How IT Failure Creates Value: Recoverable Disruption in Continuous Feature Innovation[*]

Ankur Jaiswal[‡] Hüseyin Tanriverdi

McCombs School of Business, The University of Texas at Austin

Research in Progress

Preliminary Draft: Please Do Not Cite or Circulate

October 28, 2026

Click here for the latest version.

Abstract

IT failure increasingly arises from new feature use, as digital platforms release new features continuously into systems that knowledge workers already depend on. Yet research on IT reliability treats IT failure as a cost that offsets the value of new features, and research on coping with IT events evaluates workers' responses as if the interrupted work survives the event intact. Drawing on coping theory, we argue that the consequence of an IT failure depends on the recoverability of the interrupted work, whether the work survives and can still be completed, and on the worker's coping strategy: IT failure can raise performance when the work is recoverable or the worker adopts a problem-focused coping strategy, and lower it when the work is not recoverable or the worker adopts an emotion-focused coping strategy. We examine these arguments using Real User Monitoring traces of 34 million actions and roughly 312,000 sales opportunities on a top U.S. InsurTech CRM platform, estimating a causal mediation system by two-stage least squares and instrumenting both new feature use and IT failure with shift-share instruments. Preliminary findings reveal that new feature use increases IT failure, which in turn raises performance and carries about 22 percent of the total effect of new feature use. Descriptive evidence on coping strategies shows that workers persist after IT failures in internal-facing work, and reroute or abandon more after IT failures in customer-facing work. These results suggest that the performance effects of digital innovation depend both on the capabilities new features add and on how workers cope with the IT failures they produce, with implications for research on coping, IT reliability, digital innovation and the business value of IT.

Keywords: *IT failure; business value; recoverability; coping; feature innovation; knowledge work; sales performance; CRM; causal mediation*

[*]I am especially grateful to all the members of my dissertation committee, Sirkka L. Jarvenpaa, Ashish Agarwal, Raghunath Singh Rao and Ram Ranganathan, for their detailed feedback and continuous guidance throughout the various stages of this project. I also thank Ayush Kanodia for his help at many points in this project. I am very grateful to the anonymous Insurance CRM platform for access to the proprietary data analyzed here. They gave generously of their time in explaining how the system is structured and data are recorded, and how the work it supports is carried out in practice. That guidance continues to shape this study, the essays of my dissertation, and the future stream of work that I am building upon.

[‡]Email: ankur_jaiswal@utexas.edu

1 Introduction

IT failure increasingly arises from digital innovation, which now takes the form of continuous feature releases into systems already embedded in organizational work (Nambisan et al., 2017; Yoo et al., 2010). It affects workers who depend on a system for their ongoing tasks while the system itself keeps changing. Each release can expand what workers are able to do while introducing IT failure into the work that relies on the system. IT failures cost a worker about one and three-quarter hours of work time a week (Figure 1), and office workers in the United Kingdom were reported to be "left waiting for 2.03 hours each week" (Citrix, 2017). The IT failures that disrupt work most often follow a change to a system already in use, from the rollout of a new electronic health record at the US Department of Veterans Affairs (Donovan-Smith, 2022) to the configuration and database changes behind major cloud outages in 2025 (Moneylife Digital Team, 2025; Shantz, 2025) (Figure 2). Generative AI features add a probabilistic form of IT failure, in which the output can be wrong while the system works as designed (Furr et al., 2025), and workers in one survey spent 2.2 hours a week identifying and correcting AI errors (Hinds & Leonardi, 2026).

The consequence of an IT failure for a worker's performance is less uniform than its cost to organizations suggests. At the organizational level, IT failures reduce market value (Bharadwaj et al., 2009): a single faulty update to widely shared security software disrupted thousands of organizations in 2024 at an estimated cost above $5 billion (Sanjay, 2026; Yahalom, 2025), and one production change at Amazon was followed by 6.3 million lost orders (Kim, 2026). At the individual level, IT-mediated disruptions can raise performance, lower it or do both (Addas & Pinsonneault, 2015). Reports of IT failures at work describe workers continuing the work by hand or with another tool, waiting for the system to return, or venting frustration, and losses concentrate where the work could not be completed while the system was down (Figures 3 and 4). Accounts of new technologies at work, including generative AI, describe a similar range: workers who feel threatened by a new system resist or disengage from it (Hermann et al., 2026), workers who remain accountable for its decisions override it (Narayandas, 2026), and the skills that matter most surface when a new tool breaks and a worker improvises a fix (Saatçi et al., 2026). The effect of IT failure on performance therefore depends on the worker's coping strategy.

Research on IT reliability nonetheless treats IT failure as a cost. Research on digital innovation emphasizes how new capabilities enable new or improved forms of work, whereas research on IT reliability treats IT failures as disruptions that interfere with task execution and diminish the value organizations obtain from technology (Addas & Pinsonneault, 2018; Butler & Gray, 2006; Triche & Walden, 2018). Taken together, these perspectives imply a tradeoff: new features create value through the capability they add, and the IT failures that accompany them offset part of that value.

An alternative is that IT failure carries part of the value of new feature use. An IT failure

can reveal information that normal operation keeps hidden, disrupt established routines and prompt workers to reconsider how a task is performed. Research on coping with IT events treats a discrepant IT event as both a threat and an opportunity: it puts the task at risk, and it gives the user a chance to learn something about the technology (Ortiz de Guinea & Webster, 2013). Research on learning from failure suggests that small failures generate learning when individuals can respond quickly and the domain is familiar enough to permit adaptation (Sitkin, 1992). In continuously evolving systems, IT failures may therefore lead workers to re-engage with a task, retry the action and adapt, so that IT failure carries part of the performance effect of new feature use.

Coping theory explains how individuals respond to events that threaten their goals: a person appraises what is at stake and what can be done, and then acts on the problem or regulates the emotions it raises (Lazarus & Folkman, 1984). Information systems research has applied coping theory to IT events and linked coping to performance, measured with a newly implemented system or on a task that the worker resumes after the event (Bala & Venkatesh, 2016; Ortiz de Guinea & Webster, 2013; Weinert, 2019). In sales, an opportunity can be lost when work on it stalls: a customer leaves, a quote expires, a deal moves to a competitor (Musalem et al., 2023). When an IT failure occurs in such work, its consequence for performance depends on whether the work can still be completed and on the worker's coping strategy. A coping strategy that completes the work and corrects what the IT failure revealed can raise performance.

Hence, IT failure can play different roles in the performance effect of new feature use. It can offset the capability that new features add, or it can carry part of that effect, depending on workers' coping strategies. That role also depends on what remains possible after the IT failure: whether the work can still be completed. Accordingly, we frame the following research questions:

> ***R1.*** *How does IT failure affect the relationship between new feature use and a worker's performance?*
>
> ***R2.*** *How do the recoverability of the work and workers' coping strategies shape the effect of IT failure on performance?*

Using proprietary sales pipeline records and Real User Monitoring traces from a U.S. InsurTech CRM platform, we examine how new feature use, IT failure and coping strategies relate to the performance of insurance agents. CRM platforms are among the workplace systems in which work-disrupting IT failures are reported, alongside generative AI services and health records systems (Figure 5). The focal work is an agent's portfolio of sales opportunities in the customer acquisition process, where performance is the conversion of those opportunities. The pipeline records cover roughly 312,000 opportunities, and the traces record more than 34 million actions from January to July 2024, including every task an agent initiates, every IT failure error raised against it and what the agent does next. New feature use and IT failure are both endogenous: agents

choose how intensively to use new features, and IT failure reflects conditions on the platform. Each is therefore instrumented with its own shift-share design, the first through the platform's staggered feature releases across workflow modules and the second through the error load of each module among agents in other agencies. We estimate a causal mediation system with agent and week fixed effects to answer R1, and we describe the coping strategies behind R2 at the agent-week.

Preliminary results answer R1. New feature use raises IT failure and raises performance directly, and IT failure raises performance, so the IT failures that new feature use produces carry about 22 percent of its total effect on performance. The indirect effect through IT failure, like the direct effect, is positive. Descriptive evidence is relevant to R2: after IT failures in internal-facing work, agents retry, reload and resume quickly, and after IT failures in customer-facing work, they reroute and abandon more often. These patterns are consistent with recoverability as a condition on the effect of IT failure on performance, which the hypotheses state and the episode-level design will test.

The study makes four contributions. First, it extends research on coping with IT failure: studies that link coping to performance assume that the work survives the IT failure intact (Bala & Venkatesh, 2016; Ortiz de Guinea & Webster, 2013), and we relax this assumption by theorizing the recoverability of the work, whether the work survives an IT failure and can still be completed, as a condition on the effect of IT failure on performance, and by showing that a problem-focused coping strategy can improve the work as well as restore it. Second, it extends research on digital innovation by showing that new feature use affects performance through two joint pathways, the capability it adds and the IT failures it produces, with IT failure carrying about 22 percent of the total effect. Third, it contributes to research on IT reliability and failure by showing that IT failure, which this research treats as a reliability loss, becomes a recoverable disruption that can raise performance when the interrupted work is recoverable. Fourth, it contributes to research on the business value of IT by showing that part of the value of digital innovation is realized through workers' coping strategies after IT failure, alongside the capabilities the technology provides.

The remainder of the paper proceeds as follows. Section 2 reviews research on IT failure, IT interruptions and coping with IT events, and identifies the assumption in coping research that this study revises. Section 3 presents the research model and develops the hypotheses. Section 4 describes the setting, measures and identification strategy, and the measures of coping strategies and recoverability. Section 5 reports the preliminary results, and Section 6 discusses contributions and boundary conditions.

2 Theoretical Background

Table 1 codes prior studies from three literatures that bear on IT failure at work. Research on IT

failure and reliability examines its consequences for the firm and how organizations sustain reliable performance with information systems (Banker et al., 2021; Bharadwaj et al., 2009; Butler & Gray, 2006). Research on IT interruptions examines events that break the continuity of individual work and relates them to individual performance (Addas & Pinsonneault, 2015; Weinert et al., 2022). Research on coping with IT events theorizes how users respond to such events and links their responses to performance (Bala & Venkatesh, 2016; Beaudry & Pinsonneault, 2005; Ortiz de Guinea & Webster, 2013); it is the lens of this paper.

[Insert Table 1 about here]

2.1 IT Failure and Its Consequences

Prior research has examined the consequences of IT failure for the firm. Bharadwaj et al. (2009) find that publicly reported IT failures reduce firm market value, and Triche and Walden (2018) find that the impression management strategy a firm adopts after an IT failure shapes the market's reaction. Other studies trace IT failure to how systems are deployed and how they age. Banker et al. (2021) theorize that technical debt in CRM systems may cause system disruptions that impair firm performance, and may also expedite deployment and enable idiosyncratic functionality that enhances it. Tiwana and Safadi (2024) find that systems atrophy as they age and that atrophy increases bugginess.

Butler and Gray (2006) examine how organizations achieve reliable performance with information systems, and distinguish reliability that rests on routines from reliability that rests on mindfulness, the attention individuals and groups give to unexpected events. Aanestad and Jensen (2016) extend this view to the period after implementation and show how collective mindfulness supports the adaptation of an information system in use. Research on the response to IT failure has also examined the provider. Najjar et al. (2022) apply service-dominant logic to IS incident resolution, treat an IS service failure as a value-diminishing event, and identify responsive handling, supportive communicating and effective resolving as components of recovery, with the promptness and completeness of the fix shaping user recovery satisfaction.

2.2 IT Interruptions and Individual Performance

Addas and Pinsonneault (2015) define IT interruptions as IT-based events that capture attention and break the continuity of a primary task. Depending on the relevance and structure of their content, interruptions can raise individual performance, lower it or do both, and one class, system intrusions, is induced by technology that is slow, unreliable or discrepant from expectations. Weinert (2019) finds that IT unreliability lowers end-user performance, and in a laboratory experiment that simulated a one-minute computer freeze, instrumental support reduced techno-exhaustion and

physiological arousal and raised end-user performance. In this experiment and in its extension to repeated freezes (Weinert et al., 2022), performance is measured on a laboratory task that resumes after the event.

2.3 Coping with IT Events and Performance

In the transactional theory of stress and coping, a person facing a disruptive event appraises what is at stake and what can be done about it, and the outcome depends on both (Lazarus & Folkman, 1984). Problem-focused coping acts on the cause of the disruption. Emotion-focused coping regulates the emotions it raises and leaves the situation as it is. People who feel in control tend toward problem-focused coping; people with little control tend toward emotion-focused coping. Beaudry and Pinsonneault (2005) develop a coping model of user adaptation to IT events, in which users appraise a significant IT event as an opportunity or a threat and judge their control over the technology, the work and themselves; these two appraisals yield four adaptation strategies. Weinert (2018) describes the research that followed as a process from the IT event through appraisal to a coping strategy and its outcome, and calls for work on how coping strategies reduce the effect of IT events on job outcomes.

Bala and Venkatesh (2016) study coping with newly implemented systems, in two field studies of an enterprise resource planning system and a product lifecycle management system. Appraisals of opportunity, threat and control lead employees to one of four technology adaptation behaviours: exploitation, exploration-to-innovate, exploration-to-revert and avoidance. Exploration-to-revert adapts the new system to earlier work habits, often through workarounds. The authors expect it to lower job performance, because managers judge employees by how well they work with the new system. Both organizations kept the new systems voluntary, so that work could continue if the systems failed.

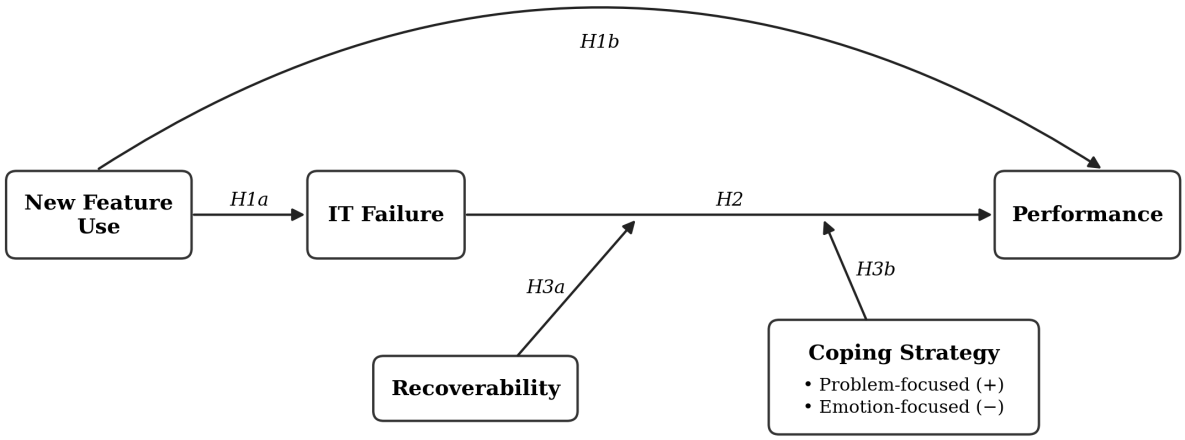
Ortiz de Guinea and Webster (2013) study systems already in use. They define a discrepant IT event as an unexpected problem, misunderstanding or difficulty with the IT being used. Such events trigger negative emotion and adaptive behaviour. Some are resolved quickly; others cannot be overcome. The events in their experiment are not fatal by design: participants could carry on with the task whatever happened, and the authors note that they studied only events that could be overcome or ignored. The study relates the behaviour that follows to performance on the task the participant resumes, as do the laboratory studies of IT unreliability reviewed above. Salo et al. (2020) show that users coping with failing applications move through sequences of responses, and that users who switch away impose a cost on the provider. Outside information systems, coping flexibility is linked to the performance of salespeople through lower emotional exhaustion (Anwar et al., 2026). Technostress research examines how coping with the demands of ongoing IS use weakens their negative effect on IT-enabled productivity (Pirkkalainen et al., 2019).

