_{ik}$) to measure customer digital literacy.

Note that because many sales officers cover multiple locations, our environmental and customer variables can vary across accounts opened by the same individual sales officer. This allows us to identify the impact of these variables on TAT. The summary statistics of the environmental and customer variables appear in Table 2.

Table 2. Summary Statistics for Location Characteristics

Variables	Mean	Std. dev	Min	Max
$PercMphone_{ik}$	0.617	0.057	0.305	0.701
$PercBank_{ik}$	0.635	0.053	0.374	0.878
$PercTV_{ik}$	0.672	0.174	0.118	0.954
$PercNet_{ik}$	0.056	0.026	0.005	0.242

5.2. Empirical Model

The empirical model we use to test the propositions derived in the "Theory & Research Model" section is formulated as follows:

$$TAT_{ik} = \alpha_i N_{ik}^{\beta_i} e^{\varphi_C C_{ik} + \varphi_E E_{ik} + \varphi_X X_{ik} + \mu_{ik}} \tag{1}$$

In this model, the unit of analysis is "an account opened using tablet banking technology by a sales officer." In Equation (1), TAT_{ik} denotes the turnaround time of the kth account opened by sales officer i using the tablet banking technology. N_{ik} captures the stock of tablet banking experience sales officer i has accumulated at the time when he or she opens the kth account, which is measured by the cumulative number of accounts opened using the tablet technology. α_i reflects individual i's TAT performance on the first account he or she opened using the tablet technology (the "baseline efficiency"), and β_i represents the learning rate. Note that we do not impose a negative sign in front of β_i, and therefore, a negative value of β_i indicates the presence of a learning effect in the case of individual i. C_{ik} represents the set of customer-side variables associated with the focal account, including $PercTV_{ik}$ and $PercNet_{ik}$, and φ_c is a vector of parameters, each element of which captures the effect of one variable in C_{ik} on TAT. Similarly, E_{ik} represents the set of environmental variables associated with the focal account, including $PercMphone_{ik}$ and $PercBank_{ik}$, and φ_E contains their corresponding parameters. We also include control variables X_{ik} as two account type dummies for HSA and SSA, respectively, and each element in φ_X captures the systematic difference in TAT between HAS or SSA and other account types. φ_c, φ_E, and φ_X are all assumed to be common across individuals, which implies that the customer, environmental, and account-type variables affect the TAT of accounts opened by different sales officers in the same way. μ_{ik} in the model represents unobserved random performance shock and is introduced exponentially into the model. We assume that μ_{ik} for individual i follows $N(0, \sigma^2_{\mu_i})$ and allow $\sigma^2_{\mu_i}$ to be individual specific as well. $\sigma^2_{\mu_i}$ reflects the stability of individual i's performance.

Taking natural logarithm of the Equation (1), we obtain the following expression:

$$LnTAT_{ik} = \gamma_i + \beta_i LnN_{ik} + \varphi_c C_{ik} + \varphi_E E_{ik} + \varphi_X X_{ik} + \mu_{ik} \tag{2}$$

where $\gamma_i = \ln(\alpha_i)$.

Accounting for Individual Heterogeneity in Learning

We allow "baseline efficiency," learning rate, and performance stability (γ_i, β_i, and $\sigma^2_{\mu_i}$) to be individual-specific and estimate the effect of observed sales officer-level characteristics on these parameters. To capture such relationships, we introduce observed time-invariant individual sales officer attributes into the model in a hierarchical fashion:

$$\boldsymbol{\theta_i} = \boldsymbol{\delta}'\boldsymbol{Z_i} + \boldsymbol{\varepsilon_{\theta_i}} \tag{3}$$

In Equation (3), $\boldsymbol{\theta_i} = [\gamma_i, \beta_i, \ln(\sigma^2_{\mu_i})]$[7] is an $n\theta$-element column vector with $n\theta = 3$. $\boldsymbol{Z_i}$ is an nz-element column vector of individual-specific characteristics for individual i, including a first element that has the constant value 1. $\boldsymbol{\delta}$ is a $nz \times n\theta$ matrix of parameters, which describes the relationship between the individual-specific variables and the set of individual-specific parameters $\boldsymbol{\theta_i}$. Variables in $\boldsymbol{Z_i}$ include $Ln(Tenure_i)$, $Ln(N_i^{old})$, and $Ln(AvgTAT_i^{old})$, as well as a dummy variable indicating whether sales officer i holds a bachelor or higher degree in science or technology ($DegreeST_i$)[8] as a control. Note that the log transformation is applied to all variables in Table 1 to reduce the skewness of those variables. In addition, because γ_i represents the logarithm of the baseline TAT using the tablet banking technology, using the logarithm of the average TAT ($Ln(AvgTAT_i^{old})$) in the traditional process to measure sales officers' performance in the old system ensures the comparability of the performance in the old and the new systems. Each column in the $\boldsymbol{\delta}$ matrix contains the parameters that describe the linear relationship

[7] The variance of μ_{ik} should be a positive value, while the logarithm of the variance can be any value between negative infinity and positive infinity. To facility the estimation, we assume the bound-free parameter $\ln(\sigma^2_{\mu_i})$, instead of $\sigma^2_{\mu_i}$ itself, to be a linear combination of $\boldsymbol{Z_i}$.

