What's the Weather Like? The Effect of Team Learning Climate, Empowerment Climate, and Gender on Individuals' Technology Exploration and Use

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Abstract: Given the pervasive use of teams in organizations coupled with high levels of investment in collaboration technology, there is increasing interest in identifying factors that affect the exploration and use of a broader scope of system features so that firms can benefit from the use of such technology. Prior research has called for a deeper understanding of how managers can encourage greater innovation with technology in the workplace. Drawing on the team climate and technology use literatures, we identify team learning climate and team empowerment climate as key factors that affect employees' propensity to explore a new system's features. We develop and test our

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multilevel model on team climate, team technology exploration, and team technology use in a field study involving 268 employees embedded in 56 work teams. Three main findings come out of this research. First, the results reveal that the two types of team climate differ in their cross-level effects on individual intention to explore, such that team learning climate promotes greater intention to explore, whereas team empowerment climate reduces employees' intention to explore the technology. In addition, we find that team learning climate and team empowerment climate interact in shaping individual intention to explore, such that the presence of a strong learning climate is more effective in promoting intention to explore when teams also have a strong empowerment climate. Second, the findings show that men and women are affected differently by team climate. We find that for men, team empowerment climate has no influence on intention to explore, whereas for women there is a significant negative cross-level effect. Finally, we find that intention to explore has a positive effect on usage scope, suggesting an important link between team climate, individual cognition, and the scope of features used by employees in team settings. Taken together, the model and results highlight the important role of team climate and gender—and the interplay between them—as drivers of technology feature exploration. Our findings, especially those related to team empowerment climate, are counterintuitive when compared to prior literature and offer useful insights for managers. On the one hand, managers should consider leveraging team learning climate to intrinsically stimulate employees to engage in exploration of technology. On the other hand, managers should be cautious and guard against saddling employees with too many additional responsibilities during the stages of exploration and experimentation with system features. It is possible that through an expanded set of responsibilities and expectations fostered by team empowerment climate, employees may be experiencing work overload, thus reducing their likelihood of exploring a broader set of technology features. Managers should be especially attentive to this based on the gender composition of their teams.

Key words and phrases: collaboration technology, intention to explore, multilevel research, postadoption use, team climate, team technology use, usage scope.

Investments in information technology (IT) continue to make up a significant proportion of organizational budgets [62]. In an effort to enhance their ability to leverage the knowledge resources embedded in their employees, organizations have been increasingly emphasizing investments in collaboration technologies in particular. For example, companies such as Pfizer and Applied Materials are investing in collaboration technologies to boost their problem-solving capabilities and overall firm productivity [73]. A report by Gartner identified collaboration technology as one of the top 10 strategic technologies that firms would invest in for 2011 [28]. This reveals two important trends in organizations. First, given the increasing complexity of business-related issues, organizations are increasingly relying on teams as a structure for organizing employees. According to recent estimates, over 80 percent of Fortune 500 companies utilize team-based structures to organize work. Thus, a majority of employees are involved in some form of teamwork as a fundamental part of their jobs [42]. Teams often have better informational resources compared to individuals and therefore are better equipped to solve complex, knowledge-intensive problems. Second, organizations are investing heavily in acquiring and deploying collaboration technologies in an effort to take advantage of their employees' expertise. Such technologies enable firms to more efficiently draw upon expertise across the entire enterprise. Indeed, a study by Bughin and Chui reports that companies have experienced significant improvements in access to knowledge and access to internal experts as a result of collaboration technology [17]. As investment in IT shifts increasingly toward collaborative technologies, managers and researchers alike have a significant interest in understanding how best to foster extensive use of these systems in their work.

Despite significant gains in explaining and predicting individual usage intentions and behaviors toward IT, organizations are still facing problems related to the underutilization of newly implemented technologies [56, 84]. Previous research has found that individuals underutilize newly introduced technologies, often using just a narrow set of features [44]. As Jasperson et al. note, users of these newly implemented systems "employ quite narrow feature breadths, operate at low levels of feature use, and rarely initiate technology- or task-related extensions of the available features" [44, p. 526]. Commenting on a similar issue from a managerial perspective, Ahuja and Thatcher observe that it is "an everyday challenge for managers to find ways of facilitating IT-based innovation and creativity" [2, p. 428]. Unfortunately, the limited use of new technology features by employees for work-related innovation obstructs potential IT-related job performance improvement and hampers organizational efforts to realize returns from their IT investments [2, 38, 44]. With this in mind, it is important to understand the factors that affect the breadth of features employees use and investigate ways in which these features can be incorporated into their work.

Managers have had a difficult time identifying potential levers that affect employees' willingness to engage in innovative behaviors with newly implemented technologies [2, 44]. *Intention to explore*—defined as one's "willingness and purpose to explore a new technology and find potential use" [66, p. 373]—reflects employees' propensity for engaging in such behavior. Unfortunately, despite the increasing reliance on the team-based structures mentioned above, relatively little research has focused on the team-level factors that affect users' intention to explore new technology features and how the willingness to explore is effectively translated into usage behaviors that are tied to a wider breadth of feature use (henceforth referred to as "usage scope").

