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The Technostress Paradox: Understanding When CRM Systems and Their AI Functions Hurt or Help Sales Performance

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Abstract

Despite the rapid growth of the CRM industry and widespread integration of artificial intelligence (AI) into CRM applications, many organizations struggle to ensure their employees use technology effectively to drive sales performance optimization. We address this paradox by investigating how CRM systems and their AI functions impact salesperson performance through both positive and negative stress mechanisms. Drawing on the Challenge-Hindrance Stressor Framework and Job Demands–Resources model, we theorize a curvilinear relationship between CRM infusion and sales performance, mediated by two opposing mechanisms: technostress and salesperson bricolage. In Study 1, we find that technostress (self-undermining behavior) and bricolage (job crafting behavior) explain dual pathways through which CRM infusion influences sales performance. Study 2 extends these findings by demonstrating that AI-assisted adaptive selling steepens the curvilinear effects of CRM infusion—enhancing bricolage and mitigating technostress. Our results offer novel insights into technology-induced stress and adaptive behavior in digitally transforming sales environments.

Keywords: CRM Infusion, Artificial Intelligence, Technostress, Bricolage, Sales Performance, Challenge-Hindrance Stressor Framework

1. Introduction

Amidst rapid digitalization, the global customer relationship management (CRM) market is forecast to grow 10.17% between 2025 and 2029 (Statista, 2025). Providers like Salesforce, SAP, and Microsoft have aggressively incorporated artificial intelligence (AI) tools—Einstein GPT, SAP Sales Cloud's guided selling, and Dynamics 365 Copilot respectively—into their CRM systems, aiming to automate routine sales tasks, improve analytics, and enhance customer engagement. Despite these innovations, a persistent paradox remains: organizations struggle to optimize CRM usage among their salesforce (Dickie et al., 2022; Sundaram et al., 2007). Academic literature reflects this tension. While CRM systems are broadly acknowledged to improve salesperson performance, actual usage often lags, and results have been inconsistent. Many organizations treat CRM systems as digital filing cabinets rather than strategic sales enablers (Dickie et al., 2022). Prior studies have produced mixed findings on the CRM-performance relationship (see Table 1), including some showing no effect (e.g., Ohiomah et al., 2019; Román & Rodríguez, 2015) and others suggesting a curvilinear relationship (e.g., Ahearne et al., 2004).

— insert Table 1 here —

Similar challenges have been observed with AI sales tools (Hautamäki & Heikinheimo, 2025; Jarotschkin, Soykoth, & Chaker, 2025; Khalil et al., 2025). For example, the AI-powered CRM systems outlined earlier provide many useful functions such as AI-powered sales content, customer data integration, predictive analysis, real-time conversations, and meeting summaries. However, many salespeople have found interpreting AI-generated results, aligning these with strategic goals, and incorporating them seamlessly into their workflow to be challenging (Dickie et al., 2022). Hence, while AI solutions promise to enhance productivity, they can simultaneously overwhelm employees with cognitive, technical, and emotional demands (Koponen et al., 2025).

This inconsistency between the continued investment in CRM technologies and the limited, sometimes adverse performance outcomes begs deeper theoretical investigation into the mechanisms shaping CRM effectiveness. Hence, we theorize and test a curvilinear relationship between CRM infusion and sales performance. Particularly, we examine how the embeddedness of CRM applications in salespeople's daily routines—termed CRM infusion—can initially hinder but ultimately enhance performance. This conceptualization of technology usage represents the deepest level of technology engagement, i.e., far beyond the initial acceptance of technology (Hunter & Panagopoulos, 2015). Infusion reflects a salesperson's ability to maximize the CRM's capabilities, integrating the technology's functionalities into their everyday sales workflow, to drive productivity (Jones, Sundaram, & Chin, 2002; Sundaram et al., 2007). Drawing on the Challenge-Hindrance Stressor Framework 2.0 (CHSF2; Podsakoff et al., 2023), we conceptualize CRM infusion as a challenge stressor, and explore how varying intensities of CRM infusion drive either a challenge or a hindrance appraisal, and subsequent impacts on sales performance.

Additionally, we propose two mediating mechanisms that explain how CRM infusion shapes sales performance: technostress and salesperson bricolage. To explore these dual pathways, we align the CHSF2 with the Job Demands–Resources (JD-R) model to propose and confirm that CRM infusion initiates a self-undermining path via technostress and a motivational path via bricolage. These processes may coexist and exert differential effects depending on the intensity of CRM infusion.

Technostress refers to a transactional process of stress appraisal and coping precipitated by technology usage (Tarafdar, Cooper, & Stich, 2019). Traditional views have framed technostress as inherently negative, but recent literature highlights its dual nature: either motivating performance (techno-eustress) or hindering it (techno-distress), depending on individual appraisals and available coping resources (Tarafdar et al., 2024). In contexts like Microsoft's Copilot implementation, salespeople who receive insufficient support may experience anxiety and reduced confidence, leading to counterproductive behaviors such as avoidance, fatigue, or burnout—hallmarks of the "hindrance" path in stress theory.

In contrast, salesperson bricolage—the ability to improvise by recombining limited resources—reflects a proactive, adaptive behavior triggered by resource constraints (Epler & Leach, 2021; Ahmad et al., 2024). Salespeople frequently operate in resource-constrained, fast-evolving environments, especially when integrating sophisticated CRM tools. We show that higher levels of CRM infusion can promote bricolage by enhancing access to customer insights and enabling tailored selling strategies. Bricolage thus functions as a "motivational" mechanism within the CHSF2 framework.

Furthermore, given that 60% of sales tasks are predicted to be AI-automated by 2028 (Gartner, 2023), we investigate the role of AI-assisted adaptive selling in moderating these effects. We conceptualize AI broadly, focusing on AI-enabled functions embedded in CRM systems such as enhanced analytics and customer engagement, rather than on a specific type of AI. While CRM AI functions offer personalization and automation capabilities, they also introduce new sources of cognitive load. Consistent with the CHSF2, we find that AI-assisted adaptive selling ultimately enhances the motivational process during salespeople's CRM infusion by supporting adaptive behaviors and minimizing resource inadequacies. Although salespeople may face frustration and anxiety at early stages of AI integration—reflecting hindrance stress, we find that successful use of AI functions can buffer technostress and amplify bricolage. This dynamic is evident in organizations deploying AI-augmented CRMs like Salesforce Einstein GPT, where users can face early frustration but ultimately experience improved performance once acclimated.

By leveraging leading workplace stress frameworks with examples from AI-enhanced CRM systems, our study offers explanations for the light and dark sides of CRM infusion. Our dual-study design further strengthens external validity: Study 1 tests the mediated curvilinear relationships using data from salespeople in the United Kingdom; Study 2 examines the moderating effect of AI-assisted adaptive selling using a United States sample. Collectively, our research provides timely insights into how organizations can better support salespeople's CRM infusion, accounting for both the stress-inducing and motivational potential of sales technologies. The subsequent sections provide an overview of our theoretical frameworks, hypothesis development, analysis, and discussion of implications for theory and practice.

2. Theoretical Background and Hypotheses

2.0. Challenge-Hindrance Stressor Framework 2.0 (CHSF2)

The Challenge-Hindrance Stressor Framework (CHSF) (Cavanaugh et al., 2000) is a prominent framework widely used in organizational stress research (Podsakoff et al., 2023). According to the CHSF, job stressors can be categorized as: 1) *challenge stressors* – "job demands that promote the accomplishment of job tasks and the personal development of the individual"; and 2) *hindrance stressors* – "job demands that are perceived as barriers or obstacles that thwart the accomplishment of job tasks and personal development of the individual" (Podsakoff et al., 2023, p. 169). Generally, challenge stressors drive a motivational process leading to positive job outcomes, whereas hindrance stressors are responsible for psychological or physical strain, leading to negative job outcomes (Podsakoff et al., 2023).

The CHSF also suggests that any stressor (challenging or hindering) ultimately leads individuals to experience a negative psychological state since stressors tax energy during stress coping (e.g., LePine et al., 2004; Podsakoff et al., 2023). Earlier conceptualizations of the CHSF suggest separate causal pathways for challenge and hindrance stressors. However, the conceptualization of challenge stressors requires further consideration since they can be perceived as hindering, and do not always lead to positive outcomes (Downes et al., 2020). To address these issues, Podsakoff et al.'s (2023) updated framework, the CHSF2 explains one of the possibilities that such cases occur—that up to moderate intensities of challenge stressors may be perceived as potential for personal gain and goal achievement; however, the same stressor at higher intensities may be perceived as hindering and an obstacle to personal growth and achievement.

Consistent with Podsakoff et al.'s (2023) CHSF2, we use JD-R as a supporting framework to comprehensively explore dual mediating pathways between challenge stressors and performance. The JD-R model shows that challenge stressors can lead to *job crafting*, "employees' personal initiative to change their job demands and job resources in order to better align the design of the job with their own abilities and preferences," and is an important component of the resources gain cycle (Bakker, Demerouti & Sanz-Vergel, 2023, p. 33). This path reflects the motivational process in CHSF2. The JD-R model also shows that hindrance stressors can lead to *self-undermining*, "employees' dysfunctional behaviors that create obstacles and may undermine performance," which occurs when the strain of job demands leads to maladaptive behaviors (Bakker, Demerouti, & Sanz-Vergel, 2023, p. 33). This second path leads to strain and negative outcomes described in CHSF2. Importantly, JD-R acknowledges the possibility of technology being a double-edged sword, providing the salesperson with resources which result in positive outcomes (e.g., increased work efficiency); but also hindering demands which drive negative outcomes (e.g., burnout) (Demerouti, 2025).

To ensure the relevance of our theoretical model to the sales context, we selected bricolage (job crafting) and technostress (self-undermining) as important mediators that the sales literature has identified as typical salespeople behaviors and experiences in an era of rapidly increasing technology dependence. There is evidence that salespeople engage in bricolage by utilizing existing technologies to solve problems at hand (Ahmad et al., 2024; Epler et al., 2024). Similarly, technostress has been shown to increase salespeople's work demands and insecurity (Demerouti, 2025; Tarafdar, Pullins, & Ragu-Nathan, 2014). We identified and confirmed the relevance of these mediators from transcribed interviews with 23 B2B sales directors in the UK. The sample quotes that represent bricolage and technostress dimensions are provided in Appendix A (supplement). We also consulted with academic sales research experts to validate our theoretical model before proceeding with data collection.

In Study 1, we investigate the curvilinear relationship between CRM infusion and sales performance via the mediating effects of salesperson bricolage (i.e., job crafting) and technostress (i.e., self-undermining). Subsequently in Study 2, we investigate the moderating role of AI-assisted adaptive selling (i.e., job resource) in CRM infusion's relationship with bricolage and technostress, respectively.