[8] The underlying logic here is that sales officers with a technology or science degree may be more willing/ready to adopt new technologies.

between variables in $\boldsymbol{Z_i}$ and one element in $\boldsymbol{\theta_i}$. For example, if we denote the first column of the $\boldsymbol{\delta}$ matrix as $\boldsymbol{\delta_{\cdot 1}}$, then $\gamma_i = \boldsymbol{\delta'_{\cdot 1} Z_i}$. A negative element in $\boldsymbol{\delta'_{\cdot 1}}$ indicates that the corresponding individual-level characteristic contributes negatively to γ_i; in other words, a larger value of this variable will lead to a "better (smaller)" baseline efficiency. Similarly, a negative element in $\boldsymbol{\delta'_{\cdot 2}}$ indicates that the corresponding individual-level characteristic negatively affects β_i, or equivalently, the larger value this characteristic takes, the faster an individual can learn from their past tablet banking experience. $\boldsymbol{\varepsilon_{\theta_i}}$ captures the remaining variation in θ_i that cannot be explained by $\boldsymbol{Z_i}$. $\boldsymbol{\varepsilon_{\theta_i}}$ is also an $n\theta$-element vector and is assumed to follow $MVN(0, \Sigma_{\varepsilon_\theta})$, where $\Sigma_{\varepsilon_\theta}$ is an $n\theta \times n\theta$ variance-covariance matrix.

5.3. Estimation and Results

We use hierarchical Bayes Markov Chain Monte Carlo (MCMC) methods to estimate our empirical model. More specifically, we use the Gibbs sampler to recursively make draws from the full conditional distributions of sub-vectors of the parameter vector and use the Metropolis-Hastings algorithm to make draws for parameters for which the conditional distributions are not directly drawn. The full details of the likelihood, the full conditional distributions, and the sampling algorithm appear in the online appendix.

Individual Learning Parameter Estimates

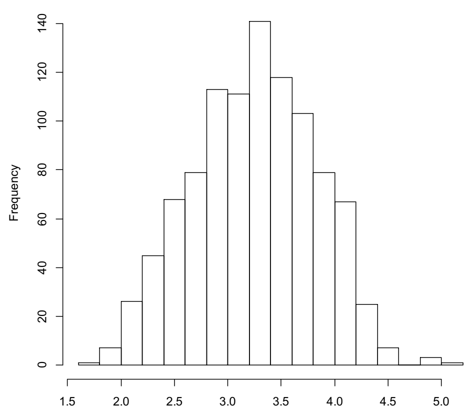
We summarize the mean and standard deviation of the posterior means of the individual-level parameters in Table 3. In addition, we show histograms of the distribution of the posterior means of the individual-level parameters in Figure 4. We can see from both the table and the histograms that most individuals have a positive γ_i. The average of the posterior means of individuals' learning-rate parameter, β_i, across individuals is negative, which suggests that the majority of sales officers indeed learn from their experience of opening an account using the tablet banking technology. This is consistent with our expectation that the TAT decreases as individuals' experience with tablet banking increases. The standard deviation of the posterior means of β_i turns out to be quite large, which suggests significant variation among individual sales officers in terms of their learning rate. There is a fraction of sales officers whose efficiency does not improve as they accumulate more experience with tablet banking. In fact, 159 of the 994 individuals in our sample have a positive posterior mean for β_i. The average of the posterior mean of $log(\sigma^2_{\mu_i})$ is negative as well, which suggests that most individuals' performance is consistent. However, the standard deviation of the posterior means of $\sigma^2_{\mu_i}$ across individuals is again large, indicating significant heterogeneity in individual sales officers' performance stability.

Table 3. Individual-Level Parameter Estimates ($\boldsymbol{\theta_i}$)

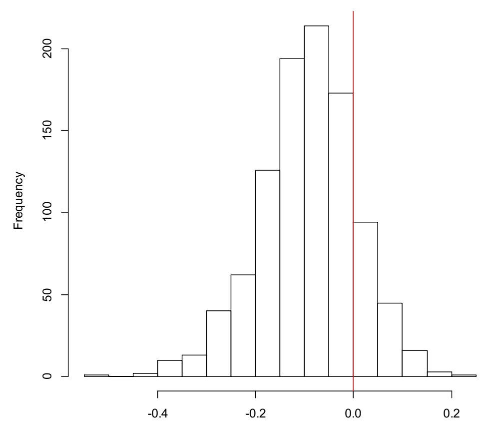
Parameter	Mean Among Individuals	Standard Deviation Among Individuals
γ_i	3.249	0.572
β_i	-0.093	0.098
$log(\sigma^2_{\mu_i})$	-0.433	0.348

Notes: For each individual, the posterior distribution of each parameter has a mean and standard deviation. The mean and standard deviation reported here are the mean and standard deviation of the individual-level posterior means.