Across these studies, the work survives the IT event intact, so a coping strategy is adaptive if it restores the worker's use of the system or returns the worker to the task, and the best it can do is restore the starting point. The assumption fits the settings in which it was developed: during an implementation, the earlier way of working and the new system coexist, and in a laboratory, the task is preserved for the participant. Secondary appraisal in this research accordingly concerns the user's control over the technology and the event, while the work the event interrupts remains available. Ongoing work need not survive an IT failure: in sales, an opportunity can be lost when work on it stalls (Musalem et al., 2023). When an IT failure occurs during such work, what can be done depends on whether the work survives the IT failure, which brings the condition of the work into secondary appraisal.

3 Research Model and Hypotheses

We theorize how new feature use affects performance, and how the IT failures that new features produce shape that effect, through the transactional theory of stress and coping (Lazarus & Folkman, 1984). An IT failure is a discrepant IT event (Ortiz de Guinea & Webster, 2013), and the worker's coping strategy after it follows from what the IT failure puts at stake and what can be done about it. The argument begins with the event that sets the process in motion, the worker's use of a newly released feature, and Figure 6 summarizes the research model.

Figure 6. Research Model



3.1 New Feature Use as an IT Event

Beaudry and Pinsonneault (2005) treat both the implementation of a new IT and significant modifications made to an existing IT as IT events. Later work distinguishes IT events that arise from IT use from those that arise from IT change, and notes that IT events occur both when the technology

does not behave as expected and when the user is not able to use it appropriately (Weinert, 2019). A platform that releases features continuously modifies the technology its workers depend on. A release becomes an IT event for a worker when the worker uses the new feature, so the construct is the worker's use of newly released features, distinct from the release itself and from the decision to adopt. New feature use exposes the worker to IT failure from two sides. Software that is updated more frequently develops more defects (Pang & Tanriverdi, 2022), and a worker is less able to use a feature appropriately before having used it. A competing explanation is that workers who use new features are more active on the platform, and activity alone creates more occasions for IT failure.

Hypothesis 1a. *The more a worker uses newly released features, the more IT failure the worker experiences.*

New features are released to extend what workers can accomplish, and a worker who appraises a new feature as an opportunity can take advantage of what it offers to maximize the benefits of the change (Beaudry & Pinsonneault, 2005). Performance benefits are most likely when workers recognize a match between the requirements of a task and an application's features, and apply those features selectively to exploit that fit (Jasperson et al., 2005). Exploration-to-innovate, the coping-derived behaviour of using a technology to find new ways of accomplishing one's tasks, raises job performance (Bala & Venkatesh, 2016). New feature use should therefore raise performance through the capability it adds. The same use also produces IT failures, whose effect on performance depends on the coping strategies workers adopt.

Hypothesis 1b. *The more a worker uses newly released features, the higher the worker's performance, apart from the effect that runs through IT failure.*

3.2 IT Failure as a Mediator of New Feature Use

New feature use affects performance in two ways. It affects performance directly, through the capability it adds. It also affects performance indirectly, through the IT failures it produces. An IT failure is both a threat and an opportunity for the worker. It is a threat because it puts the completion of the interrupted work process at risk. It is an opportunity because, as the worker tries to resolve it, the worker can learn something about the technology that the worker did not know before, and the discrepant IT event becomes a discovery. An IT failure also need not be fatal: it can be a nuisance that does not prevent the completion of the task (Ortiz de Guinea & Webster, 2013). A first IT failure lowers task performance, and task performance improves when the IT failure recurs (Weinert, 2019). Efforts that take advantage of the opportunity in an IT event raise the individual's efficiency and effectiveness (Beaudry & Pinsonneault, 2005). An IT failure can thus lower performance or raise it. Part of the effect of new feature use on performance therefore runs through the IT failures it produces.

Hypothesis 2. *IT failure mediates the relationship between new feature use and performance.*

3.3 Recoverability, Coping Strategy and Performance

Whether an IT failure lowers or raises performance depends on what remains possible after it. Secondary appraisal asks whether anything can be done. For an IT failure, the answer depends on the work it disrupts. We define recoverability as the degree to which the interrupted work process remains available for completion after the IT failure. The interrupted work process remains available when its state is preserved, so that a retry resumes the step rather than restarting it, and when an alternative route to complete the step exists. Recoverability is a property of the task and the technology, fixed before the worker adopts a coping strategy, and it differs from four neighbouring constructs. Recovery is the provider's response to an IS service failure, judged by the promptness and completeness of the fix (Najjar et al., 2022). Reliability is the capacity of an organization to sustain performance when systems behave unexpectedly (Butler & Gray, 2006). A coping strategy is the worker's response, which recoverability precedes. Recoverability is closest to the distinction between discrepant IT events that are fatal, which obstruct the completion of the task, and those that are nuisances, which do not (Ortiz de Guinea & Webster, 2013). That distinction classifies the event by its effect on the task. Recoverability is defined by two conditions of the interrupted work process: the work state is preserved, and an alternative route exists. When both hold, the interrupted work process can still be completed.

An IT failure does not have a single consequence for performance; its consequence depends on whether the interrupted work process can still be completed after it. When the interrupted work process is recoverable, the worker can still complete it. The error that the IT failure raises indicates which requirements of the work process are not yet met, and meeting them can improve the work process beyond its state before the IT failure, so the IT failure can raise performance. When the interrupted work process is not recoverable, the step cannot be completed, and the outcome the work process serves can be lost when work on it stops (Musalem et al., 2023), so the IT failure lowers performance. Recoverability also enters the worker's secondary appraisal: situations that hold the possibility of change are met with more problem-focused coping, and a coping strategy is adaptive when it fits the demands of the situation (Lazarus & Folkman, 1984). Recoverability therefore conditions the effect of IT failure on performance.

Hypothesis 3a. *Recoverability moderates the relationship between IT failure and performance, such that the effect of IT failure on performance is positive when recoverability is high and negative when it is low.*

The worker's coping strategy also conditions the effect of IT failure on performance. Problem-

focused coping strategies act on the IT failure: the worker retries or corrects the action, completes the step through another route, or reorganizes the sequence of the work. An emotion-focused coping strategy withdraws from the IT failure and leaves the situation as it is. The two kinds correspond to the technology adaptation behaviours derived from coping theory: exploitation, exploration-to-innovate and exploration-to-revert act on the technology or the work, and avoidance withdraws from it (Bala & Venkatesh, 2016). A problem-focused coping strategy completes the step that the IT failure stopped, and it can also improve the interrupted work process. When the IT failure reveals a missing or invalid entry, completing the entry often requires further information from the party the work process serves, and persistence, consistency and speed of contact raise the likelihood that the work process reaches its outcome (Ohiomah et al., 2019). Later tasks then use the corrected record, while uncorrected errors propagate from one task to the next as a transaction moves through a business process (Bai et al., 2012). Exploration-to-revert, in which the worker completes the step by fitting the IT to earlier work processes, has the same effect. This departs from the expectation, in that research, that exploration-to-revert lowers job performance, because performance on the interrupted work process depends on whether the work is completed, whatever the route. An emotion-focused coping strategy leaves the step incomplete, and the outcome the work process serves can be lost, as when the interrupted work process is not recoverable.

> **Hypothesis 3b.** *The coping strategy moderates the relationship between IT failure and performance, such that the effect of IT failure on performance is positive under a problem-focused coping strategy and negative under an emotion-focused coping strategy.*

The consequence of a coping strategy for performance appears over a longer horizon than the task. Adaptive behaviours can lower performance on the immediate task, because time is needed to turn the effort into results, and can raise performance over a longer period, because they use the opportunities that a discrepant IT event offers (Ortiz de Guinea & Webster, 2013). The consequence also extends beyond the interrupted work process. What the worker learns about the technology while resolving an IT failure applies to later IT failures and to other work processes. A corrected record is used by tasks in other work processes. Time not spent on an abandoned work process is spent on others. Performance is therefore observed over the worker's portfolio of work processes in a week, the level at which these consequences accumulate.

4 Methodology

4.1 Empirical Setting and Sample

We address the research questions using proprietary data from a leading InsurTech SaaS CRM provider whose platform serves more than 1,000 small and medium independent insurance agencies

across the United States.[1] The workers in our theory are the insurance agents who use the platform to work their sales opportunities. The setting records continuous feature releases and the work agents perform on the platform at the level of individual actions. We combine structured pipeline records[2] with Real User Monitoring trace data[3] capturing more than 34 million user actions across approximately half a million user sessions and more than four million task initiations by users from January to July 2024. The platform spans over 200 workflow modules and 145,000 interaction configurations. These data allow us to observe agents' new feature use[4], the IT failures they meet while performing work, their coping strategies after each IT failure, and their performance at the agent-week level. Variable definitions and the composition of the IT failure measure across task categories and by cause are reported in Tables 2 to 4.

The sample is constructed by applying inclusion criteria at the agency, agent and task levels, so that observations reflect active, observable customer acquisition activity on the platform. Agencies are included if they maintain an active acquisition pipeline, generate a minimum[5] volume of monthly business during the study window, and have at least a minimum number of licensed agents operating on the platform. Agents are included where trace data are available for the study window, so that new feature use, IT failure and coping strategies are observed on the same agent-weeks as performance. The estimation sample for the main results is the core sample; measures defined on only a subset of agent-weeks are estimated on correspondingly fewer observations, as each table reports.

[Insert Tables 2 to 4 about here]

[1] Access to the data is governed by a signed non-disclosure agreement with the business provider. All regression analyses are estimated on the raw, unscaled data. The platform collectively manages premiums exceeding $8 billion across diverse property and casualty portfolios; variables that could reveal commercially sensitive scale or operational details are reported after applying confidential scaling and standardization.

[2] A dealcard is a centralized record serving as the core record for agents and CRM system developers, functioning as a data repository for each sales opportunity: it captures customer details, product type, pricing, and process updates as the deal progresses through the pipeline. The acquisition pipeline averages 312,000 dealcard records over the study period. A dealcard is equivalently a sales opportunity (Hartmann et al., 2025).

[3] Trace data consist of timestamped records of user actions within the system, capturing behaviours such as logging in or out, page views, and button clicks. A task initiation is a single invocation of a platform feature to deliver a defined functional capability. From a developer's perspective, it also captures computational resources used, bugs, frictions, and modular environments affecting deployment of features and modular integrations. These data are collected unobtrusively as by-products of system usage, providing a detailed log of activities as users engage with the platform. The literature describes trace data as "residues left behind by multiple types of behavior" (Lindberg, 2020) and as "logs of employee behavior," characterised by natural occurrence rather than active production for research purposes (Grover et al., 2020).

[4] The CRM features examined were identified through systematic sampling in consultation with the platform, selecting features most relevant to the sales agent; specific counts and release dates are withheld under the NDA.

[5] Specific thresholds cannot be disclosed under the NDA.

4.2 Econometric Model

We test Hypotheses 1a, 1b and 2 with a causal mediation system at the agent-week. The agent-week is the level at which the consequences of coping after an IT failure accumulate across the agent's work processes, and the level at which the instruments vary, through module-week shocks weighted by each agent's module shares. Decomposing the total effect of feature use requires sequential ignorability (Imai et al., 2010), and both of its conditions fail here for structurally independent reasons: feature use is a behavioural choice correlated with unobserved time-varying agent-level factors, while IT failure reflects platform-side conditions driven by distinct forces. The agent-level factors at issue are unobserved time-varying skill, effort, opportunity quality and workload, any of which may raise conversion while also raising how intensively an agent takes up newly released features. That independence forecloses single-instrument identification. Dippel et al. (2020) recover mediation effects with one instrument only by assuming that treatment and mediator share a common unobserved confounder, which is precisely what fails here; when the endogeneity sources differ, each endogenous variable requires its own instrument (Celli, 2022; Frölich & Huber, 2017). We therefore estimate a linear structural system with a dedicated instrument for each.

$$IT\ Failure_{it} = \beta_1\, New\ CRM\ Feature\ Use_{it} + \boldsymbol{\gamma}_1'\mathbf{X}_{it} + \alpha_i + \tau_t + v_{it} \tag{1}$$

$$Performance_{it} = \varphi_1\, New\ CRM\ Feature\ Use_{it} + \boldsymbol{\gamma}_2'\mathbf{X}_{it} + \alpha_i + \tau_t + u_{it} \tag{2}$$

$$Performance_{it} = \delta_1\, New\ CRM\ Feature\ Use_{it} + \delta_2\, IT\ Failure_{it} + \boldsymbol{\gamma}_3'\mathbf{X}_{it} + \alpha_i + \tau_t + \varepsilon_{it} \tag{3}$$

$New\ CRM\ Feature\ Use_{it}$ and $IT\ Failure_{it}$ are the endogenous variables, and each is instrumented separately. Equation (1) is the mediator equation, reported in Table 5. Equation (2) is the reduced form, in which performance is regressed on feature use with the mediator omitted, so that φ_1 carries the direct and indirect pathways together and estimates the total effect in one step; it is reported in column 2 of Table 6. Equation (3) adds the mediator and separates the two. $New\ CRM\ Feature\ Use_{it}$ is agent i's new feature use in week t. $Performance_{it}$ is agent i's sales performance in week t, operationalised as conversion, the number of later-stage deals that convert in that agent-week relative to all of the agent's active deals at both stages; the exhibits report it under that name. $IT\ Failure_{it}$ is the share of that agent-week's session time spent on tasks that do not complete. δ_1 is the direct pathway from feature use to performance, $\beta_1\delta_2$ is the indirect pathway running through IT failure, and $\delta_1 + \beta_1\delta_2$ is the total effect, which φ_1 estimates directly.

[Insert Table 5 about here]

[Insert Table 6 about here]

$\mathbf{X}_{it}$ is the same control vector in all three equations and contains *New GenAI Use*, *Incidence of Failure*, *Feature Breadth*, *Platform Time*, *Product Complicatedness* and *Customer Complicatedness* at both the qualification and the conversion stage, *Process Activity Burden*, *Bundling Intensity*, *Portfolio Value*, *Portfolio Age* and *Portfolio Size*. Feature Breadth controls for how widely the agent explores the platform in the week, so that New CRM Feature Use is identified separately from general exploration of the IT (Bala & Venkatesh, 2016). α_i and τ_t are agent and week fixed effects. The controls are not constrained to take the same coefficients across the three equations, so each equation carries its own $\boldsymbol{\gamma}$.