2.1. The curvilinear effect of CRM infusion on sales performance

Sales researchers have investigated the effect of salespeople's technology usage on performance according to various conceptualizations summarized in Table 2. Given our focus on the optimized use of CRM, whose importance has been emphasized in previous research (e.g., Jones, Sundaram, & Chin, 2002), our investigation centers on the infusion conceptualization. Technology infusion, "the extent to which a salesperson maximizes the potential of the technology," is considered the highest level of technology usage (Sundaram et al., 2007, p. 103). When salespeople infuse technology into their daily operations, they can leverage the technology with minimal cognitive expense, giving them the advantage of maximizing their sales performance (Sundaram et al., 2007). Infusion differs from other technology usage variables such as “adoption” and “acceptance”, and reflects the effective embeddedness of CRM in daily sales routines, rather than mere use frequency; and was developed to link technology usage to individual performance (Sundaram et al., 2007).

— insert Table 2 here —

This study challenges previous findings on the CRM–performance relationship (See Table 1), suggesting a curvilinear relationship between CRM infusion and performance. According to the CHSF2, individuals appraise stressors as challenging when they perceive them as having the potential for personal gain and goal achievement; but the same stressor may be appraised as hindering when perceived to be an obstacle to personal growth (Podsakoff et al., 2023). We believe that CRM infusion can be perceived as challenging or hindering based on shifting appraisals as increasing levels of CRM infusion influence the salesperson’s perception of their stressors.

Salespeople are required to manage and optimize the time spent on clients, technology, and other duties (Ahearne et al., 2004). At very low levels of CRM infusion, there is limited embeddedness of CRM in the selling process. For example, the salesperson may only be using CRM for recording calls and taking meeting notes, or as a planning tool for call and email reminders—tasks that do not necessarily drive sales performance (Hunter, 2019; Moutot & Bascoul, 2008). Thus, at very low levels of CRM infusion, technology-related job demands are minimal, and will unlikely have a significant impact on sales performance.

However, as salespeople further embed CRM into the sales process, they must explore and master new features (Azer & Alexander, 2024). During this process of mastery, salespeople must overcome: (1) inertia—relying on proven processes to avoid learning new methods or procedures; and (2) trade-offs—believing that the costs (time, productivity loss) of deepening their knowledge of technology are greater than the potential benefits (Jones, Sundaram, & Chin, 2002). Importantly, this process of increasing infusion may require salespeople to alter their routines so that technology can be used to its fullest potential (Sundaram et al., 2007). For example, embedding CRM tools into the selling process could require the salesperson to also spend time on preparatory tasks such as inputting useful client data to benefit from the CRM's analytical capabilities, reviewing training manuals or videos to improve operational efficiency, updating computer system software, and seeking assistance from IT support services. Such additional demands required to benefit from CRM as infusion increases consume salespeople's resources (time and energy), and detract from primary selling goals (i.e., closing deals and securing contracts). Consequently, we propose that as salespeople's CRM infusion increases from low to moderate levels, they appraise their interaction with the CRM as hindering, resulting in a negative relationship with performance.

Conversely, salespeople infusing CRM from moderate to high levels are more likely to have a better command of the CRM's functions and can better reap the benefits of its analytical capabilities. These salespeople have already invested time to deepen their knowledge of the CRM's productivity-enhancing tools. At these higher levels of CRM infusion, despite continuously facing job demands, the salesperson is more likely to appraise the interaction as challenging. This challenging appraisal occurs because the salesperson's increased CRM infusion above moderate levels creates more resources than demands. In essence, the CRM is highly embedded in the sales process, such that salespeople require less cognitive effort to navigate the technology. They use the CRM to drive task efficiency, positively driving performance. Therefore, we hypothesize:

H1: CRM infusion has a curvilinear relationship with sales performance, such that the relationship is negative for up to moderate levels of infusion, after which the relationship turns positive.

2.2. The mediating effect of technostress

When individuals interact with technology, technostress can manifest through the perception of five different techno dis-stress creators or techno-stressors: *techno-overload*, increased and faster workload due to the use of sales technologies; *techno-invasion*, a perception that the use of technologies is invading personal life; *techno-complexity*, feeling incompetent to use sales technologies; *techno-insecurity*, job insecurity and fear of being replaced by technology or individuals with superior technological skills; and *techno-uncertainty*, an unsettling feeling of constantly being required to learn and adjust to new sales technologies (Tarafdar, Cooper, & Stich, 2019; Tarafdar et al., 2024). Based on the CHSF2, techno-stressors reflect both challenge (e.g., complexity, workload, work pace) and hindrance (e.g., uncertainty, ambiguity) stress characteristics. Overall, they have the potential to either lead to strain or a motivational process, with differential impacts on performance. Hence, we investigate how CRM infusion drives performance via technostress, albeit curvilinearly.

Expanding from its earlier focus on negative consequences, contemporary technostress research has aligned more closely with the occupational stress literature, which maintains that stress can be both negative (distress), leading to burnout; and/or positive (eustress), promoting job performance (LePine et al., 2004; Tarafdar, Cooper, & Stich, 2019). Technostress is more likely to lead to a positive outcome when the individual appraises the stress as challenging—that is, having the potential to drive growth through skill development and goal attainment (Tarafdar, Cooper, & Stich, 2019). Challenge appraisals also implicitly require individuals to feel they have the necessary resources to overcome stress (Bakker, Demerouti, & Sanz-Vergel, 2023).

In the context of this dual nature of technostress, we propose that lower perceptions of technostress stemming from CRM infusion are motivational, and positively drive performance. However, higher levels of technostress beyond a threshold negatively impact performance. CHSF2 supports this indirect curvilinear relationship by explaining that a strong positive direct effect between the challenge stressor and performance can withstand the negative indirect effects of work strain, but excessive demands lead to a hindrance appraisal which results in negative outcomes through increased strain (Podsakoff et al., 2023). The JD-R model provides further support, where techno-stressors are conceptualized as self-undermining behaviors. Thus, increased strain from greater technology use will likely drive negative outcomes (Tarafdar, Cooper, & Stich, 2019). For example, in attempting to better embed CRM applications into their selling tasks, salespeople may need to work overtime (techno-overload), and cancel or modify personal plans (techno-invasion).

Hence, we argue that low perceptions of techno-stressors can push the salesperson to spend personal resources (e.g., time, energy) to discover the best ways to embed CRM to drive sales performance. This process was evident from interviews we conducted with sales professionals regarding embedding sales technology into their roles:

> *"I'm seeing a lot more people spending a lot of time learning a lot of digital and LinkedIn Learning [...] I guess around staying relevant, [...] I don't want to become irrelevant if I'm irrelevant, I'm redundant".* (B2B tool supplier, sales director).

> *"Trying to grasp the technology and understand how to use it effectively has caused them some concern. And I think the cadence. That caused them some concern"* (Professional services, CEO & founder).

"At the beginning we didn't have the technologies in place, so there's a lot of frustration around getting technology up and running" (Distribution and logistics, Head of sales operations).

However, unsurprisingly greater intensities of techno-stressors beyond a threshold become counterproductive to driving performance because they will be more resource-taxing. Consequently, we propose that whilst infusing CRM into sales activities, only salespeople experiencing low perceptions of technostress will enjoy the motivation that drives sales performance. On the other hand, at higher levels beyond a threshold, technostress will lead to an increasingly degrading effect on their sales performance. Thus, we hypothesize:

H2: Technostress mediates the indirect curvilinear relationship between CRM infusion and sales performance.

2.3. The mediating effect of sales bricolage

Salesperson bricolage is "a salesperson's ability to effectively utilize available resources by assessing, reconfiguring, and working to leverage them in order to meet new challenges and create opportunities" (Epler & Leach, 2021, p. 115). Salesperson bricolage includes *customer-level adaptations* to assess, realign, and reassign available resources during the selling process; and *resource-level adaptations* such as strategic behaviors in response to the business and economic environment to maintain sales performance (Epler & Leach, 2021). Based on the CHSF2, we conceptualize bricolage as motivational behavior, which entails the control and allocation of resources to drive performance and counter withdrawal behaviors (Podsakoff et al., 2023). This conceptualization of bricolage is similar to the concept of 'job crafting' within the JD-R model—proactive steps to change job demands and resources, and increase personal and job resources to meet performance goals (Bakker, Demerouti, & Sanz-Vergel, 2023).

Given our conceptualization of CRM infusion as a challenging job demand, we investigate how it ultimately drives the motivational path that improves performance via bricolage, albeit in a curvilinear fashion. We expect that as salespeople increasingly embed CRM in the sales process, there will be a resultant increase in bricolage, which in turn drives performance. For example, as salespeople increase CRM infusion, they can better utilize the CRM's analytical tools and access useful customer insights that enable customer- and resource-level adaptations in the selling process. The relevance of bricolage regarding sales technology was evident in our interviews shown in the following quotes:

> *"You do have to be a little bit more rigorous around the use of the CRM type softwares. I think you've got to be comfortable and conversant with all of the different online platforms, and you've got to understand customer limitations around technology. You gotta be able to adapt and find different channels to get your message across..."* (Oil and gas industry, sales manager).

> *"We had to adapt the skills to be able to continue to support my customer via digital platforms."* (B2B tool supplier, regional business director).

We propose that because increasing levels of bricolage correspond with a positive reappraisal of stress, this challenge appraisal of resource constraints and subsequent proactive behavior positively drives performance (Podsakoff et al., 2023). The JD-R model supports this framing of bricolage as job crafting behavior, allowing the salesperson to perpetuate a gain cycle where available resources are optimized to generate other resources, reduce job demands, and ultimately drive sales performance (Bakker, Demerouti, & Sanz-Vergel, 2024). Thus, we hypothesize:

> **H3**: Salesperson bricolage mediates the indirect curvilinear relationship between CRM infusion and sales performance.

2.4. The interactive effect of AI-assisted adaptive selling.

Sales organizations that invested in AI alongside their sales technology have reported significant increases in revenue and return on investment (Dickie et al., 2022). AI assistance enhances sales strategies by aiding creativity in addressing customer inquiries and persuasion, increasing product and service personalization, and strengthening customer loyalty (Jia et al., 2024; Ledro et al., 2025). However, like other sales technologies, AI implementation presents nuanced opportunities and challenges (Jarotschkin, Soykoth, & Chaker, 2025). With many CRM application providers embedding AI assistance onto their platforms, we explore how AI-assisted adaptive selling can influence bricolage and technostress, which we have previously argued can have positive and negative effects respectively on the indirect relationship between CRM infusion and sales performance.