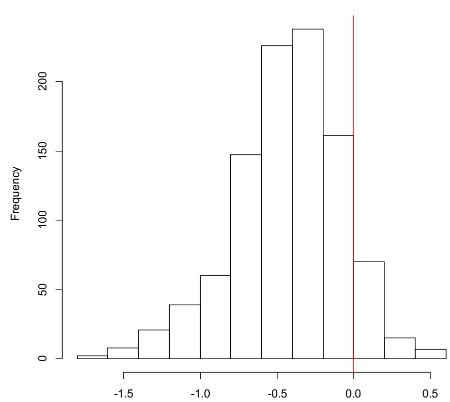
Figure 4: Histogram of Posterior Means of Individual-Specific Parameters



Histogram of Posterior Means of γ_i



Histogram of Posterior Means of β_i



Histogram of Posterior Means of $log(\sigma^2_{\mu_i})$

Estimation of the Effect of Customer and Environmental Variables: $\boldsymbol{\varphi_c}$ and $\boldsymbol{\varphi_E}$

In Table 4, we present the estimates of $\varphi = \{\varphi_c,\ \varphi_E,\ \varphi_X\}$, which do not vary across individuals. The parameter estimates for all elements in φ are "significant" in the sense that the 95% credible intervals of their posterior distributions do not include zero. Both $PercNet_{ik}$ and $PercTV_{ik}$ are negatively correlated with the tablet banking TAT, indicating higher efficiency in the process. Because $PercNet_{ik}$ is a proxy for customers' digital literacy in the account location, this result supports our propositions that it may be easier for sales officers to work with technology-savvy and well-educated customers, and thus it takes less time to open an account for these customers. The negative effect of $PercTV_{ik}$ on TAT confirms our proposition that the account-opening process is more efficient when customers are more informed and aware of the tablet banking service.

The mobile phone penetration rate ($PercMphone_{ik}$) and the banking rate ($PercBank_{ik}$) of the account location both have a positive effect on TAT, which provide evidence for our proposition that mobile connection quality is positively associated with sales officers' account-opening performance and that market saturation is negatively associated with sales officers' account-opening performance. Locations with a higher mobile phone penetration are likely to have a worse connection quality due to the limited bandwidth of the current mobile infrastructure in India; this reduced connection quality can negatively affect sales officers' productivity. Locations with high banking penetration have probably already tapped the bankable segment of the neighborhood. Thus, any new customers that are acquired in these locations are likely to be relatively less bankable due to reasons such as a lack of documentation, a lack of desire to bank, a lack of good credit history, and so forth. Acquiring new customers in locations with a high banking penetration rate is likely to be more difficult. On the contrary, locations with low banking penetration offer a relatively large pool of untapped and potentially bankable clients.

Table 4. Pooled Parameter Estimates (φ)

Parameter	Mean	Standard Deviation
$\varphi - PercMphone_{ik}$	0.901**	0.070
$\varphi - PercNet_{ik}$	-0.342**	0.075
$\varphi - PercBank_{ik}$	0.906**	0.052
$\varphi - PercTV_{ik}$	-0.122**	0.050
$\varphi - HSA_{ik}$	0.334**	0.018
$\varphi - SSA_{ik}$	0.129**	0.031

Notes. Posterior mean and standard deviations are reported.
*The 90% credible interval does not include zero.
**The 95% credible interval does not include zero.

We also find that HSA TAT is significantly larger than SSA TAT. This is likely due to standardized and streamlined process of opening SSAs with company employees. Accounts opened for individual customers are subject to the specific context of each customer, such as the particular combination of features desired in a bank account. In addition, many different scenarios might render a customer ineligible for opening an account and thus must be addressed. Addressing the idiosyncrasies of opening household accounts relative to the standardized process of opening salaried accounts likely explains the relatively larger TAT times for opening HSA accounts.

Estimation of the Effect of Individual-Specific Factors on Learning

As we show in Figure 5, there is a negative correlation between γ_i and β_i, indicating interesting learning dynamics where individuals with higher baseline efficiency tend to learn slower. We study this further with our estimation of the effect of observed sales officer characteristics on heterogeneity in individual learning dynamics (the $\boldsymbol{\delta}$ parameter matrix), the results of which we summarize in Table 5. Each column in the table represents an individual-specific parameter, and each row corresponds to individual-specific characteristics (including the constant term). The value reported in the cell at the intersection of an individual-specific parameter and an individual characteristic represents the estimated effect of that individual characteristic on the individual-specific parameter.

