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IT Use and Job Outcomes: A Longitudinal Field Study of Technology Contingencies

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Abstract

As information technology (IT) continues to be an integral yet evolving component in work settings, organizations need to ensure that they realize value from IT. Prior studies examining the post-adoption consequences of IT use in terms of employee job outcomes have been inconclusive with respect to the magnitude and direction of these impacts—i.e., the positive, negative, and nonsignificant impacts of IT use on job outcomes. The question of under what conditions IT use leads to favorable job outcomes over time thus remains largely unanswered. We develop a model of IT-related contingencies that integrates core constructs from the IT adoption research with two key job outcomes: *job satisfaction* and *job performance*. We hypothesize that in the post-adoption phase, *technology-job fit* is a key moderator of the relationships between IT use for supporting sales operations and job outcomes. Further, we suggest a theoretical extension of the classical predictors of IT adoption—*perceived usefulness* and *perceived ease of use*—as we expect them to moderate the effect of IT use on job performance over time. We tested our model in a longitudinal field study among 295 field sales personnel over a 24-month period. We found that although IT use had a negative effect on job satisfaction during the post-adoption phase, this effect was moderated by technology-job fit such that the negative effect was significantly attenuated by technology-job fit. We also found that perceived usefulness, perceived ease of use, and technology-job fit enhanced the positive effect of IT use on job performance. Our findings offer insights into the mechanisms and conditions related to the post-adoption impacts of IT use on key job outcomes.

Keywords: Technology Adoption, IT Use, Technology-Job Fit, Job Satisfaction, Job Performance

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1 Introduction

Since the emergence of information technology (IT) in organizational settings, individuals' adoption and use of IT has been a dominant research stream in the information systems (IS) literature (e.g., Chau & Hu, 2002; Davis et al., 1989; Dwivedi et al., 2019; Lowry et al., 2013, 2015; Maruping et al., 2017; Shiau & Chau, 2016; Thong et al., 2002, 2006; Venkatesh et al., 2003, 2008; Venkatesh et al., 2012, 2016). IS research has made significant progress in understanding the adoption of IT by (1) examining the comparative explanatory power of different models, (2) investigating determinants of key constructs in the models and moderators of key relationships, and (3) integrating key constructs from different models into a more robust theory (see Blut et al., 2022; Venkatesh et al., 2012, 2016). The next phase in this journey of IS research emphasized post-adoption consequences and impacts of IT use (e.g., Robert & Sykes, 2017; Sykes, 2015, 2020; Sykes & Venkatesh, 2017; Zhang & Venkatesh, 2017). In particular, researchers have used a plethora of theoretical lenses and methodologies to examine how IT affects various individual-level outcomes such as job outcomes. Understanding such consequences of IT use is important because if IT use does not lead to favorable outcomes for users, the long-term success and viability of an IT will be questionable (Sabherwal et al., 2006; Srivastava et al., 2015; Sykes, 2015, 2020; Sykes & Venkatesh, 2017; Tarafdar et al., 2019; Venkatesh, 2006; Venkatesh et al., 2003; Venkatesh et al., 2007; Venkatesh et al., 2016), especially in an era of major pandemics that continue to infuse more ITs into work (Venkatesh, 2020).

A common theme across prior studies has been proposing antecedents as new exogenous and moderation mechanisms leading to behavioral intention or IT use and, ultimately, outcomes (Venkatesh et al., 2016). Such studies are built on the assumption that the parsimony of the traditional predictors in TAM and UTAUT may be limiting. Studies examining the impact of IT use on job outcomes, such as job satisfaction and job performance, have suggested inconsistent patterns with respect to the magnitude and direction of this impact. This is the case even in studies making assumptions about the value of IT in terms of the ability to support work rather than the dark side of IT (e.g., stress, overload, misuse). Specifically, although several studies have found a positive effect of IT use on one or more job outcomes (e.g., Ahearne et al., 2008; Bala & Venkatesh, 2016; Goodhue & Thompson, 1995; Hsieh, Rai, & Xu, 2011; Zhang & Venkatesh, 2017), many studies have reported negative (e.g., Bala & Bhagwatwar, 2018; Tarafdar et al., 2019; Venkatesh et al., 2010; Venkatesh et al. 2016) and nonsignificant effects (e.g., Lucas & Spitler, 1999).

Prior studies have also suggested that IT use could reduce job satisfaction and improve job performance at the same time, as employees may find it challenging to leave their comfort zone and may thus experience stress (e.g., Stich et al., 2019; Venkatesh et al., 2021a). For instance, Venkatesh et al. (2021a) found that a shift to remote work (using IT) due to the COVID-19 pandemic induced job strain and reduced satisfaction. Organizational behavior (OB) studies are also relevant because of their focus on job outcomes. OB research has recognized IT as an important aspect of today's businesses that is transforming the workplace and jobs (e.g., Colbert et al., 2016; Orlikowski & Scott, 2008; Parker et al., 2017; Ray et al., 2013) but has focused less on the impact of IT on job outcomes. Studies have mostly focused on understanding how IT transforms work and role configuration (e.g., Sergeeva et al., 2020) and interferes with work-life balance (e.g., Butts et al., 2015). It is unclear, however, under what circumstances IT influences job performance and career advancement in multiple professions (Colbert et al., 2016)—a phenomenon that is highly relevant and related to the post-adoption of IT. Thus, a reexamination of the impact of the classical predictors of IT use and their impact on employees' jobs is important for unearthing why IT's effects on job outcomes are inconsistent over time and whether all employees equally benefit from it—especially considering the assumption that ITs are deployed to support work, enhance performance, and realize value.

Against this backdrop, we examine IT- and job-related conditions under which IT use leads to favorable job outcomes. Our research question is the following: *When and how does IT use lead to positive job outcomes?* We suggest that as employees interact with an IT during the post-adoption phase, their emerging assessment of an IT's usefulness, ease of use, and fit with their job will shape the effects of IT use on job outcomes over time. We propose and test a model of IT-related contingencies that integrates the classical predictors of IT adoption using the technology acceptance model (TAM; Davis et al., 1989) with two key job outcomes: job satisfaction and job performance. We incorporate two IT perceptions, i.e., *perceived usefulness* and *perceived ease of use*, and a job-related perception, i.e., *technology-job fit*, as moderators of the relationship between IT use and job outcomes. We expect that these moderators will provide an additional angle to explain inconclusive findings related to IT use and job outcomes. During a major IT implementation, we conducted a 24-month study among 295 field sales personnel and found support for our research model.

We contribute to the IT adoption and use literature by developing and testing a comprehensive nomological network that (1) explains the impact of IT use on job outcomes using a longitudinal data analytic approach, (2) redefines the role of the classical predictors of IT use (i.e., perceived usefulness and perceived ease of use) as technology contingencies in the post-adoption phase, and (3) introduces the notion of technology-job fit as another technology contingency in the relationship between IT use and job outcomes. By going beyond the direct effects of IT use on job outcomes, we enrich and extend this body of literature by identifying *when* and *how* IT use leads to job outcomes. Thus, our findings offer one angle to resolve inconclusive evidence of post-adoption consequences of IT use by highlighting the role of these technology contingencies that buffer the effect of IT use on job outcomes. These contingencies are potential areas of intervention that managers might consider to ensure that employees will realize value from IT implementation—ultimately, contributing to value in their organizations.

2 Theoretical Background

2.1 Technology Acceptance Model (TAM) and Leading Paradigms

The existing body of knowledge on TAM explains IT use as a behavior that is enacted by a potential adopter's or user's mental representation. The mental representation links goals to specific actions that are instrumental to accomplishing these goals (Venkatesh & Davis, 2000). We adopt a similar perspective to explain the impact of IT use on job outcomes over time. In this section, we present an overview of the classical predictors of IT use and propose that such predictors continue to shape the effects of IT use on job outcomes over time.

TAM posits that two beliefs—i.e., *perceived usefulness* and *perceived ease of use*—determine one's *behavioral intention* to use an IT, which in turn predicts *IT use* (Brown et al., 2015; Davis et al., 1989; Venkatesh & Bala, 2008; Venkatesh et al., 2016; Xu et al., 2017a; Xu et al., 2017b). Perceived usefulness is defined as the extent to which an employee believes that using an IT will enhance their productivity on the job and perceived ease of use is defined as the extent to which an employee believes that using an IT will require minimum effort (Davis et al., 1989; Venkatesh & Bala, 2008; Venkatesh et al., 2003). Different theoretical perspectives that view mental representations as drivers of behavior—i.e., action identification theory (Vallacher & Wegner, 1987; Vallacher & Kaufman, 1996), behavioral decision-making theories (e.g., image theory) (Beach & Mitchell, 1996, 1998), motivational theories (work-motivation theory; Locke & Latham, 1990; Vroom, 1964; motivational model of technology acceptance and use; Davis et al., 1992; Ke et al., 2013), and knowledge and learning theories (e.g., Anderson, 1983)—have been used in prior research to justify TAM relationships.

Triangulating the major propositions of these theories and empirical findings based on these theories, prior research (e.g., Davis & Venkatesh, 2004; Dwivedi et al., 2019; Hong et al., 2006; Maruping et al., 2017; Venkatesh & Davis, 2000; Venkatesh et al., 2003) has suggested that individuals use their higher-level goals or purposes associated with their job as a basis for deciding instrumental action sequences in the context of an IT. Perceived usefulness, a cognition of instrumental benefits of an IT, represents a higher-level goal with a desired outcome (e.g., enhanced job performance) and a motivation to perform a behavior—i.e., IT use. In contrast, perceived ease of use is a cognition related to the means and tactics (in other words, procedural knowledge) to use an IT (Davis & Venkatesh, 2004). It is a lower-level goal that helps attain a higher-level goal by performing a certain behavior—i.e., here, IT use.

In assessing the effect of the TAM beliefs on behavior, behavioral intention plays an important mediating role (Davis et al., 1989; Maruping et al., 2017; Venkatesh et al., 2003, 2008). Moderate to high intention-behavior correlations have been reported across a wide range of behaviors (see Ajzen, 1991; Venkatesh et al., 2008) and meta-analyses have found an overall correlation of about 0.500 (Albarracin et al., 2001; Sheeran & Webb, 2016; Sheppard et al., 1988). Such a pattern is well-justified, given that the theory of reasoned action, a key theoretical base for TAM, has consistently predicted behavior in different contexts using intention as a proximal determinant of behavior (McEachan et al., 2016; Sheppard et al., 1988). A similar relationship has been supported in IT adoption research using self-reported use measures (e.g., Davis et al., 1989; Maruping et al., 2017; Taylor & Todd, 1995) and actual use measures (e.g., Morris & Venkatesh, 2000; Venkatesh & Morris, 2000; Venkatesh et al., 2000; Venkatesh et al., 2002). Some prior studies have excluded intention and studied the direct effects of TAM predictors on use while other studies have excluded use and focused only on intention; we include both intention and use to test a complete intention-based model that is consistent with much prior TAM research and the root social psychology theories of reasoned action and planned behavior (Ajzen, 1991; Ajzen & Fishbein, 1980; Sheeran & Webb, 2016; Venkatesh et al., 2003, 2008).