Adaptive selling is the salesperson's ability to customize their selling approach, using a customer-oriented lens to alter sales behaviors in response to changing circumstances in the sales process (Chen & Zhou, 2022; Kim & McFarland, 2024). Based on this concept, we define AI-assisted adaptive selling as the use of AI tools to adapt to changing circumstances during the sales process by facilitating typical adaptive selling behaviors. Some ways that AI tools can assist salespeople in adaptive selling include: greater personalization of offers (Chen & Zhou, 2022), highlighting what signals to pay attention to from clients, providing solutions to complex client questions to close a sale, or tailoring targeted client promotions based on customer segmentation (Salesforce, 2025). In essence, the AI function enhances the salesperson's selling effectiveness and experience, mechanisms that explain how adaptive selling drives positive outcomes in the selling process (Chaker et al., 2025).

Given rapid advances in AI sales tools, salespeople may find that they are constantly having to update their technical knowledge to optimize sales. Salespeople who employ AI-assisted adaptive selling functions would be better able to identify creative and innovative solutions (Jia et al., 2024; 2022, Khalil et al., 2025), access client information faster, and leverage CRM analytical functions to complement their own resourcefulness to reconfigure client solutions (McClure et al., 2024). However, salespeople infusing CRM from low up to moderate levels may find initial attempts using AI-assistance demanding. This friction arises because AI tools may introduce complexity into familiar, established processes, thereby impacting their bricolage ability. Additionally, to optimize the benefits of AI, some level of experimentation may be necessary (Hautamäki & Heikinheimo, 2025). This experimental process may make initial attempts at bricolage unsuccessful. Nevertheless, from moderate to high levels of CRM infusion, an increased ability to leverage AI assistance could subsequently help the salesperson better utilize informational resources and improve their bricolage abilities. Consequently, we propose that salespeople's use of AI-assisted adaptive selling negatively influences the relationship between CRM infusion and bricolage for up to moderate levels of CRM infusion, after which, its influence becomes positive.

AI-assisted adaptive functions can help employees work more efficiently and devise innovative solutions to work hurdles (Khalil et al., 2025). In providing these job resources, AI can reduce employees' perception of technostress (e.g., reduce work overload and complexity, and increase work-life balance). For example, some AI-assisted adaptive selling tools (e.g., sales-i on SugarCRM) can readily provide actionable insights on thousands of customer data and products, freeing time (i.e., resources) for salespeople. Nevertheless, these AI-assistance tools also place additional demands on salespeople. Apart from dealing with the possible complexity and intrusiveness of AI tools, AI may also heighten employees' job insecurity (Khalil et al., 2025). Therefore, at up to moderate levels, we argue that AI-assisted adaptive selling can be perceived as a hindering job demand, amplifying the negative effects of CRM infusion on technostress. However, for subsequently higher levels of CRM infusion above the threshold, AI-assisted adaptive selling becomes an important resource the salesperson can leverage to make their tasks more efficient. Salespeople's use of AI at these higher levels would make them less susceptible to the self-undermining attributes of technostress. Thus, we put forward the following hypotheses:

H4a: AI-assisted adaptive selling has a steepening effect on the curvilinear relationship between CRM infusion and salesperson bricolage, such that the relationship becomes more negative for initial increases in infusion but more positive for subsequent increases beyond the threshold.

H4b: AI-assisted adaptive selling has a steepening effect on the inverted curvilinear relationship between CRM infusion and technostress, such that the relationship becomes more positive for initial increases in infusion but more negative for subsequent increases beyond the threshold.

— insert Figures 1 & 2 here—

3. Methodology and Analysis

3.1. Study 1 – Testing the Mediation Mechanisms of Technostress and Bricolage

3.1.1. Sample and Data Collection

We collected survey data from a panel of B2B salespeople in the UK through Qualtrics, a common sampling method in B2B sales research (Peasley et al., 2020). Out of 207 responses, eight responses were incomplete, leaving a final sample of 199 B2B salespeople working full-time in various industries i.e., manufacturing (31.2%), retail and consumer (12.1%), business services (10.1%), technology (7.0%), and financial services (6.0%). The sample was 30% female with a median age of 38 and had an average of 9 years of sales experience—characteristics consistent with contemporary sales research (e.g., Epler & Leach, 2021; Epler et al., 2024).

3.1.2. Measures

We used established multi-item scales from prior research to operationalize all constructs (see Table 3). Items were measured using seven-point Likert scales (1 = strongly disagree, 7 = strongly agree). To ensure conceptual precision and contextual relevance, we asked respondents to evaluate their experiences specifically in relation to the CRM system they use in their daily work. We modified Jones, Sundaram, and Chin's (2002) three-item technology infusion scale to measure CRM infusion. Similarly, all five techno-stressor dimensions (Tarafdar, Pullins, & Ragu-Nathan, 2014) were adapted to reflect stress perceptions arising from CRM interaction. We measured salesperson bricolage using Epler and Leach's (2021) seven-item scale. Unlike previous research examining similar and related constructs, Epler et al. (2024) argue this conceptualization of bricolage specifically reflects salespeople behaviors, rather than a disposition or trait. This contextualization ensures that responses reflect situational (state) assessments rather than enduring individual dispositions, thereby addressing concerns about trait–state variance raised in prior bricolage studies. Finally, we asked participants to self-rate their sales performance using four items adapted from Behrman and Perreault (1982).

We included control variables based on their theoretical relevance to increase the robustness of our model and to rule out alternative explanations. We controlled for sales experience (experience as a sales professional) and job tenure (length of service with current employer) (Mullins & Agnihotri, 2022); remote work (Golden, 2007); sales-specific social media infusion (Bata et al., 2018) using a modified version of Jones, Sundaram and Chin's (2002) 3-item technology-infusion scale; and behavior-based sales control—activity control (five items) and capability control (five items) from Kohli et al. (1998). These factors were shown to influence sales attitudes and performance in prior studies (e.g., Ahmad et al., 2024; Mullins & Agnihotri, 2022).

3.1.3. Reliability and Validity

We conducted a confirmatory factor analysis (CFA) to evaluate the convergent and discriminant validity of the study measures. Given the exploratory nature of the study and a smaller than conventional sample size, the measurement model fit the data well ($\chi2/df$ = 1855.032/1138 = 1.630, CFI = 0.900, IFI = 0.901, RMSEA = 0.056). The standardized loadings of all measurement items to their constructs were significant ($p < 0.05$), demonstrating convergent validity (see Table 3). We assessed discriminant validity following two approaches. First, all values of the average variances extracted (AVE) exceeded the threshold of 0.50, and their square roots were greater than the correlations with other constructs (Fornell & Larcker, 1981). Second, we examined the heterotrait-monotrait ratio (HTMT) and ensured that HTMT values were below the cut-off value of 0.90 (Henseler, Ringle, & Sarstedt, 2015; see Appendix B in supplement). We confirmed the reliability of the study's latent variable measures, all of which exceeded the Cronbach's α threshold of 0.70 (Nunnally & Bernstein, 1994). Table 4 summarizes correlations and descriptive statistics for Study 1 variables.

— insert Tables 3 & 4 here —

Common Method Bias

To mitigate potential common method bias (CMB), we used procedural remedies including randomizing item order, assuring respondents of anonymity and confidentiality, and emphasizing that there were no right or wrong answers (Podsakoff et al., 2003). Additionally, we applied post-hoc statistical tests to check the potential impact of CMB (Podsakoff et al., 2003). First, we conducted Lindell and Whitney's (2001) correlational marker technique, which has been shown to be effective in detecting CMB (Bozionelos and Simmering, 2022). We used another latent construct, sales orientation (Thomas, Soutar, & Ryan, 2001) as our marker variable, which had the second-lowest correlation with bricolage ($r = 0.013$) in Study 1, providing a conservative adjustment factor. We partialed out this coefficient for each pair of the Study 1 variables, and compared with the unadjusted bivariate correlations. There were no substantive changes in the significance of the correlations between our main constructs. Additionally, we assessed variance inflation factors (VIF) and found that all values were well below the recommended threshold of 3.3 (Kock, 2015).Together, these tests provided evidence that CMB is unlikely to pose a concern in our analysis. Furthermore, the inclusion of both positive and negative relationships in the theoretical model reduce the likelihood of CMB (Peasley et al., 2020).

3.1.4. Analysis & Results

We conducted hierarchical regression analyses on SPSS, mean-centering all predictors to facilitate interpretation of interaction and quadratic terms. Predictors were entered sequentially: (Step 1) control variables (sales experience, job tenure, remote work, social media infusion, behavior control); (Step 2) independent variable (CRM infusion); (Step 3) squared term of independent variable. All variance inflation factors (VIF) were below 5.0, indicating no multicollinearity concerns.

Table 5 (Model 4) shows a positive linear relationship between CRM infusion and sales performance, corroborating findings of recent studies (e.g., Ohiomah et al., 2019). However, consistent with H1, the squared term for CRM infusion was also positive ($\beta = 0.087$, $p = 0.021$), indicating a curvilinear relationship. To determine whether this relationship was U-shaped, we followed procedures outlined in Haans, Pieters, and He (2016): (Test 1) squared term significance and expected sign; (Test 2) sufficiently steep slope at low and high values of the predictor variable; and (Test 3) turning point within the observed data range. We used ±2 SD to define low and high CRM infusion values. Figure 3 illustrates that as CRM infusion increases, sales performance rises at an accelerating rate. However, even at -2SD below mean values of CRM infusion, the relationship with sales performance is already positive, albeit at a lower rate (Slope CRM-low = 0.105, $p = 0.137$; Slope CRM-high = 0.600, $p = 0.000$; turning point at -2.500, or 3.455 on a 7-point scale). Thus, the relationship is curvilinear but not U-shaped; instead resembling a J-curve, where benefits are more pronounced at higher CRM infusion levels (Khalil et al., 2025). Hence, salespeople at low CRM infusion exhibit modest gains, while moderate to high infusion yields increasingly stronger performance improvement.

— insert Table 5 here —

— insert Figure 3 here —

We used the MEDCURVE macro (Hayes & Preacher, 2010) to estimate nonlinear indirect effects through technostress and bricolage, using 10,000 bootstrap samples at -1 SD, mean, and +1 SD levels of CRM infusion. Prior to running the MEDCURVE macro, we tested individual paths of the mediation hypotheses to confirm if these should be selected as linear or quadratic in the MEDCURVE macro parameters. The results of the regressions of the individual paths between CRM infusion and sales performance via both mediators—technostress and bricolage, were all significant and quadratic. Hence, we assumed quadratic relationships for all individual paths when selecting the MEDCURVE macro parameters. Table 6 provides a summary of the pre-tests and subsequent MEDCURVE results for Study 1, while Appendix C (see supplement) provides a more detailed discussion of the pretests.