Climate has been identified as a critical element influencing work-related innovation in organizational contexts and thus constitutes a useful perspective for understanding how an environment can affect individuals' willingness to explore a technology [7]. Climate can be especially effective in shaping individuals' behavior when enacted in a localized setting such as a team [51], given the task and outcome interdependence they embody [89]. Consequently, employees' behavior and reaction toward novel situations—such as exploring and integrating a new technology into one's work—is likely to be molded by shared interpretations and experiences among team members [37]. In addition, as organizational social collectives, teams can enact localized structures that drive the process of exploring technology features for work purposes. Thus, our first goal is to examine the role played by team climate in influencing individual willingness to explore a technology and how the willingness to explore is translated into behaviors that reflect greater usage scope.

Research has shown that men and women respond differently to new technology introductions (e.g., [65, 84, 86]). Other research has even suggested that men and women differ in their propensity to innovate with technology in the workplace [2]. However, differences in the extent to which men and women differ in their reactions to team climate interventions remain hitherto unexplored. This underscores the need to understand how team-level interventions affect exploration intentions across employees of different gender within teams. Hence, our second goal is to incorporate gender as an important contingency that may influence the effects of team climate in shaping user technology exploration.

Our research into team climate and gender and their implications for exploration intentions and usage scope makes several key contributions to the literature. First, although recent research has begun to examine technology adoption decisions in team settings (e.g., [15, 74]), little research has examined how team climate affects individual users' exploration and usage patterns. Consequently, we extend understanding of how managerial interventions can affect individual exploration toward a more expansive individual use of a technology's features so as to support team member work. Second, we add to the extant literature by incorporating the contingent role of gender in examining the question of "for whom is support really supportive?" While it is broadly understood that gender affects users' adoption decisions [84, 86], little is known about how effective team-level interventions are in promoting exploration-oriented behaviors among men versus women. Finally, our examination of the predictors of usage scope responds to recent calls for research to better understand technology use from a feature perspective [18, 44]. Indeed, prior research has tended to treat IT as a black box rather than as a collection of features [44]. We identify intention to explore as an important cognition underlying usage scope and identify key antecedents of this cognition. By responding to this call, we shed light on technology usage and move beyond treating it as a black box.

Theoretical Background

Exploration of Technology Features

The exploration of technology features emerges when a new technology has been installed and made available to users in an organization. However, compared to traditional views of use—that is, as duration, frequency, and intensity—it provides a finer level of granularity in understanding how employees are making use of the system. That is, rather than being descriptive of employees' use of the system as a whole, a feature-centric view recognizes that the set and breadth of features that any given employee uses can differ [22, 32]. As Jasperson et al. [44] note, such a view is much more consistent with the notion of technology-in-use in that it reflects an appreciation for technology as a collection of features and a user as an agent who can employ any configuration of these features in his or her work. Further, as evidenced in the extant literature, differences in the specific features used can have important implications for employees' ability to effectively do their jobs [18, 38]. Ahuja and Thatcher [2] suggest that utilization of a broader range of features provides significant benefits to users by enabling them to innovate with the technology—that is, finding productive uses for the technology in their work.

As noted earlier, intention to explore is defined as a user's willingness to explore a new technology with the purpose of finding potential applications to his or her work [66]. Hence, intention to explore reflects an individual's willingness to survey various features of the technology as well as his or her desire to engage in an active thought process about how to incorporate the various aspects of the technology into one's work. Nambisan et al. [66] suggest that intention to explore reflects employees' need for knowledge about how the technology can potentially enhance their work productivity, underscoring its instrumental underpinnings. Through this lens, intention to explore is a relevant cognition for understanding the motivational factors driving employees' sensemaking process in relation to new technology. Given the significant amount of attention that intention to use a technology has received in the literature, it is important to note that there are distinct differences between intention to explore and intention to use a new technology. Intention to use reflects a user's willingness to use a technology. It does not necessarily reflect *how* one plans to use the technology—that is, the nature of use. Thus, it is ill suited for adopting a feature-centric view of use, much less understanding why some users employ a broader set of features compared to others. In contrast, intention to explore reflects a user's conscious plan to actively survey the various features of a new technology [54, 66]. This exploration behavior can lead to the discovery of methods for leveraging the technology to support one's work [66, 82]. This is an important distinction because we believe that this emphasis on exploration is consistent with technology sensemaking and a broader scope of feature use [82]. Unfortunately, there is currently a paucity of research on the antecedents and outcomes of user intention to explore [54, 82], especially in the team context. Within a team context, team climate represents an important lever that managers can use to provide a localized environment that is supportive of such IT innovation behavior [7, 51]. However, Ahuja and Thatcher [2] also note that in gauging the effectiveness of any intervention one needs to consider the possible influence of gender differences. Hence, as we will discuss below, the effectiveness of these team-level interventions in fostering individual intention to explore is expected to vary across individual team members of different gender. This multilevel relationship between climate, gender, intention to explore, and usage scope is illustrated in our research model in Figure 1.