2.2 IT Adoption/Use and Job Outcomes

Organizations invest in IT to enhance individual and organizational performance. IT implementations involve social changes that affect individual behaviors and structural changes that alter information flows and job structures within the organization (Bala & Venkatesh, 2013; Barley, 1986; Boudreau & Robey, 2005; Lapointe & Rivard, 2005; Morris & Venkatesh, 2010; Venkatesh et al., 2010). Thus, studying the effect of IT use in terms of duration or frequency of use (e.g., Devaraj & Kohli, 2003; Venkatesh et al., 2016) on job outcomes is important to fully understand how employees respond to IT implementations.

A closer assessment of prior work indicates a possible pattern. Previous research has shown that employees who perceive the IT as deskilling and/or disruptive (e.g., changes to their job and work processes) have lower job satisfaction (e.g., Bala & Venkatesh, 2013; Kraut et al., 1989; Morris & Venkatesh, 2010; Venkatesh et al., 2010, 2016) and employees who have positive perceptions about IT have neutral to positive job satisfaction perceptions (e.g., Barker, 1995; Morris et al., 2002; Zhang & Venkatesh, 2017). Table 1 highlights a sample of relevant studies. Our observation is consistent with the belief that IT use leads to positive outcomes only if it has a good fit with the tasks it supports (Cooper & Zmud, 1990; Goodhue & Thompson, 1995; Thompson et al., 1991; Zhang & Venkatesh, 2017).

Table 1. Sample of Studies Linking IT to Job Outcomes

Study	Journal	Technology or context	IT use or implementation	Job outcomes	Key findings
Ahearne et al. (2008)	*Management Science*	Sales technology in a pharmaceutical setting	Archival: total time spent on core screens and total screen hits	Job performance	Through its influence on salesperson behavior and characteristics, IT *increases* job performance.
Bala & Venkatesh (2013)	*MIS Quarterly*	Enterprise systems (shakedown phase)	Perceived technology characteristics in terms of complexity, reconfigurability, and customization	Job satisfaction	Perceptions of changes in job characteristics *decrease* job satisfaction.
Bala & Venkatesh (2016)	*Management Science*	Enterprise systems	Implementation characteristics in terms of experiential and psychological engagements	Job performance and job satisfaction	Through its influence on exploration-to-innovate, not-to-revert, and exploitation behaviors, IT *improves* both job outcomes.
Barker et al. (1995)	*Journal of Organizational and End User Computing*	End user computing	Rockart and Flannery's taxonomy of end user computing activity	Job satisfaction	With sufficient computing activity levels, IT *increases* job satisfaction.
Kraut et al. (1989)	*Communications of the ACM*	Computerized records system for sales	Implementation event (pre-and post-event status)	Productivity and job satisfaction	Perceptions of work tasks *increase* job satisfaction and productivity.
Morris et al. (2002)	*Information Resources Management Journal*	Virtual team work	Frequency of use, duration of use, variety of applications used, and variety of tasks performed	Job satisfaction	Satisfaction with virtual team *increases* job satisfaction.
Morris & Venkatesh (2010)	*MIS Quarterly*	Enterprise systems (shakedown phase)	Implementation event (pre- and post-event status)	Job satisfaction	IT alters the effects of job characteristics (e.g., autonomy) such that they *decrease* job satisfaction.
Venkatesh et al. (2010)	*Production and Operations Management*	IT to support service processes in a bank	Implementation event (locations with/without IT systems)	Job satisfaction and job performance	Through its influence on job characteristics and psychological states, IT *decreases* job performance and job satisfaction.
Zhang & Venkatesh (2017)	*MIS Quarterly*	Telecommunications company	Counts of the number of postings, searches, comments, and ratings	Job performance	Through online and offline social networks, IT *increases* job performance.

Such an observation is deeply rooted in two main leading paradigms: work motivation and action theories (e.g., Locke & Latham, 1990; Vallacher & Wegner, 1987). Work motivation theories emphasize a conception-matching process in which individuals map acts to ultimate goals—a key process that we expect will continue to evolve during the post-adoption phase. Action theories emphasize cognitive specification of particular actions and their link to goal achievement—a fundamental mechanism that we expect will shape the effects of IT use during the post-adoption phase.

If an employee is unable to cope with the environmental stresses that a new IT creates, the specific IT may not result in higher productivity (Bala & Venkatesh, 2016; Beaudry & Pinsonneault, 2005; Cummings, 1994). Further, we suggest that perceptions of usefulness and ease of use likely play a dual role in IT use contexts—in addition to their explanatory role as predictors of behavioral intention (and subsequent) use, they likely moderate the relationship between IT use and job performance. We expect this dynamic to be particularly active in the post-adoption phase, as employees gain and develop experiences that will continue to shape their IT perceptions over time (Venkatesh & Bala, 2008). These IT-related contingencies will likely buffer the positive effects of IT use on job performance.

Synthesizing decades of research on IT adoption and use, Venkatesh and Bala (2008) presented an extension of TAM linking four different types of determinants to IT adoption. As depicted in Figure 1, we extend this framework to the post-adoption phase by (1) linking job outcomes—i.e., job satisfaction and job performance—to IT use, (2) redefining the role of the classical TAM predictors as IT-related contingencies over time, and (3) theorizing technology-job fit as a key moderator of IT use and the job outcomes relationship. Our research model is theoretically consistent with prior research that has examined the relationship between IT use and job outcomes (e.g., Bala & Bhagwatwar, 2018; Sykes, 2015, 2020; Sykes & Venkatesh, 2017; Venkatesh et al., 2010). Our model is also broadly consistent with recent discourse that has emphasized the need to study contextual and temporal factors, as well as outcomes of IT use such as job outcomes (Blut et al., 2022; Venkatesh et al., 2016).

3 Theory Development

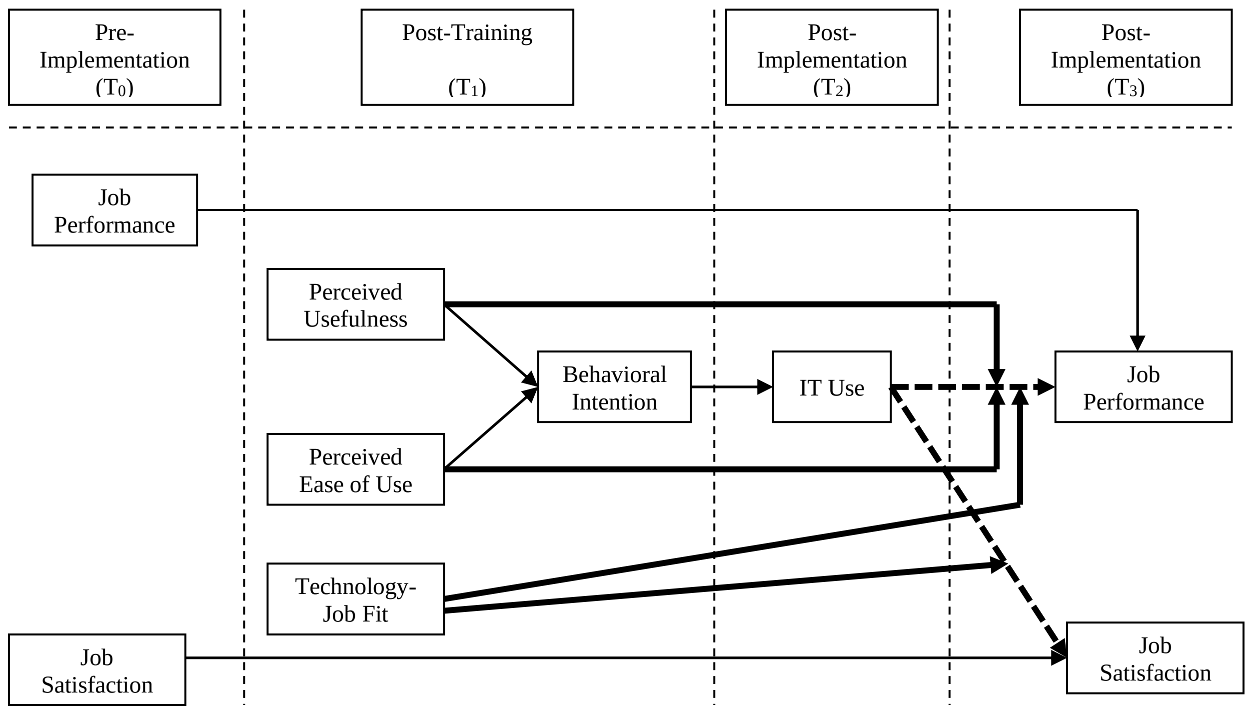
The main argument underlying our extended, dynamic model of job outcomes (Figure 1) is that as employees interact with an IT during the post-adoption phase, their continued assessment of the IT's usefulness, ease of use, and fit with their job will shape the effects of IT use on job outcomes over time. Specifically, a mental assessment of the match between the IT and anticipated consequences in terms of job outcomes extends from the pre-adoption phase (Venkatesh & Davis, 2000) to the post-adoption phase. In the following sections, we elaborate on our expectation that after controlling for pre-implementation job performance and job satisfaction, IT use will influence post-implementation job performance and job satisfaction and that this relationship will be moderated by technology contingencies.

3.1 Effects of IT Use on Job Performance

Building on and consistent with prior research on the effects of IT use and job performance (e.g., Ahearne et al., 2008; Sykes & Venkatesh, 2017; Zhang & Venkatesh, 2017), we theorize that *efficiency* will emerge as a mechanism that explains the effects of IT use on job performance over time. Although the main assumption is that IT offers several underlying capabilities that transform work and ultimately enhance job performance, dynamic work settings introduce conditions that warrant attention to efficiency. Efficiency is a key aspect of job performance (Beal et al., 2003; Campbell et al., 1992). IT use can help employees become more efficient in their job—i.e., through the ability to meet pre-defined task goals or emerging business needs with the least amount of input. Organizations implement IT to support and/or automate business processes (Bala & Venkatesh, 2013; Boudreau & Robey, 2005; Davenport, 2000; Davenport et al., 1996). By definition, business processes have a defined objective (Davenport, 2000) that is achieved with the help of an IT. IT use can help employees perform tasks in an efficient manner and achieve process objectives. Efficiency can be gained in terms of time required to perform a task so that more tasks can be performed in less time using fewer resources—i.e., through easy access to data needed to perform a task. For example, an employee who takes and processes customer orders can handle more orders in a shorter period of time using an IT-based order management system than by processing orders manually. The system provides timely and accurate information about the price of a product, inventory level, and shipping details and can thereby help the employee become more efficient.