For H2, the indirect effect of CRM infusion on sales performance via technostress was negative and significant at moderate levels of CRM infusion (θ = -0.036, 95%CI [-0.098, -0.000]), positive but nonsignificant at low levels (θ = 0.003, 95%CI [-0.030, 0.033]), and negative but nonsignificant at high levels (θ = -0.036, 95%CI [-0.112, 0.001]). These results provide limited evidence that increasing CRM infusion reduces performance via technostress, giving only partial support for H2.

For H3, the indirect effect of CRM infusion on sales performance through bricolage was positive and significant at moderate (θ = 0.091, 95%CI [0.008, 0.193]) and high (θ = 0.202, 95%CI [0.036, 0.455]) CRM levels, but nonsignificant at low levels (θ = 0.010, 95%CI [-0.046, 0.062]). These results also indicate partial support for H3, suggesting that higher CRM infusion promotes sales performance via bricolage, with effects increasing from moderate to high levels.

Post-hoc Analysis

We conducted post-hoc tests to show the robustness of our model. First, we reversed the causal direction of H1 to examine whether sales performance has a curvilinear relationship with CRM infusion. Table 1 in Appendix D shows that this relationship is insignificant (β = 0.060, p = 0.263). Similarly, we used the MEDCURVE macro (Hayes & Preacher, 2010) to examine the reverse-causal direction of the mediated relationships using the same parameters as in the main analysis. For H2, the mediation was insignificant for each magnitude of CRM infusion (low θ = -0.001, 95%CI [-0.020, 0.009]; moderate θ = -0.009, 95%CI [-0.049, 0.011]; high θ = -0.018, 95%CI [-0.098, 0.014]). We also found insignificant results for H3 (low θ = -0.001, 95%CI [-0.048, 0.034]; moderate θ = 0.003, 95%CI [-0.061, 0.060]; high θ = 0.012, 95%CI [-0.090, 0.139]). Finally, we analyzed alternative models for H2 and H3, treating the mediators as moderators instead. Tables 2 and 3 in Appendix D show the results of the curvilinear moderation of technostress (β = 0.047, p = 0.250) and bricolage (β = -0.079, p = 0.071) to be insignificant. Overall, these results do not provide evidence of reverse causal relationships in Study 1 and show that technostress and bricolage are better suited as mediators rather than moderators, consistent with the application of the CHSF2 and JD-R frameworks.

— insert Table 6 here —

3.2. Study 2 – Examining the Moderating Effects of AI-assisted Adaptive Selling

3.2.1. Sample and Data Collection

Study 2 explored the moderating role of AI-assisted adaptive selling in the curvilinear relationships between CRM infusion and the mediators—technostress and salesperson bricolage. To test these effects and validate Study 1 findings in a different context, we collected survey data from a U.S. sample of salespeople via Prolific. Eligibility criteria required participants to be employed full-time in account management, sales, or business development; and to use verified CRM applications. We received 349 responses and, after quality checks to remove incomplete or outlier cases, retained 317 valid observations. Participants represented diverse industries, mainly retail and service (25.9%), finance and insurance (19.9%), and professional, scientific, and technical services (10.4%). Most respondents were aged 26-41 (53.6%), 46.7% were female, and 75.1% held a university degree. The majority (45.1%) had been in their current sales role for up to three years, with average CRM use of 4.6 hours per day. Participants were compensated at a rate of USD $13 per hour.

3.2.2. Measures

We used established measures from prior research to operationalize all constructs on 5-point Likert scales (1 = strongly disagree, 5 = strongly agree). The main constructs—CRM infusion, technostress, and bricolage—were measured as in Study 1. The moderator, AI-assisted adaptive selling, was assessed using a seven-item scale adapted from Chen and Zhou's (2022) measure for adaptive selling capability. Participants were instructed to consider the AI-enabled features of their CRM systems when responding.

The analyses included control variables theoretically linked to performance outcomes: salesperson agility (Kalra, Lee, & Dugan, 2023), grit (Epler & Leach, 2021). We also controlled for B2B sales context (dummy coded), Salesforce[1] CRM usage (54.9% of the sample, dummy coded), daily CRM usage (Ayyagari, Grover, & Purvis, 2011), and time since last CRM training.

3.2.3. Reliability and Validity

We conducted a confirmatory factor analysis (CFA) to evaluate the convergent and discriminant validity of the study measures. The model demonstrated good fit (χ^2/df =

[1] Salesforce had the largest global market share for CRM applications (21.7%), ahead of Microsoft (5.9%), Oracle (4.4%), and SAP (3.5%) as ranked by the International Data Corporation (Salesforce, 2024).

1458.390/880 = 1.657, CFI = 0.934, IFI = 0.935, RMSEA = 0.046). All item loadings were significant ($p < 0.05$), supporting convergent validity (see Table 3). Two items each from bricolage and grit, and one from techno-uncertainty, were removed due to low loadings. Discriminant validity was supported since all AVE values exceeded 0.50, the square roots of AVEs were greater than inter-construct correlations (Fornell & Larcker, 1981), and all HTMT values were below the cut-off point of 0.90 (Henseler et al., 2015; see Appendix B in supplement). Reliability was also confirmed, with Cronbach's α values above 0.70 for all latent constructs (Nunnally & Bernstein, 1994). Table 7 presents the descriptive statistics and correlations among all study variables.

— insert Table 7 here —

Common method bias

We applied the same procedures as in Study 1 to minimize and assess potential CMB. Post hoc, we applied Lindell and Whitney's (2001) correlational marker technique. We used the second-lowest correlation among the Study 2 latent constructs (between AI-assisted adaptive selling and agility; $r = 0.089$) as a conservative adjustment factor. We partialed out this coefficient for each pair of the Study 2 variables, and compared with the unadjusted bivariate correlations. As there were no substantive changes in the significance of the correlations between our main constructs, we can conclude that CMB poses little concern in our study. All VIF values were below 3.3, indicating no multicollinearity or CMB concerns. Furthermore, testing both positive and negative relationships helps reduce CMB likelihood (Peasley et al., 2020).

3.2.4. Analysis & Results

Similar to the analytical approach in Study 1, we used hierarchical regression analyses in SPSS to test the hypothesized curvilinear and moderating relationships. All independent variables were mean-centered to aid interpretability. Predictors were entered sequentially:

(Step 1) control variables (Salesforce CRM, B2B sales, CRM daily use, CRM training tenure, agility, and grit); (Step 2) independent variable (CRM infusion); (Step 3) squared term of independent variable; (Step 4) moderator (AI-assisted adaptive selling); (Step 5) linear interaction terms; (Step 6) curvilinear interaction terms. All VIFs were below 5.0, indicating no multicollinearity.

The results in Tables 8 and 9 show that Study 2 replicated Study 1's main effects—confirming U-shaped and inverted U-shaped relationships respectively between CRM infusion and bricolage ($\beta = 0.102$, $p = 0.000$; Slope CRM-low = -0.501, $p = 0.000$; Slope CRM-high = 0.372, $p = 0.000$; turning point at -0.755, or 2.831 on a 5-point scale; Figure 4) and technostress ($\beta = -0.103$, $p = 0.000$; Slope CRM-low = 0.549, $p = 0.000$; Slope CRM-high = -0.332, $p = 0.000$; turning point at -0.544, or 3.042 on a 5-point scale; Figure 5). Table 10 provides a summary of all the direct curvilinear relationships tested in Study 1 and 2, and confirms the resultant shapes of the relationships.

According to Haans, Pieters and He (2016), moderators may affect a curvilinear relationship by shifting the turning point or altering the steepness of the curve. Our results supported H4a, showing that AI-assisted adaptive selling strengthened the positive curvilinear effect of CRM infusion on bricolage ($\beta = 0.063$, $p = 0.002$). As shown in Figure 6, salesperson bricolage is higher and the curve steeper when AI-assisted adaptive selling (AI) is +1SD above the mean; but bricolage is lower and not as easily facilitated for below mean values of AI usage. Similarly, results supported H4b, indicating that AI-assisted adaptive selling intensified (i.e., steepened) the negative curvilinear relationship between CRM infusion and technostress ($\beta = -0.095$, $p = 0.000$). Figure 7 shows that technostress declines more sharply when AI-assisted adaptive selling is high (+1SD), but the curve flattens at lower AI usage. The hypotheses were also tested without control variables. Model 1 in Tables 8 and 9 confirmed consistent patterns, reinforcing the robustness of our findings across model specifications.

Post-hoc Analysis

We conducted post-hoc tests to show the robustness of our Study 2 model. We reversed the causal directions of H4a and H4b to examine whether AI-assisted adaptive selling moderated the curvilinear relationships. Tables 4 and 5 in Appendix D (see supplement) show insignificant results and do not provide evidence of reverse causation for our model: H4a: (β = -0.034, p = 0.678); H4b: (β = -0.082, p = 0.255).

— insert Tables 8, 9, and 10 here —

— insert Figures 4, 5, 6, and 7 here —

4. Discussion

This study offers a fresh perspective on the inconsistent findings surrounding the CRM–performance relationship. Drawing on the CHSF2 and supported by the JD-R model, we proposed and confirmed a curvilinear relationship between CRM infusion and salesperson performance. We found that technostress and bricolage act as opposing mechanisms—hindering and enhancing sales performance respectively. Furthermore, AI-assisted adaptive selling strengthens these curvilinear effects. Together, these findings advance theory and provide practical insights into technology-enabled selling.

4.1. Theoretical Implications

This study contributes to sales technology research in several ways. First, it challenges the long-standing paradox surrounding CRM effectiveness (e.g., Ahearne et al., 2004; Román & Rodríguez, 2015). Whereas prior research typically assumes linear effects (e.g., Avlonitis & Panagopoulos, 2005; Ko & Dennis, 2004), we show that the effect of CRM infusion on sales performance follows a nonlinear pattern, where lower levels of embeddedness are associated with job demands from increased cognitive load, whereas higher levels drive superior performance. Integrating the CHSF2 and JD-R model (Bakker & Demerouti, 2017, Bakker, Demerouti, & Sanz-Vergel, 2023, Podsakoff et al. 2023), we demonstrate that the same stressor, CRM infusion, can be appraised as either challenging or hindering depending on its intensity. While the expected U-shape did not emerge, we observed a J-shaped relationship, where performance rises sharply at higher levels of infusion. This result suggests that once salespeople overcome an adjustment phase, CRM systems can evolve from a short-term inconvenience into a long-term performance enabler (Khalil et al., 2025). The finding reconciles earlier contradictions by showing that benefits accrue only when CRM becomes deeply integrated into daily routines.