Those fixed effects, together with the controls in $\mathbf{X}$, address only part of the problem. Agent fixed effects absorb what is time-invariant about an agent, such as persistent skill, and week fixed effects absorb what is common to all agents in a week, such as seasonal demand. Neither absorbs a shock specific to one agent in one week, nor the possibility that feature use responds within the week to the same conditions that produce IT failure, so that part of an apparent mediation effect would reflect reverse causality.

A design that randomly assigned each agent's feature use and IT failure exposure every week would address both problems: randomising feature use independently of unobserved skill would make skill orthogonal to it, and randomising IT failure independently of feature use would break the path running from performance back to the mediator. Neither can be assigned experimentally in the field, so we pursue a quasi-experimental design in which each endogenous variable is instrumented separately, drawing on shocks unrelated to any individual agent's performance. This requires a level of variation below the agent: shares and shocks are defined over the platform's CRM workflow modules, the modular components through which agents complete their work, each separately identifiable in the trace data by the module associated with every user action.

The mediator and outcome equations, Equation (1) and Equation (3), are estimated by two-stage least squares (2SLS) with standard errors clustered at the agent level; full estimates for all three equations appear in Table 5 and Table 6. Because the average causal mediation effect (ACME) is a product of coefficients, its sampling distribution is skewed, and the Sobel (1982) normal approximation yields low power and unbalanced confidence limits (Fritz & MacKinnon, 2007; MacKinnon et al., 2004). Inference therefore relies on a cluster bootstrap resampling agents, re-estimating the mediator and outcome equations within each replicate so that the correlation between the paths propagates; bias-corrected 95% intervals are the inferential criterion.

4.3 Identification Strategy

Both endogenous variables, *New CRM Feature Use*$_{it}$ and *IT Failure*$_{it}$, are instrumented using the exogenous-shifts shift-share framework of Borusyak et al. (2022, 2025). Each instrument takes the form

$$Z_{it} = \sum_{m} s_{im,t-1}\, g_{mt} \tag{4}$$

where m indexes the platform's CRM workflow modules, $s_{im,t-1}$ is agent i's lagged share of workflow engagement attributable to module m, and g_{mt} is a module-week shock determined at the platform level. Shares are built from the prior week's click activity and normalised so that $\sum_m s_{im,t-1} = 1$ within each active agent-week, which makes them predetermined relative to the contemporaneous shock.[6] Identification under this design also rests on two conditions on the shocks themselves: dispersion[7] and independence[8] Both conditions are maintained in the present analysis, pending shock-level diagnostics.

The share construction rests on the structure of the work itself. Advancing a deal requires the joint completion of tasks spread across several interdependent workflow modules, so no single module carries a deal on its own: an O-ring production structure (Demirer et al., 2026; Gans & Goldfarb, 2026; Kremer, 1993). An agent's exposure to a platform-level disturbance is therefore governed by how that agent's work is distributed across modules, which is what the click-based shares measure. Identification is attributed entirely to quasi-random variation in the shocks. Under the exogenous-shifts route the orthogonality condition applies to the shift rather than to the shares, which is what permits the exposure shares themselves to be endogenous.

4.3.1 Instrument for New CRM Feature Use

$$Z_{it}^{\text{feature}} = \sum_{m} s_{im,t-1}\, g_{mt}^{\text{feature}}, \qquad g_{mt}^{\text{feature}} = \sum_{w} \mathbb{1}\{r_{wm} \le t\} \tag{5}$$

The shock g_{mt}^{feature} is the cumulative stock of platform-controlled CRM feature releases active in module m by week t, where r_{wm} is the week in which release wave w takes effect in module m.[9] The platform introduced new features through successive, staggered release waves, and the

[6] The trace data record every user action together with the workflow module in which it occurs, so engagement can be aggregated to the agent-module-week level. Shares are formed from click counts in the preceding week and sum to one within each active agent-week.

[7] If the shocks are concentrated in a small number of module-weeks rather than spread across many, the instrument effectively collapses to a handful of large shocks, and the asymptotic properties that justify treating the shift-share estimator as consistent no longer apply (Borusyak et al., 2022).

[8] If the shocks are correlated with one another, the design carries less independent identifying variation than the number of module-weeks suggests (Adão et al., 2019), and a shock correlated with an omitted, module-wide confound could present as exogenous variation in *New CRM Feature Use* or in *IT Failure*. The exogenous-shifts route avoids defending the exogeneity of agents' module exposure shares directly, a requirement Goldsmith-Pinkham et al. (2020) show is demanding and one we consider implausible here, since agents' historical module reliance reflects their own workflow patterns.

[9] The platform introduced new CRM features in staggered release waves across the study window, each wave expanding capability in a subset of workflow modules. The shock accumulates the waves that have taken effect in a module by week t, so it is a dated treatment-intensity measure rather than a post-release indicator. Release dates and feature identities are withheld under the non-disclosure agreement.

cumulative shock accumulates active release exposure across those waves as each takes effect week by week. Release timing and scope are set by the platform's product-development decisions at the system level and vary across workflow modules. No individual agent can alter when a release ships or which module it reaches: releases are deployed platform-wide rather than directed at any agent, and a single agent's engagement is a negligible share of the activity in any module. The shift is therefore plausibly independent of any individual agent's conversion outcomes within the same week.

4.3.2 Instrument for IT Failure

$$Z_{it}^{\text{failure}} = \sum_{m} s_{im,t-1}\, g_{m,t,-a(i)}^{\text{failure}}, \qquad g_{m,t,-a(i)}^{\text{failure}} = \sum_{j \notin a(i)} \sum_{v \in V_{jmt}} e_v \tag{6}$$

The shock is the module's weekly error load, defined as the total number of runtime errors a CRM workflow module raises across every action executed against it on the platform in week t by agents outside the focal agency. V_{jmt} is the set of actions agent j executes against module m in week t, e_v is the number of errors raised while action v executes, and $a(i)$ is the focal agent's agency; the outer sum is the population of agents the shock is built from, and the condition on it is what removes the focal agency. Errors enter the shock through the same log that defines IT failure in the measure: a task joins F_{isk} (Table 2) when at least one error is logged against it, and e_v counts those same logged errors at the level of the action that raised them.[10]

A module is a subsystem of the platform whose internal linkages are exercised each time its interface is assembled. Near-decomposable systems are characterised by the frequency of intra-component linkage relative to intercomponent linkage (Simon, 1962). An error is a coded dependency that does not resolve. Whereas the module's dependency structure characterises the linkages it must complete, its error load characterises that structure as evaluated at the code state then deployed.

Variation in this quantity across weeks originates in the platform's development cycle. A code change introduces a defect, the platform's developers monitor error incidence continuously and remediate detected defects, and the module returns to its maintained baseline. The series is accordingly a sequence of transient deviations generated by release and remediation decisions,

[10]The measure is the real-user-monitoring error count for a CRM workflow module, defined as the number of runtime errors raised while the module's interface executes one action, summed over the platform's actions against that module in the week. These comprise unhandled exceptions and errors written to the browser console. Systems research characterises a web page by the content fetched in rendering it (Butkiewicz et al., 2011) and treats a page load as a structure of linked activities whose dependencies can be recovered and traced (Wang et al., 2013), so a dependency that does not resolve is recorded as an error on the same trace. Real-user monitoring is the established means of observing a deployed system as it actually operates, in place of synthetic conditions (Cito et al., 2015), which is what allows the series to be read as realised subsystem activity. A task initiation is classified as failed when at least one error is logged against it.

which the platform's development team takes on its own schedule in response to platform-wide telemetry rather than to the work of any individual agent.

The series carries no individual agent's behaviour. Each error requires an action to raise it, but the shock aggregates all actions taken against the module by agents outside the focal agency, so that aggregation recovers the module's propensity to fail under its current code state rather than the conduct of any single agent. The focal agency is excluded in full, which removes the agents whose portfolio composition and demand conditions most closely resemble those of the focal agent. Two features of the construction further restrict the variation entering the instrument. Exposure shares are lagged and sum to one within each agent-week, so an increase in error incidence common to all modules in a given week enters the instrument as a constant and is absorbed by the week fixed effects; only relative variation across modules is retained. Agent fixed effects absorb persistent differences in the modules through which an agent works. The shift is therefore plausibly independent of any individual agent's conversion outcomes within the same week.

Under the exogenous-shifts route the orthogonality condition applies to the shift rather than to the shares, so the exposure shares themselves require no exogeneity defence (Borusyak et al., 2022). Underidentification and weak-instrument diagnostics for both first stages are reported in Table 5 and Table 6.

4.3.3 Exclusion Restrictions

Z_{it}^{feature} is required to affect sales performance only through $\textit{New CRM Feature Use}_{it}$, the agent's novelty-weighted intensity of engagement with newly released CRM features (Table 2). Platform-controlled deployments expand the functionality available within a workflow module but do not themselves generate sales outcomes; performance is affected only insofar as agents engage with the released features, which is what $\textit{New CRM Feature Use}_{it}$ measures. Agent and week fixed effects absorb time-invariant differences in workflow exposure and common temporal shocks that may coincide with release timing.

Z_{it}^{failure} is required to affect performance only through $\textit{IT Failure}_{it}$, the focal agent's IT failure. Error incidence among agents in other agencies reflects platform-level infrastructure conditions in shared workflow modules; these conditions propagate to the focal agent through shared system exposure, raising the probability of IT failure in that agent's own task initiations while having no direct bearing on that agent's sales outcomes. The leave-one-agency-out construction removes within-agency channels, such as correlated performance shocks or resource-sharing arrangements, through which neighbouring error incidence could reach the focal agent's sales outcomes by a route other than $\textit{IT Failure}_{it}$. Both restrictions are maintained assumptions rather than testable implications of the design.

4.4 Coping Strategies and Recoverability

The coping strategy measures are defined at the agent-week from the ordered sequence of tasks in each session (Table 2). Each measure is computed over the week's IT failure tasks and follows the interrupted work process after each IT failure. The measures follow the distinction between problem-focused coping, which acts on the problem at hand, and emotion-focused coping, which manages the distress it causes without changing the situation (Lazarus & Folkman, 1984). Bala and Venkatesh (2016) specify four technology adaptation behaviours within this distinction: exploitation, the use of an IT's recommended features to perform one's tasks; exploration-to-innovate and exploration-to-revert, which search the IT for new ways of working or for ways back to earlier habits; and avoidance, an emotion-focused attempt not to use the IT. Page Retry and Short Reload record the agent continuing the interrupted work process through the same sub-module that failed, which corresponds to exploitation. Reroute Rate records the agent continuing it through a different sub-module, which corresponds to exploration in either direction. Workflow Deviation records how far the agent's next tasks depart from the routine mix of executed work, which corresponds to adapting the work by modifying procedures and routines (Beaudry & Pinsonneault, 2005). Abandonment records the agent leaving the interrupted work process with no further task on it in the session, which corresponds to avoidance. After each IT failure the agent continues through the same sub-module, continues through a different one, or leaves, so Page Retry, Reroute Rate and Abandonment sum to one. Recovery Time records how quickly the interrupted work process resumes with an executed task. Appraisals and emotion-focused coping are internal to the worker, so the analysis compares observable coping strategies across the situations in which each appraisal is likely.

Recoverability is approximated by the kind of work an IT failure interrupts. Internal-facing work pools coordinating, recording and integrating tasks, and an IT failure in such work more often leaves the work state preserved, so that the agent can continue the interrupted work process and execute the task. Customer-facing work pools curating and communicating tasks, and when an IT failure disrupts an exchange with a customer, the work state is often lost, and the agent may be unable to continue the interrupted work process simply by retrying the task. Internal-facing work therefore stands for more recoverable IT failures, and customer-facing work for less recoverable ones. Each coping strategy measure is regressed on the agent-week's internal-facing and customer-facing IT failure, and the difference between the two coefficients compares coping strategies across the two kinds of work (Table 9).

5 Results

Column 2 of Table 5 and columns 4 and 5 of Table 6 are estimated by two-stage least squares, using the instruments set out in the identification strategy; the remaining columns are ordinary least squares (OLS). The causal effects reported below come from those specifications.

5.1 The Causal Mediation System

New feature use causally increases IT failure. The OLS association is negative, −0.022 ($p<0.05$, column 1 of Table 5), identified across agents who have chosen different levels of *New CRM Feature Use*. The causal effect is 0.248 ($p<0.01$, column 2), with Kleibergen–Paap rk LM 62.98 and Cragg–Donald Wald F 159.40, which supports Hypothesis 1a.

Under OLS, the mediator carries almost none of the association. Column 2 of Table 6 is the reduced form, where the coefficient on *New CRM Feature Use* is 0.018 ($p<0.05$) and is the OLS total effect. Adding *IT Failure* in column 3 leaves that coefficient at 0.019 and puts the mediator at 0.023 ($p<0.05$).

The causal effects are substantially larger than their OLS counterparts and carry the same signs. In column 4 of Table 6, where *New CRM Feature Use* alone is treated as endogenous, the causal effect of *New CRM Feature Use* on *Conversion* is 0.291 ($p<0.01$) and the coefficient on *IT Failure* is 0.034 ($p<0.01$). In column 5, where *New CRM Feature Use* and *IT Failure* are both treated as endogenous, the causal effects are 0.235 ($p<0.01$) and 0.266 ($p<0.05$) respectively. The direct effect of new feature use supports Hypothesis 1b. First stages are strong in both columns, with Kleibergen–Paap rk LM of 63.53 and 79.97 and Cragg–Donald Wald F of 162.93 and 65.94. The positive causal effect of *IT Failure* on *Conversion* is consistent with IT failure carrying part of the value of new feature use.

Both instruments are strongly relevant. The Sanderson–Windmeijer F is 68.30 in the single-endogenous system of column 2 of Table 5, and 64.38 for *New CRM Feature Use* and 88.22 for *IT Failure* in the two-endogenous system of column 5 of Table 6 (Table 7). The coefficient on Z_{it}^{feature} is negative because the novelty weight in the index (Table 2) falls as an innovation diffuses and adoption spreads, so modules with more cumulative releases carry more widely adopted features and a lower novelty-weighted index; the direction does not bear on identification, which turns on how strongly the instrument moves the variable. Both instruments enter each first stage, as system estimation requires, and the Sanderson–Windmeijer statistics confirm that each endogenous variable is separately identified.

[Insert Table 7 about here]

The indirect pathway accounts for approximately 22 percent of the total effect of new feature

use on performance. Table 8 reports the causal mediation results from column 2 of Table 5 and column 5 of Table 6: the a-path is 0.248 ($p<0.01$) and the b-path 0.266 ($p<0.05$), giving an average causal mediation effect of 0.066 ($p<0.05$), an average direct effect of 0.235 ($p<0.01$) and an average total effect of 0.300 ($p<0.01$). Bias-corrected bootstrap intervals exclude zero for all three, which supports Hypothesis 2. The average total effect is estimated on the two-stage least squares system and is therefore not directly comparable with the OLS total effect of 0.018 in column 2 of Table 6.