We find that $LnTenure_i$ and LnN_i^{old} both positively affect γ_i. In other words, sales officers who have been with the bank for a longer period of time and those who recently opened a larger number of accounts using the traditional system start out with a larger TAT. These results are consistent with our propositions related to the effect of experience in the old system on the sales officers' starting account-opening performance in the new system. As we discussed previously, this may be due to the reason that tablet banking requires sales officers to unlearn the routines associated with the traditional process. In addition, the correlation between $LnAvgTAT_i^{old}$ and γ_i is also positive and significant, which confirms our expectation that sales officers who have a lower average TAT (i.e., perform better) in the traditional process will also have a lower γ_i, a better baseline efficiency. The dummy variables for having a bachelor or higher degree in science or technology does not seem to affect γ_i significantly, suggesting that sales officers with a bachelor or higher degree in science or technology do not perform significantly better or worse immediately after switching to tablet banking compared with those who hold a degree in arts or management.[9,10]

Both LnN_i^{old} and $LnAvgTAT_i^{old}$ negatively affect β_i, the learning rate, while sales officer tenure does not significantly affect the learning rate. The estimated negative effect of $LnAvgTAT_i^{old}$ on β_i suggests that sales officers who performed well in the traditional process tend to have a larger β_i, indicating a slower learning speed. This supports our proposition regarding the effect of expertise on learning under disruption. Better performers in the old system have a lower incentive to learn the new process. For sales

[9] The baseline group also includes individuals who have a high school degree. However, these individuals only account for 1.81% of the sample. Therefore, the baseline group TAT is largely determined by the TATs of individuals who hold a bachelor or higher degree in arts or management.

[10] As a robustness check, we estimate an alternative model, in which we classify employees' degree into arts, science, technology, and management, as well as high school. We create one dummy variable for each of the arts, science, technology, and management degrees, denoted as A, S, T, and M, respectively. The baseline category is high school. The estimation results of this alternative model are largely the same as the results of the main model presented here.

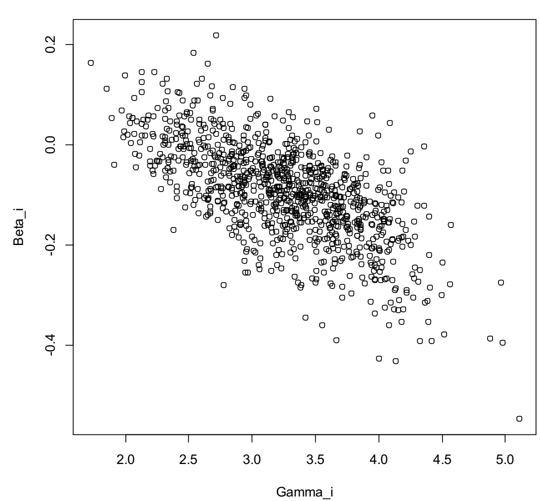
officers who did not perform as well in the traditional process because of some gaps in required selling skills, tablet banking might offer an opportunity to improve their performance. The negative relationship between LnN_i^{old} and β_i indicates that if an individual opened more accounts using the traditional system recently, he or she can learn faster, even though this person may start with a worse baseline efficiency. This contradicts our expectation that sales officers who opened more accounts before the introduction of tablet banking will learn at a slower rate. A discussion with the bank managers revealed that sales officers who have a more recent account experience, both in the traditional system or the tablet banking system, are more involved in this business function. Opening accounts is a significant component of their job responsibility. These sales officers are likely to be more incentivized to learn the new tablet-based system, which offsets a hindrance effect of their recent experience on their learning. It turns out that sales officers' tenure with the bank does not significantly affect their learning rate, and the proposition that individuals with longer tenure tend to learn slower is not supported.

Table 5. Individual-Level Heterogeneity Parameters (δ)

Individual-Specific Characteristics	γ_i	β_i	$log(\sigma^2_{\mu_i})$
$Constant$	1.014**(0.254)	0.141 (0.080)	-0.217 (0.172)
$LnTenure_i$	0.094** (0.037)	-0.005 (0.012)	0.162** (0.023)
$LnAvgTAT_i^{old}$	0.435** (0.056)	-0.040** (0.017)	-0.033 (0.036)
LnN_i^{old}	0.051** (0.019)	-0.019** (0.006)	-0.092** (0.013)
$DegreeST_i$	0.051 (0.050)	0.003 (0.016)	0.067* (0.035)

Notes: The numbers within the parentheses are the posterior standard deviations.
*The 90% credible interval does not include zero.
**The 95% credible interval does not include zero.