Second, this study advances the salesperson stress literature by identifying dual mechanisms that explain how CRM infusion affects job outcomes. Technostress represents a hindrance-oriented appraisal that reduces performance, particularly when CRM systems are complex or poorly aligned with workflows (Tarafdar, Cooper, & Stich, 2019; LePine et al., 2004). This relationship is especially salient when CRM systems are unfamiliar, complex, or poorly integrated with sales routines. Although the direction and magnitudes of the mediating effect of technostress on the CRM-performance relationship were consistent with our theorization—i.e., technostress positively driving performance at low levels of infusion, but detrimental at moderate and high levels—we only found significant results for moderate levels of CRM infusion. These insignificant effects may point to context-specific variables at the technology, individual, or organizational level impacting performance, which we address as future research opportunities in the concluding section.

In contrast, bricolage emerged as a challenge-oriented response that fosters creativity and adaptation, consistent with job crafting behaviors (Epler & Leach, 2021; Ahmad et al., 2024). Salespeople engaging in bricolage behavior actively reconfigure resources and experiment with CRM tools to enhance outcomes. The positive mediation effect—especially at moderate and high levels of infusion—illustrates how resourceful adaptation mitigates the downsides of technology-driven demands. Together, these results reinforce the CHSF2's view that challenge stressors can yield either positive or negative outcomes depending on the balance of opposing forces (Podsakoff et al., 2023). Consequently, the insignificant effect on sales performance via bricolage at low levels of CRM infusion may point to greater strain at initial stages of embedding technology into sales processes. By contrast, salespeople at higher levels of CRM infusion experience less strain, become better bricoleurs, and benefit from higher sales performance. Overall, this dual-pathway perspective enriches theoretical understanding of how digital technologies simultaneously create pressure and enable agency in work settings.

Third, we extend research on sales professionals' AI usage by showing that AI-assisted adaptive selling moderates the curvilinear effects between CRM infusion and the corresponding mediating mechanisms. Our findings underscore that the benefits of AI depend on the salesperson's degree of AI integration into daily work. Our results also align with contemporary studies that show that whilst AI usage may drive productivity, like most technologies, it can be cognitively demanding (e.g., Koponen et al., 2025). AI does not automatically improve performance, but acts as a resource amplifier, helping skilled users interpret data and tailor customer interactions more effectively. This insight contributes to growing discussions on human–AI collaboration in sales and service settings (Jarotschkin, Soykoth, & Chaker, 2025; Hautamäki & Heikinheimo, 2025; McClure et al., 2024).

4.2. Managerial Implications

Our findings carry several actionable insights for sales and technology managers. First, CRM systems should not be rolled out under the assumption that greater usage always translates to better performance. Between low and moderate levels of infusion, salespeople may experience confusion, role conflict, and frustration—particularly if systems are complex or insufficiently aligned with workflows (Khalil et al., 2025; Dickie et al., 2022). Such misalignment also applies to launching new AI features without proper onboarding, as observed in early rollouts of Salesforce Einstein GPT. Managers must recognize that salespeople’s ability to effectively embed CRM into their roles is sensitive to poor implementation.

Second, firms should consider stress-management interventions and adaptive support strategies that reduce the risk of salespeople’s technostress. These might include personalized training, digital coaching, and peer mentoring programs. Additionally, HR and IT teams should collaborate to monitor signs of technology-related stress such as working longer hours and anxiety over job security; and offer stress management support where needed (Tarafdar, Cooper, & Stich, 2019).

Third, to unlock the positive effects of CRM infusion, organizations must create an environment that fosters bricolage. This means encouraging experimentation, empowering salespeople to reconfigure resources, and recognizing adaptive problem-solving. The example of SAP Sales Cloud suggests that sales teams thrive when allowed to creatively integrate system insights into their workflows, rather than strictly adhering to top-down scripts. Encouraging such behaviors can help sellers develop the resourcefulness needed to convert CRM systems into strategic assets.

Fourth, our findings point to the conditional value of AI-assisted selling tools. Rather than assuming AI features will immediately improve sales productivity, managers must treat them as cognitive resources that require socialization and practice. Tools like Microsoft Copilot or SAP's guided selling analytics are most effective when users have already developed a solid foundation with CRM functionalities. Firms should therefore stage the rollout of AI tools and provide sandbox environments or pilot groups to foster confidence and mastery.

Finally, organizations should continuously assess whether their CRM investments are fostering performance-enhancing behaviors or stress-inducing burdens. This may involve developing KPIs not just for CRM usage, but for salesperson well-being, adaptive behaviors, and innovation.

5. Limitations and Future Research Directions

As with any scientific endeavor, we identify limitations that offer avenues for future research. First, while our two-study design strengthens generalizability, the data are cross-sectional, limiting causal inference. Conceptually, technology use precedes technostress (Tarafdar, Cooper, & Stich, 2019), which theoretically mitigates concerns of reverse causality. Nonetheless, unobserved confounding factors may still affect the observed relationships, suggesting caution in interpreting causality. Additionally, potential endogeneity cannot be entirely ruled out. Future research could address this issue using longitudinal designs or field experiments to test the temporal dynamics of CRM infusion, especially transitions from technostress to bricolage; or by employing statistical techniques such as instrumental variable estimation. Relatedly, while we employed established scales for all study measures and contextualized them to ensure alignment with the technology usage and sales literatures, issues related to state variance remain. We suggest that future studies employ experimental design with randomization or experience sampling procedures to account for inter-individual variability.

Second, our measure of AI-assisted adaptive selling focused on perceived helpfulness of AI features. This approach may not fully capture actual interaction behaviors. Future research could incorporate more objective system-use data (e.g., log data, AI usage analytics) to examine how different AI functionalities interact with salesperson behavior or take a more granular approach to investigate how AI augmentation vs. automation affect different stages of sales (McClure et al., 2024). Alternatively, future studies could develop a sales context-specific measure for CRM AI-infusion, encompassing features like predictive analytics, automated summaries, and prospect targeting. Given the growing importance of AI in selling, such a measure would significantly advance sales research. Furthermore, future studies might explore customer relationship outcomes of salespeople's AI usage to offer a fuller view of how AI impact the sales process.

Third, our study was conducted within the Anglo-American context. Future work could examine how cultural and organizational context moderates these effects, particularly in emerging markets where technology infrastructure levels vary (Adeniji & Igarashi, 2022). Fourth, while we focused on individual-level mechanisms, future studies could explore team-level dynamics, such as knowledge sharing, collaborative bricolage, or leader behavior in CRM-rich environments.

Fifth, although our research focused on CRM systems, the theoretical model can be extended to other enterprise software tools, such as digital service platforms, knowledge management systems, or ERP solutions. Finally, future research could explore how individual traits (e.g., learning orientation, openness to experience) shape the transition from technostress to bricolage.

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7. Tables and Figures

Table 1. Key literature on the relationship between sales technologies and salesperson performance

Source	Empirical setting	Theory	Sales technology	Operationalization of sales technology usage	Effect type	Mediators	Moderators	Key findings
Ahearne et al. (2004)	131 salespeople in pharmaceutical industry	Technology acceptance models	CRM	Utilization	Curvilinear	-	-	Inverted U-shaped relationship between CRM usage and sales performance.
Ko & Dennis (2004)	1340 U.S. salespeople in pharmaceutical industry	Not specified	SFA	The number of knowledge documents displayed on an individual sales representative's screen	Linear (+)	-	- Experience - Expertise	- SFA usage is positively related to salesperson performance. - This association is stronger in cases of high expertise. - Experience is not a significant moderator in this link.
Avlonitis & Panagopoulos (2005)	240 U.S. salespeople in pharmaceutical industry	Technology acceptance model	CRM	Acceptance	Linear (ns)	-	-	CRM acceptance is not significantly associated with performance.
Jelinek et al. (2006)	156 U.S. salespeople in mail, messaging, and document management solutions industries	Interactional psychology theory	SFA	Adoption	Linear (+)	-	-	SFA adoption is positively related to salesperson performance.
Senecal et al. (2007)	130 salespeople in industrial equipment and steel industries	-	CRM	Extent of usage, i.e., occasional, regular or heavy usage	Linear (ns)	-	-	Occasional and heavy CRM users report higher performance levels than moderate users.
Ahearne et al. (2007)	187 American salespeople from pharmaceutical; 112 American salespeople from consumer-packaged goods	Not specified	CRM	Acceptance	Linear (+)	- Knowledge - Call productivity - Targeting - Presentation skills	-	- CRM acceptance has a positive effect on salesperson performance; mediated by call productivity, targeting, and sales presentation skills (both mediated by knowledge).
Hunter and Perreault (2007)	154 American salespeople from consumer-packaged goods	Task-technology fit	Sales technologies	Frequency	Linear (+, relationship building; (-administrative performance)	- Sharing market knowledge - Proposing integrative solutions	-	- Using STs for communicating and analyzing information drives relationship performance via partial mediation. - Using STs for accessing information drives administrative performance, but usage for analysis had a negative relationship.
Sundaram et al. (2007)	85 U.S. salespeople in insurance industry	The theory of planned behavior	SFA; CRM	Frequency Routinization Infusion	Linear (+)	-	-	-Routinization increases IT-enabled administrative performance but not IT-enabled salesperson performance. -Infusion increases both IT-enabled

								salesperson performance and IT-enabled administrative performance. -Frequency has no influence on sales performance.
Ahearne et al. (2008)	137 salespeople in pharmaceutical industry	Task-technology fit theory	SFA; CRM	Total time spent on the application and total screen hits on the application	Linear (ns)	- Customer service - Salesperson adaptability	-	Usage has no direct influence on salesperson performance, but is mediated via customer service and salesperson adaptability.
Hunter & Panagopoulos (2015)	303 Greek salespeople in pharmaceutical industry	Commitment theory	CRM	Infusion	Linear (+)	-	Sales force intelligence norms	Infusion positively related with sales performance, but no significant moderation of sales force intelligence norms.
Román & Rodríguez (2015)	265 salespeople across diverse industries	Job demands-resources (JD-R) theory; the cognitive selling paradigm	Sales technologies	Use of targeting, planning, scheduling and reporting software on a frequency scale	Linear (ns)	- Salesperson qualification skills -Customer-oriented selling	Salesperson technology self-efficacy	- Usage indirectly influences salesperson performance via qualification skills and customer-oriented selling. - Technology self-efficacy positively moderates influence of technology use on customer-qualification skills and customer-oriented selling.
Ohiomah et al. (2019)	108 sales professionals across diverse industries in North America, Australia, New Zealand, the United Kingdom, and Brazil	Technology-task-fit theory	CRM (Lead Management System)	Usage	Linear (ns)	- Adaptive selling - Call quantity - Technical skills - Salesmanship skills	-	Only adaptive selling, technical skills, and salesmanship skills significantly mediate the relationship between the usage and sales performance.
Chen et al. (2020)	229 Chinese salespeople in finance industry	Coping theory	CRM	Routinization Infusion	Linear (+)	Adaptive behavior	-	Two aspects of adaptive behavior (i.e., interpersonal adaption and offering adaption) mediate the impacts of the postadoption of CRM applications (i.e., routinization and infusion) on employees' service performance.
This study (2025)	**Study 1: 199 British salespeople (B2B) in various industries Study 2: 317 U.S. salespeople (B2B & B2C) in various industries**	**Job demands-resources (JD-R) theory; Challenge–hindrance stress framework**	**CRM (Study 1); AI-embedded CRM (Study 2)**	**Infusion**	**Curvilinear**	**-Technostress -Bricolage**	**AI-assisted adaptive selling**	**- Study 1: Infusion has a curvilinear relationship with sales performance; bricolage (positively) and technostress (negatively) mediate this relationship. - Study 2: AI-assisted adaptive selling positively (negatively) moderates/steepens the curvilinear relationship between infusion and bricolage (technostress).**