Team Climate

Information systems research is increasingly acknowledging the important role that contextual factors—beyond the individual—play in affecting technology-related behavior. For instance, Gallivan et al. highlight the need for research to incorporate "influences at levels beyond the individual user that shape how employees use IT in their jobs" [27, p. 155], noting that such influences could exist at the level of the

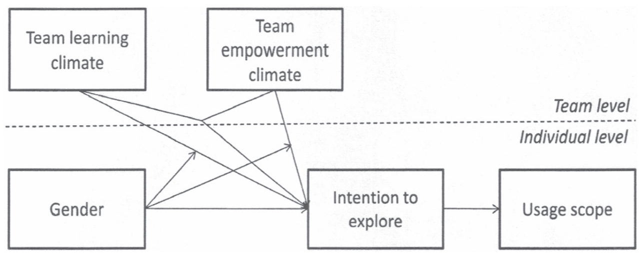

Figure 1. A Research Model of Team Climate, Gender, User Intention to Explore, and Usage Scope

workgroup. Most recently, Liang et al. [51] investigated the influence of team innovation climate on physicians' adoption of medical technology. Clearly, the team environment has the potential to play a central role in shaping employees' behavior regarding new technology [27, 51]. At the team level of analysis, climate is defined as team members' shared perceptions of the kinds of behaviors, practices, and procedures that are supported within a team [76], and it influences team members' behaviors through a social information processing mechanism [31]. The role of team climate is particularly critical in uncertain or nonroutine circumstances because team members can rely on social cues of team climate to guide their actions in a way that is supported within the team. Because new technology introductions often have significant uncertainty associated with them [32, 64], it is critical that teams have guidelines in place to enable their members to cope with such disruptive events [90, 91], and team climate provides such guidelines. Two types of climate have emerged as being particularly influential in affecting individuals under such circumstances: team learning climate and team empowerment climate.

Cross-Level Influence of Team Learning Climate

Team learning climate refers to the extent to which team members have a shared perception that the team supports practices that promote experimentation, innovation, and risk taking as well as an environment in which team members favor inquiry and dialogue and which encourage collaboration [23]. Ahuja and Thatcher [2] emphasize the need for an organizational environment that reflects attitudes that are supportive of innovative behavior. Such supportive environments serve as a stimulant for innovation with IT. Amabile et al. [7] found that innovation was highest in teams that developed a climate that was supportive of experimentation. Collectively, this extant body of work suggests that an environment that supports and values experimentation and dialogue should be conducive for individuals' exploration of IT. Building on this logic, team learning climate is expected to increase individuals' intention to explore a new technology. Prior research has underscored that learning about IT and incorporating it into one's daily work is a social process. In the context of software training, Galletta et al. [26] found that employees' attitudes toward a new system were strongly shaped by the attitudes of their co-workers and could negatively or positively influence intention to use. Similarly, George et al. [29] highlight the limitations in traditional, individual-focused approaches to training employees on new systems, arguing instead for a more socially oriented approach that recognizes the important role played by fellow employees in providing positive reinforcement to support IT-related learning. George et al.'s [29] study of two work groups found that the usage patterns of employees (utilizing the same newly introduced system) was shaped by the values and norms of the work group to which each belonged. Collectively, this body of work underscores the important role that can be played by one's teammates in shaping how a new technology will be used [27].

Because teamwork requires coordination and cooperation among team members [89], the process of experimentation with new technology can be personally risky for individuals as they engage in a trial-and-error process of identifying solutions that work [23]. A common fear among team members is that their experimental actions will precipitate negative reactions from their interdependent teammates [23, 71]. Thus, it becomes important for there to be norms that emphasize the value of such behavior so that employees can engage in exploration of the technology without fear of reprisal. Team learning climate fosters such behavior because team members collectively promote experimental activities that are an integral part of innovating with IT. Individuals who are immersed in an environment that stimulates and supports experimentation and learning are more likely to generate new and creative ideas [7, 83]. Consequently, team members are likely to form an intention to explore the technology, to the degree that they see it as being a socially desirable behavior. In sum, we expect team learning climate to be positively related to individual intention to explore:

> *Hypothesis 1: Team learning climate will have a positive cross-level influence on user intention to explore.*

Cross-Level Influence of Team Empowerment Climate

Team empowerment climate reflects the extent to which team members have a shared perception of policies, practices, and behaviors that promote information sharing, autonomous action, responsibility, and accountability [76]. Information sharing refers to the provision of potentially sensitive information to team members. Autonomous action refers to policies and practices that encourage team members to act without seeking supervisor approval. Responsibility and accountability pertain to the delegation of decision-making rights to team members [76]. With high levels of team empowerment climate, team members understand that taking initiative, being autonomous and accountable in their actions, and sharing information are expected and desired. Thus, empowerment encourages team members to be self-regulating, self-monitoring, and self-sanctioning so as to ensure high performance [76]. Through information sharing, team members are encouraged to share insights about discoveries made in their use of the new technology. This gives team members potentially useful information that may stimulate them to probe the system further. This type of peer-based co-discovery has been instrumental in facilitating the use of new systems (e.g., [27]). Gallivan et al. [27] underscore that co-discovery of computer systems promoted a better understanding of system features and how to use them to complete tasks effectively. Mutual information sharing between teammates promotes greater curiosity about the technology, prompting team members to want to explore the system further. With autonomy, team members have the freedom to devote time to exploring the technology's various features as well as potential applications for work. Work autonomy has been associated with better job performance. With greater freedom to structure one's work tasks and scheduling, team members are able to direct their resources toward self-enhancing activities. To the degree that extended feature use is viewed as being performance enhancing, team members are more likely to form intentions to explore ways in which to enhance task performance using the system. Prior creativity research suggests that employees are more likely to exhibit creativity in their work when they perceive higher degrees of autonomy [7, 76]. Ahuja and Thatcher [2] found a positive relationship between autonomy and the extent to which employees try to innovate with IT. Finally, through greater responsibility and accountability, team members are more likely to explore ways in which to find efficiencies that can be gained through the system. Collectively, these elements of team empowerment climate are expected to promote a greater level of engagement with the system, exhibited via higher intention to explore:

> *Hypothesis 2: Team empowerment climate will have a positive cross-level influence on user intention to explore.*

Joint Effects of Team Learning Climate and Team Empowerment Climate

In addition to being independent drivers of intention to explore, we expect team learning climate and team empowerment climate to interact in their effects on such intention. Specifically, team empowerment climate is expected to moderate the relationship between team learning climate and user intention to explore. While team learning climate stipulates specific behaviors—such as experimentation and risk taking—that are espoused by the team [23], team empowerment climate emphasizes the work structures—such as autonomous decision making and accountability for work performance—that are endorsed within the team [76]. Thus, the two types of team climate complement each other by combining both espoused behaviors and the work structures within which those behaviors are enacted. As elucidated in H1, team learning climate should positively influence user intention to explore the technology. However, this form of team climate could be more efficacious in promoting higher levels of exploration intention if work structures that support the desired behavior are in place. By providing greater levels of autonomy, information sharing, and accountability for how employees should structure their work, high levels of team empowerment climate promote an environment in which the experimental behaviors espoused by team learning climate can be enacted [23]. Employees have the autonomy to take time in their workday to explore various features of the technology, examine how the features they currently use might be used differently, and examine how to accomplish their work tasks using other technology features that may not be part of their existing repertoire [2]. Team learning climate, therefore, is expected to have a stronger effect on user intention to explore. In contrast, when team empowerment climate is low, employees do not perceive that they have the freedom to structure their workday or determine how they utilize their time. Consequently, although experimentation and risk taking may appear to be espoused through team learning climate, employees may be reluctant to pursue such behavior given their structured work environment. Under such conditions, the effect of team learning climate on user intention to explore is expected to be weaker:

> *Hypothesis 3: Team learning climate and team empowerment climate will have an interactive effect on user intention to explore such that the cross-level relationship between team learning climate and intention to explore will be weaker when team empowerment climate is low compared to when it is high.*

Gender and Technology Exploration

A preponderance of research has shown that women and men differ in the way they process and react to events in the workplace. Gender schema theory suggests that women and men encode and process information differently, and that this results in different cognitive structures that shape their perceptions [49]. These underlying schemas tend to manifest in the decisions, perceptions, and actions of women and men [1]. The extant literature on gender schema consistently reveals two patterns that differentiate women and men. First, compared to women, men tend to place a greater emphasis on instrumentality and achievement in the workplace. O'Neil [68] argued that men tend to focus on work and work-related accomplishments. Similarly, Hoffman [36] suggested that, compared to women, men are more motivated by achievement needs, and other research has pointed to the fact that men place a greater emphasis on achievement and accomplishment in the workplace (e.g., [49, 61]). Second, compared to men, women tend to have stronger affiliation needs and place greater significance on social relationships [20, 36]. Consequently, women tend to be more open to collective influence from social others, whereas men tend to assert independence [10, 80]. In their meta-analysis of the job attitudes of women and men, Konrad et al. [49] found that women value job attributes such as working with other people and the opportunity to help others, whereas men value job attributes such as performance recognition, promotion opportunity, and task significance. These differences between women and men have also manifested within the IT adoption domain.

The literature on IT adoption has found that women and men base their decisions and actions about new technology on different underlying schema. Venkatesh and Morris [84] found that perceived usefulness had a stronger effect on behavioral intention among men compared to women and that these differences persisted over the long term. They also found that women placed a greater emphasis on social cues in forming their behavioral intention to use the IT. Similarly, Venkatesh et al. [86] found that attitude toward technology had a stronger influence on behavioral intention among men than women. Much of this research suggests that instrumentality is a strong motivation for IT use among men, given their task and achievement orientation [35, 65, 84]. We believe that these gender differences in the instrumentality associated with IT in the workplace will also manifest in users' decisions to explore newly implemented systems.

Nambisan et al. [66] noted that intention to explore reflects a user's orientation toward identifying productivity-enhancing uses of various features of the technology. As indicated earlier, this underscores an instrumental underpinning of intention to explore as it reflects a means to potentially enhancing one's accomplishment in the workplace. Indeed, Nambisan et al. [66] argued that intention to explore is based on the anticipation of potential work-related benefits the technology might have. Magni et al. [54] found that intention to explore is driven by instrumental motivations. In light of the prior literature underscoring men's emphasis on achievement and accomplishment in the workplace [61, 84], we expect that men are more likely to form an intention to explore the new technology. For men, intention to explore is well aligned with the objective of enhancing work performance:

Hypothesis 4: Men will have a higher level of intention to explore compared to women.