[Insert Table 8 about here]

5.2 Where IT Failure Arises

The remaining results are descriptive. They show where IT failure arises and what workers do after it, which bears on Hypotheses 3a and 3b (Section 4.4) without testing them. IT failure is concentrated in communicating and recording work. IT failure occupies 2.67% of session time. Of that total, communicating accounts for 47.1% of incidence and 41.3% of IT failure time, and recording for 35.0 and 38.2% (columns 1 and 2 of Table 3); integrating follows at 11.5 and 15.4%, and coordinating and curating together account for under 7% on either basis.

The two largest categories differ in what causes their IT failures. Across all IT failure time, 41.9% is system-caused and 58.2% user-caused (columns 1 and 2 of Table 4). IT failures in communicating work are predominantly system-caused, at 30.9 of their 41.3 percentage points, while IT failures in recording work are almost entirely user-caused, at 37.7 of 38.2.

The aggregate effect of IT failure arises from internal-facing work and is partly offset by customer-facing work. Figure 7 reports the decomposition of the aggregate effect of 0.062 across the five categories: the contribution of recording is 0.064 ($p<0.05$) and that of integrating 0.037 ($p<0.10$), while the contribution of communicating is -0.051 ($p<0.05$), and coordinating and curating are not distinguishable from zero. The decomposition is descriptive rather than causal, so we use the trace data to examine behaviour following each kind of IT failure.

[Insert Figure 7 about here]

5.3 How Individual Workers Cope

Workers persist after IT failures in internal-facing work and redirect their effort after IT failures in customer-facing work. Table 9 reports six regressions of the standardized coping strategy measures on internal-facing and customer-facing IT failure. After internal-facing IT failure, *Page retry* rises by 0.069 ($p<0.01$, column 1), *Short reload* by 0.106 ($p<0.01$, column 2), and *Recovery time* falls by 0.319 ($p<0.01$, column 3). After customer-facing IT failure, *Page retry* and *Short reload* are unchanged (columns 1 and 2), *Recovery time* falls by less, 0.132 against 0.319 (column 3), and

Reroute rate rises by 0.659 ($p<0.01$, column 4). *Abandonment* and *Workflow deviation* rise after both forms of IT failure, at 0.916 against 0.549 in column 5 and 1.291 against 0.328 in column 6. Every difference between the two blocs is significant, with p-values from 0.007 to below 0.001.

[Insert Table 9 about here]

After IT failures in internal-facing work, where the work state is more often preserved, workers persist; after IT failures in customer-facing work, they reroute, deviate and abandon more. Persisting after IT failures in internal-facing work, and abandonment after IT failures in customer-facing work, are consistent with the secondary appraisal that underlies Hypothesis 3a; the rise in rerouting points to the route condition of recoverability, which customer-facing work may leave open after the work state is lost. Because the two blocs differ in many ways besides recoverability, the patterns describe rather than test Hypotheses 3a and 3b.

6 Discussion

Continuous feature innovation creates an important tension for organizations that depend on digital platforms. New features are introduced to improve what workers can accomplish, yet introducing those features into systems already being used for ongoing work can also create instability and IT failure. A conventional reliability perspective suggests that these IT failures should erode at least some of the performance benefits created by innovation. Our findings reveal a more nuanced relationship. New feature use causally improves performance while also increasing IT failure. More surprisingly, IT failure itself has a positive aggregate effect on conversion and transmits approximately 22 percent of the total effect of new feature use on performance. The direct and indirect pathways therefore complement rather than offset one another. In this setting, feature innovation creates value not only through the capabilities it provides, but also through workers' coping strategies after some of the IT failures it generates.

6.1 Contributions to Research

Our theory and preliminary findings contribute to research on coping with IT failure, digital innovation, IT reliability and failure, and the business value of IT.

6.1.1 Coping with IT Failure: Recoverability and the Interrupted Work

First, we contribute to research on coping with IT failure by relaxing an assumption about the work. Studies that link coping to performance judge a coping strategy by whether it restores the worker's use of the system or returns the worker to a task that survives the IT event intact (Bala & Venkatesh, 2016; Ortiz de Guinea & Webster, 2013; Weinert, 2019). We judge a coping strategy by whether

it completes the work, given what the IT failure has left, and argue that a coping strategy that also corrects what the IT failure exposed can leave the work stronger than it would have been without the IT failure. The revision changes the evaluation of particular coping strategies. Exploration-to-revert, which prior theory treats as maladaptive because it delays proficiency with a new system, becomes a route to completing the work when the system fails. The revision also brings a property of the interrupted work into coping theory: recoverability, whether the work survives the IT failure and whether another route remains, conditions the effect of IT failure on performance. The causal estimates are consistent with this account at the agent-week, since IT failure raises performance and carries part of the effect of new feature use; the episode-level tests of Hypotheses 3a and 3b remain the next step.

6.1.2 Continuous Feature Innovation: Capability and Disruption as Joint Pathways

Second, we extend research on digital innovation by showing that the performance consequences of continuous feature innovation cannot be understood solely through the capabilities that new features provide. Digital innovation research emphasizes the recombinability and continuing evolution of digital technologies (Nambisan et al., 2017; Yoo et al., 2010), while feature-level perspectives direct attention to how users engage particular technological capabilities within established systems (Karahanna et al., 2019). Our findings show that continuous feature innovation has another consequential property: new functionality is introduced into a production environment in which workers are already dependent on the system. Innovation can therefore simultaneously expand capability and generate operational instability.

This observation changes how the performance effects of continuous feature innovation can be conceptualized. A natural expectation is that new features create a positive capability pathway while any IT failures accompanying their introduction constitute an offsetting reliability cost. We find instead that the two pathways can be complementary. New feature use directly increases performance, but it also increases IT failure, which in turn positively affects performance. The mediation analysis shows that this indirect pathway is economically meaningful, accounting for approximately 22 percent of the total effect of new feature use on performance.

The implication is not that instability is inherently valuable. Rather, our results suggest that capability creation and disruption can be jointly produced by continuous digital innovation, and both can become pathways through which innovation affects performance. This expands the theoretical treatment of continuous feature innovation beyond the question of whether newly introduced functionality is adopted and useful to include what happens when that functionality destabilizes the work system into which it is introduced.

6.1.3 IT Failure: From Reliability Loss to Recoverable Disruption

Third, we contribute to research on IT reliability and failure by challenging the assumption that the performance consequence of IT failure is negative. Prior IS research provides strong reasons to regard reliability as a desirable property of information systems and IT failure as costly (Butler & Gray, 2006). At the organizational level, IT failures can destroy market value, require organizational responses, and interrupt technology-dependent operations (Bharadwaj et al., 2009; Triche & Walden, 2018). At the individual level, interruptions can impose attentional and performance costs (Addas & Pinsonneault, 2018). Our positive aggregate estimate for IT failure appears inconsistent with this conventional expectation.

The additional analyses suggest a way to reconcile these perspectives. What matters may not simply be whether technology fails, but whether the work interrupted by that IT failure remains recoverable. An IT failure during internal-facing work can interrupt task execution without eliminating the underlying task opportunity. A worker whose attempt to record information fails can return to the record, reload the page, retry the action, and complete the work. The IT failure creates a disruption, but the worker retains an opportunity to respond to it. By contrast, an IT failure during customer-facing work can occur against an external clock. A failed communication with a waiting customer may compromise an interaction that cannot simply be recreated by retrying the same action later.

Our category-level decomposition is consistent with this distinction. IT failures in recording work make the largest positive contribution to the aggregate effect of IT failure, whereas IT failures in communicating work make the largest negative contribution. Because this decomposition is descriptive rather than causal, it should not by itself be interpreted as establishing the causal role of recoverability. However, the trace evidence on coping strategies is consistent with the proposed mechanism. Workers respond to internal-facing IT failures with greater retry, rapid reload, and faster resolution, whereas customer-facing IT failures are associated with rerouting, abandonment, and greater departure from routine. These behavioral differences are difficult to reconcile with a simple explanation in which highly engaged workers merely experience more IT failures and also perform better.

Together, these findings suggest a shift in the theoretical question surrounding IT failure. Rather than asking simply whether IT failure harms or improves performance, research should ask when disrupted work permits recovery and how workers respond when it does. We introduce recoverability as a useful organizing concept for answering that question. IT failure may become productive when it creates an interruption from which the worker can re-engage, adapt, and recover; it remains costly when the disruption compromises an opportunity that cannot readily be restored.

This perspective also connects IT reliability research to research on learning from failure. Sitkin (1992) argues that relatively small failures can generate learning when they are sufficiently

bounded, permit rapid response, and occur in domains familiar enough to support interpretation. Digital work provides a setting in which such responses can be observed behaviorally. Retry, reload, recovery time, rerouting, abandonment, and workflow deviation capture what workers actually do immediately after technology fails. The results suggest that the informational and adaptive consequences of IT failure depend importantly on the structure of the work in which the IT failure occurs.

6.1.4 The Business Value of IT: Value Realized Through Coping

Fourth, we contribute to research on the business value of IT. Studies of technology-enabled work have established that technology use can improve individual productivity and performance, including in customer-facing work and, more recently, in settings involving generative AI (Ahearne et al., 2008; Brynjolfsson et al., 2025; Noy & Zhang, 2023). These studies attribute the value of technology use to the capabilities the technology provides. Our findings show that part of the value of new feature use is realized through the IT failures it produces and the coping strategies workers adopt after them.

More broadly, this finding illustrates why understanding the business value of digital innovation may require studying not only successful technology use but also the frictions generated during use. Some consequences conventionally classified as implementation or operational costs may interact with worker behavior in ways that alter the value ultimately realized from technology. The performance effects of digital innovation may therefore reside partly in workers' responses to imperfect technology, rather than solely in frictionless use of the capabilities that technology provides.

6.2 Implications for Practice

The findings also have implications for managers of continuously evolving digital platforms and for organizations that depend on those platforms for knowledge work. The most immediate implication is not that organizations should tolerate IT failure because IT failure improves performance. The aggregate positive relationship masks important differences across types of work. Some IT failures appear compatible with recovery and productive re-engagement, while others coincide with abandonment and lost opportunities. Treating all IT failures as equivalent can therefore obscure where reliability matters most.

This suggests a more selective approach to reliability management. Conventional operational metrics often emphasize aggregate IT failure rates, uptime, error incidence, or time lost to IT failure. These measures remain important, but they may be insufficient for prioritizing reliability investments. Managers should also consider where in the workflow IT failures occur, whether the

interrupted task can be recovered, and workers' coping strategies after the IT failure.

IT failures occurring during customer-facing activities deserve particular attention. When an IT failure disrupts communication with a customer, the worker may be unable to recreate the interaction simply by retrying the task. Such IT failures can therefore threaten opportunities that are perishable. Reliability investments in customer-facing workflows may generate value not merely by reducing downtime, but by protecting interactions that cannot easily be recovered once disrupted.

Internal workflows present a different managerial problem. Our findings do not imply that firms should intentionally introduce IT failures into these activities. Rather, they suggest that the consequences of IT failures that do occur may depend on whether systems make recovery easy. Platform designers can therefore complement investments in preventing IT failure with investments in recovery from IT failure. Preserving entered information, enabling rapid retry, maintaining workflow state, providing intelligible error feedback, and allowing workers to resume interrupted tasks may reduce the cost of unavoidable IT failures and potentially facilitate productive re-engagement.

The results also have implications for the management of continuous software releases. Vendors commonly face pressure to increase release velocity while maintaining reliability. Our findings suggest that the relevant managerial tradeoff may be more granular than a simple choice between innovation speed and system stability. Release and testing resources could be prioritized according to the recoverability of the workflows affected by a feature. New functionality touching customer-facing or otherwise less recoverable activities may warrant particularly stringent testing and staged deployment, whereas IT failures in highly recoverable internal workflows may pose different operational risks.

Real-user monitoring data can support this more selective approach. The same behavioral traces used in our analysis (retry, reload, recovery time, rerouting, abandonment, and workflow deviation) could supplement conventional technical reliability measures. An IT failure followed immediately by successful retry conveys different operational information from an error followed by abandonment or termination of the session. Organizations can therefore evaluate IT failures not only by their technical incidence but also by their behavioral aftermath.

Taken together, these implications suggest a shift from pursuing reliability uniformly toward managing the consequences and recoverability of IT failure. Organizations should continue to prevent IT failures, particularly where IT failures threaten nonrecoverable customer or business opportunities. But when some IT failures are unavoidable in continuously evolving digital systems, managers can also design technologies and workflows that help workers recover effectively when disruption occurs.

6.3 Boundary Conditions and Future Research

Several features of our study define important boundaries for these conclusions and opportunities for future research. Hypotheses 3a and 3b are stated, and the agent-week evidence describes rather than tests them. The next step is to test them at the level of the IT failure episode, measuring recoverability at the moment of each IT failure from whether the work state is preserved and whether an alternative route exists, and identifying the effect of the coping strategy, which the worker chooses, by comparing workers hit by the same platform incident and by exploiting releases that change whether the work state is preserved. The theory concerns deterministic IT failure, in which a requested action does not complete and the IT failure is visible when it occurs, and IT failures that arise in the worker's own use of a feature, where the worker can act on the situation. System-wide outages, in which the worker depends on others to restore the system, and probabilistic generative AI, in which the output may be wrong while the action appears to succeed (Hinds & Leonardi, 2026), are boundary conditions. The empirical setting is a single SaaS CRM platform used by insurance agents, and the work is characterized by repeated interaction with a familiar digital environment. These characteristics may be especially conducive to recovery because workers can draw on accumulated task and system knowledge when IT failures occur. Whether similar responses emerge in less familiar, more safety-critical, or more tightly coupled work remains an open question.

Future research could directly manipulate or exploit exogenous variation in task recoverability to identify its causal role. Such research could examine whether recovery opportunities, task familiarity, the severity of IT failure, or the reversibility of interrupted work determine when IT failure becomes productive or costly.

Future research could also distinguish more explicitly among different sources of IT failure. In our setting, IT failures arise from both system-side and user-side causes, and their distribution varies across task categories. Understanding whether workers learn differently from IT failures they attribute to themselves versus IT failures they attribute to the technology could further refine the recoverability mechanism. Similarly, repeated exposure to IT failure may eventually generate frustration or workarounds rather than productive adaptation, suggesting that the benefits associated with bounded, recoverable disruption may have limits.

Finally, the continuing evolution of digital platforms makes the relationship between innovation and reliability increasingly important. As organizations adopt systems that are updated continuously, and as increasingly complex and probabilistic technologies become embedded in work, the assumption that innovation can first be implemented and then stabilized becomes less tenable. Future research should therefore examine innovation and reliability as jointly evolving properties of digital work systems rather than as separate stages of technology implementation.