Table 2. Definitions of technology usage

Usage variable	Definition
Acceptance	Based on technology acceptance models (Davis 1986; Venkatesh and Davis, 2000), acceptance refers to a salesperson's decision to use technology based on their perception of the technology's ease of usage and usefulness (Ahearne, Srinivasan, and Weinstein, 2004; Sundaram et al., 2007).
Frequency	The amount of time a salesperson uses technology (Sundaram et al., 2007; Ahearne, Srinivasan, and Weinstein, 2004).
Adoption	Salespeople's technology usage spanning from initial implementation to frequent and full use throughout the sales process (Schiellewaert et al., 2005).
Routinization	The efficient use and integration of technology into work patterns (Sundaram et al., 2007).
Infusion	Salesperson's effort to effectively use technology to its fullest potential in the post-implementation stage, far beyond the initial acceptance of the technology (Hunter and Panagopoulos, 2015). The extent to which a salesperson maximizes the potential of a technology in order to enhance productivity (Sundaram et al., 2007)

Table 3. Factor loadings for Studies 1 and 2

Construct and Items	**Study 1 λ**	**Study 2 λ**
Social Media Infusion		
1. I am using social media to its fullest potential for supporting my own work	0.878	-
2. I am using all capabilities of social media in the best fashion to help me on the job	0.875	-
3. My use of social media on the job has been integrated and incorporated at the highest level	0.805	-
Behavioral Control		
Activity Control		
1. My manager informs me about the sales activities I am expected to perform.	0.670	-
2. My manager monitors my sales activities.	0.777	-
3. My manager informs me on whether I meet their expectations on sales activities.	0.723	-
4. If my manager feels I need to adjust my sales activities, they tell me about it.	0.830	-
5. My manager evaluates my sales activities.	0.757	-

Capability Control		
1. My manager has standards in which my selling skills are evaluated.	0.802	--
2. My manager periodically evaluates the selling skills I use to accomplish a task.	0.819	-
3. My manager provides guidance on ways to improve selling skills and abilities.	0.768	-
4. My manager evaluates how I make sales presentations and communicate with customers.	0.823	-
5. My manager assists by suggesting why using a particular sales approach may be useful.	0.717	-
CRM infusion		
1. I am using CRM to its fullest potential for supporting my own work	0.850	0.909
2. I am using all capabilities of CRM in the best fashion to help me on the job	0.800	0.874
3. My use of CRM on the job has been integrated and incorporated at the highest level	0.764	0.855
Technostress		
Overload		
1. I am forced by this technology to work much faster	0.795	0.819
2. I am forced by this technology to do more work than I can handle	0.894	0.731
3. I am forced by this technology to work with very tight time schedules	0.888	0.813
4. I am forced to change my work habits to adapt to new technologies	0.766	0.586
5. I have a higher workload because of increased technology complexity	0.806	0.793
Invasion		
1. I spend less time with my family due to this technology	0.790	0.832
2. I have to be in touch with my work even during my vacation due to this technology	0.757	0.811
3. I have to sacrifice my vacation and weekend time to keep current on new technology	0.919	0.887
4. I feel my personal life is being invaded by this technology	0.815	0.910
Complexity		
1. I do not know enough about this technology to handle my job satisfactorily	0.846	0.753
2. I need a long time to understand and use new technologies	0.888	0.825
3. I do not find enough time to understand and use new technologies	0.843	0.735
4. I find new recruits to this organization know more about computer technology than I do	0.766	0.625
5. I often find it too complex for me to understand and use new technologies	0.897	0.808
Uncertainty		
1. There are always new developments in the technologies we use in our organization	0.713	Del.
2. There are constant changes in computer software in our organization	0.831	0.501
3. There are constant changes in computer hardware in our organization	0.829	0.891
4. There are frequent upgrades in computer networks in our organization	0.855	0.898

Insecurity		
1. I feel a constant threat to my job security due to new technologies	0.876	0.760
2. I have to constantly update my skills to avoid being replaced	0.709	0.658
3. I am threatened by co-workers with newer technology skills	0.892	0.821
4. I do not share my knowledge with my co-workers for fear of being replaced	0.787	0.726
5. I feel there is less sharing of knowledge among co-workers for fear of being replaced	0.786	0.814
Bricolage		
1. I usually find workable solutions to new challenges by using our existing resources	0.655	0.744
2. I use any existing resource that seems useful to responding to a new problem or opportunity	0.705	0.698
3. When I face new challenges, I put together workable solutions from existing resources	0.680	0.763
4. I combine resources to accomplish new challenges that the resources were not originally intended to accomplish	0.776	Del.
5. To deal with new challenges I access resources at low or no cost and combine them with what I already have	0.737	0.653
6. When dealing with new problems or opportunities I immediately take action by assuming that I will find a workable solution	0.725	Del.
7. I deal with new challenges by applying a combination of our existing resources and other resources inexpensively available to me.	0.709	0.672
Sales performance		
1. I have been able to generate high dollar sales better than other salespeople in my organization	0.800	-
2. I have been able to maintain the profitability of my territory better than other salespeople in my organization	0.752	-
3. I have been able to develop strong customer relationships better than other salespeople in my organization	0.705	-
4. I have been able to exceed sales targets and objectives for my territory better than other salespeople in my organization	0.700	-
AI-assisted adaptive selling		
I use the AI functions of the CRM application to:		
1. Easily change to another selling approach	-	0.790
2. Experiment with different sales approaches	-	0.798
3. Effectively close sales	-	0.867
4. Develop pricing systems to respond more quickly to market changes	-	0.859
5. Adapt contracts to customer needs	-	0.870
6. Change product delivery schedules to satisfy customers	-	0.859
7. Modify products to satisfy customers	-	0.878
Agility		
1. I strive to experiment and try new things	-	0.776

2. I strive to accept challenges easily	-	0.791
3. I strive to accept responsibility and accountability	-	0.702
4. I strive to introduce new slants on old ideas	-	0.728
Grit		
1. I have achieved a goal that took years of work	-	Del.
2. I have overcome setbacks to conquer an important challenge	-	Del.
3. I finish whatever I begin	-	0.656
4. I am a hard worker	-	0.659
5. I am diligent	-	0.826
Study 1: $\chi 2/df = 1855.032/1138 = 1.630$, CFI = 0.900, IFI = 0.901, RMSEA = 0.056 Study 2: $\chi 2/df = 1458.390/880 = 1.657$, CFI = 0.934, IFI = 0.935, RMSEA = 0.046		

Table 4. Study 1 descriptive statistics and correlations

	1	2	3	4	5	6	7	8	9
1. Sales Experience	--								
2. Job Tenure	0.567**	--							
3. Remote Work	-0.062	-0.031	--						
4. Social Media Infusion	-0.186**	-0.085	-0.030	**0.853**					
5. Behavior Control	-0.127	-0.049	0.002	0.533**	**0.773**				
6. CRM Infusion	-0.089	0.032	-0.011	0.459**	0.526**	**0.806**			
7. Bricolage	0.004	0.001	-0.008	0.318**	0.501**	0.312**	**0.714**		
8. Technostress	-0.230**	0.021	0.043	0.294**	0.157*	0.140*	0.195**	**0.828**	
9. Sales Performance	-0.059	0.051	0.046	0.378**	0.379**	0.451**	0.417**	0.220**	**0.740**
Mean	13.290	9.280	4.180	5.791	5.872	5.955	5.663	4.492	5.569
SD	8.468	6.256	1.692	1.170	0.894	0.947	0.853	1.219	0.931
CR				0.889	0.937	0.847	0.878	0.980	0.828
AVE	-	-	-	0.728	0.598	0.649	0.509	0.686	0.548
Cronbach's Alpha	-	-	-	0.887	0.923	0.847	0.879	0.949	0.829

Note: Square roots of AVEs are in bold along diagonal

Table 5. Study 1 regression results for sales performance

	Sales Performance											
	Model 1			Model 2			Model 3			Model 4		
	Base Model β (SE) *p-Value*			Covariates β (SE) *p-Value*			CRM β (SE) *p-Value*			CRM^2 β (SE) *p-Value*		
Intercept	5.478	(0.067)	*0.000*	2.691	(0.472)	*0.000*	3.760	(0.531)	*0.000*	3.903	(0.529)	*0.000*
Covariates												
Sales Experience				-0.004	(0.009)	*0.626*	-0.003	(0.008)	*0.757*	-0.006	(0.009)	*0.452*
Job Tenure				0.016	(0.012)	*0.167*	0.012	(0.011)	*0.301*	0.011	(0.011)	*0.313*
Remote work				0.030	(0.036)	*0.406*	0.030	(0.034)	*0.378*	0.027	(0.034)	*0.421*
Social Media Infusion				0.200	(0.061)	*0.001*	0.141	(0.061)	*0.022*	0.115	(0.061)	*0.064*
Behavior Control				0.256	(0.079)	*0.001*	0.135	(0.083)	*0.104*	0.135	(0.082)	*0.101*
Predictors												
CRM Infusion (CRM)	0.595	(0.082)	*0.000*				0.292	(0.075)	*0.000*	0.435	(0.096)	*0.000*
CRM^2	0.102	(0.037)	*0.006*							0.087	(0.038)	*0.021*
F Change	7.694**			9.569***			15.351***			5.400*		
Adjusted -R^2	0.225**			0.178***			0.235***			0.252*		
Highest VIF	1.797			1.524			1.628			2.524		