Figure 5: Scatter Plot of γ_i and β_i



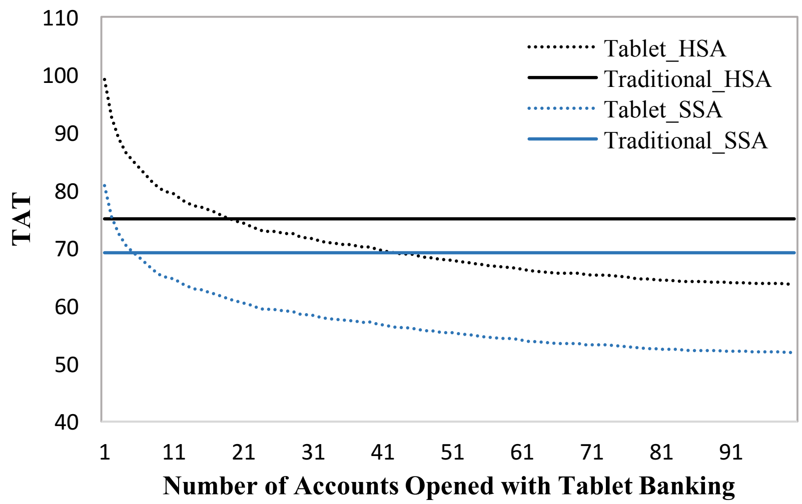
It is worthwhile to note that the different signs of the elements that correspond to $LnTenure_i$, LnN_i^{old}, and $LnAvgTAT_i^{old}$ in the first column and second column of the $\boldsymbol{\delta}$ matrix contribute to the negative correlation between γ_i and β_i demonstrated in Figure 5. Another source of this negative correlation is the covariance between the first two elements in the $\boldsymbol{\varepsilon}_{\boldsymbol{\theta}_i}$vector. The estimated covariance between these two elements is -0.060, which further adds to the negative correlation between γ_i and β_i.

Estimation of the Business Value of Tablet Banking Technology

After estimating the model, we can examine the overall effect of the adoption and usage of the tablet banking technology on sales officers' account-opening performance. Figure 6 compares the TAT at different values of N_{ik} after the adoption of tablet banking with the TAT in the traditional process. The black and blue solid lines in the figure represent the median TAT for HSAs and SSAs opened within the last three months before the adoption of the tablet banking system, respectively. The black and blue dotted lines show the evolution of the median TAT for HSAs and SSAs in the tablet banking system across sales officers, as a function of N_{ik}, the number of accounts a sales officer has opened using the tablet banking technology. The two dotted lines are simulated; we take the posterior means of all 994 sales officers' individual-specific parameters, θ_i, and then form a hypothetical "average location," whose $PercMphone_{ik}$, $PercNet_{ik}$, $PercBank_{ik}$, and $PercTV_{ik}$ are set at the mean level reported in Table 2. We simulate each individual sales officer's TAT for opening an HSA/SSA account in this "average location" at different N_{ik} values and then report the median TAT across all 994 individuals in our sample.

As Figure 6 shows, in both the HSA and the SSA cases, immediately after the switch from the traditional account-opening process to the tablet banking process, sales officers' TAT increases – the starting point of the dotted lines, the TAT in the tablet banking system for HSAs/SSAs, is higher than the median HSA/SSA TAT in the traditional system. However, as sales officers accumulate more experience with the tablet banking system, their TAT in the tablet banking system drops significantly and converges to a much lower level. The fact that the TAT in the tablet banking system falls below the TAT in the traditional system is strong evidence of the positive effect of the adoption and usage of the tablet banking technology on sales officers' productivity. These results are consistent with our expectation that there is an initial drop in sales officers' performance immediately after the switch from the traditional account-opening process to the tablet banking process, as such a business process change may pose short-term challenges to employees; however, the majority of sales officers can learn from their experience with the new tablet banking technology and eventually achieve a performance improvement.

Figure 6: TAT Comparison (Tablet Banking Process vs. Traditional Process)



Robustness Checks

To ensure the robustness of our empirical results, we perform multiple robustness checks.

First, in the data used to estimate the main model, we combine SSAs opened within one hour as a single record. To test whether our estimation results are sensitive to the choice of the period length used to group the SSAs, we combine the SSAs opened within one day as a single record and re-estimate our model. The estimation results are very similar to the results presented above.

Second, in the main model, we classify sales officers' degrees into science/technology degrees and non-science/-technology degrees. In an alternative model, we classify their degrees into arts, science, technology, management, and high school. We create one dummy variable for each of the arts, science, technology, and management degrees. The baseline category is then the high school degree. The estimation results of this alternative model are largely the same as those of the main model; moreover, none of the dummy variables for the degree categories are significantly correlated with sales officers' baseline efficiency and learning speed. This again confirms that sales officers' performance in the tablet banking system is not affected by the degree and background they have, which is somewhat counterintuitive because it is typically believed that individuals with a technology background will adapt faster and better to technology changes.

Third, one may argue that the learning dynamics of sales officers who adopt the tablet banking technology early may be different from those who adopt the tablet banking technology late. To allow for this possibility, we introduce into the model two more individual-level dummy variables, "early" and "late," with "early" equaling 1 if the focal individual switched to the tablet banking system before the first quartile of the observed adoption dates and "late" equaling 1 if the focal individual switched to the tablet banking system after the third quartile of the observed adoption dates. We summarize the estimation results of the new model in Tables 6.1–6.3. As these tables show, the estimates of $\boldsymbol{\theta_i}$ and φ in this alternative model are very similar to those in the main model. Interestingly, we find that early adopters typically have a worse starting point TAT but learn faster. The worse starting-point efficiency might be due to the immaturity of the system at the launch of tablet banking. Early adopters may experience more problems with the system, which hurts their starting-point performance. As problems or bugs in the new system are being fixed, the quality of the system itself improves over time, and the late adopters can start with a more mature and higher-quality system. However, early adopters are likely to be more receptive to new technology and thus are more motivated to learn. Therefore, their learning speed is higher.