H1a: IT use has a positive effect on job performance.

Work motivation theories (e.g., Locke & Latham, 1990), a leading paradigm in IT adoption and use research, suggest that employees develop beliefs about whether a specific IT can add value or reduce costs in terms of the work activity processes in place (Venkatesh & Davis, 2000; Venkatesh et al., 2003). We argue that, in dynamic work settings where employees interact and engage with clients over time, such beliefs emerge as an influential factor that shapes the effects of IT use on job performance. Further, the role of beliefs about IT value extend beyond the initial phases of IT adoption and use. As they attempt to address client needs and engage with them, we argue that employees will continue to map IT use to job performance over time—i.e., a particular act toward an ultimate outcome within their emerging mental assessment. The notion of perceived usefulness from TAM and the similar "relative advantage" construct from the innovation diffusion literature emphasizes the explicit relationship between perceived added value and use (Venkatesh et al., 2003). Thus, we expect that the effect of continued use of an IT is amplified if individuals perceive that the IT adds value to their work processes by enhancing their efficiency. Given the consistent effects of perceived usefulness as a driver of continued IT use (Davis et al., 1989; Venkatesh et al., 2003, 2008), it is likely that employees will realize benefits from sustained use of an IT only if usefulness expectations are actually met, ultimately allowing job performance benefits to accrue.



Note: The same structural model is used to predict T_4 job performance and job satisfaction.

New relationships; not theorized and tested in prior research

Existing relationships; additional theoretical mechanisms presented

Figure 1. Research Model

In other words, if individuals continue to perceive an IT to be useful (e.g., that using the IT will provide an opportunity to enhance efficiency in the workplace), they will be in a good position to materialize and/or maximize their efficiency through IT use—i.e., benefits maximization (Bala & Venkatesh, 2016; Beaudry & Pinsonnault, 2005). Therefore, we predict that IT use has a stronger effect on job performance under conditions of higher perceived usefulness.

H1b: The effect of IT use on job performance is moderated by perceived usefulness such that the effect is stronger when IT is perceived to be more useful.

If an IT is perceived to be easy to use, employees do not have to worry about the procedural knowledge that is required to use the IT (Davis et al., 1989; Venkatesh, 2000; Venkatesh et al., 2003). Employees can use the IT effortlessly and be mindful of its capabilities, which can help improve their job performance (Davis et al., 1989). For example, enterprise systems are generally difficult to learn and use (Bala & Venkatesh, 2013). Even with increasing experience with these systems, employees still must spend much time executing the rigid sequence of acts needed to accomplish their work processes (Bala & Venkatesh, 2013; Boudreau & Robey, 2005). The complexity of these systems induces a substantial cognitive burden on employees, which may affect their ability to perform their tasks efficiently. In contrast, if an IT is easy to use, employees' experiences will involve less distraction and effort (they will not have to seek help and support), and they can instead explore various features to find potential applications in work processes, thus leading to enhanced job performance (Bala & Venkatesh, 2016; Robert & Sykes, 2017; Venkatesh, 2000). Hence, we anticipate that IT use leads to greater job performance under conditions of higher perceived ease of use.

H1c: The effect of IT use on job performance is moderated by perceived ease of use such that the effect is stronger when IT is perceived to be easier to use.

3.2 Effects of IT Use on Job Satisfaction

Job satisfaction is an important affective reaction of employees toward their job and work environment. It is the degree to which an individual's professional job-related needs are met by their current job (Judge et al., 2017; O'Reilly & Caldwell, 1981; O'Reilly & Chatman, 1986). The relationship between IT use and job satisfaction has been theorized and tested in prior research (e.g., Bala & Venkatesh, 2016, Stich et al., 2019, Venkatesh et al., 2010; Zhang & Venkatesh, 2017). We offer two mechanisms that were not explicitly used in prior research to justify this relationship: *job enrichment* and *job transformation*. Job enrichment is a vertical expansion of jobs that increases the degree to which employees control the planning, execution, and evaluation of their work (Robbins, 1996). IT has the potential to enrich various facets of an employee's job, such as task identity, skill variety, autonomy, and task significance (Campion et al., 2005; Hackman & Oldham, 1975, 1980; Morris & Venkatesh, 2010; Venkatesh et al., 2010). Job transformation is the degree to which employees believe that aspects of their job have been altered by organizational change—e.g., an IT implementation (Griffin, 1991). The implementation of an IT can potentially transform mundane work processes and tasks into robust, efficient, and interesting sets of activities, thereby enriching and transforming the nature of work performed by employees (Morris & Venkatesh, 2010; Venkatesh et al., 2010). For instance, sales support applications could offer capabilities beyond keeping track of sales, sending emails, and setting appointments/reminders, as sales personnel can use them to create and deliver professional and engaging sales experiences for their clients. Prior research has suggested that one of the reasons for low job satisfaction is the mundane nature of the job and low task variety (Fried & Ferris, 1987; Hackman & Oldham, 1980; Lee & Mowday, 1987). A new IT can boost work-related intrinsic motivation by enhancing and transforming an employee's job, which would in turn improve outcomes such as job satisfaction (e.g., Ke et al., 2013; Morris & Venkatesh, 2010; Venkatesh et al., 2010).

H2: IT use has a positive effect on job satisfaction.

3.3 The Moderating Role of Technology-Job Fit

IT use may not have a long-lasting impact on an employee's job if the IT is not relevant to the employee's job and does not fit with emerging requirements to complete job goals and underlying tasks. Action theories, another leading paradigm in IT adoption and use research, emphasize the importance of mental representations linking instrumental behaviors to higher-level goals. As suggested by action theories (e.g., Vallacher & Wegner, 1987), employees continuously assess the match between the cognitive specification of particular actions or behaviors, including IT use and achievement of job tasks in their work setting. In the post-adoption stage, we suggest that *technology-job fit*—i.e., the degree to which an IT helps employees accomplish their portfolio of tasks—is an important moderator in the relationship between IT use and job outcomes. Technology-job fit is conceptually different from perceived usefulness in that it does not incorporate the notion of performance improvement due to the use of an IT. In other words, high technology-job fit does not automatically suggest that an IT will enhance employees' job performance. Technology-job fit is conceptually similar to the notion of task-technology fit (TTF) Goodhue & Thompson, 1995) and compatibility (see Venkatesh et al., 2003). Although the importance of task-technology fit has been underscored in prior IT implementation research, to the best of our knowledge, this is one of the first studies suggesting that task-technology fit can emerge as a moderator of the effect of IT use on job outcomes.

We argue that technology-job fit strengthens the positive relationship between IT use and job performance in two ways. First, perceptions of technology-job fit require a greater understanding of how features and capabilities of an IT can help employees perform their tasks—i.e., through the mental representation of relevant actions. Employees are more likely to explore and exploit these features to enhance their job performance (Bala & Venkatesh, 2016). With experience over time, employees continue to engage in a mental assessment of features in relation to task goals (Venkatesh & Davis, 2000). Hence, relative to employees who develop low awareness or perceptions of technology-job, fit, employees with high technology-job fit will experience greater improvement in job performance. Second, employees who believe that an IT fits with their jobs will be intrinsically and extrinsically motivated to deploy their emerging IT use experiences in accomplishing tasks. We argue that such employees will perceive that the IT is relevant to their job and that the use of IT can help them improve their job performance. Hence, they will place more importance on IT use as a means of achieving better job performance when technology-job fit is high.

H3a: The effect of IT use on job performance is moderated by technology-job fit such that the effect is stronger when technology-job fit is higher.

We theorize in H2 that IT use leads to greater job satisfaction by enriching and transforming jobs. We maintain that technology-job fit strengthens this relationship by helping employees understand how the features and capabilities of an IT enhance and transform various facets of their jobs. For example, if an employee perceives that an IT does not fit with their needs in terms of data and functionalities, it is unlikely that the employee will find that the IT enriches their job and the employee will likely experience negative affect or, even worse, stress (Bala & Venkatesh, 2016). In contrast, greater knowledge of an IT's capability to influence various facets of a job will motivate employees to seize opportunities in their IT use experiences in many different ways (Jasperson et al., 2005) to accomplish tasks. The strong potential to accomplish tasks using an IT will result in employees developing positive emotional responses to their job from an appraisal of the job as fulfilling or congruent with their values and expectations. As a result, employees will be more satisfied with their jobs as they use IT in the presence of high technology-job fit.

H3b: The effect of IT use on job satisfaction is moderated by technology-job fit such that the effect is stronger when technology-job fit is higher.

4 Method

We conducted a longitudinal field study at an organization implementing a new IT (see Section 4.2 for more details of the new IT). The longitudinal design helped us understand the impact of IT use on job outcomes over time and limit common method bias. In this section, we discuss the context of the study, participants, measures, and the data collection procedure.

4.1 Organization and Participants

We collected data from field sales personnel of a financial services firm in the U.S. The firm employed nearly 2,800 employees, with 366 being field sales personnel who were introduced to a new IT. Of these 366 field sales personnel, 13 employees were excluded because of their close involvement with the entire design and development process and 20 employees exercised their right to not participate in the study—i.e., they did not participate from the start of the study or withdrew from the study even though they continued to work at the participating organization. Additionally, three employees were terminated by the firm and were excluded from the study. Of the 330 individuals, 295 were still employed at the organization at the end of the two-year duration of the study. The participants had an average organizational tenure of 3.50 years, with a standard deviation of 1.2. The average age of the participants was 33.60, with a standard deviation of 6.10. Of the 295 participants, 81 were women (27.50%). The participants were responsible for selling various investment packages, including mutual funds and retirement plans, to employees in various client organizations.

Given the longitudinal nature of the study, it is important to document and describe significant organizational changes that overlapped with the adoption, implementation, and post-training time frame encompassing this study. The implementation of the IT was the primary initiative in the organization during our study period. Like other service industry counterparts, this organization was focused on customer-facing initiatives that would increase the value of its services to customers. No significant changes were made to the composition of the sales force, barring voluntary turnover and terminations. Finally, the compensation or incentive structures were not changed because of or independent of the IT implementation.