References

Aanestad, M., & Jensen, T. B. (2016). Collective mindfulness in post-implementation IS adaptation processes. *Information and Organization*, *26*(1-2), 13–27. doi: 10.1016/j.infoandorg.2016.02.001

Adão, R., Kolesár, M., & Morales, E. (2019). Shift-share designs: Theory and inference. *The Quarterly Journal of Economics*, *134*(4), 1949–2010. doi: 10.1093/qje/qjz025

Addas, S., & Pinsonneault, A. (2015). The many faces of information technology interruptions: a taxonomy and preliminary investigation of their performance effects. *Information Systems Journal*, *25*(3), 231–273. doi: 10.1111/isj.12064

Addas, S., & Pinsonneault, A. (2018). E-Mail Interruptions and Individual Performance: Is There a Silver Lining? *MIS Quarterly*, *42*(2), 381–405. doi: 10.25300/MISQ/2018/13157

Ahearne, M., Jones, E., Rapp, A., & Mathieu, J. (2008). High touch through high tech: The impact of salesperson technology usage on sales performance via mediating mechanisms. *Management Science*, *54*(4), 671–685. doi: 10.1287/mnsc.1070.0783

Ahearne, M., Pourmasoudi, M., & Habel, J. (2025). Inside sales structures and firm performance. *Journal of the Academy of Marketing Science*, *53*(5), 1356–1378. doi: 10.1007/s11747-025-01085-6

Anwar, A., Kim, C. L., & McClure, C. E. (2026). Leveraging Coping Flexibility to Ease Emotional Exhaustion in Salespeople. *Journal of Personal Selling & Sales Management*, *46*(1), 58–77. doi: 10.1080/08853134.2025.2591673

Bai, X., Nunez, M., & Kalagnanam, J. R. (2012). Managing data quality risk in accounting information systems. *Information Systems Research*, *23*(2), 453–473. doi: 10.1287/isre.1110.0371

Bala, H., & Venkatesh, V. (2016). Adaptation to Information Technology: A Holistic Nomological Network from Implementation to Job Outcomes. *Management Science*, *62*(1), 156–179. doi: 10.1287/mnsc.2014.2111

Balachander, S., Ghosh, B., & Stock, A. (2010). Why bundle discounts can be a profitable alternative to competing on price promotions. *Marketing Science*, *29*(4), 624–638. doi: 10.1287/mksc.1090.0540

Banker, R., Liang, Y., & Ramasubbu, N. (2021). Technical Debt and Firm Performance. *Management Science*, *67*(5), 3174–3194. doi: 10.1287/mnsc.2019.3542

Basu, A. K., Lal, R., Srinivasan, V., & Staelin, R. (1985). Salesforce compensation plans: An agency theoretic perspective. *Marketing Science*, *4*(4), 267–291. doi: 10.1287/mksc.4.4.267

Beaudry, A., & Pinsonneault, A. (2005). Understanding User Responses to Information Technology: A Coping Model of User Adaptation1. *MIS Quarterly*, *29*(3), 493–524. doi: 10.2307/25148693

Beaudry, A., & Pinsonneault, A. (2010). The Other Side of Acceptance: Studying the Direct and Indirect Effects of Emotions on Information Technology Use. *MIS Quarterly*, *34*(4), 689–710. doi: 10.2307/25750701

Benaroch, M., & Fink, L. (2021). No Rose without a thorn: Board IT competence and market reactions to operational IT failures. *Information & Management*, *58*(8), 103546. doi: 10.1016/j.im.2021.103546

Benbya, H., Nan, N., Tanriverdi, H., & Yoo, Y. (2020). Complexity and Information Systems Research in the Emerging Digital World. *MIS Quarterly*, *44*(1), 1–18. doi: 10.25300/MISQ/2020/13304

Bharadwaj, A., Keil, M., & Mähring, M. (2009). Effects of Information Technology Failures on the Market Value of Firms. *Journal of Strategic Information Systems*, *18*(2), 66–79. doi: 10.1016/j.jsis.2009.04.001

Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-Experimental Shift-Share Research Designs. *The Review of Economic Studies*, *89*(1), 181–213. doi: 10.1093/restud/rdab030

Borusyak, K., Hull, P., & Jaravel, X. (2025). A Practical Guide to Shift-Share Instruments. *Journal of Economic Perspectives*, *39*(1), 181–204. doi: 10.1257/jep.20231370

Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at Work. *The Quarterly Journal of Economics*, *140*(2), 889–942. doi: 10.1093/qje/qjae044

Butkiewicz, M., Madhyastha, H. V., & Sekar, V. (2011). Understanding website complexity: measurements, metrics, and implications. In *Proceedings of the 2011 ACM SIGCOMM conference on Internet measurement conference* (pp. 313–328). New York, NY, USA: Association for Computing Machinery. doi: 10.1145/2068816.2068846

Butler, B. S., & Gray, P. H. (2006). Reliability, Mindfulness, and Information Systems. *MIS Quarterly*, *30*(2), 211–224. doi: 10.2307/25148728

Celli, V. (2022). Causal Mediation Analysis in Economics: Objectives, Assumptions, Models. *Journal of Economic*

Surveys, *36*(1), 214–234. doi: 10.1111/joes.12452

Chung, D. J., & Narayandas, D. (2017). Incentives versus reciprocity: Insights from a field experiment. *Journal of Marketing Research*, *54*(4), 511–524. doi: 10.1509/jmr.15.0174

Cito, J., Gotowka, D., Leitner, P., Pelette, R., Suljoti, D., & Dustdar, S. (2015). Identifying web performance degradations through synthetic and real-user monitoring. *Journal of Web Engineering*, *14*(5-6), 414–442.

Citrix. (2017, December 11). 11th December: The Day Brits Would Wrap Up Work for Christmas if IT Issues Didn't Restrict Productivity. *Total Telecom Plus*.

Demirer, M., Horton, J. J., Immorlica, N., Lucier, B., & Shahidi, P. (2026). *Chaining Tasks, Redefining Work: A Theory of AI Automation* (Working Paper Series No. 34859). National Bureau of Economic Research. Retrieved from https://www.nber.org/papers/w34859 doi: 10.3386/w34859

Dippel, C., Ferrara, A., & Heblich, S. (2020). Causal Mediation Analysis in Instrumental-Variables Regressions. *The Stata Journal*, *20*(3), 613–626. doi: 10.1177/1536867X20953572

Donovan-Smith, O. (2022, April 27). Officials Interrogated Over System Flaws. *The Spokesman-Review*, A1.

Elie-Dit-Cosaque, C. M., & Straub, D. W. (2011). Opening the black box of system usage: user adaptation to disruptive IT. *European Journal of Information Systems*, *20*(5), 589–607. doi: 10.1057/ejis.2010.23

Feng, Y. K., Yu, N. Y., Tam, K. Y., & Lai, M. C. (2024). Effective Intervention in User Adaptation: A 2×2 Coping Framework Entailing Implementation and Contextual Factors. *Journal of the Association for Information Systems*, *25*(4), 962–989. doi: 10.17705/1jais.00884

Fong, J., & Waisman, C. (2025). The effects of delay in bargaining: Evidence from eBay. *Management Science*, *71*(12), 9976–9997. doi: 10.1287/mnsc.2023.01562

Fritz, M. S., & MacKinnon, D. P. (2007). Required Sample Size to Detect the Mediated Effect. *Psychological Science*, *18*(3), 233–239. doi: 10.1111/j.1467-9280.2007.01882.x

Frölich, M., & Huber, M. (2017). Direct and Indirect Treatment Effects: Causal Chains and Mediation Analysis with Instrumental Variables. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *79*(5), 1645–1666. doi: 10.1111/rssb.12232

Furr, N., Gaarlandt, J., Mohan, S., & Shipilov, A. (2025, November 25). AI Agents Aren't Ready for Consumer-Facing Work, but They Can Excel at Internal Processes. *Harvard Business Review*.

Galluch, P., Grover, V., & Thatcher, J. (2015). Interrupting the Workplace: Examining Stressors in an Information Technology Context. *Journal of the Association for Information Systems*, *16*(1), 1–47. doi: 10.17705/1jais.00387

Gans, J. S., & Goldfarb, A. (2026). *O-Ring Automation* (Working Paper Series No. 34639). National Bureau of Economic Research. Retrieved from https://www.nber.org/papers/w34639 doi: 10.3386/w34639

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, *110*(8), 2586–2624. doi: 10.1257/aer.20181047

Grover, V., Lindberg, A., Benbasat, I., & Lyytinen, K. (2020). The perils and promises of big data research in information systems. *Journal of the Association for Information Systems*, *21*(2), 268–291. doi: 10.17705/1jais.00601

Guesalaga, R., & Kapelianis, D. (2015). When do salespeople pursue and win deals? A two-stage model of sales opportunity outcomes. *Journal of Business and Industrial Marketing*, *30*(7), 817–829. doi: 10.1108/JBIM-06-2014-0120

Hartmann, N. N., Wieland, H., Chaker, N. N., Habel, J., & Tyler, F. J. (2025). Sales content platforms and opportunity conversion. *Production and Operations Management*, 10591478251413339. doi: 10.1177/10591478251413339

Hermann, E., Puntoni, S., & Morewedge, C. K. (2026). Why Gen AI Feels So Threatening to Workers. *Harvard Business Review*, *104*(2), 54–63.

Hinds, R., & Leonardi, P. (2026, August 5). How Much Time Do Your Employees Spend Botsitting? *Harvard Business Review*.

Imai, K., Keele, L., & Tingley, D. (2010). A General Approach to Causal Mediation Analysis. *Psychological Methods*, *15*(4), 309–334. doi: 10.1037/a0020761

Jasperson, J. S., Carter, P. E., & Zmud, R. W. (2005). A comprehensive conceptualization of post-adoptive behaviors associated with information technology enabled work systems. *MIS Quarterly*, *29*(3), 525–557. doi: 10.2307/25148694

Karahanna, E., Chen, A., Liu, Q. B., & Serrano, C. (2019). Capitalizing on Health Information Technology to Enable

Digital Advantage in U.S. Hospitals. *MIS Quarterly*, *43*(1), 113–140. doi: 10.25300/MISQ/2019/12743

Keramidis, P., & Shollo, A. (2026). The realisation of IS business value: a value-reflexive perspective. *European Journal of Information Systems*, *35*(2), 280–300. doi: 10.1080/0960085x.2025.2607449

Kim, E. (2026, March 10). Amazon Orders 90-Day Reset After Code Mishaps Cause Millions of Lost Orders. *Business Insider*.

Kremer, M. (1993). The O-Ring Theory of Economic Development. *The Quarterly Journal of Economics*, *108*(3), 551–575. doi: 10.2307/2118400

Lazarus, R. S., & Folkman, S. (1984). *Stress, Appraisal, and Coping*. New York: Springer.

Lindberg, A. (2020). Developing theory through integrating human and machine pattern recognition. *Journal of the Association for Information Systems*, *21*(1), 90–116. doi: 10.17705/1jais.00593

MacKinnon, D. P., Lockwood, C. M., & Williams, J. (2004). Confidence Limits for the Indirect Effect: Distribution of the Product and Resampling Methods. *Multivariate Behavioral Research*, *39*(1), 99–128. doi: 10.1207/s15327906mbr3901_4

Mattern, J., Tarafdar, M., Klein, S., & Schellhammer, S. (2024). Thriving in a bruising job: How high achieving IT professionals can cope with occupational demands. *Information Systems Journal*, *34*(6), 1902–1934. doi: 10.1111/isj.12513

Moneylife Digital Team. (2025, November 19). Cloudflare CEO Says Global Internet Meltdown Triggered by Faulty Database Update, Not a DDoS Attack. *Moneylife*.

Moshki, H., & Barki, H. (2016). An Exploratory Study on Behavioral and Emotional Coping with IT-Enabled Government Surveillance. In *Proceedings of the 49th hawaii international conference on system sciences (hicss)* (pp. 3636–3645). doi: 10.1109/HICSS.2016.455

Musalem, A., Olivares, M., & Yung, D. (2023). Balancing agent retention and waiting time in service platforms. *Operations Research*, *71*(3), 979–1003. doi: 10.1287/opre.2022.2418

Najjar, M. S., Kettinger, W. J., & Kettinger, L. D. (2022). IS incident recovery and service value: a service-dominant logic view. *European Journal of Information Systems*, *31*(4), 492–524. doi: 10.1080/0960085x.2020.1869915

Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital Innovation Management: Reinventing Innovation Management Research in a Digital World. *MIS Quarterly*, *41*(1), 223–238. doi: 10.25300/MISQ/2017/41:1.03

Narayandas, D. (2026). Why Even Your Best Employees Override AI Systems That Work. *Harvard Business Review*, *104*(6), 42–49.

Nastjuk, I., Trang, S., Grummeck-Braamt, J.-V., Adam, M. T. P., & Tarafdar, M. (2024). Integrating and synthesising technostress research: a meta-analysis on technostress creators, outcomes, and IS usage contexts. *European Journal of Information Systems*, *33*(3), 361–382. doi: 10.1080/0960085x.2022.2154712

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, *381*(6654), 187–192. doi: 10.1126/science.adh2586

Ohiomah, A., Andreev, P., Benyoucef, M., & Hood, D. (2019). The role of lead management systems in inside sales performance. *Journal of Business Research*, *102*, 163–177. doi: 10.1016/j.jbusres.2019.05.018

Ortiz de Guinea, A., & Webster, J. (2013). An Investigation of Information Systems Use Patterns: Technological Events as Triggers, the Effect of Time, and Consequences for Performance. *MIS Quarterly*, *37*(4), 1165–1188.

Pang, M.-S., & Tanriverdi, H. (2022). Strategic roles of IT modernization and cloud migration in reducing cybersecurity risks of organizations: The case of U.S. federal government. *The Journal of Strategic Information Systems*, *31*(1), 101707. doi: 10.1016/j.jsis.2022.101707

Pirkkalainen, H., Salo, M., Tarafdar, M., & Makkonen, M. (2019). Deliberate or Instinctive? Proactive and Reactive Coping for Technostress. *Journal of Management Information Systems*, *36*(4), 1179–1212. doi: 10.1080/07421222.2019.1661092

Poláková-Kersten, M., Khanagha, S., van den Hooff, B., & Khapova, S. N. (2023). Digital transformation in high-reliability organizations: A longitudinal study of the micro-foundations of failure. *The Journal of Strategic Information Systems*, *32*(1), 101756. doi: 10.1016/j.jsis.2023.101756

Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The Consequences of Technostress for End Users in Organizations: Conceptual Development and Empirical Validation. *Information Systems Research*, *19*(4), 417–433. doi: 10.1287/isre.1070.0165

Rao, R. S., Viswanathan, M., John, G., & Kishore, S. (2021). Do activity-based incentive plans work? Evidence from a large-scale field intervention. *Journal of Marketing Research*, *58*(4), 686–704. doi: 10.1177/00222437211020013

Rinta-Kahila, T., Penttinen, E., Salovaara, A., Soliman, W., & Ruissalo, J. (2023). The Vicious Circles of Skill Erosion: A Case Study of Cognitive Automation. *Journal of the Association for Information Systems*, *24*(5), 1378–1412. doi: 10.17705/1jais.00829

Saatçi, B., Ivory, C., & Toraldo, M. L. (2026). Spot New Tech Skills Emerging From the Workforce. *MIT Sloan Management Review*, *68*(1), 49–53.

Sabnis, G., Chatterjee, S. C., Grewal, R., & Lilien, G. L. (2013). The sales lead black hole: On sales reps' follow-up of marketing leads. *Journal of Marketing*, *77*(1), 52–67. doi: 10.1509/jm.10.0047

Salo, M., Makkonen, M., & Hekkala, R. (2020). The Interplay of IT Users' Coping Strategies: Uncovering Momentary Emotional Load, Routes, and Sequences. *MIS Quarterly*, *44*(3), 1143–1175. doi: 10.25300/MISQ/2020/15610

Sanjay. (2026, September 20). If AI Could Wipe Out Humanity, Why Isn't Building It a Crime? *BW Businessworld*.