Table 6.1. Individual-Level Parameter Estimates ($\boldsymbol{\theta_i}$)

Parameter	Mean Among Individuals	Standard Deviation Among Individuals
γ_i	3.260	0.583
β_i	-0.089	0.111
$log(\sigma^2_{\mu_i})$	-0.438	0.355

Notes: For each individual, the posterior distribution of each parameter has a mean and standard deviation. The mean and standard deviation reported here are the mean and standard deviation of the individual-level parameter means.

Table 6.2. Pooled Parameter Estimates ($\boldsymbol{\varphi}$)

Parameter	Mean	Standard Deviation
$\varphi - PercMphone_{ik}$	0.855**	0.043
$\varphi - PercNet_{ik}$	-0.293**	0.051
$\varphi - PercBank_{ik}$	0.854**	0.087
$\varphi - PercTV_{ik}$	-0.091*	0.050
$\varphi - HSA_{ik}$	0.341**	0.017
$\varphi - SSA_{ik}$	0.177**	0.047

Notes. Posterior mean and standard deviations are reported
*The 90% credible interval does not include zero.
**The 95% credible interval does not include zero.

Table 6.3. Individual-Level Heterogeneity Parameters ($\boldsymbol{\delta}$)

Individual-Specific Characteristics	γ_i	β_i	$log(\sigma^2_{\mu_i})$
$Constant$	1.391**(0.243)	0.059 (0.086)	-0.119 (0.167)
$Lntenure_i$	0.073** (0.031)	0.002 (0.011)	0.166** (0.022)
$LnTAT_i^{old}$	0.353** (0.054)	-0.020*(0.012)	-0.055 (0.036)
LnN_i^{old}	-0.016 (0.017)	-0.007 (0.005)	-0.109** (0.014)
$DegreeST_i$	0.032 (0.051)	0.006 (0.017)	0.070* (0.034)
$Early_i$	0.808** (0.060)	-0.169** (0.019)	0.170 (0.036)
$Late_i$	0.032 (0.059)	-0.001 (0.021)	-0.024 (0.044)

Notes: The numbers within the parentheses are the posterior standard deviations.
*The 90% credible interval does not include zero.
**The 95% credible interval does not include zero.

6. Managerial Implications

The findings from our research have several managerial implications for firms to successfully manage the transition to disruptive mobile customer engagement platforms such as Tab Banking in an emerging-market context. First, our results indicate that firms should carefully manage the training of their employees in these new platforms. As evident in the posterior distributions of the parameters in our empirical model, our research findings highlight that the initial performance in the new platform and the rate of learning on these platforms vary across employees with different tenure and past performance in the traditional system. Thus, firms may need to customize their training programs to match the individual needs of their employees. In addition, firms may also need to manage initial expectations of performance on the new platform based on employees' experience and performance in the old system. For example, if the pool of employees selected for the new system did not perform that efficiently in the old system, our results indicate that their initial performance in the new platform may be worse than the average, though they will catch up over time. This expectation needs to be managed within the firm, especially a few days after the initial platform has been launched.

Second, our results illustrate the significance of environmental factors, such as the mobile phone penetration rate and banking penetration rate, in determining the efficiency of account opening in these new customer engagement platforms. A unique aspect of rolling out enterprise applications on mobile digital platforms such as tablets is that the firm does not manage the full technology stack on which the platform operates. For example, as our results indicate, the quality of the mobile network can be a significant determinant of performance. Thus, firms need to understand the nature of mobile phone penetration and carefully manage its impact. This need is further amplified in an emerging-market context such as India, where the variation in mobile network quality is particularly high. Our results also highlight the need for firms to understand and manage the impact of bank market penetration on the efficiency of the processes deployed on these platforms. As firms expand their reach to markets with high banking penetration, they need to prepare their employees to engage with customers from the bottom of the income pyramid who are not currently in the formal financial system and possibly first-time bankers. This may require new processes and methods to track customer identity for verification.

Finally, our results highlight the importance of customer-related factors, such as customer awareness and digital literacy, in determining the performance efficiency on these new platforms. The nature of engagement with customers on these mobile platforms is co-creative and requires active participation from the customers. Customer awareness and digital literacy are two factors that may present unique challenges to firms in the emerging-market context, as variations across these factors can be significantly high. Our findings suggest that firms may need to tap various channels and media to better inform and prepare their customers for engagement on these mobile platforms. In summary, our results highlight the need for managing both individual-level employee training and the impact of external factors to encourage successful adoption of these emerging mobile customer engagement platforms.

7. Conclusions

Disruptive mobile platforms are transforming customer engagement across industries. These platforms also have significant economic and social implications in the emerging-market context. For example, the relevance of physical bank branches comes under question when the general population is increasingly comfortable with the idea of mobile banking (Dermish et al. 2011). In the context of emerging markets such as India, given the policy and infrastructure constraints of physical branches, mobile platforms may be a faster path toward inclusive capitalism. These mobile platforms allow banks to reach their customers at a place and time of their choice instead of waiting for customers to show up at their crowded branches. In addition, interactions with the customers can de personalized and co-creative, thus rendering these platforms disruptive.