4.2 New IT

The new IT implemented was a sales suite software solution intended to support the sales process. Field sales personnel were equipped with a laptop and a software suite that helped provide information about the various products and services (e.g., investment packages, including mutual funds and retirement plans). Also included in the software suite was the ability to compare the client's portfolio and its performance with standard indicators (e.g., S&P 500) and other hypothetical portfolios. The software suite was developed in-house with the assistance of a consulting company. The requirements definition phase included interviews with key stakeholders and field sales personnel—i.e., potential users. Some field sales personnel also served on the design team that followed a joint application development (JAD) methodology. Storyboards and screen designs were developed and user feedback was solicited. This was followed by the development of a prototype, which was also tested among 10 field service personnel. The entire development process took approximately seven months followed by a month-long pilot among the same 10 field sales personnel who participated in the early phases of design and development. As noted earlier, none of the participants in any of the stages of the design process were actually included in our final sample. The IT was managed by the firm's IT team of 40 employees.

4.3 Measurement

We used validated scales from prior IS and OB research to measure the various perceptual constructs. The TAM constructs of perceived usefulness and perceived ease of use were measured using items adapted from Davis et al. (1989)—these scales have been extensively applied to measure user perceptions of various systems (see Maruping et al., 2017; Venkatesh et al., 2003, 2011). Technology-job fit was measured using the scale adapted from Thompson et al. (1991). The original scale measured PC-job (personal computer-job) fit, which emphasizes quality of output, time for completing tasks, and effectiveness. We adapted the scale to replace PC with the specific IT. Job satisfaction was measured using the scale adapted from O'Reilly and Caldwell (1981) and Venkatesh et al. (2010). The objective outcomes—actual system use and sales performance—were measured using archival data provided by the organization. Use was measured by system logs of actual duration of use (e.g., Ahearne et al., 2008; Morris & Venkatesh, 2000; Venkatesh & Morris, 2000; Venkatesh et al., 2008, 2000)—idle times greater than five minutes were also logged so that they could be excluded in determining active use.

This approach of eliminating idle time ensured that the measurement of use was not just the duration that the user was logged into the system but rather the time of active use. Consistent with previous research measuring actual use, we took the average time over a given period (Ahearne et al., 2008; Collopy, 1996; Venkatesh & Morris, 2000). Given that our context involved field sales, we operationalized performance based on the number of products/services/clients using archival records. Guided by Benitez et al. (2020), we also classified job performance as a composite-formative construct given that it is an emergent construct in a particular organizational context (i.e., managers "think" that this is the best way to measure performance in the sales domain) rather than a behavior. Hence, we extracted three formative indicators from that context: number of new clients, number of programs (e.g., 401K, IRA) invested in, and amount invested. For instance, a larger number of new clients, number of programs, and amount invested indicate higher performance. These were the typical indicators of salesperson performance assessment at the participating firm and were therefore representative performance metrics for our purpose.

Table 2 presents the various scales used and the results related to the measurement model. Consistent with recent studies that develop models with formative and reflective constructs, we assessed loadings for scales with reflective indicators and weights for the scale using formative indicators (e.g., Sun et al., 2019; Sykes, 2020). For scales with reflective indicators, the internal consistency reliability (ICR) was greater than 0.800. Also, all loadings were greater than 0.700 and cross-loadings were lower than 0.300, thus supporting convergent and discriminant validity. We also generated the standardized root mean squared residual (SRMR) to assess the fit between the proposed measurement model and the data. The SRMR value for our specified model was 0.068—indicating good model fit (Benitez et al., 2020)

Table 2. Measures and Measurement Model Results

Constructs	**Loadings (reflective) / weights (formative)**				
	T_0	**T_1**	**T_2**	**T_3**	**T_4**
Perceived ease of use (reflective)	**-**	**.838**	**.851**	**-**	**-**
Interacting with the system does not require a lot of my mental effort.	-	.814	.823	-	-
My interaction with the system is clear and understandable.	-	.879	.853	-	-
I find the system to be easy to use.	-	.828	.872	-	-
I find it easy to get the system to do what I want it to do.	-	.837	.812	-	-
Perceived usefulness (reflective)	**-**	**.833**	**.823**	**-**	**-**
Using the system enables me to accomplish tasks more quickly.	-	.814	.798	-	-
Using the system enhances my effectiveness on the job.	-	.816	.820	-	-
Using the system makes it easier to do my job.	-	.872	.853	-	-
Behavioral intention to use an IT (reflective)	**-**	**.880**	**.852**	**-**	**-**
Assuming I had access to the system, I intend to use it.	-	.842	.837	-	-
Given that I had access to the system, I predict that I would use it.	-	.803	.822	-	-
I plan to use the system in the next <n> months.	-	.881	.861	-	-
IT use (single indicator)	**-**	**-**	**NA**	**NA**	**NA**
Archival data from system logs.	-	-	NA	NA	NA
Technology-job fit (reflective)	**-**	**.707**	**.743**	**-**	**-**
The system can increase the quantity of output for the same amount of effort	-	.742	.751	-	-
Using the system has no effect on the performance of my job.	-	.733	.775	-	-
Using the system decreases the time needed for my important job responsibilities.	-	.714	.802	-	-
Using the system significantly increases the quality of output of my job.	-	.741	.751	-	-
Using the system increases the effectiveness of performing job tasks.	-	.704	.788	-	-
Job satisfaction (reflective)	**.813**	-	-	**.773**	**.791**
Overall, I am satisfied with my job.	.787	-	-	.741	.848
I would prefer another, more ideal job. (reverse-scored)	.802	-	-	.824	.773
I am satisfied with the important aspects of my job.	.881	-	-	.750	.733
Job performance (formative)	NA	-	-	NA	NA
Number of new clients.	.532	-	-	.503	.441
Number of programs (e.g., 401K, IRA, etc.) invested in.	.523	-	-	.514	.462
Amount invested.	.469	-	-	.413	.403

Note: Bolded numbers are internal consistency reliabilities (ICR); NA: not applicable. For constructs with reflective indicators, regular typeface numbers are item loadings (all cross-loadings were less than 0.340). Loadings and weights are significant with $p < 0.001$.

4.4 Procedure

The study was conducted over a 24-month period in a naturally occurring field setting of the IT implementation in the organization. We collected data at five points in time over the 24-month period using survey and archival records (see Figure 2). Interviews with management and employees were conducted to better understand the strategic vision and goals of the firm, the role of IT in meeting these goals, and the processes and procedures used when implementing the new IT. Specific to the IT implementation, prior to the design and development of the software suite, the organization held focus groups with all salespeople to determine their needs. We followed a careful selection process in engaging the consulting company to design and build the software suite. As noted earlier, 20 field sales personnel remained involved during various phases of the design and development process. Top management expected that the IT would help create competitive advantage for the organization, enhance the ability of salespeople to respond to clients' questions during sales sessions, and reduce callbacks and other forms of costly follow-up interactions. It was believed that such prompt responses would help close sales at the time of the meeting. Top management members, both within and outside the sales hierarchy, were strong proponents of the system and its use was strongly encouraged although not mandatory for the first two years, which included our study period.

All salespeople participated in a mandatory five-day training program that had a dual emphasis. Salespeople were acclimated to the new IT and were provided with hands-on experience to get comfortable with the IT. The trainers focused on what the firm and sales management perceived to be appropriate use of the tools across a range of different customer interactions. Several examples in the form of use cases were employed to emphasize the applicability of the IT to various client situations. The participants also had an opportunity to learn via actual situations (cases) described when they used the tool during training to provide potential solutions for the situations presented. Given the number of field sales personnel, the training was conducted over a 10-week period with each training group being restricted to about 35 employees. A short survey was administered before the training (T_0) to capture baseline data. Each respondent's survey used a unique identifier (barcode) to facilitate the tracking of responses over time and to administer follow-up surveys at the appropriate time.

Immediately after the five-day training (T_1), participants completed a survey on their perceptions of the IT characteristics—i.e., perceived usefulness, perceived ease of use, behavioral intention, and technology-job fit. We again collected data about these variables six months after T_1. In addition to IT characteristics, we obtained archival objective IT use data over the preceding six months. We used the IT characteristics data from T_1 to predict IT use, measured between T_1 and T_2.

Six months after T_2 (12 months post-implementation), we collected data on employees' job performance and job satisfaction (T_3). Perceptions measured at T_0, T_1, and T_2 could, therefore, be used to predict post-implementation outcomes without serious concerns about common method bias. We also collected IT use data to predict job performance and job satisfaction at T_4 (12 months after T_3) We conducted a short survey at T_4 to collect data about job performance and job satisfaction. We used predictors from T_2 and T_3 again to predict job outcomes measured at T_4.