Moderating Role of Gender

We expect the cross-level influence of team learning climate on intention to explore to be stronger for women compared to men. Team learning climate promotes experimentation and sharing of discoveries and lessons learned among team members [23]. Such efforts increase the amount of knowledge that is available within the team [23]. This emphasis encourages team members to engage in an ongoing dialogue about how they are incorporating the technology and its features into their work. As such, it underscores the social aspect of engaging with the technology. Given their emphasis on social exchanges, women are likely to be prompted to explore technology when the environment supports such behavior and encourages social sharing of the experience. A meta-analysis by Konrad et al. [49] shows that women prefer such job environments, where interpersonal exchange is prevalent. Prior research suggests that women tend to respond more favorably to contexts that involve interpersonal goals and exchange [80]. Research also suggests that women are more attuned to social cues about desirable behavior [84, 86]. Therefore, to the extent that experimentation is socially desired within the team, women are more likely to respond in kind. In contrast, men tend to be more independent in their actions and are therefore less responsive to social cues about desirable behavior. As such, team learning climate should play less of a role in forming their intention to explore when compared to women:

Hypothesis 5: The cross-level influence of team learning climate on user intention to explore will be stronger for women than for men.

Team empowerment climate is expected to have different effects for women and men. According to prior literature, men and women differ in their affinity for work environments that emphasize autonomy and accountability [49]. As discussed earlier, compared to women, men tend to emphasize the instrumentality and an achievement orientation in the workplace. This kind of orientation typically leads men to value work contexts that provide autonomy as well as present the challenge of accountability and responsibility. In an environment characterized by empowerment climate, men are more likely to leverage the autonomy, accountability, and initiative taking of the environment to engage in activities that have an instrumental value for them [2]. Because of the intrinsic instrumental value of technology exploration described before, a greater level of empowerment climate would lead men to engage in exploration activities for discovering productivity-enhancing uses of the technology.

Conversely, women tend to be more attuned to social cues about desired behaviors. Within the context of team empowerment climate, it is clear that taking responsibility for performing assigned tasks, being accountable for performance, and autonomously deciding how and when to accomplish tasks is valued. Consequently, women are likely to focus their attention on such task accomplishment and avoid engaging in technology exploration behaviors that may not contribute to this objective. Furthermore, technology-induced change puts additional strain on employees as they cope with a new way of working [5, 64]. The incidence of anxiety and overload has been found to be higher among women in such cases [14, 41], tempering their engagement with technology. This, combined with expectations of accountability and responsibility, can create a sense of overload for women, while it represents a way to reap instrumental advantage from the technology for men. This reasoning is corroborated by previous research that has found that women are less likely to engage in exploratory behaviors with technology when they experience work overload [2].

Hypothesis 6a: The cross-level influence of team empowerment climate on user intention to explore will be positive for men.

Hypothesis 6b: The cross-level influence of team empowerment climate on user intention to explore will be negative for women.

User Intention to Explore and Usage Scope

Intentions serve as an important precursor to actual behavior [87]. This link between intentions and behavior has been demonstrated across a wide variety of behaviors [78], including technology use [55, 79, 87]. As an internally formulated motivation, intention to explore reflects conscious plans that an individual has to examine and interact with various aspects of a technology so as to identify how it may be incorporated into one's work [66]. As Nambisan et al. [66] note, this motivation is based on perceptions of expected work-related benefits that will be derived from successful innovation with the technology. Because the intended behavior is itself experimental in nature, there is an implicit recognition that various attempts may not always yield positive outcomes. Nevertheless, individuals who have formulated such conscious plans are prepared to engage in a trial-and-error process of search and discovery with the technology.

The use of a broad array of features reflects a behavior that is consistent with exploration intentions. Ahuja and Thatcher [2] suggest that trying to innovate is an important link between intention and actual behavior. Consistent with this idea, we suggest that the use of a wide variety of technology features reflects this notion of trying; that is, by using various features of a technology and exploring ways to incorporate those features into one's work, an individual is in effect trying to innovate. Intention to explore underlies this trying behavior since it represents an internal psychological commitment to engage in such behavior. The exploration of various technology features is a key part of the sensemaking process that individuals undergo as they incorporate these features into their work [40]. Jasperson et al. [44] refer to this as substantive technology use—that is, a reflective approach to using a feature or set of features in a technology. This feature exploration process is an individual cognitive intervention that serves as an input into technology-related sensemaking and associated work outcomes [38, 44, 54]. Consequently, we expect intention to explore to lead to the use of a broader set of technology features:

> *Hypothesis 7: User intention to explore a new technology will be positively associated with usage scope.*