Table 6. MEDCURVE analysis summary

Step 1: **Individual Path Pre-test Regression**	**Step 2:** **MEDCURVE Instantaneous Effect**
Path $H2_a$: CRM Infusion ∩ Technostress: (β = -0.133, *p* < 0.012) Path $H2_b$: Technostress ∪ Performance: (β = 0.130, *p* = 0.000)	H2: CRM Infusion ∩ Technostress ∪ Performance Low: θ = 0.003, 95%CI [-0.030, 0.033] Mod: θ = -0.036, 95%CI [-0.098, -0.000] High: θ = -0.036, 95%CI [-0.112, 0.001]

Path H3$_a$: CRM Infusion ∪ Bricolage: ($\beta = 0.094$, $p = 0.006$) Path H3$_b$: Bricolage ∪ Performance: ($\beta = 0.172$, $p = 0.000$)	H3: CRM Infusion ∪ Bricolage ∪ Performance Low: $\theta = 0.010$, 95%CI [-0.046, 0.062] Mod: $\theta = 0.091$, 95%CI [0.008, 0.193] High: $\theta = 0.202$, 95%CI [0.036, 0.455]

Table 7. Study 2 descriptive statistics and correlations

	1	2	3	4	5	6	7	8	9	10
1. Salesforce CRM	--									
2. B2B Sales	0.066	--								
3. CRM Daily Use	-0.097	-0.047	--							
4. CRM Training Tenure	-0.015	-0.047	-0.179**	--						
5. Agility	0.062	0.056	-0.024	-0.103	**0.750**					
6. Grit	0.035	-0.035	0.016	-0.103	0.420**	**0.718**				
7. CRM Infusion	0.086	-0.146**	0.312**	-0.201**	0.210**	0.286**	**0.880**			
8. AI Adaptive Selling	0.000	-0.186**	0.267**	-0.267**	0.089	0.107	0.418**	**0.847**		
9. Technostress	-0.048	-0.101	0.292**	-0.138*	-0.115*	-0.182**	0.021	0.265**	**0.779**	
10. Bricolage	0.108	-0.062	0.030	-0.042	0.346**	0.322**	0.259**	0.080	-0.239**	**0.707**
Mean	0.550	0.410	4.550	3.100	4.194	4.502	3.586	2.622	2.243	4.174
SD	0.498	0.493	3.017	1.529	0.641	0.551	1.070	1.182	0.703	0.536
CR	-	-	-	-	0.837	0.759	0.911	0.946	0.971	0.833
AVE	-	-	-	-	0.563	0.516	0.774	0.717	0.607	0.500
Cronbach's Alpha	-	-	-	-	0.836	0.728	0.911	0.949	0.927	0.832

Note: Square roots of AVEs are in bold along diagonal

Table 8. Study 2 regression results for bricolage

	Model 1			Model 2			Model 3			
	Base Model β (SE) *p-Value*			Covariates β (SE) *p-Value*			CRM β (SE) *p-Value*			
Intercept	4.019	(0.038)	*0.000*	2.289	(0.270)	*0.000*	2.506	(0.281)	*0.000*	2.6
Covariates										
Salesforce CRM				0.100	(0.056)	*0.074*	0.083	(0.056)	*0.139*	0.0
B2B Sales				-0.080	(0.057)	*0.161*	-0.056	(0.057)	*0.325*	-0.0
CRM Training Tenure				0.004	(0.019)	*0.827*	0.010	(0.019)	*0.575*	0.0
CRM Daily Use				0.007	(0.009)	*0.450*	-0.001	(0.010)	*0.939*	-0.0
Agility				0.217	(0.048)	*0.000*	0.202	(0.048)	*0.000*	0.1
Grit				0.202	(0.056)	*0.000*	0.171	(0.056)	*0.003*	0.1
Predictors										
CRM Infusion (CRM)	0.189	(0.034)	*0.000*				0.075	(0.029)	*0.010*	0.1
CRM^2	0.137	(0.028)	*0.000*							0.1
AI-Assisted Selling (AI)	-0.100	(0.035)	*0.005*							
Linear Interactions										
CRM x AI	0.049	(0.028)	*0.076*							
Curvilinear Interactions										
CRM^2 x AI	0.072	(0.021)	*0.000*							
F Change	11.713***			10.740***			6.667*			
Adjusted -R^2	0.162***			0.156***			0.171*			
Highest VIF	3.270			1.231			1.300			

Model 4			Model 5			Model 6			Model 7		
CRM^2 β (SE) *p-Value*			Predictors β (SE) *p-Value*			Linear Interactions β (SE) *p-Value*			Curvilinear Interactions β (SE) *p-Value*		
644	(0.274)	*0.000*	2.649	(0.275)	*0.000*	2.647	(0.275)	*0.000*	2.730	(0.272)	*0.000*
099	(0.054)	*0.069*	0.099	(0.054)	*0.070*	0.097	(0.054)	*0.075*	0.083	(0.054)	*0.125*
066	(0.055)	*0.233*	-0.071	(0.056)	*0.208*	-0.074	(0.056)	*0.187*	-0.074	(0.055)	*0.184*
005	(0.018)	*0.803*	0.003	(0.018)	*0.891*	0.005	(0.019)	*0.803*	-0.001	(0.018)	*0.976*
004	(0.010)	*0.652*	-0.004	(0.010)	*0.708*	-0.003	(0.010)	*0.759*	-0.004	(0.010)	*0.695*
188	(0.046)	*0.000*	0.189	(0.047)	*0.000*	0.188	(0.047)	*0.000*	0.191	(0.046)	*0.000*
134	(0.055)	*0.016*	0.133	(0.055)	*0.017*	0.133	(0.055)	*0.017*	0.114	(0.055)	*0.040*
154	(0.033)	*0.000*	0.159	(0.034)	*0.000*	0.162	(0.035)	*0.000*	0.135	(0.035)	*0.000*
102	(0.023)	*0.000*	0.102	(0.023)	*0.000*	0.091	(0.026)	*0.000*	0.120	(0.027)	*0.000*
			-0.014	(0.026)	*0.597*	-0.020	(0.027)	*0.461*	-0.089	(0.035)	*0.011*
						0.022	(0.026)	*0.399*	0.039	(0.027)	*0.140*
									0.063	(0.020)	*0.002*
	20.530***			0.279			0.715			9.562**	
	0.220***			0.219			0.218			0.239**	
	1.787			1.921			1.939			3.364	

Table 9. Study 2 regression results for technostress

	Model 1			Model 2			Model 3			
	Base Model β (SE) *p-Value*			Covariates β (SE) *p-Value*			CRM β (SE) *p-Value*			
Intercept	2.396	(0.051)	*0.000*	3.429	(0.361)	*0.000*	3.334	(0.379)	*0.000*	3.1
Covariates										
Salesforce CRM				-0.011	(0.075)	*0.879*	-0.004	(0.075)	*0.959*	-0.0
B2B Sales				-0.140	(0.076)	*0.065*	-0.150	(0.077)	*0.050*	-0.1
CRM Training Tenure				-0.054	(0.025)	*0.029*	-0.057	(0.025)	*0.023*	-0.0
CRM Daily Use				0.062	(0.013)	*0.000*	0.066	(0.013)	*0.000*	0.0
Agility				-0.041	(0.064)	*0.526*	-0.034	(0.064)	*0.596*	-0.0
Grit				-0.237	(0.074)	*0.002*	-0.223	(0.076)	*0.004*	-0.1
Predictors										
CRM Infusion (CRM)	-0.093	(0.045)	*0.041*				-0.033	(0.039)	*0.405*	-0.1
CRM^2	-0.173	(0.037)	*0.000*							-0.1
AI-Assisted Selling (AI)	0.284	(0.047)	*0.000*							
Linear Interactions										
CRM x AI	0.009	(0.037)	*0.815*							
Curvilinear Interactions										
CRM^2 x AI	-0.104	(0.028)	*0.000*							
F Change	13.627***			8.606***			0.696			
Adjusted -R^2	0.156***			0.126***			0.145			
Highest VIF	3.270			1.231			1.300			

Model 4			Model 5			Model 6			Model 7		
CRM[2] β (SE) *p-Value*			Predictors β (SE) *p-Value*			Linear Interactions β (SE) *p-Value*			Curvilinear Interactions β (SE) *p-Value*		
195	(0.375)	*0.000*	3.140	(0.366)	*0.000*	3.133	(0.365)	*0.000*	3.008	(0.361)	*0.000*
020	(0.074)	*0.787*	-0.017	(0.073)	*0.816*	-0.020	(0.072)	*0.779*	0.001	(0.071)	*0.984*
140	(0.075)	*0.064*	-0.092	(0.075)	*0.217*	-0.101	(0.075)	*0.177*	-0.101	(0.073)	*0.167*
051	(0.025)	*0.039*	-0.031	(0.025)	*0.209*	-0.026	(0.025)	*0.296*	-0.018	(0.024)	*0.458*
069	(0.013)	*0.000*	0.062	(0.013)	*0.000*	0.064	(0.013)	*0.000*	0.065	(0.013)	*0.000*
021	(0.064)	*0.743*	-0.027	(0.062)	*0.667*	-0.029	(0.062)	*0.641*	-0.034	(0.061)	*0.577*
186	(0.076)	*0.015*	-0.180	(0.074)	*0.016*	-0.180	(0.074)	*0.015*	-0.150	(0.073)	*0.040*
112	(0.045)	*0.014*	-0.161	(0.046)	*0.000*	-0.155	(0.046)	*0.000*	-0.115	(0.047)	*0.014*
103	(0.031)	*0.000*	-0.102	(0.030)	*0.000*	-0.128	(0.035)	*0.000*	-0.172	(0.036)	*0.000*
			0.141	(0.035)	*0.000*	0.126	(0.036)	*0.000*	0.230	(0.046)	*0.000*
						0.053	(0.035)	*0.130*	0.028	(0.035)	*0.434*
									-0.095	(0.027)	*0.000*
11.106***			16.585***			2.306			12.389***		
0.153***			0.194***			0.197			0.226***		
1.787			1.921			1.939			3.364		

Table 10. Summary of Study 1 and Study 2 direct curvilinear relationships and U shape tests