Schmitz, C., Lee, Y.-C., & Lilien, G. L. (2014). Cross-selling performance in complex selling contexts: An examination of supervisory- and compensation-based controls. *Journal of Marketing*, *78*(3), 1–19. doi: 10.1509/jm.12.0421

Schryen, G. (2013). Revisiting IS business value research: what we already know, what we still need to know, and how we can get there. *European Journal of Information Systems*, *22*(2), 139–169. doi: 10.1057/ejis.2012.45

Shantz, I. (2025, October 29). Microsoft's Azure Cloud Service Outage Causes Global Disruptions. *The Toronto Sun*.

Simon, H. A. (1962). The architecture of complexity. *Proceedings of the American Philosophical Society*, *106*(6), 467–482.

Sitkin, S. B. (1992). Learning Through Failure: The Strategy of Small Losses. *Research in Organizational Behavior*, *14*, 231–266.

Sobel, M. E. (1982). Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models. *Sociological Methodology*, *13*, 290–312. doi: 10.2307/270723

Spetz, J., & Maiuro, L. S. (2004). Measuring Levels of Technology in Hospitals. *The Quarterly Review of Economics and Finance*, *44*(3), 430–447. doi: 10.1016/j.qref.2004.05.006

Tan, T. F., & Netessine, S. (2014). When does the devil make work? An empirical study of the impact of workload on worker productivity. *Management Science*, *60*(6), 1574–1593. doi: 10.1287/mnsc.2014.1950

Tanriverdi, H., & Du, K. (2020). Corporate strategy changes and information technology control effectiveness in multibusiness firms. *MIS Quarterly*, *44*(4), 1573–1617. doi: 10.25300/MISQ/2020/14223

Tanriverdi, H., Kwon, J., & Im, G. (2025). Taming Complexity in the Cybersecurity of Multihospital Systems: The Role of Enterprise-wide Data Analytics Platforms. *MIS Quarterly*, *49*(1), 243–273. doi: 10.25300/MISQ/2024/17752

Tarafdar, M., Pullins, E. B., & Ragu-Nathan, T. S. (2015). Technostress: negative effect on performance and possible mitigations. *Information Systems Journal*, *25*(2), 103–132. doi: 10.1111/isj.12042

Tiwana, A., & Safadi, H. (2024). Atrophy in Aging Systems: Evidence, Dynamics, and Antidote. *Information Systems Research*, *35*(1), 66–86. doi: 10.1287/isre.2023.1218

Tiwana, A., & Safadi, H. (2026). Silence Inside Systems: Roots and Generativity Consequences. *Information Systems Research*, *37*(1), 584–602. doi: 10.1287/isre.2022.0586

Triche, J. H., & Walden, E. (2018). The Use of Impression Management Strategies to Manage Stock Market Reactions to IT Failures. *Journal of the Association for Information Systems*, *19*(4), 333–357. doi: 10.17705/1jais.00494

Vieira da Cunha, J., Carugati, A., & Leclercq-Vandelannoitte, A. (2015). The dark side of computer-mediated control. *Information Systems Journal*, *25*(4), 319–354. doi: 10.1111/isj.12066

Wang, X. S., Balasubramanian, A., Krishnamurthy, A., & Wetherall, D. (2013). Demystifying page load performance with WProf. In *Proceedings of the 10th USENIX conference on Networked Systems Design and Implementation* (pp. 473–486). USA: USENIX Association.

Weinert, C. (2018). Coping with Discrepant Information Technology Events: A Literature Review. In *Proceedings of the 26th european conference on information systems (ecis)*. Portsmouth, UK. (Research Paper 137)

Weinert, C. (2019). *Coping with the Dark Side of Information Technology: Theoretical Foundation and Empirical Evidence* (Doctoral dissertation, Otto-Friedrich-Universität Bamberg). doi: 10.20378/irbo-54581

Weinert, C., Maier, C., Laumer, S., & Weitzel, T. (2022). Repeated IT Interruption: Habituation and Sensitization of User Responses. *Journal of Management Information Systems*, *39*(1), 187–217. doi: 10.1080/07421222.2021.2023411

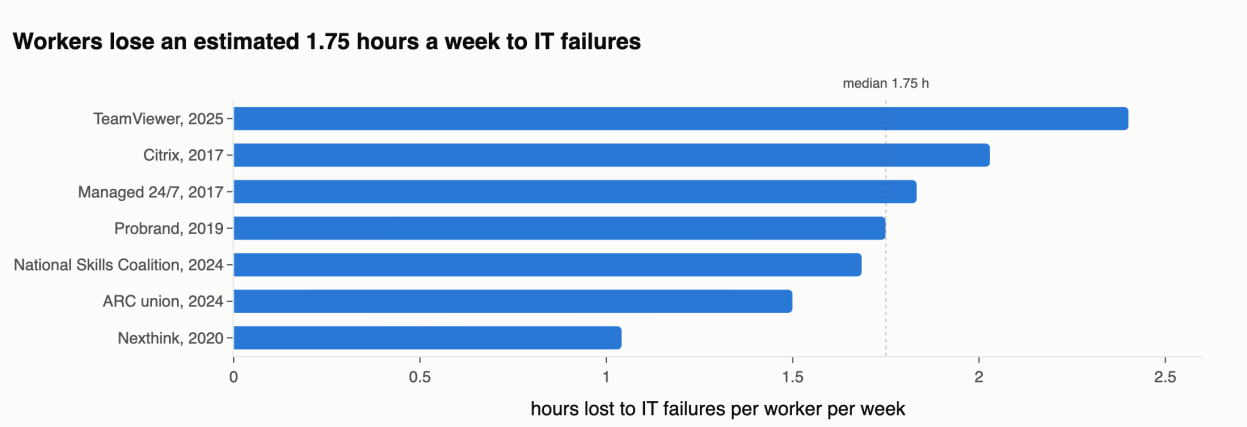
Xu, Y., Tan, T. F., & Netessine, S. (2022). The impact of workload on operational risk: Evidence from a commercial bank. *Management Science (INFORMS)*, *68*(4), 2668–2693. doi: 10.1287/mnsc.2021.4019

Yahalom, R. (2025, January 10). What the 2024 CrowdStrike Glitch Can Teach Us About Cyber Risk. *Harvard Business Review*.

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). The New Organizing Logic of Digital Innovation: An Agenda for Information Systems Research. *Information Systems Research*, *21*(4), 724–735. doi: 10.1287/isre.1100.0322

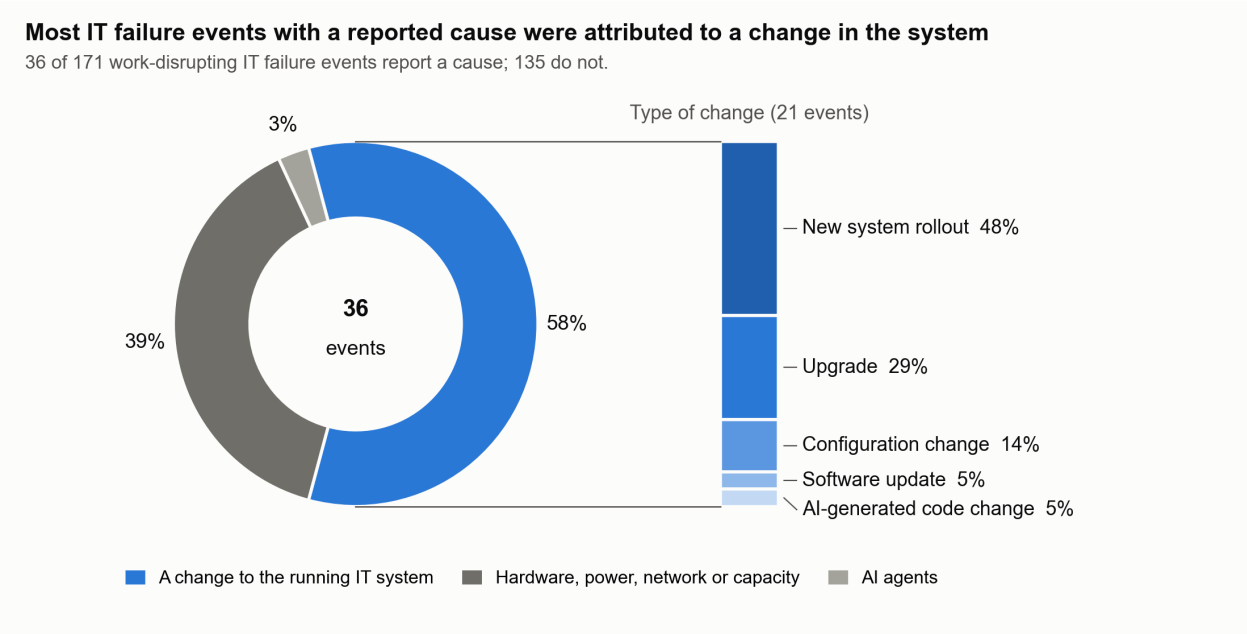
Zhao, X., Xia, Q., & Huang, W. (2020). Impact of technostress on productivity from the theoretical perspective of appraisal and coping processes. *Information & Management*, *57*(8), 103265. doi: 10.1016/j.im.2020.103265

Figure 1. Work Time Lost to IT Failures per Worker per Week



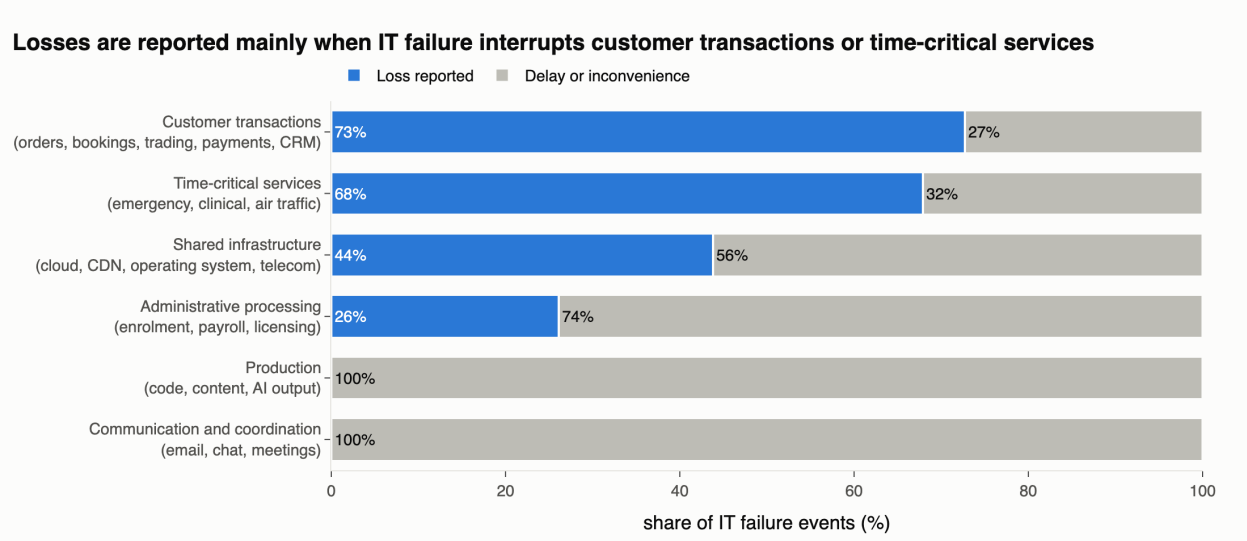
Note. Each point is one survey, labelled by its sponsor and year, converted to hours per week; the dashed line is the median. Most surveys are vendor-sponsored and are industry estimates. Source: surveys reported in Dow Jones Factiva news coverage, 2017 to 2025.

Figure 2. Reported Cause of Work-Disrupting IT Failure Events and Type of Change, 2016 to 2026



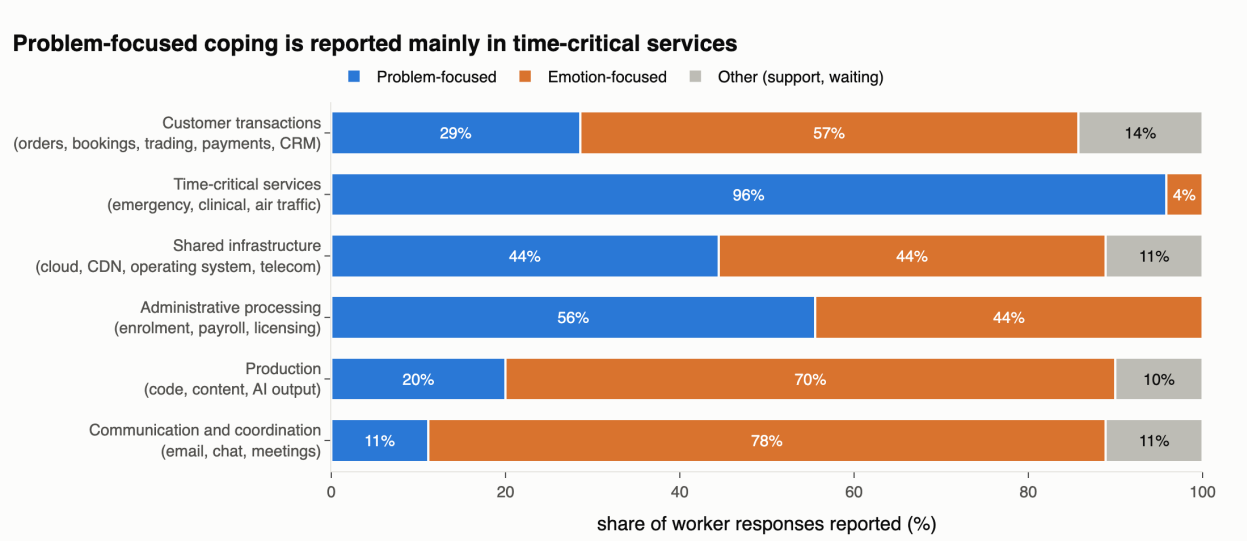
Note. One search targeted update-related IT failures, so the share of change describes the sample, not all IT failures. Source: Dow Jones Factiva news coverage, 2016 to 2026; authors' coding.