To the best of our knowledge, this research is among the first attempts to understand the success factors in deriving business value from mobile customer engagement platforms. There are several limitations to our work that can be addressed in future research. Contextual data such as customer-specific factors, mobile infrastructure, and banking intensity in our study were available at an aggregate level rather than at the individual customer level. We observe this data at the geographical cluster level (several clusters make up a city) rather than at the individual customer level. Future studies could examine the impact of these factors and measure them with a finer granularity. In addition, although we observe individual sales officer performance over time in our research, we do not observe the nature of sales officer–customer interactions. This limits our ability to derive insights into how the co-creative interplay between the sales officer and the customer occurs on the digital platform. Finally, the business value focus of these platforms in our research is measured in the time it takes the sales officer to open an account. Future research could broaden the business value measures to include quality, in terms of errors or customer satisfaction and future engagement.

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Online Appendix: Hierarchical Bayesian Estimation

As discussed in the Data and Empirical Analysis Section, the parameters in our model can be divided into two groups: (1) parameters that vary across individual sales officers (individual-specific parameters, $\boldsymbol{\theta}_i$) and (2) parameters that do not vary across individual sales officers (pooled parameters, $\boldsymbol{\varphi}$, $\boldsymbol{\delta}$, and $\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon_\theta}}$). We use MCMC methods to estimate parameters in our model. To be more specific, the Gibbs sampler is applied to recursively make draws from the following conditional distribution of the model parameters:

$$\{\boldsymbol{\theta_i}\}|LnTAT_i, LnN_i, \boldsymbol{X_i}, \boldsymbol{Z_i}, \boldsymbol{\delta}, \boldsymbol{\varphi}, \boldsymbol{\Sigma}_{\boldsymbol{\varepsilon_\theta}}\}$$

$$\boldsymbol{\delta}|\{\boldsymbol{\theta_i}\}, \boldsymbol{Z}, \boldsymbol{\Sigma}_{\boldsymbol{\varepsilon_\theta}}$$

$$\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon_\theta}}\big|\{\boldsymbol{\theta_i}\}, \boldsymbol{Z}, \boldsymbol{\delta}$$

$$\boldsymbol{\varphi}|LnTAT, LnN, \boldsymbol{X}, \{\boldsymbol{\theta_i}\}$$

The additional notations $LnTAT_i, LnN_i,$ and $\boldsymbol{X_i}$ denote the stack of $LnTAT_{ik}$, the stack of LnN_{ik}, and the stack of $\boldsymbol{X_{ik}}$ of all accounts sales officer i opened. The notations $LnTAT, LnN,$ and $\boldsymbol{X}$ without the i subscript denote the collection of $LnTAT_i, LnN_i,$ and $\boldsymbol{X_i}$ across all individual sales officers. Further, the posterior distributions of $\{\boldsymbol{\theta_i}\}$ and $\boldsymbol{\varphi}$ do not belong to any conjugate family, and therefore, we use the Metropolis-Hasting method to generate new draws. Each iteration involves four steps.

Step 1: Generate $\{\boldsymbol{\theta_i}\}$

The conditional distribution of $\{\boldsymbol{\theta_i}\}$ is

$$f\left(\{\boldsymbol{\theta_i}\}\,\middle|LnTAT_i, LnN_i, \boldsymbol{X_i}, \boldsymbol{Z_i}, \boldsymbol{\delta}, \boldsymbol{\varphi}, \boldsymbol{\Sigma}_{\boldsymbol{\varepsilon_\theta}}\right) \propto |\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon_\theta}}|^{-1/2} exp\,[-1/2(\boldsymbol{\theta}_i - \boldsymbol{\delta}'\boldsymbol{Z_i})'\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon_\theta}}^{-1}(\boldsymbol{\theta}_i - \boldsymbol{\delta}'\boldsymbol{Z_i})]L(LnTAT_i)$$

where $L(LnTAT_i)$ is the likelihood of observing the vector of $LnTAT_i$. Clearly, this posterior distribution does not have a closed form; therefore, we use the Metropolis-Hasting method to generate new draws with a random walk proposal density. The increment random variable is multivariate normally distributed with its variances adapted to obtain an acceptance rate of approximately 20% (Atchade, 2006). The probability that the proposed $\boldsymbol{\theta_i}$ will be accepted is calculated using the following formula ($\boldsymbol{\theta}_i^{Prop}$ represents the proposed new $\boldsymbol{\theta_i}$ in this current iteration. When accept=1, $\boldsymbol{\theta}_i^{r+1} = \boldsymbol{\theta}_i^{Prop}$; otherwise, $\boldsymbol{\theta}_i^{r+1} = \boldsymbol{\theta}_i^{r}$.)