Method

Sample and Participants

To test our research model, we conducted a field study in two large European firms. One of the participating firms was based in the retail industry and the other was based in the banking industry. The participating firms were the sites for recent new collaboration technology introductions. Specifically, both firms had recently implemented a new collaborative technology system to support all technology-mediated communications among employees for such activities as agenda sharing, information sharing, mobility management, and event coordination. Use of the system was strongly encouraged by upper management. However, there was no policy in place for noncompliance, underscoring that system use was voluntary. The participating firms each employed a team-based structure for organizing work. Team members interacted with their teammates to accomplish their tasks, and each team was responsible for a portfolio of customers and was accountable for managing and satisfying customers' needs and requests (e.g., providing assistance, designing promotional campaigns, processing claims, providing funding services). All of the teams had a clearly defined membership, operated within organizational boundaries, and worked on more than one measurable task. Furthermore, although some of each team member's daily tasks could be described as being independent (e.g., going to customer sites to show a promotional campaign), much of the team functioning and performance was highly interdependent since the teams could decide how to manage their work (e.g., division of labor, allocation of resources, performance monitoring, knowledge sharing, complex problem resolution). Interviews with each company's management about their teams' day-to-day activities revealed workflow that represented sequential and pooled interdependence. For instance, teams in the retail firm included employees focused on (1) promotion campaign idea generation, (2) managing paperwork for financing of promotions, and (3) conducting customer surveys. The work of each team member was dependent on input from other team members, as is often the case with interdependent teamwork.

Across the two firms, a total of 810 employees comprising 129 teams were targeted for participation in the study. Data were collected in two waves. The first survey was administered to participants about 1.5 months after the roll-out of the system and was designed to measure the demographic information of participants, control variables, technology exploration intention, as well as empowerment and learning climate. At the time of the first wave of data collection, all of the participants received initial training on the system in order to show the potential of the system and to develop awareness about its features.

In the second wave of data collection, which occurred several months after the first wave, we administered the second questionnaire to measure participants' usage scope. In the first wave (time 1), 410 usable responses from 69 teams were received. The respondents of the first phase were invited to participate in the second wave of data collection. In the second wave of data collection (time 2), 268 usable surveys from members of 56 teams who responded to both time 1 and time 2 surveys were collected. To assess whether nonresponse bias was a concern, we compared employees who participated in both waves of data collection with employees who only participated in the first wave and found no statistically significant differences in demographics (e.g., age, gender, organizational tenure), intention to explore, and usage scope. Only teams with 70 percent of their members responding to the survey were included in the final analysis. Of the total number of participants in the study, 43 percent were women. The average age of the participants was 42.32 (SD [standard deviation] = 8.63). On average, the participants had been with their respective firms for about 7 years.

Measurement

We operationalized the constructs in the model using existing scales. Several of the constructs in the model are conceptualized at the team level of analysis. In dealing with these variables, we followed previous research that recommends the use of a referent-shift consensus approach in wording the items for those constructs representing a shared perspective within the team [48]. The referent-shift approach is particularly suitable in dealing with variables that represent a shared meaning (such as climate) since they shift the referent of the construct from the individual ("I") to the team as a whole ("we/the team") [19]. Using this approach, individuals within each team are responding with reference to the team, thus justifying aggregation of their individual scores [43, 47]. However, before proceeding with the aggregation, it is necessary to (1) ensure that there is convergence in the way individuals within each team are responding to the scale and (2) ensure there is sufficient between-team variability in the responses to the scales. This is accomplished by calculating the within-group agreement index ($r_{wg(j)}$) and the intraclass correlation coefficients (ICCs) [11, 47, 67].

The $r_{wg(j)}$ indicates the extent to which group members' responses to the survey converge greater than would be expected by chance [43]. In other words, high values of $r_{wg(j)}$ represent a situation in which respondents' ratings of a phenomenon are highly similar to each other. The suggested threshold for a high level of agreement within the team is a mean $r_{wg(j)}$ of 0.70 [11, 47]. The ICC(1) reflects between-group variance in individual responses. In particular, the ICC(1) compares the variance between teams to the variance within teams using the individual ratings of each respondent. It essentially represents the proportion of variance in individual responses that is attributable to between-team differences. Previous research suggests that in field research, a cutoff value of ICC(1) for aggregation is 0.12 [75]. The ICC(2) indicates the reliability of the group-level means [11]. It essentially answers the question, how reliable are the group means within a sample [47]. ICC(2) tends to be higher for samples with large team sizes compared to samples of teams with small team sizes [11]. In essence, group means based on many within-team respondents are more stable than group means based on few within-team respondents [47]. It is broadly recognized that in field research, where team sizes tend to be smaller, values as low as 0.50 have been deemed acceptable (e.g., [52, 53, 57]).

Team Learning Climate

A five-item scale from Marsick and Watkins [58] was used to measure team learning climate. The reliability of the scale is 0.79. The mean $r_{wg(j)}$ for the team learning climate scale is 0.91. Results of a one-way analysis of variance (ANOVA)—using team membership as the factor—indicate significant differences across teams in the level of team learning climate ($F = 1.79$, $p < 0.01$). The ICC(1) is 0.15, indicating significant between-team variation. The ICC(2) is 0.54, suggesting adequate stability in the team-level means [11]. Thus, individual scores for team learning climate were aggregated to the team level by averaging the scores of team members. Data on team learning climate were collected during the first wave of measurement (time 1).