Figure 3. Share of IT Failure Events with a Reported Loss, by the Kind of Work Interrupted, 2016 to 2026



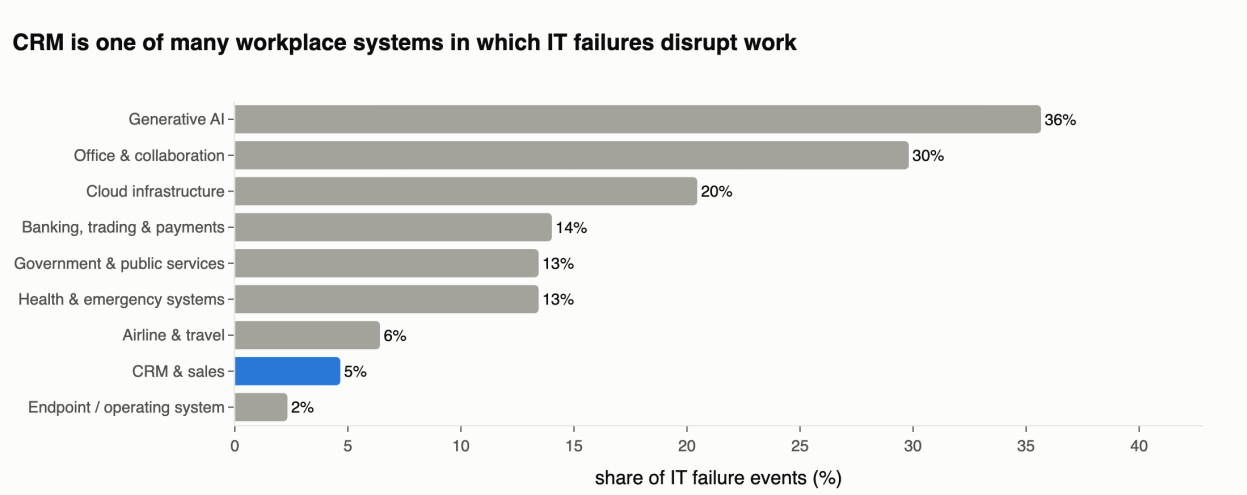
Note. Each of the 171 events is coded by hand for the kind of work interrupted and for the consequence reported; a loss is lost transactions or services, a quantified monetary loss, or harm to people, and events with no loss reported are coded as delay or inconvenience. News reports consequences more often for transaction and service failures than for outages of productivity tools, so losses in the latter may be understated. Source: Dow Jones Factiva news coverage, 2016 to 2026; authors' coding.

Figure 4. Worker Responses to IT Failure, by the Kind of Work Interrupted, 2016 to 2026



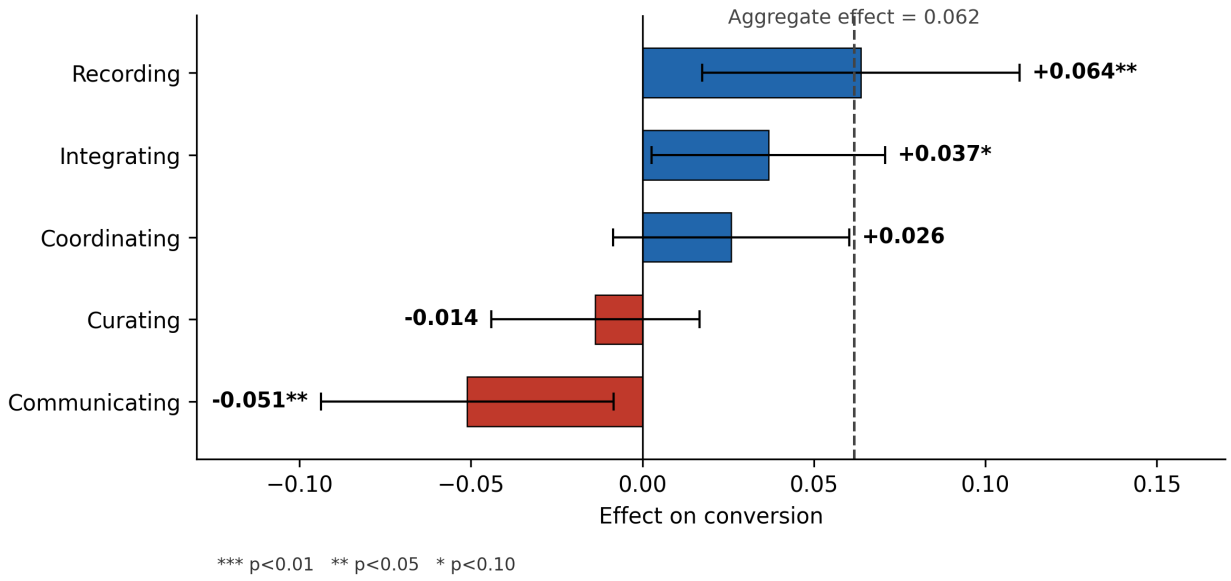
Note. Worker and user responses reported in each event, coded by hand from news text and grouped by kind of coping; an event can report several responses, so shares are of reported responses. Responses by vendors and providers are not shown. Most events are large outages, in which coping is largely collective. Source: Dow Jones Factiva news coverage, 2016 to 2026; authors' coding.

Figure 5. Types of System Involved in Work-Disrupting IT Failure Events, 2016 to 2026



Note. Systems identified by keyword in each article's headline and opening and pooled over an event's articles; an event can involve more than one system, so shares sum to more than 100 percent. Generative AI and health systems are over-represented because two searches targeted them. Source: Dow Jones Factiva news coverage, 2016 to 2026.

Figure 7. Shapley Decomposition of the Aggregate IT-Failure Effect



Note. The figure decomposes the aggregate effect of IT failure on conversion into the contribution of each of five categories of knowledge work. A category's contribution is its average marginal contribution across all possible combinations of the five categories, so the contributions sum to the aggregate. The aggregate effect of 0.062 is the estimate obtained when all five categories enter together. Each estimate is from OLS on conversion with the same controls and fixed effects as the main specifications. Standard errors are bootstrapped and clustered by agent.

Table 1. Prior Studies of IT Failure, Interruption and Worker Response

Study	Construct examined	Unit	Mechanism
IT failure and firm value			
Bharadwaj et al. (2009)	IT failures and market value loss	Firm	Event study within a resource-based view
Benaroch and Fink (2021)	Board IT competence moderating market reaction to operational failures	Firm	Agency theory, governance reduces investor uncertainty
Najjar et al. (2022)	IS incident recovery and service value	Organization	Service-dominant logic, value co-created during recovery
ICT interruptions and performance			
Addas and Pinsonneault (2015)	Interruption taxonomy and individual performance	Individual	Attentional depletion and task-switching cost
Galluch et al. (2015)	ICT interruptions, stressors and strain	Individual	Stressor-strain model
Weinert et al. (2022)	Repeated interruption, habituation and sensitization	Individual	Conditioning theory, non-linear exposure response
Technostress			
Ragu-Nathan et al. (2008)	Technostress creators, job satisfaction and commitment	Individual	Transactional stress model with organizational inhibitors
Tarafdar et al. (2015)	Technostress and technology-enabled performance	Individual	Role theory and sociotechnical theory
Zhao et al. (2020)	Application-level stressors, appraisal, coping and productivity	Individual	Transactional theory of stress at the application level
Nastjuk et al. (2024)	Meta-analysis of technostress creators and outcomes	Individual	Synthesis of 102 studies
User coping and adaptation			
Lazarus and Folkman (1984)	Appraisal, coping and adaptation	Individual	Transactional theory of stress and coping
Beaudry and Pinsonneault (2005)	Four adaptation strategies from primary and secondary appraisal	Individual	Coping theory applied to IT events
Beaudry and Pinsonneault (2010)	Emotions and IT use through adaptation behaviours	Individual	Emotions as triggers of coping, in a survey of 249 account managers
Bala and Venkatesh (2016)	Technology adaptation behaviours and job outcomes	Individual	Appraisal and control predict four adaptation behaviours; four-wave field study of two implementations
Ortiz de Guinea and Webster (2013)	IS use patterns triggered by discrepant IT events	Individual	Coping, affect–object and automaticity; experience sampling at work and a laboratory study
Weinert (2018)	Review of coping with discrepant IT events	Individual	Event, appraisal, coping and outcome process
Weinert (2019)	Characteristics, IT events, responses and outcomes	Individual	Coping with the dark side of IT use; surveys and laboratory experiments, including a simulated computer freeze

continued on the next page

Table 1. Prior Studies of IT Failure, Interruption and Worker Response (continued)

Study	Construct examined	Unit	Mechanism
Salo et al. (2020)	Routes and sequences of coping with failing applications	Individual	Interplay of problem- and emotion-focused coping, mixed methods
Moshki and Barki (2016)	Coping with IT-enabled government surveillance	Individual	Ways of coping coded from readers' comments on news articles
Elie-Dit-Cosaque and Straub (2011)	Measures of system usage and user adaptation to disruptive IT	Individual	Coping model of user adaptation, tested in a two-by-two laboratory experiment
Pirkkalainen et al. (2019)	Proactive and reactive coping moderating technostress	Individual	Proactive versus reactive coping
Feng et al. (2024)	Intervention type by implementation phase and voluntariness	Individual	Coping extended with a time dimension
Mattern et al. (2024)	Coping portfolios and strain levels	Individual	Requisite variety and coping repertoire breadth
System atrophy			
Tiwana and Safadi (2024)	System atrophy, bugginess and developer disengagement	System	Modularity dynamics
Tiwana and Safadi (2026)	System silence and generativity	System	Attention funnelling
Banker et al. (2021)	Technical debt in CRM systems and firm performance	Firm	Shortcuts compounding maintenance obligations
High-reliability organizing			
Butler and Gray (2006)	Reliable performance through mindfulness	Organization and individual	Routine-based versus mindfulness-based reliability
Aanestad and Jensen (2016)	Collective mindfulness in post-implementation adaptation	Organization	High-reliability organizing applied after implementation
Poláková-Kersten et al. (2023)	Tension between high-reliability identity and digital transformation	Organization	Identity threat producing self-protective behaviour in the IT workforce
Rinta-Kahila et al. (2023)	Skill erosion, dependency and vulnerability	Individual and organization	Vicious circle in which automation removes practice
IS business value			
Schryen (2013)	Systematic review of IS business value research	Firm	Bibliometric synthesis
Keramidis and Shollo (2026)	Value realization as enacted practice	Organization	Value-reflexive perspective
CRM control and the representation of work			
Vieira da Cunha et al. (2015)	Burden of representation under loose coupling	Individual and organization	Loose versus tight coupling of work and record

Table 2. Variables Description

Variable	Definition and construction	
Technology use.		
	Feature-level input	**Agent-week construction**
New CRM Feature Use	A Saidin novelty-weighted index of an agent's engagement with newly released CRM features (Karahanna et al., 2019; Spetz & Maiuro, 2004). u_{kit} is agent i's weekly click count on feature k, and A_{kit} indicates whether agent i has adopted feature k by week t. Rare features receive high weight and widely adopted features near-zero weight; non-adopters contribute zero by construction. The feature set is itself time-varying, expanding with each platform-controlled release wave, and the weights are recomputed each week to reflect both the growing set and the evolving cross-agent adoption distribution.	$a_{kt} = 1 - \frac{1}{N}\sum_i A_{kit}$ $New\,CRM\,Feature\,Use_{it} = \sum_k a_{kt}\,u_{kit}$
New GenAI Use	A Saidin index on the same novelty-weighting logic, applied to GenAI releases. GenAI reaches agents as capability updates: each release updates the platform's GenAI functionality and supersedes the one before it, so a single version is active in any given week. G_{it} is agent i's GenAI minutes in week t, $k(t)$ the version active in week t, and r_k the release week of version k. Adoption accumulates within a version and resets when the next begins, so the weight tracks the novelty of whichever version is currently active. Releases falling in the same week form a single version, effective from the next complete week.	$G_{ikt} = G_{it}\,\mathbb{1}\{k = k(t)\}$ $A_{ikt} = \mathbb{1}\Big\{\sum_{s=r_k}^{t} G_{iks} > 0\Big\}$ $a_{kt} = 1 - \frac{1}{N}\sum_i A_{ikt}$ $New\,GenAI\,Use_{it} = \sum_k a_{kt} G_{ikt}$ $= a_{k(t),t}\,G_{it}$
Feature Breadth	The share of distinct platform workflow features accessed by agent i in week t: unique features visited, divided by the total distinct feature groups observed across all panel agents. A broad range of features in use indicates exploration of the IT, and a narrow, recommended set indicates exploitation (Bala & Venkatesh, 2016).	
Platform Time	The total time agent i spends in the platform in week t, summed over the week's sessions: $\sum_{s\in S_{it}} d_{is}$, where d_{is} is session s's total duration and S_{it} is the set of agent i's sessions in week t.	
	Session-level input	**Agent-week construction**
IT Failure	Within session s, F_{isk} is the set of tasks of category k that fail, d_j the time the agent spends on task j, and d_{is} the session's total duration. A task is recorded as failed when an error is logged against it, so the time spent on it yields no completed work. S_{it} is the set of agent i's sessions in week t. IT Failure enters estimation on the agent-weeks in which failure occurs, with an incidence dummy included as a control.	$\tau_{isk} = \frac{\sum_{j\in F_{isk}} d_j}{d_{is}}$ $IT\,Failure_{ikt} = \frac{1}{\lvert S_{it}\rvert}\sum_{s\in S_{it}} \tau_{isk}$ $IT\,Failure_{it} = \sum_{k=1}^{5} IT\,Failure_{ikt}$
Incidence of Failure	An indicator equal to one if agent i records at least one failed task in week t, and zero otherwise.	$D_{it} = \mathbb{1}\Big\{\sum_{s\in S_{it}}\sum_k \lvert F_{isk}\rvert > 0\Big\}$

continued on the next page

Table 2. Variables Description (continued)

Variable	Definition and construction

Coping strategies. Each measure is computed over the IT failure tasks of agent i in week t and is undefined in weeks without an IT failure.

- Session $s \in S_{it}$ is an ordered sequence of tasks $(j_1, \ldots, j_{n_s})$ with $\tau(j_1) < \cdots < \tau(j_{n_s})$.
  In plain terms: a session is the agent's tasks in the order they were performed.
- Task j carries a time stamp $\tau(j)$; a workflow module $m(j)$ and sub-module $m.b(j)$, the screen b within module m; an error count $e(j)$ and its IT failure tag $\varphi(j) = \mathbb{1}\{e(j) > 0\}$; and a deal $d(j) \in \mathcal{D}_{it}$, with customer segment $c_{d(j)}$ and funnel stage. A task with $\varphi(j) = 0$ is an executed task.
  In plain terms: each task records when it happened, where in the platform it happened, whether the platform executed it, and which deal it served.
- $F_{it} = \{\, j \in s,\ s \in S_{it} :\ \varphi(j) = 1 \,\}$ is the set of IT failure tasks.
  In plain terms: the tasks in the week tagged as IT failures.
- $A_j = \{\, j' \in s :\ d(j') = d(j),\ \tau(j') > \tau(j) \,\}$ is the remainder of the interrupted work process: the later tasks in the session that serve the same deal as j.
  In plain terms: what the agent still does on the interrupted work process after the IT failure.
- $j^+ = \arg\min_{j' \in A_j} \tau(j')$ is the successor of j in its work process, and $j^\circ = \arg\min_{j' \in A_j,\ \varphi(j')=0} \tau(j')$ is its first executed successor.
  In plain terms: j^+ is the agent's next task in the interrupted work process, and j° is the next executed task in it.
- For $j = j_h$, $W_j = \{j_{h+1}, j_{h+2}, j_{h+3}\} \cap s$ is the window of the next three tasks, and $P_j(m) = \frac{1}{|W_j|} \sum_{j' \in W_j} \mathbb{1}\{m(j') = m\}$ is its module mix.
  In plain terms: the three tasks after the IT failure, and how they divide across modules.
- $R_i(m)$ is the share of agent i's executed tasks over the sample period that fall in module m.
  In plain terms: the agent's routine mix of executed work across modules.