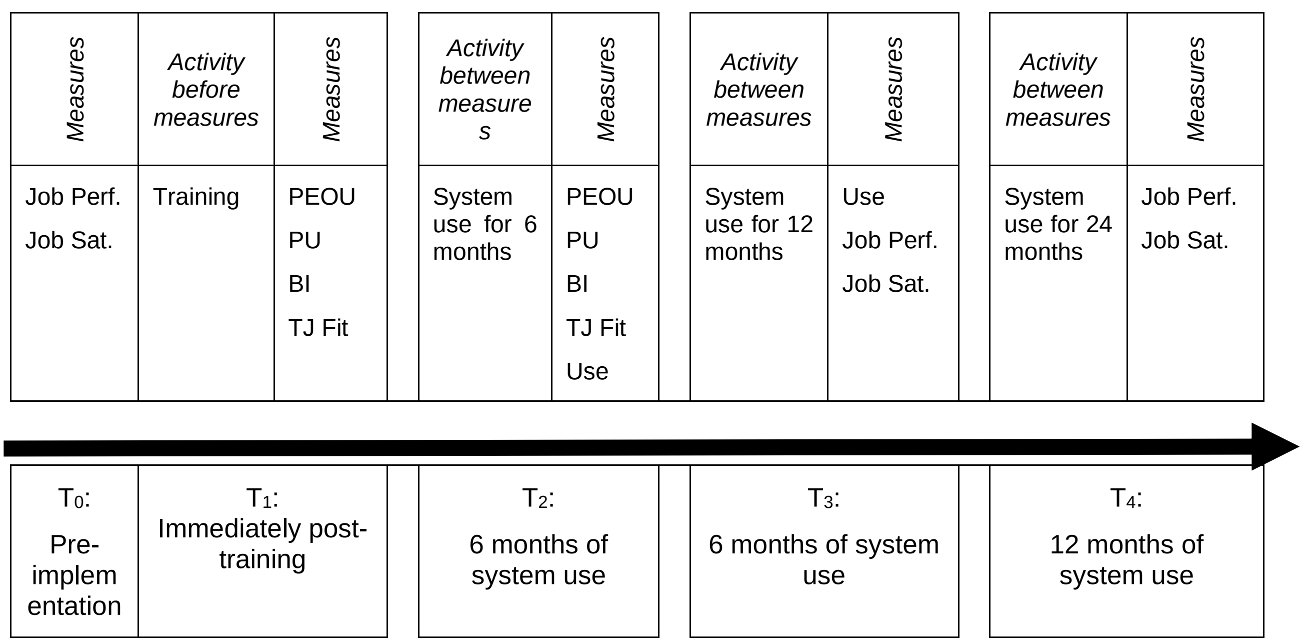


Figure 2. Summary of Study Design with Points of Measurement

5 Results

We used partial least squares (PLS) to analyze the data following the guidelines for PLS analysis and several exemplars in IS research (Bala & Venkatesh, 2016; Hair et al., 2017; Lowry & Gaskin, 2014). In particular, we used SmartPLS v.3 (Ringle et al., 2015). IT use and job performance were modeled using formative indicators, and other constructs were modeled using reflective indicators. PLS is particularly known for its ability to handle both formative and reflective constructs in the same structural model. We used the measurement model to examine the reliability and validity of the various scales. Table 3 reports the descriptive statistics, average variance extracted (AVE), and correlations.

The descriptive statistics suggest that the mean values for behavioral intention and job performance dropped slightly at T_2 and T_3, respectively. All AVEs, where applicable, were greater than the interconstruct correlations, thus supporting discriminant validity. We further assessed discriminant validity using the heterotrait-monotrait (HTMT) ratio test for the reflective predictors. To pass this test, the HTMT ratio must be less than 1 (Henseler et al., 2015). Table 4 reports HTMT ratios at both points in time. The HTMT ratio between each pair of constructs at T_1 and T_2 is less than 1. Cumulatively, this provided further support for convergent and discriminant validity.

The correlation matrix revealed a mix of expected and unexpected outcomes. The TAM correlations were consistent with prior research, with the perceived usefulness-use correlation being the highest of the three correlations. The job outcomes—i.e., job performance and job satisfaction—were correlated in the direction expected. In examining the correlations across the TAM constructs and job outcomes, there was one surprising correlation—IT use was negatively correlated with job satisfaction.

5.1 Explaining the TAM Relationships

Consistent with much prior research (see Venkatesh et al., 2003), we found that perceived usefulness and perceived ease of use were significant predictors of behavioral intention with perceived usefulness being the stronger predictor (see Table 5). These two variables explained 28.2% to 30.1% of the variance in behavioral intention. Behavioral intention was a significant predictor of IT use and explained 25.2% to 31.4% of the variance in IT use. Thus, the original TAM relationships were supported in our study.

5.2 Explaining Job Outcomes

We estimated three different models to test hypotheses related to job performance and job satisfaction. The first model provided a baseline examining the effects of pre-implementation job performance and job satisfaction. The second model built on the first model and included IT use. The third model examined the additional predictive power associated with our hypotheses. Given that we specified job performance as a composite-formative construct, we estimated the structural model using PLS-PM Mode B (see Table 6). Regarding job satisfaction, a reflective construct, we reestimated the structural model using the consistent PLS estimator or PLSc (see Table 7). Both tables report quality criteria to assess model fit using SRMR values. The lower the values the better the fit between the proposed model and the data (Benitez et al., 2020). For example, SRMR values should be below 0.080. Model fit criteria, shown in Table 6, indicate that SRMR values for the models predicting job performance were below the 95% and 99% quantiles of the corresponding reference distribution—suggesting good model fit (Benitez et al., 2020). SRMR values for the models predicting job satisfaction were below the 95% and 99% quantiles of the corresponding reference distribution (Table 7)—suggesting good model fit.

Although prior job performance was shown to be indeed predictive of future job performance, the R^2 was only 13.4% when examining job performance in the year immediately after the implementation (T_3). IT use and prior job performance together improved the prediction to an R^2 of 21.5%. The most interesting and predictive model was the full model—i.e., Model 3. Here, although prior job performance was still significant, IT use interacted with both perceived usefulness and perceived ease of use to have a positive effect on job performance at T_3. IT use also interacted with technology-job fit to influence job performance. The interaction effects revealed interesting patterns, as they highlighted that IT use contributed to job performance best when technology-job fit, perceived usefulness, and perceived ease of use were high (see Figures 3a, 4a, and 5a for an interaction plot for perceived usefulness, perceived ease of use, and technology-job fit, respectively). The pattern was similar for the 2nd year post-implementation (T_4)—as the employees became more familiar with the IT solution, the effect of the previous year's job performance on 2nd year post-implementation job performance (T_4) became stronger. The interaction effects were similar to T_3 for perceived usefulness and perceived ease of use (marginally weaker). Further, the interaction effect of technology-job fit and IT use on job performance at T_4 was stronger (than the T_3 effect) highlighting that IT use contributed to job performance best when technology-job fit, perceived usefulness, and perceived ease of use were high (see Figures 3b, 4b, and 5b). Overall, the results indicated strong support for H1a, H1b, H1c, and H3a. Further, the SRMR value was below 0.080—indicating good model fit (Benitez et al., 2020). Although our model specification addresses temporal precedence by measuring the variables at multiple points in time, there may be potential endogeneity among the dependent variables. Hence, we respecified the model by including a direct path from job satisfaction to job performance.

Table 3. AVEs, Descriptive Statistics, and Correlations

	Constructs	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	$PEOU_{T1}$	3.813	1.172	712															
2	PU_{T1}	4.221	1.234	.352***	.821														
3	BI_{T1}	4.910	1.712	.231***	.291***	.852													
4	Use_{T1-T2}	11.864	3.940	.333***	.572***	.497***	-												
5	TJ Fit_{T1}	3.848	1.414	.142*	.191**	.143*	.172**	.713											
6	Job $Perf._{T0}$	5.081	1.603	.194**	.256***	.103	.383***	.102	-										
7	Job $Sat._{T0}$	5.614	1.388	.073	.168**	.294***	.393***	.075	.261***	.732									
8	$PEOU_{T2}$	3.992	1.062	.213***	.142*	.292***	.151*	.313***	.082	.098	.860								
9	PU_{T2}	4.302	1.265	.192**	.402***	.202**	.290***	.152*	.192**	.142*	.242***	.843							
10	BI_{T2}	4.873	1.788	.163*	.353***	.342***	.353***	.162**	.141*	.182**	.197**	.344***	.834						
11	Use_{T2-T3}	14.008	4.603	.101	.362***	.311***	.362***	.083	.166**	.141*	.173**	.313***	.562***	.845					
12	TJ Fit_{T2}	4.062	1.348	.143*	.174**	.140*	.133*	.102	.158*	.192**	.132*	.093	.173**	.133*	.724				
13	Job $Perf._{T3}$	4.813	1.889	.244***	.342***	.194**	.444***	.173**	.193**	.132*	.092	.169**	.141*	.294***	.103	-			
14	Job $Sat._{T3}$	4.584	1.063	.238***	.310***	.213***	-.413***	.194**	.212***	.142*	.102	.201**	.195**	-.273***	.142*	.314***	.742		
15	Job $Perf._{T4}$	5.100	1.701	.097	.293***	.242***	.192**	.143*	.243***	.122*	.143*	.168**	.214***	.213***	.153*	.343***	.291***	-	
16	Job $Sat._{T4}$	4.801	1.014	.072	.277***	.213***	-.213***	.132*	.267***	.163**	.132*	.231***	.192**	-.262***	.083	.213***	.283***	.458***	.801

Note: PEOU: perceived ease of use; PU: perceived usefulness; BI: behavioral intention; Use: IT use; TJ Fit: technology-job fit; Job Perf.: job performance; Job Sat.: job satisfaction. In the columns with a number as a header, the diagonal elements are AVEs and off-diagonal elements are correlations. IT use mean and standard deviation are based on average weekly use. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$; NA: not applicable.

Table 4. HTMT Ratios for the Reflective Predictors

Time	T_1			T_2		
Constructs	**PEOU**	**PU**	**BI**	**PEOU**	**PU**	**BI**
PU	.313			.363		
BI	.364	.532		.338	.555	
TJ Fit	.330	.393	.548	.331	.374	.572

Note: PEOU: perceived ease of use; PU: perceived usefulness; BI: behavioral intention; TJ Fit: technology-job fit.

Table 5. PLS Results for TAM

	Behavioral intention (T_1)		**Behavioral intention (T_2)**
R^2	.282	R^2	.301
PU_{T1}	.413***	PU_{T2}	.484***
$PEOU_{T1}$	.242***	$PEOU_{T2}$	.173**
	IT use (T_1-T_2)		**IT use (T_2-T_3)**
R^2	.252	R^2	.314
BI_{T1}	.503***	BI_{T2}	.557***

Note: PEOU: perceived ease of use; PU: perceived usefulness; BI: behavioral intention.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 6. PLS-PM Results for Job Performance

	Job performance (T_3)				**Job performance (T_4)**		
	Model 1	**Model 2**	**Model 3**		**Model 1**	**Model 2**	**Model 3**
R^2	.134	.215	.507	R^2	.260	.305	.525
Job $Perf._{T0}$	.360***	.291***	.195**	Job $Perf._{T3}$	.511***	.443***	.366***
Use_{T1-T2}		.301***	.075	Use_{T2-T3}		.147*	.073
PU_{T1}			.151*	PU_{T2}			.095
$PEOU_{T1}$			.087	$PEOU_{T2}$			.023
TJ Fit_{T1}			.027	TJ Fit_{T2}			.183**
Use_{T1-T2} x PU_{T1}			.327***	Use_{T2-T3} x PU_{T2}			.194**
Use $_{T1-T2}$ x $PEOU_{T1}$			.193**	Use $_{T2-T3}$ x $PEOU_{T2}$			.132*
Use $_{T1-T2}$ x TJ Fit_{T1}			.140*	Use $_{T2-T3}$ x TJ Fit_{T2}			.187**
PU_{T1} x $PEOU_{T1}$			.051	PU_{T2} x $PEOU_{T2}$			.062
Model fit							
SRMR Value	.062	.057	.053	SRMR Value	.070	.066	.061
SRMR HI_{95}	.069	.059	.057	SRMR HI_{95}	.073	.068	.064
SRMR HI_{99}	.071	.061	.060	SRMR HI_{95}	.075	.070	.066

Note: PEOU: perceived ease of use; PU: perceived usefulness; Use: IT use; TJ Fit: technology-job fit; Job Perf.: job performance. $p < 0.05$; **$p < 0.01$; *** $p < 0.001$. SRMR: standardized root mean squared residual.