Team Empowerment Climate

We used a scale by Seibert et al. [76] to measure team empowerment climate. The reliability of the scale is 0.83. The mean $r_{wg(j)}$ for the scale is 0.93. Results of a one-way ANOVA indicate significant differences across teams in reported levels of team empowerment climate ($F = 1.67$, $p < 0.01$). The ICC(1) and ICC(2) values for this scale are 0.22 and 0.60, respectively. Collectively, this information suggests that it is appropriate to aggregate the individual scores. Thus, we averaged the individual team empowerment climate scores within each team to compute a single team-level score. Data on team empowerment climate were collected during the first wave (time 1).

Gender

Consistent with previous research, the respondents were asked to self-report their gender. As with prior research [2, 87], we used a dummy code (0 = women, 1 = men) to operationalize this construct.

Intention to Explore

We employed a three-item measure from Nambisan et al. [66] to assess individual intention to explore the new technology. The measure has a reliability of 0.94. Data on intention to explore were collected during the first wave of measurement (time 1).

Usage Scope

To measure respondents' usage scope, we provided a table listing the features available in the system. The respondents were asked to indicate the extent to which they used each of the system features listed. The extent of use for each feature was measured on a five-point Likert-type scale with values ranging from "not at all" to "very extensively." We then computed a usage scope score for each user by creating a composite of the number of different features used and the extent to which each feature was used. This measure, therefore, reflects not only how many features each respondent used but also the extent to which each feature was used. Data on usage scope were collected during the first (time 1) and second (time 2) wave of measurement.

Control Variables

To account for potential rival explanations for our results, we included several individual- and team-level control variables that we believed to be relevant to the technology exploration context. At the individual level, drawing on Venkatesh et al. [88], we controlled for perceived usefulness of the system. Previous research has found perceived usefulness to be an important predictor of system usage intention (e.g., [46]). The reliability of the perceived usefulness scale was 0.78. In predicting the effect of intention to explore on usage scope, we controlled for usage scope measured at time 1. We also controlled for age, given its role as a determinant of behavioral intention to use new technology [63, 88]. In addition, the organizational tenure of each employee was included as a control, as well as the degree of education. At the team level we controlled for team size and for the proportion of women within each team. In testing our hypotheses, both the individual-level and the team-level controls were included in the models and were applied to the individual-level outcome variables (i.e., intention to explore, usage scope).

Procedure

The data for this study were collected in two waves. Prior to data collection, we worked closely with management in the participating firms. We conducted interviews with each firm's IT managers to get a sense of the work context and the circumstances surrounding the implementation of the new system. During our interviews with IT management, we also gathered information about the system and its features. This ensured that the questions in the survey were relevant to the firms' context. Because participants were embedded in work teams, unique IDs were used to link responses to specific teams.

This was necessary to account for team-level influences in individual outcomes as well as to compute scores for the team-level variables in the research model. We also used these unique IDs to match responses to the time 1 and time 2 surveys.

Results

To assess the measurement model, we conducted a confirmatory factor analysis (CFA). We focused on the comparative fit index (CFI) and standardized root mean square residual (SRMR) as indicators of model fit [39]. The CFI is generally accepted as the best estimate of the population value for a model [60]. Values greater than or equal to 0.90 are generally considered to represent acceptable fit [39]. The SRMR reflects the average standardized residual per degree of freedom. Values less than or equal to 0.08 are considered to represent relatively good fit for the model [39]. Our four-factor solution involving intention to explore, team learning climate, team empowerment climate, and perceived usefulness indicated that the measurement model had reasonably good fit to the data (CFI = 0.94, SRMR = 0.06, $\chi^2 = 270.7$, df [degrees of freedom] = 121, $p < 0.001$). The factor loadings are shown in the Appendix. We also assessed the fit of a common method model by adding a common method factor in which all indicators were specified to have dual loadings (on the common method factor and the corresponding latent factor). Following Podsakoff et al. [70], we constrained the correlations between the method factor and other latent constructs to zero. The fit of the common method model to the data was not significantly different from the measurement model (CFI = 0.94, SRMR = 0.05, $\chi^2 = 267.5$, df = 102, $p < 0.001$), suggesting that the addition of the common method factor did not significantly improve the model fit. Thus, concerns about common method bias are somewhat alleviated [70]. Convergent validity of the constructs was determined by examining the lambda values for the indicators and the average variance extracted (AVE). Results from the CFA indicate that all lambda values were above the recommended threshold of 0.50 [33]. In addition, all the AVEs were greater than 0.50, providing support for convergent validity. To determine whether discriminant validity is supported, we examined the square root of the AVE as well as the interconstruct correlations [25]. None of the interconstruct correlations was larger than the square root of the AVE, providing support for discriminant validity.