	Definition	Agent-week construction
Problem-focused coping strategies. *The agent acts on the IT failure to carry the interrupted work process forward.*		
Page Retry	The share of IT failures after which the agent continues the interrupted work process through the same sub-module that failed.	$\frac{1}{\lvert F_{it}\rvert} \sum_{j \in F_{it}} \mathbb{1}\{A_j \neq \varnothing,\ m.b(j^+) = m.b(j)\}$
Short Reload	The share of IT failures after which the agent continues the interrupted work process through the same sub-module within 30 seconds.	$\frac{1}{\lvert F_{it}\rvert} \sum_{j \in F_{it}} \mathbb{1}\{A_j \neq \varnothing,\ m.b(j^+) = m.b(j)\} \cdot \mathbb{1}\{\tau(j^+) - \tau(j) < 30\text{s}\}$
Reroute Rate	The share of IT failures after which the agent continues the interrupted work process through a different sub-module.	$\frac{1}{\lvert F_{it}\rvert} \sum_{j \in F_{it}} \mathbb{1}\{A_j \neq \varnothing,\ m.b(j^+) \neq m.b(j)\}$
Workflow Deviation	The average distance between the module mix of the agent's next three tasks after an IT failure and the agent's routine mix of executed work.	$\frac{1}{\lvert F_{it}\rvert} \sum_{j \in F_{it}} \left[1 - \cos(P_j, R_i)\right]$
Emotion-focused coping strategy. *The agent withdraws from the IT failure without changing the situation.*		
Abandonment	The share of IT failures after which the agent leaves the interrupted work process, with no further task on it in the session.	$\frac{1}{\lvert F_{it}\rvert} \sum_{j \in F_{it}} \mathbb{1}\{A_j = \varnothing\}$
Other.		
Recovery Time	The median time from an IT failure to the next executed task in the interrupted work process.	$\operatorname{median}_{j \in F_{it}} \left[\tau(j^\circ) - \tau(j)\right]$

continued on the next page

Table 2. Variables Description (continued)

Variable	Definition and construction

Performance. Sales performance is captured using conversion, the number of later-stage deals that convert as successful policy purchases in a given agent-week relative to all of the agent's active deals at both stages, reflecting precision-oriented execution effectiveness at the point where deals close.

	Deal-level input	Agent-week construction
Conversions	Let $\mathcal{D}_{it}$ denote the set of active deals for agent i in week t across both stages, and let N_{it} denote the number of later-stage deals that convert in week t.	$\frac{N_{it}}{\lvert\mathcal{D}_{it}\rvert}$

Portfolio characteristics. Each of these controls summarises the agent's active deal portfolio in the week as an average over the deals it contains. Let $\mathcal{D}_{it}$ denote agent i's set of active deals in week t. Because the agent manages early-stage and later-stage deals as a coupled system, the components carried at one stage remain a concurrent condition for performance at the other. Both complicatedness dimensions therefore enter at both stages.

	Deal-level input	Agent-week construction	Theory
Product Complicatedness	p_d, the product category associated with deal d.	$= \lvert\{ p_d : d \in \mathcal{D}_{it}^s \}\rvert$	Complicatedness captures the breadth of distinct components in an agent's deal portfolio, separated from complexity, which emerges through the form and dynamics of the interactions among those components (Benbya et al., 2020; Tanriverdi & Du, 2020; Tanriverdi et al., 2025). Let $s \in \{Q,\ C\}$ index the stage of the funnel, where Q denotes qualification-stage deals and C denotes conversion-stage deals; both dimensions are constructed at either stage from the same stage-specific deal set.
Customer Complicatedness	c_d, the customer segment associated with deal d.	$= \lvert\{ c_d : d \in \mathcal{D}_{it}^s \}\rvert$	
Process Activity Burden	A_d, the cumulative number of transactions and activities recorded for deal d as it progresses through the CRM workflow.	$= \frac{\sum_{d\in\mathcal{D}_{it}} A_d}{\lvert\mathcal{D}_{it}\rvert}$	The empirical models also control for the average accumulated transaction and activity burden embedded in an agent's active deal portfolio.
Bundling Intensity	B_d, the number of products linked to deal d.	$= \frac{\sum_{d\in\mathcal{D}_{it}} B_d}{\lvert\mathcal{D}_{it}\rvert}$	Cross-selling and promotional-bundling behavior is an established, distinct driver of conversion performance in the sales literature (Balachander et al., 2010; Schmitz et al., 2014). Bundling Intensity proxies for this behavior.

continued on the next page

Table 2. Variables Description (continued)

Variable	Definition and construction		
Portfolio Value	V_d, the raw dollar value of deal d.	$= \frac{\sum_{d \in \mathcal{D}_{it}} V_d}{\lvert \mathcal{D}_{it} \rvert}$	Financial incentive structure is an established, direct driver of sales effort and performance in the compensation literature (Basu et al., 1985; Chung & Narayandas, 2017; Rao et al., 2021). Because compensation in this setting is commission-linked, portfolio value proxies for this incentive: higher-value portfolios imply higher potential earnings.
Portfolio Age	G_{dt}, the number of days elapsed since deal d's creation date, as of week t.	$= \frac{\sum_{d \in \mathcal{D}_{it}} G_{dt}}{\lvert \mathcal{D}_{it} \rvert}$	Deal-cycle velocity, the idea that deals remaining open longer are subject to different urgency and closing dynamics than recently opened ones, is an established construct in sales performance research (Fong & Waisman, 2025; Guesalaga & Kapelianis, 2015). Portfolio age proxies for this dynamic.
Portfolio Size	Deal d is active in week t.	$= \lvert \mathcal{D}_{it} \rvert$	Workload, the volume of concurrent work an individual manages, is an established driver of individual performance, both generally in the operations literature (Tan & Netessine, 2014; Xu et al., 2022) and specifically for sales conversion in the marketing literature on deal volume (Ahearne et al., 2025; Sabnis et al., 2013). Portfolio size proxies for this constraint.

Table 3. Where IT Failure Falls

Task Category	Share of incidence (%) (1)	Share of IT failure time (%) (2)	Agent-weeks affected (%) (3)
Communicating	47.1	41.3	24.1
Recording	35.0	38.2	16.0
Integrating	11.5	15.4	11.4
Coordinating	4.4	2.6	4.3
Curating	2.1	2.5	2.4
Total	100.0	100.0	—

Note. IT failure accounts for 2.67% of session time. Columns 1 and 2 are shares of that total on two bases: incidence counts disrupted tasks, and IT failure time counts session time lost. Column 3 is the share of agent-weeks in which the category appears at all; it does not sum across categories, because an agent-week can involve several. Shares may not sum to 100 because of rounding.

Table 4. Source of IT Failure

Task Category	System-caused (%) (1)	User-caused (%) (2)	Group total (%) (3)
Communicating	30.9	10.4	41.3
Recording	0.5	37.7	38.2
Integrating	8.6	6.9	15.4
Coordinating	0.8	1.8	2.6
Curating	1.1	1.4	2.5
Total	41.9	58.2	100.0

Note. All entries are shares of total IT failure time. Columns 1 and 2 add across to column 3, which reproduces column 2 of Table 3. A category's internal composition is column 2 divided by column 3. Row and column totals may differ from their components by 0.1 owing to rounding.

Table 5. Mediator Equation: IT Failure

	IT Failure	
	(1)	(2)
New CRM Feature Use	**-0.022****	**0.248*****
	(0.008)	(0.074)
New GenAI Use	-0.016	-0.018
	(0.011)	(0.014)
Portfolio Size	-0.018	-0.019
	(0.024)	(0.027)
Portfolio Age	0.034**	0.034**
	(0.014)	(0.015)
Portfolio Value	-0.020	-0.028*
	(0.015)	(0.017)
Bundling Intensity	0.003	0.014
	(0.022)	(0.024)
Process Activity Burden	-0.006	-0.009
	(0.007)	(0.007)
Product Complicatedness (Conversion-Stage)	-0.003	-0.009
	(0.017)	(0.018)
Customer Complicatedness (Conversion-Stage)	0.007	0.006
	(0.015)	(0.016)
Product Complicatedness (Qualification-Stage)	0.010	-0.011
	(0.023)	(0.029)
Customer Complicatedness (Qualification-Stage)	-0.017	-0.022
	(0.025)	(0.026)
Feature Breadth	-0.031***	-0.130***
	(0.009)	(0.029)
Platform Time	0.045***	-0.000
	(0.012)	(0.017)
Constant	-0.004	—
	(0.003)	
Estimator	OLS	2SLS
Observations	16,408	16,408
Agent FE	Yes	Yes
Week FE	Yes	Yes
Adj R-sq	0.172	-0.131
Model F-statistic	4.001	3.257
Kleibergen–Paap rk LM	—	62.980***
Cragg–Donald Wald F	—	159.400***

Note. Clustered standard errors. *** p<0.01, ** p<0.05, * p<0.1. Column 2 instruments New CRM Feature Use.

Table 6. Outcome Equation: Conversion

	Conversion				
	(1)	(2)	(3)	(4)	(5)
IT Failure			**0.023****	**0.034*****	**0.266****
			(0.011)	(0.012)	(0.118)
New CRM Feature Use		**0.018****	**0.019****	**0.291*****	**0.235*****
		(0.009)	(0.009)	(0.088)	(0.085)
Incidence of Failure	0.025	0.026	0.023	0.025	0.001
	(0.018)	(0.018)	(0.017)	(0.018)	(0.022)
New GenAI Use	0.013	0.013	0.013	0.011	0.015
	(0.009)	(0.010)	(0.009)	(0.012)	(0.011)
Portfolio Size	0.387***	0.387***	0.387***	0.386***	0.391***
	(0.044)	(0.044)	(0.044)	(0.043)	(0.043)
Portfolio Age	-0.442***	-0.441***	-0.442***	-0.442***	-0.451***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Portfolio Value	0.218***	0.217***	0.218***	0.210***	0.217***
	(0.029)	(0.029)	(0.029)	(0.031)	(0.030)
Bundling Intensity	0.136***	0.137***	0.137***	0.148***	0.146***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.036)
Process Activity Burden	0.236***	0.236***	0.236***	0.234***	0.235***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Product Complicatedness (Conversion-Stage)	0.448***	0.447***	0.447***	0.440***	0.442***
	(0.035)	(0.035)	(0.035)	(0.036)	(0.035)
Customer Complicatedness (Conversion-Stage)	0.151***	0.151***	0.151***	0.149***	0.148***
	(0.029)	(0.029)	(0.029)	(0.030)	(0.029)
Product Complicatedness (Qualification-Stage)	0.021	0.019	0.019	-0.002	-0.000
	(0.036)	(0.036)	(0.036)	(0.037)	(0.036)
Customer Complicatedness (Qualification-Stage)	0.037	0.037	0.037	0.032	0.037
	(0.049)	(0.049)	(0.049)	(0.046)	(0.045)
Feature Breadth	-0.030***	-0.037***	-0.036***	-0.136***	-0.105***
	(0.011)	(0.012)	(0.012)	(0.035)	(0.035)
Platform Time	0.027*	0.024	0.023	-0.023	-0.017
	(0.015)	(0.015)	(0.015)	(0.021)	(0.021)
Constant	0.737***	0.737***	0.738***	—	—
	(0.008)	(0.008)	(0.008)		
Estimator	OLS	OLS	OLS	2SLS	2SLS
Observations	16,408	16,408	16,408	16,408	16,408
Agent FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
Adj R-sq	0.674	0.675	0.675	0.452	0.450
Model F-statistic	195.122	181.380	170.082	163.104	169.381
Kleibergen–Paap rk LM	—	—	—	63.532***	79.970***
Cragg–Donald Wald F	—	—	—	162.932***	65.936***

Note. Clustered standard errors. *** p<0.01, ** p<0.05, * p<0.1. Column 4 instruments New CRM Feature Use alone; column 5 instruments New CRM Feature Use and IT Failure.

Table 7. First-Stage Instrument Relevance

	New CRM Feature Use		*IT Failure*
	(1)	(2)	(3)
Z_{it}^{feature}	-0.721***	-0.720***	-0.179***
	(0.087)	(0.087)	(0.046)
Z_{it}^{failure}	—	-0.044***	0.111***
		(0.016)	(0.012)
Observations	16,408	16,408	16,408
Controls	Yes	Yes	Yes
Agent/Week FE	Yes/Yes	Yes/Yes	Yes/Yes
R-squared	0.478	0.478	0.213
SW F-statistic	68.30	64.38	88.22
KP rk LM	62.98	79.97	79.97
KP Wald rk F	68.30	40.40	40.40
CD Wald F	159.40	65.94	65.94

Note. Standard errors clustered by agent in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Column 1 is the first stage of the single-endogenous system estimated in column 2 of Table 5; columns 2 and 3 are the two first stages of the system estimated in column 5 of Table 6.

Table 8. Causal Mediation Results

	Estimate	BC 95% CI
a-path: *New CRM Feature Use* → *IT Failure*	0.248***	[0.126, 0.419]
b-path: *IT Failure* → *Conversion*	0.266**	[0.023, 0.509]
Average causal mediation effect (ACME)	0.066**	[0.006, 0.152]
Average direct effect (ADE)	0.235***	[0.054, 0.402]
Average total effect (ATE)	0.300***	[0.137, 0.493]

Note. *** p<0.01, ** p<0.05, * p<0.10. Intervals are bias-corrected (BC) bootstrap percentile intervals, which shift the percentile endpoints to correct for the skew in the bootstrap distribution of a product of coefficients.

Table 9. Coping Strategies after Internal-Facing and Customer-Facing IT Failure

	Page retry	**Short reload**	**Recovery time**	**Reroute rate**	**Abandonment**	**Workflow deviation**
	(1)	(2)	(3)	(4)	(5)	(6)
Internal-facing IT failure	0.069***	0.106***	−0.319***	0.019	0.549***	0.328***
	(0.021)	(0.022)	(0.039)	(0.039)	(0.050)	(0.048)
Customer-facing IT failure	−0.025	0.003	−0.132***	0.659***	0.916***	1.291***
	(0.026)	(0.026)	(0.049)	(0.057)	(0.067)	(0.063)
Difference	**0.094*** **	**0.103*** **	**−0.187*** **	**−0.640*** **	**−0.367*** **	**−0.964*** **
p (difference)	0.007	0.004	0.001	<0.001	<0.001	<0.001
Observations (agents)	12,094	12,094	6,489	12,094	12,094	12,094
	(571)	(571)	(529)	(571)	(571)	(571)

Note. Each column is a separate OLS regression of a standardized coping strategy measure on internal-facing and customer-facing IT failure. Internal-facing pools coordinating, recording and integrating; customer-facing pools curating and communicating. Columns 1, 2, 4 and 6 measure problem-focused coping strategies, column 5 an emotion-focused coping strategy, and column 3 the time to resume. Difference is the internal-facing coefficient minus the customer-facing coefficient, both estimated in the same regression, and its p-value is a Wald test of their equality. Column 3 is estimated only on agent-weeks in which a failure occurred. *** p<0.01, ** p<0.05, * p<0.10.