Table 7. PLSc Results for Job Satisfaction

	Job satisfaction (T_3)				**Job satisfaction (T_4)**		
	Model 1	**Model 2**	**Model 3**		**Model 1**	**Model 2**	**Model 3**
R^2	.159	.231	.433	R^2	.251	.322	.423
Job $Sat._{T0}$	.398***	.235***	.198***	Job $Sat._{T3}$	.501***	.333***	.265***
Use_{T1-T2}		-.321***	-.097	Use_{T2-T3}		-.221***	-.078
TJ Fit_{T1}			.146*	TJ Fit_{T2}			.190**
Use_{T1-T2} x TJ Fit_{T1}			.236***	Use_{T2-T3} x TJ Fit_{T2}			.169**
Model fit							
SRMR Value	.073	.070	.068	SRMR Value	.070	.066	.062
SRMR HI_{95}	.075	.072	.070	SRMR HI_{95}	.072	.069	.065
SRMR HI_{99}	.077	.075	.073	SRMR HI_{95}	.075	.071	.069

Note: Use: IT use; TJ Fit: technology-job fit; Job Sat.: job satisfaction. $p < 0.05$; **$p < 0.01$; *** $p < 0.001$. SRMR: standardized root mean squared residual. Complete model was reestimated with PLSc.

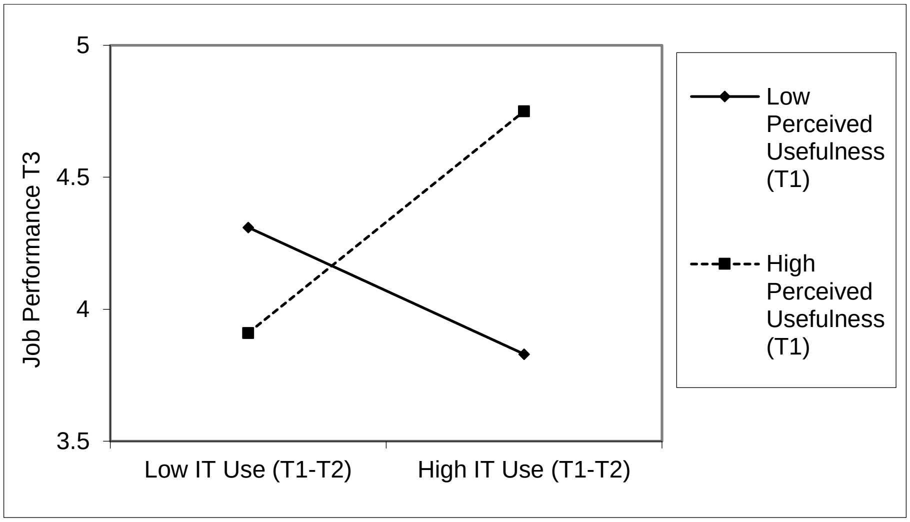


Figure 3a. Interaction of Perceived Usefulness T1 and IT Use T1-T2 on Job Performance T3

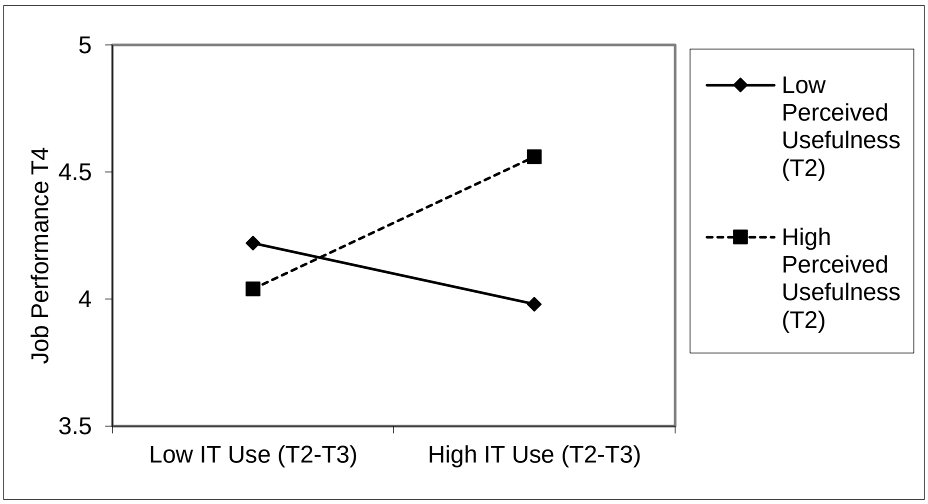


Figure 3b. Interaction of Perceived Usefulness T2 and IT Use T2-T3 on Job Performance T4

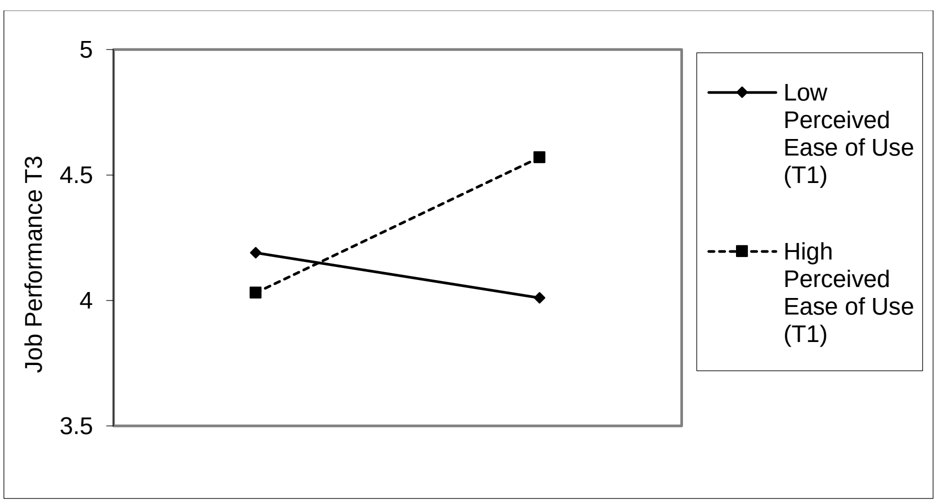


Figure 4a. Interaction of Perceived Ease of Use T1 and IT Use T1-T2 on Job Performance T3

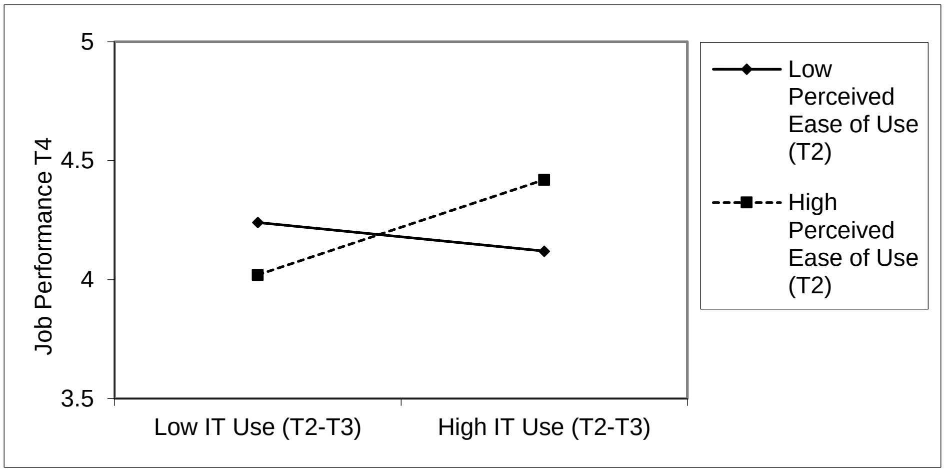


Figure 4b. Interaction of Perceived Ease of Use T2 and IT Use T2-T3 on Job Performance T4

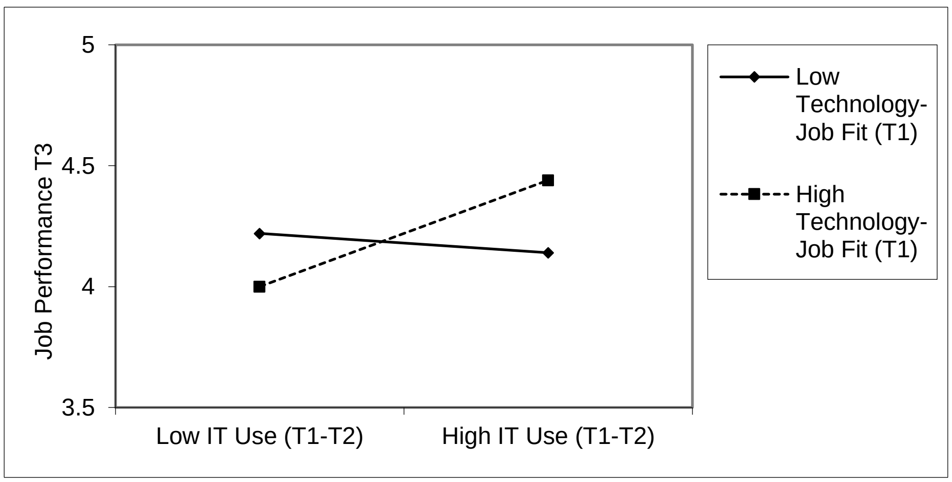


Figure 5a. Interaction of Technology-Job Fit T1 and IT Use T1-T2 on Job Performance T3