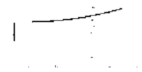
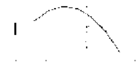
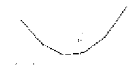
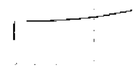
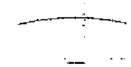
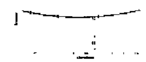
Relationship	Linear	Quadratic	Slope Significance Test	Turning Point	Shape
Study 1					
CRM Infusion → Sales Performance	β = 0.292, *p* = 0.000	β = 0.087, *p* = 0.021	CRM-low = 0.105, *p* = 0.137 CRM-high = 0.600, *p* = 0.000	3.455 (7-scale)	J Shape 
CRM Infusion → Technostress	β = -0.015, *p* = 0.883	β = -0.133, *p* = 0.012	CRM-low = 0.271, *p* = 0.022 CRM-high = -0.359, *p* = 0.004	5.079 (7-scale)	Inverted U Shape 
CRM Infusion → Bricolage	β = 0.049, *p* = 0.473	β = 0.094, *p* = 0.006	CRM-low = -0.153, *p* = 0.040 CRM-high = 0.292, *p* = 0.000	4.875 (7-scale)	U Shape 
Technostress → Sales Performance	β = 0.085, *p* = 0.114	β = 0.130, *p* = 0.000	Technostress-low = -0.365, *p* = 0.000 Technostress-high = 0.268, *p* = 0.000	4.069 (7-scale)	U Shape 
Bricolage → Sales Performance	β = 0.317, *p* = 0.000	β = 0.172, p = 0.000	Bricolage-low = -0.053, *p* = 0.278 Bricolage-high = 0.681, *p* = 0.000	4.110 (7-scale)	J Shape 
Study 2					
CRM Infusion → Technostress	β = -0.033, *p* = 0.405	β = -0.103, *p* = 0.000	CRM-low = 0.549, *p* = 0.000 CRM-high = -0.332, *p* = 0.000	3.042 (5-scale)	Inverted U Shape 
CRM Infusion → Bricolage	β = 0.075, *p* = 0.010	β = 0.102, *p* = 0.000	CRM-low = -0.501, *p* = 0.000 CRM-high = 0.372, *p* = 0.000	2.831 (5-scale)	U Shape 

Figure 1: Study 1 conceptual model

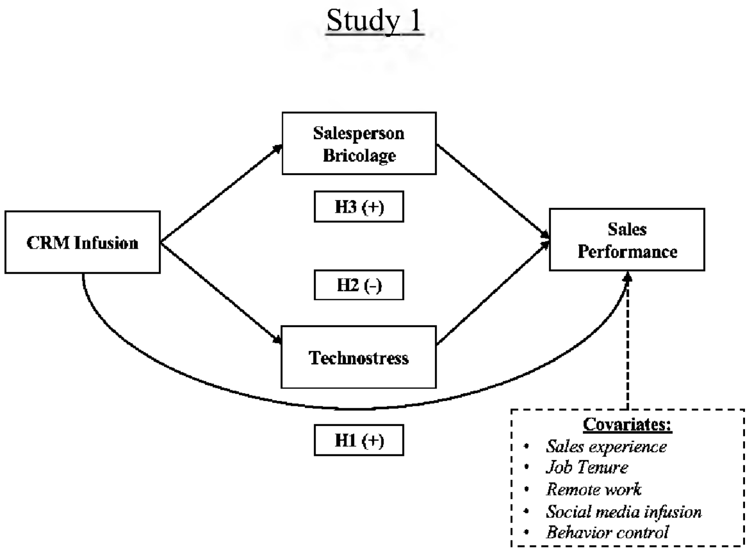


Figure 2: Study 2 conceptual model

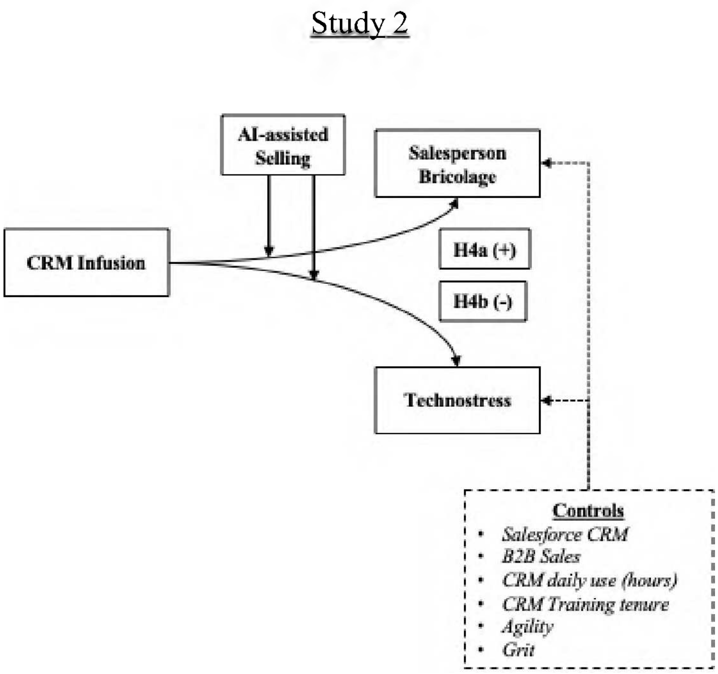


Figure 3. The curvilinear relationship between CRM infusion and sales performance - Study 1

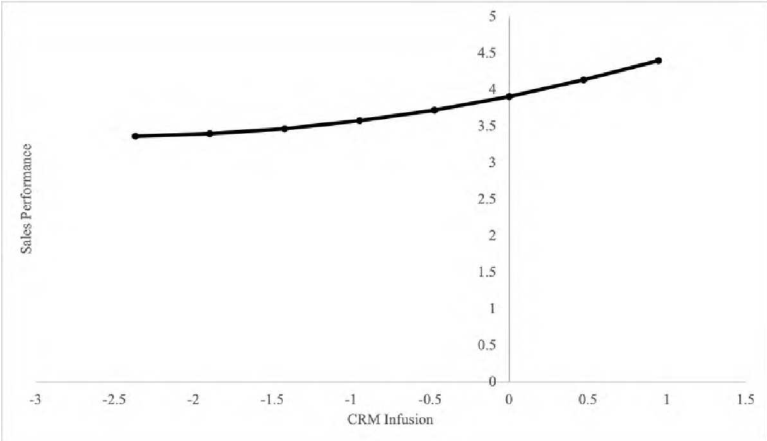


Figure 4. The curvilinear relationship between CRM infusion and bricolage - Study 2

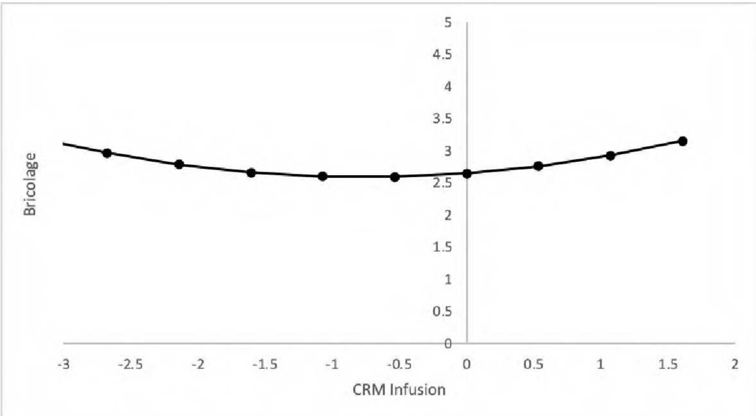


Figure 5. The curvilinear relationship between CRM infusion and technostress - Study 2

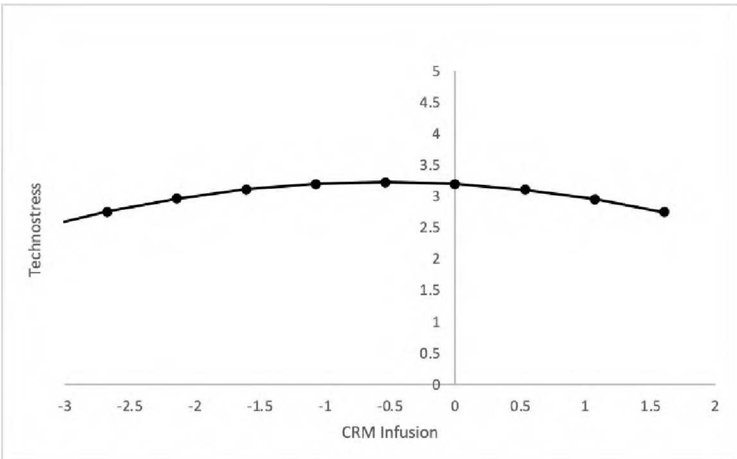


Figure 6. The influence of AI-assisted adaptive selling on the curvilinear relationship between CRM infusion and bricolage- Study 2

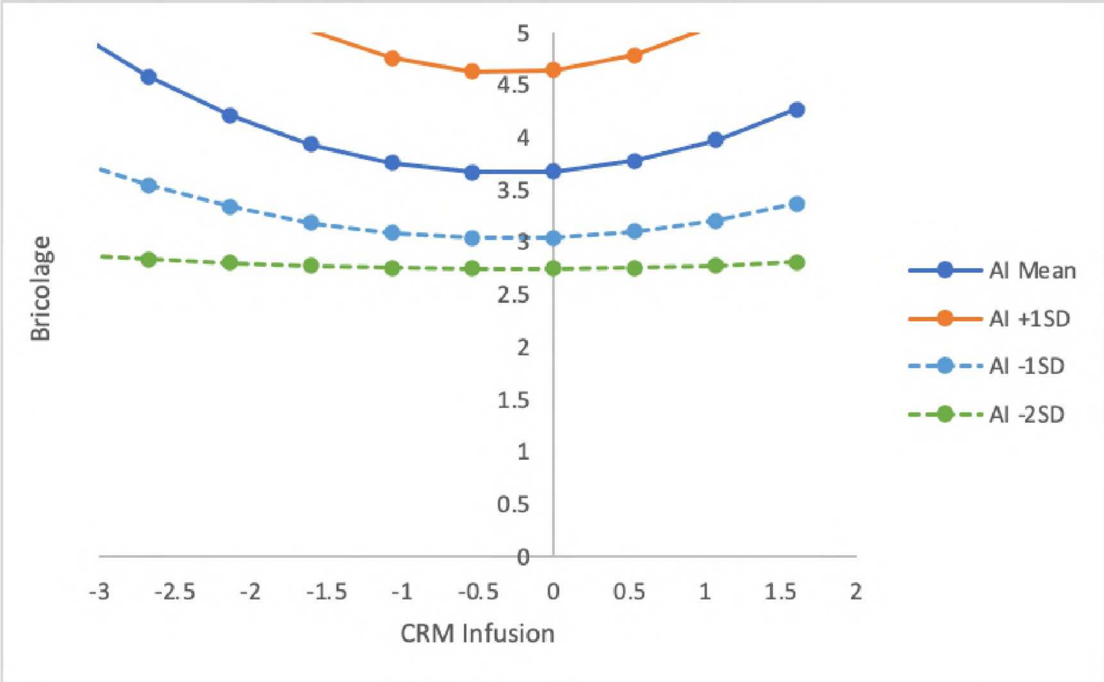


Figure 7. The influence of AI-assisted adaptive selling on the curvilinear relationship between CRM infusion and technostress - Study 2