$$Pr(accept) = \min\{1, \frac{[exp\,(-1/2(\boldsymbol{\theta}_i^{Prop} - \boldsymbol{\delta}'\boldsymbol{Z_i})'\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon_\theta}}^{-1}(\boldsymbol{\theta}_i^{Prop} - \boldsymbol{\delta}'\boldsymbol{Z_i}))]L(LnTAT_i|\boldsymbol{\theta}_i^{Prop})}{[exp\,(-1/2(\boldsymbol{\theta}_i^{r} - \boldsymbol{\delta}'\boldsymbol{Z_i})'\boldsymbol{\Sigma}_{\boldsymbol{\varepsilon_\theta}}^{-1}(\boldsymbol{\theta}_i^{r} - \boldsymbol{\delta}'\boldsymbol{Z_i}))]L(LnTAT_i|\boldsymbol{\theta}_i^{r})}\}$$

Step 2: Generate $\boldsymbol{\delta}$

Define $\mathbf{v}\boldsymbol{\delta}$ = vec($\boldsymbol{\delta}'$)

$$[\mathbf{v}\boldsymbol{\delta}|\{\boldsymbol{\theta_i}\}, \boldsymbol{Z}, \boldsymbol{\Sigma_{\varepsilon_\theta}}] \sim MVN(\boldsymbol{u_n}, \boldsymbol{V_n})$$

where

$\boldsymbol{V_n} = [(\boldsymbol{Z}'\boldsymbol{Z} \otimes \boldsymbol{\Sigma}_{\boldsymbol{\varepsilon_\theta}}^{-1}) + \boldsymbol{V_0^{-1}}]^{-1}$,

$\boldsymbol{u_n} = \boldsymbol{V_n}[(\boldsymbol{Z}' \otimes \boldsymbol{\Sigma^{-1}})vec(\boldsymbol{\theta}') + \boldsymbol{V_0^{-1}}\boldsymbol{u_0}]$,

$\boldsymbol{Z} = (\boldsymbol{Z}_1', \boldsymbol{Z}_2', \ldots, \boldsymbol{Z}_N')$ is an N×nz matrix of covariates, and

$\boldsymbol{\theta} = (\boldsymbol{\theta}_1', \boldsymbol{\theta}_2', \ldots, \boldsymbol{\theta}_N')$ is an N×$n\theta$ matrix which stacks $\{\boldsymbol{\theta_i}\}$.

We define diffuse priors by setting:

u_0 = vector of (0′s) with length $= n\theta \cdot nz$, and $V_0 = 100 I_{n\theta \cdot nz}$.

Step 3: Generate $\boldsymbol{\Sigma_{\varepsilon_\theta}}$

$$[\boldsymbol{\Sigma_{\varepsilon_\theta}}|\{\boldsymbol{\theta_i}\},\ \boldsymbol{Z}, \boldsymbol{\delta}] \sim IW(f_0 + N, G_0^{-1} + \textstyle\sum_{i=1}^{N}(\boldsymbol{\theta}_i - \boldsymbol{\delta}'\boldsymbol{Z_i})'(\boldsymbol{\theta}_i - \boldsymbol{\delta}'\boldsymbol{Z_i}))$$

where the prior hyper-parameter f_0 is set to $n\theta + 5$, and G_0 is set to $I_{n\theta}$.

Step 4: Generate $\boldsymbol{\varphi}$

The conditional distribution of $\boldsymbol{\varphi}$ is

$$f(\boldsymbol{\varphi}|LnTAT, LnN, \boldsymbol{X}, \{\boldsymbol{\theta_i}\}) \propto \left|\Sigma_{\boldsymbol{\varphi_0}}\right|^{-\frac{1}{2}} exp\,[-1/2(\boldsymbol{\varphi} - \boldsymbol{\varphi_0})'\Sigma_{\boldsymbol{\varphi_0}}^{-1}(\boldsymbol{\varphi} - \boldsymbol{\varphi_0})]L(LnTAT)$$

Similar to what we have done for $\{\boldsymbol{\theta_i}\}$, we use the Metropolis-Hasting methods to make draws for $\boldsymbol{\varphi}$. The probability of acceptance is

$$\Pr(accept) = \min\{1, \frac{[exp\,(-1/2(\boldsymbol{\varphi}^{Prop} - \boldsymbol{\varphi_0})'\Sigma_{\boldsymbol{\varphi_0}}^{-1}(\boldsymbol{\varphi}^{Prop} - \boldsymbol{\varphi_0}))]L(LnTAT|\boldsymbol{\varphi}^{Prop})}{[exp\,(-1/2(\boldsymbol{\varphi}^{r} - \boldsymbol{\varphi_0})'\Sigma_{\boldsymbol{\varphi_0}}^{-1}(\boldsymbol{\varphi}^{r} - \boldsymbol{\varphi_0}))]L(LnTAT|\boldsymbol{\varphi}^{r})}\}$$

$\boldsymbol{\varphi_0}$ is set to a $n\varphi$×1 vector of zeros and $\Sigma_{\boldsymbol{\varphi_0}} = 100 I_{n\varphi}$, where $n\varphi = \dim(\boldsymbol{\varphi})$.