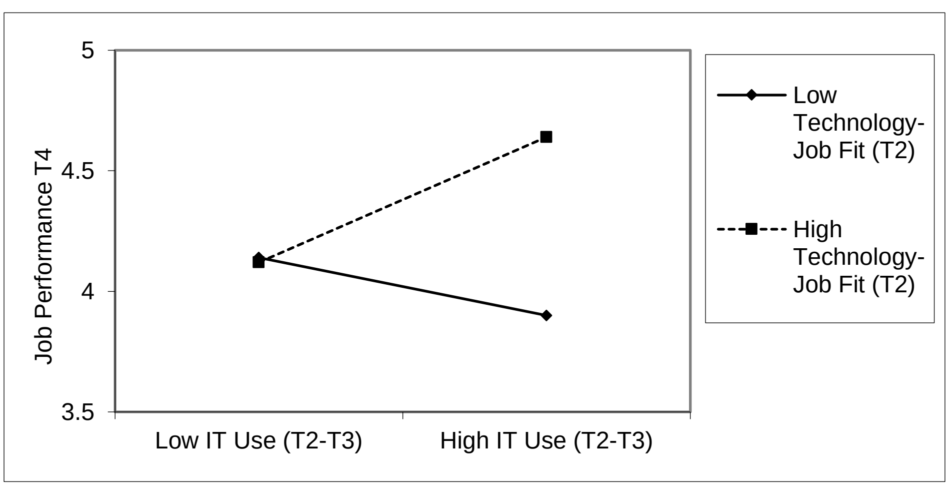


Figure 5b. Interaction of Technology-Job Fit T2 and IT Use T2-T3 on Job Performance T_4

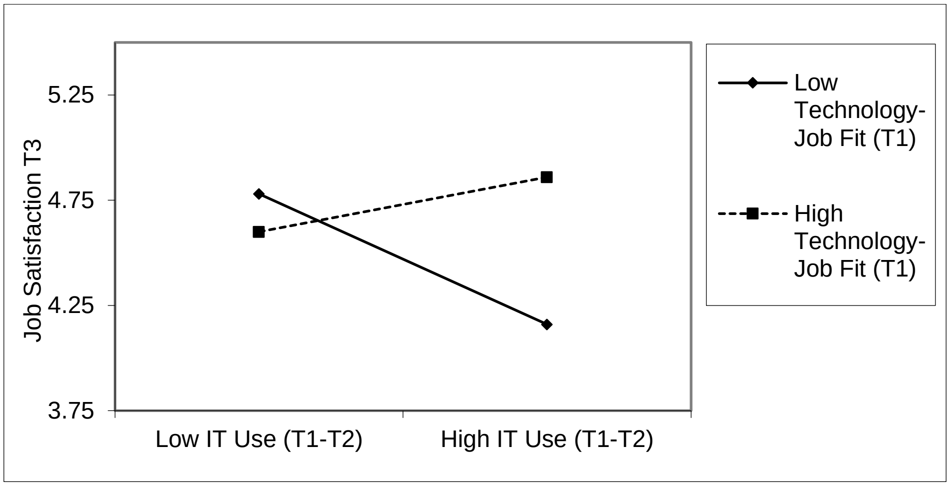


Figure 6a. Interaction of Technology-Job Fit T1 and IT Use T1-T2 on Job Satisfaction T_3

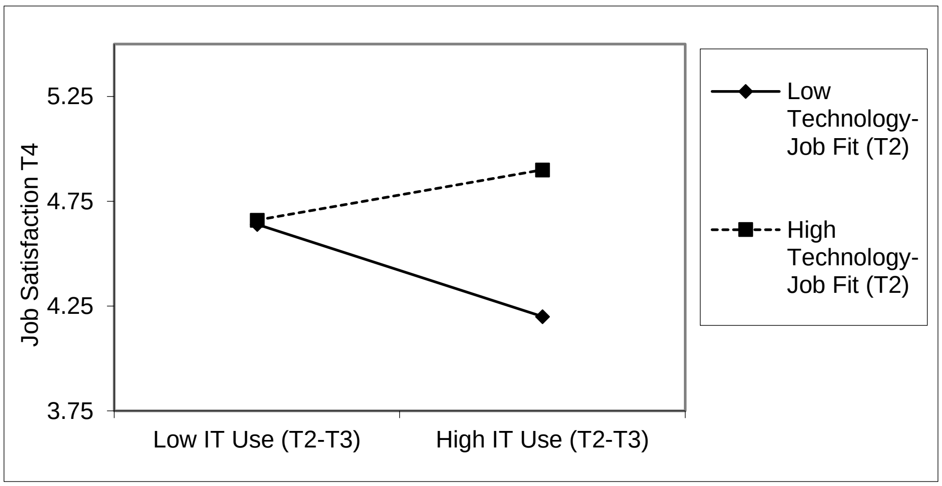


Figure 6b. Interaction of Technology-Job Fit T_2 and IT Use T_2-T_3 on Job Satisfaction T_4

The results indicate that job satisfaction did not predict job performance when IT use was included in the model (see Appendix A). Although job satisfaction had a weak effect on job performance in Model 1, controlling for this effect did not change the pattern of results. We also respecified the model with technology-job fit as a formative construct and found the results to be consistent (see Appendix B).

To better understand patterns underlying the significant moderation effects, we provide interaction plots in Figures 3 through 6. The findings related to the prediction of job satisfaction were particularly interesting. Although previous job satisfaction did influence post-implementation job satisfaction, the R^2 was only 15.9%. When IT use was added to the model, the variance explained increased to 23.1% but IT use had a negative effect. The full model with interactions revealed another interesting pattern. Once again, technology-job fit was a key moderator of the relationship between IT use and job satisfaction. The results indicate that, in the presence of high technology-job fit, IT use had a positive effect on job satisfaction (see Figure 6a). The pattern was similar for the 2nd year post-implementation—similar to job performance, as the employees became more familiar with the IT solution, the effect of the previous year's job satisfaction on 2nd year post-implementation job satisfaction was stronger (see Figure 6b). Model 3 explained 50.7% and 52.5% of the variance in the job satisfaction in T_3 and T_4, respectively. Overall, we found strong support for H2 and H3b.

6 Discussion and Conclusion

The increased emphasis on IT in work settings coupled with the lack of studies on contingencies that shape the effect of IT over time motivated the need for a dynamic model of IT use and job outcomes. We tested our model with longitudinal data over a two-year period in the context of a financial services organization implementing an IT to support field sales personnel. We found that, as employees interacted with the IT during the post-adoption phase, their continued assessment of the IT's usefulness, ease of use, and fit with their job shaped the effects of IT use on their job outcomes over time. The specific findings that relate IT use to job performance and job satisfaction are interesting and important. Although one of the relationships was in the predicted direction, the other was opposite to predictions—i.e., IT use to job satisfaction. This pattern could be partially explained by the possibility that employees may be stretched too thin. In other words, even when IT use improves performance, experienced negative affect could reduce job satisfaction over time. However, in the presence of high technology-job fit, IT use had a positive effect on job satisfaction. The reality that job performance dropped (albeit only a little) and job satisfaction dropped a lot after the IT implementation was tempered somewhat by the moderation effects that suggested that under the right conditions, positive job outcomes could result. Thus, the proposed nomological network of emerging relationships among the original IT adoption constructs and job outcomes was supported.

6.1 Theoretical Contributions

Our findings call for the next phase in the journey of IT adoption research in at least four ways. First, although IT adoption research itself is mature and is an important cornerstone of IS research, contributions to the scientific knowledge in IS in general and IT adoption in particular will *not* be made by simply testing widely cited adoption models (e.g., Davis et al., 1989; Venkatesh et al., 2003) but rather by unearthing new patterns or mechanisms over time (Venkatesh et al., 2016). This sentiment has been echoed in other, earlier works on TAM as well (see Bagozzi, 2007; Venkatesh et al., 2007). The major contribution of our nomological network is that it redefines the role of the classical predictors of IT adoption (i.e., perceived usefulness and perceived ease of use) with job outcomes over time, as employees continue to (1) assess the underlying capabilities of IT, and (2) experience better job outcomes, depending on their emerging perceptions of usefulness, ease of use, and technology-job fit. By going beyond the direct effects of IT use on job outcomes, we enrich the understanding of *when* IT use leads to better job outcomes. More broadly, our results provide a basis for testing and extending research framed from a sociotechnical perspective. The sociotechnical IS research stream (e.g., Mumford, 1983) emphasizes the importance of examining IT within the context in which it is embedded (Majchrzak, 1997; Orlikowski & Scott, 2008) to understand the effects of IT on job enhancement—e.g., competence enhancing or competence destroying (Mumford, 1983). The empirical links between IT use and both job performance and job satisfaction provide researchers using this framework with specific constructs and relationships to further "peel back the onion" in order to understand the effects of IT on employees.

Second, our work suggests an avenue that resolves inconclusive evidence of post-adoption consequences of IT use by (1) highlighting the role of IT-related contingencies that buffer the effect of IT use on job outcomes, and (2) using objective and subjective outcomes over time.

The longitudinal nature of our study is helpful to understanding not only the results of the "shock" of the IT implementation process but also the somewhat longer-term impact of putting a new IT in place. Further, presenting an extended nomological network that includes both system-related and job-related constructs enriches the understanding of the impact of a new IT implementation on individuals in organizations. Our focus on job performance in terms of objective sales is also relevant to the impact of IT on organizations, as it represents a key outcome for assessing IT value in organizations. In addition, objective metrics of job performance add robustness to the validity of our findings.

Third, even though the IT use-job performance relationship was positive, the negative relationship between IT use and job satisfaction sheds light on a dilemma that employees and employing organizations continue to face over time. Individuals may derive performance gains from IT use but such gains may be offset by possible deskilling, routinizing of the job, or negative affect from being stretched too thin (e.g., using the IT despite negative perceptions), which in turn result in negative consequences such as lower job satisfaction. The counterbalancing effects imply that employees might struggle with the change in processes or norms created by IT adoption, even if there are performance gains associated with the change, because employees may find it challenging to leave their comfort zone and may consequently experience stress (e.g., Stich et al., 2019; Sykes, 2015, 2020). At a macro or organizational level, our findings highlight the potential role of digital transformation (i.e., leveraging digital technology in [re]defining an organization's value proposition) in burdening or challenging employees because of its wide scope relative to IT-enabled organizational transformation (Wessel et al., 2021). Another potential explanation may be the timing of the data collection. Although a strength of this research is the longitudinal, multipoint data collection, it is difficult to assess whether employees had a chance to fully infuse the IT (Cooper & Zmud, 1990) into their work behavior and to change expectations regarding the work practices where the IT was used (Bala & Venkatesh, 2013). It is difficult to know with certainty "how long" employees need after training to form solidified attitudes and behaviors regarding an IS or broader outcomes related to the process changes that might be associated with the IT implementation (Marcolin et al., 2000). Although two years is a fairly long duration, as it relates to the life cycle of an implementation and is among the longest primary data collection efforts in this type of IS research, especially compared to other studies of job outcomes (e.g., Bala & Venkatesh, 2013; Bala & Venkatesh, 2016; Morris & Venkatesh, 2010; Sykes, 2015, 2020), future research could include longer lags of measures to shed light on the unexpected effect of IT use on job satisfaction and offer richer conceptualizations of time and the implementation phase (Venkatesh et al., 2006; Venkatesh et al., 2021b).

Finally, our work integrates key constructs from IS and OB into a comprehensive model to theorize the impact of IT use on job outcomes. For OB research, we move beyond understanding how IT transforms work and role configuration (e.g., Sergeeva et al., 2020) and interferes with work-life balance (e.g., Butts et al., 2015) to how and under what circumstances IT influences job performance and job satisfaction (Colbert et al., 2016). Our comprehensive model sets the stage for incorporating several individual characteristics that are of interest in OB research (e.g., Big Five personality traits, learning goal orientation, performance goal orientation) with IT perceptions. The preliminary evidence favoring the prediction of job outcomes using IT perceptions as independent variables serves as a call for further integration and for further research comparing models of the core underlying phenomenon. It is possible that a model such as the one developed here is appropriate for understanding job outcomes in the context of a new IT implementation, whereas one of the models of job characteristics (e.g., Venkatesh et al., 2010; Sykes, 2015, 2020) may be more appropriate when the organizational environment is more static and employee perceptions of job characteristics fully reflect the state of the organizational environment. In times of a new IT implementation, the TAM predictors may be much more directly predictive of key outcomes. Building upon such model comparisons, it is necessary to develop an integrated model that includes IT adoption variables (Venkatesh et al., 2003; Venkatesh et al., 2012), job characteristics (Hackman & Oldham 1975, 1980), and a range of job outcomes (see Sykes, 2015, 2020) to fully capture the underlying cognitive processes.

6.2 Practical Implications

Our findings highlight key lessons for organizations contemplating or going through large-scale IT implementations. First, there is a need to instill extensive post-adoption evaluation and feedback processes to formally gauge employees' system-related and job-related perceptions in order to proactively identify potential problems. Second, even if favorable IT perceptions (e.g., high perceptions of usefulness) and significant levels of IT use are observed, other negative consequences may also be occurring. The negative relationship between IT use and job satisfaction clearly signals the need for caution when a new IT is implemented. Specifically, lower job satisfaction in the post-adoption phase will have significant negative organizational implications. Such a pattern warrants the need for organizational interventions to assuage negative feelings, especially when job characteristics are changed by the new IT, which is often the case with modern IT implementations (Morris & Venkatesh, 2010). Third, managers who are directly involved with assessing performance and designing promotion or reward programs need to be aware of some of the key dynamics that employees experience as they leverage IT in their work tasks. For some employees, IT takes some of the intrinsic rewards and personal job satisfaction out of their job/daily activities. For some employees, this may strictly be a change management issue. As articulated by one employee in an informal interview, "I liked how we used to do everything and now there are all these changes and I'm just less satisfied in my work than I used to be." For some, this discomfort may dissipate over time, whereas others may not ever let go of "the good old days." More directly, implementing IT may improve efficiency and accuracy at the expense of socialization and relationships. It is possible that prior to IT implementations, employees had to interact more with one another to gather and disseminate information, creating a positive atmosphere and sense of belongingness. Thus, organizations implementing a new IT should consider interventions that can ensure a continued sense of satisfaction among employees. Identifying and testing the efficacy of such interventions is important for practitioners and researchers alike.

6.3 Limitations and Additional Future Research Directions

Our research adopted and adapted existing scales, but some scales (e.g., technology-job fit) may be sensitive to other contexts. Hence, future research may further polish, adapt, and test the scales—and more broadly, our model—in other contexts. From an internal validity perspective, there may have also been a number of organizational decisions that were made during the two-year period beyond those associated with the IT that we could neither measure nor control. However, during this period, as noted earlier, we were not aware of any changes in compensation structure, organizational structure, or overall job expectations. Thus, although there were no significant changes in the work environment, reporting structure, or compensation that would have affected the results, it is clearly possible that events or activities in the organization influenced how certain employees felt about their job and the firm. Of course, these limitations are no different from any longitudinal field study. From the perspective of external validity, we only investigated one firm implementing a specific IT for voluntary employee adoption. This research represents a first step in furthering our understanding of the broad array of post-adoption consequences. To more fully understand the boundary conditions of this model, it should be tested with additional types of ITs, organizations, and—perhaps most importantly— scenarios in which IT implementations represent either digital transformation or IT-enabled organizational transformation (Wessel et al., 2021) as well as successful or failed IT implementations.

Our results help clarify the breadth of job outcomes that can be influenced as the IT is used; however, the model does not help us locate a mechanism that might provide an early warning about a failing IT implementation. Although problematic implementations may be obvious in some cases (e.g., the system not functioning as needed), it is possible that early perceptions of usefulness and ease of use indicate favorable employee adoption but actual and ongoing use result in IT rejection (Speier & Venkatesh, 2002). Linking IT use to broader work attitudes beyond just job outcomes could provide researchers and managers with mechanisms to favorably influence job outcomes consequent to IT implementations.

Although this research empirically demonstrated that IT implementations can influence work attitudes and behaviors, it is unclear how different employees may have responded differently to the system based on their personal innovativeness. Diffusion of innovation research (Rogers, 1995) points to the "S-curve" of individual IT adopters, with employees ranging from innovators to laggards. It is possible that different levels of innovativeness among employees influenced the amount of time needed to infuse the system into work behaviors and/or the strength of the relationships among IT use, job performance, and job satisfaction. Future research should examine IT-related psychological characteristics, such as computer playfulness and computer self-efficacy, as antecedents to beliefs/use or as moderators of key relationships, particularly with a view toward understanding the different rates of reaching a steady state among different groups of employees. For example, employees who have stronger computer skills, higher computer self-efficacy, or higher computer playfulness may exhibit stronger relationships between IT use and job satisfaction than those lower on these trait variables. If significant and substantive individual differences can be identified, managers will be in a better position to provide support and interventions appropriate for the effective management of IT-related change processes.

6.4 Conclusion

Our findings suggest that as employees interact with the IT, their continued assessment of the IT's usefulness, ease of use, and job fit will shape the effects of the IT on job outcomes over time. Thus, individual job performance gains may be counterbalanced by negative impacts on job satisfaction. Moreover, our study shows that these relationships are moderated by IT- and job-related variables such as perceived usefulness, perceived ease of use, and technology-job fit. With the revealed dynamics, our work redefines the role of the classical predictors of IT adoption as important contingencies, thus enriching our understanding of how and when IT implementation leads to favorable job outcomes. On its own, greater use of IT may not necessarily lead to enhanced job outcomes. However, this finding should not discourage managers from utilizing IT; they simply need to ensure that the right contingencies are monitored and fostered in their organizations.

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Appendix A: Alternative Model Specifications (Job Satisfaction as a Predictor)

	Job performance (T_3)				Job performance (T_4)		
	Model 1	Model 2	Model 3		Model 1	Model 2	Model 3
R^2	.154	.223	.514	R^2	.266	.304	.513
Job Perf.$_{T0}$	.298***	.261***	.191**	Job Perf.$_{T3}$	.464***	.472***	.380***
Job Sat.$_{T0}$	.151*	.095	.045	Job Sat.$_{T3}$	.147*	.096	.078
Use$_{T1-T2}$		.302***	.093	Use$_{T2-T3}$		.142*	.065
PU$_{T1}$			.131*	PU$_{T2}$			.091
PEOU$_{T1}$			.066	PEOU$_{T2}$			.033
TJ Fit$_{T1}$			.031	TJ Fit$_{T2}$			.162**
Use$_{T1-T2}$ x PU$_{T1}$			.311***	Use$_{T2-T3}$ x PU$_{T2}$			.201**
Use $_{T1-T2}$ x PEOU$_{T1}$			.164**	Use $_{T2-T3}$ x PEOU$_{T2}$			.129*
Use $_{T1-T2}$ x TJ Fit$_{T1}$			.129*	Use $_{T2-T3}$ x TJ Fit$_{T2}$			.183**
PU$_{T1}$ x PEOU$_{T1}$			.022	PU$_{T2}$ x PEOU$_{T2}$			.034

Note: PEOU: perceived ease of use; PU: perceived usefulness; Use: IT use; TJ Fit: technology-job fit; Job Perf.: job performance; Job Sat.: job satisfaction. *p < 0.05; **p < 0.01; ***p < 0.001.

Appendix B: Alternative Model Specifications (Technology-Job Fit as a Formative Construct)

	Job performance (T_3)				**Job performance (T_4)**		
	Model 1	**Model 2**	**Model 3**		**Model 1**	**Model 2**	**Model 3**
R^2	.144	.222	.481	R^2	.261	.301	.496
Job Perf.$_{T0}$	.380***	.283***	.172**	Job Perf.$_{T3}$	.511***	.483***	.341***
Use$_{T1-T2}$		.307***	.091	Use$_{T2-T3}$		.148*	.074
PU$_{T1}$			.122*	PU$_{T2}$			.088
PEOU$_{T1}$			.113*	PEOU$_{T2}$			.053
TJ Fit$_{T1}$			.043	TJ Fit$_{T2}$			.172**
Use$_{T1-T2}$ x PU$_{T1}$			.301***	Use$_{T2-T3}$ x PU$_{T2}$			.168**
Use $_{T1-T2}$ x PEOU$_{T1}$			.163**	Use $_{T2-T3}$ x PEOU$_{T2}$			.130*
Use $_{T1-T2}$ x TJ Fit$_{T1}$			.141*	Use $_{T2-T3}$ x TJ Fit$_{T2}$			.177**
PU$_{T1}$ x PEOU$_{T1}$			.048	PU$_{T2}$ x PEOU$_{T2}$			.054
	Job satisfaction (T_3)				**Job satisfaction (T_4)**		
	Model 1	**Model 2**	**Model 3**		**Model 1**	**Model 2**	**Model 3**
R^2	.160	.223	.413	R^2	.250	.302	.416
Job Sat.$_{T0}$	.401***	.221***	.195**	Job Sat.$_{T3}$	.498***	.350***	.253***
Use$_{T1-T2}$		-.287***	-.091	Use$_{T2-T3}$		-.197**	-.044
TJ Fit$_{T1}$			.134*	TJ Fit$_{T2}$			-.182**
Use$_{T1-T2}$ x TJ Fit$_{T1}$			.224***	Use$_{T2-T3}$ x TJ Fit$_{T2}$			.162**

Note: PEOU: perceived ease of use; PU: perceived usefulness; Use: IT use; TJ Fit: technology-job fit; Job Perf.: job performance; Job Sat.: job satisfaction. *p < 0.05; **p < 0.01; ***p < 0.001.

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