The correlations, descriptive statistics, Cronbach alphas, and the square root of the AVE are shown in Table 1. Given the hierarchically nested structure of the data and the cross-level relationships in the research model, it was necessary to use an analytical technique that is robust to nonindependence of observations and can account for variance at different levels of analysis simultaneously. Random coefficient modeling (RCM) is particularly well suited for this purpose because it enables researchers to model and examine relationships that span levels of analysis and can meaningfully partition the variance components in outcome variables [72]. In addition, RCM helps to reduce the potential for Type I and II errors that might arise if nonindependence of observations is not accounted for [12]. In the context of the current research, intention to explore and usage scope were individual-level outcomes that could potentially be

Table 1. Descriptive Statistics and Correlations

Variables	Mean	SD	α	1	2	3	4
1. Intention to explore	3.53	1.10	0.94	**0.92**			
2. Usage scope $_{T2}$	5.61	1.47	N/A	0.12*	N/A		
3. Gender	0.57	0.50	N/A	0.10*	0.11*	N/A	
4. Team learning climate	3.34	0.72	0.79	0.16**	0.13*	0.15*	**0.75**
5. Team empowerment climate	3.52	0.71	0.83	–0.11*	0.05	0.12*	0.58***
6. Usage scope $_{T1}$	4.58	1.75	N/A	0.13*	0.21**	0.01	0.13*
7. Perceived usefulness	2.80	0.85	0.78	0.28***	0.18**	0.02	0.22**
8. Age	42.32	8.63	N/A	–0.26***	0.01	–0.06	0.10
9. Education	1.51	0.87	N/A	–0.04	0.14*	–0.15*	–0.18**
10. Organizational tenure	7.47	0.93	N/A	–0.13*	–0.03	0.06	–0.06
11. Team size	8.71	4.96	N/A	–0.01	0.05	0.00	–0.13*
12. Proportion of women	0.36	0.17	N/A	–0.10	–0.05	0.14*	0.10

(continues)

Table 1. Continued

Variables	5	6	7	8	9	10	11
1. Intention to explore							
2. Usage scope $_{T2}$							
3. Gender							
4. Team learning climate							
5. Team empowerment climate	**0.74**						
6. Usage scope $_{T1}$	0.07	N/A					
7. Perceived usefulness	0.21**	0.25***	**0.73**				
8. Age	–0.05	–0.03	–0.06	N/A			
9. Education	–0.11	0.06	0.09	0.00	N/A		
10. Organizational tenure	–0.07	–0.12†	–0.14*	0.60***	–0.16*	N/A	
11. Team size	–0.16*	0.07	–0.03	0.11	–0.10	0.00	N/A
12. Proportion of women	0.06	–0.09	–0.09	0.01	0.05	–0.01	0.23

Notes: $N = 268$. SD = standard deviation; N/A = not applicable. Note that individual scores for team-level variables are based on team mean scores. Gender is dummy coded 0 = women, 1 = men. The square root of the average variance extracted is reported on the diagonal (boldface) where appropriate. † $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

affected by factors at the team level as well as the individual level. Given this nesting, it is possible that individual ratings of intention to explore and usage scope are more similar within teams and different between teams. RCM is able to take this into account by partitioning the variance in intention to explore and usage scope that is attributable to team-level factors and that which is attributable to individual-level factors. In comparison, more traditional analysis techniques such as partial least squares (PLS) and ordinary least squares (OLS) regression are less well suited for analyzing data that are nested across levels of analysis, because the nonindependence of observations is not taken into account when estimating coefficients. Moreover, these techniques do not use all of the information available to estimate the relationship between predictors at one level of analysis (e.g., team) and dependent variables at another level of analysis (e.g., individual). They also do not account for the fact that the relationship between two variables at the individual level of analysis can vary across different teams. Finally, neither of these techniques partitions the variance in the outcome variable into its components at different levels of analysis.

Following previous research that has dealt with individual employees nested within work teams (e.g., [52, 57]), we used hierarchical linear modeling (HLM 6.08) to test the research model [72]. The first step of HLM analysis is to determine if some of the variability in the dependent variables can be attributed to team-level phenomena [72]. Therefore, we examined the ICC(1) for intention to explore—our dependent variable. The variable had an ICC(1) of 0.11 ($\chi^2(55) = 115.48$, $p < 0.001$), suggesting that some of the variability in individual intention to explore could be attributed to between-team differences. We also determined that some of the variability in usage scope (ICC(1) = .26) could be attributed to between-team differences ($\chi^2(55) = 105.56$, $p < 0.01$), further affirming our use of HLM to test the model.

The results of the HLM models predicting intention to explore are presented in Table 2. Consistent with Liao and Rupp [53], we calculated the total variance explained in intention to explore as $R^2_{\text{total}} = R^2_{\text{within}} \times (1 - \text{ICC1}) + (R^2_{\text{between}} \times \text{ICC1})$. As the results of model 1 indicate, the main effects explained 22 percent of the total variance in user intention to explore ($\chi^2 = 106.73$, $p < 0.001$). In H1, we predicted a positive cross-level relationship between team learning climate and user intention to explore. Consistent with this hypothesis, the coefficient for team learning climate is positive and significant in predicting individual intention to explore ($\gamma = 0.50$, $p < 0.01$). H2 posited a positive cross-level relationship between team empowerment climate and user intention to explore. The coefficient for team empowerment climate is negative and significant in predicting user intention to explore ($\gamma = -0.47$, $p < 0.01$), thus highlighting a relationship opposite to the one we hypothesized.

The interaction model explained 31 percent of the total variance in user intention to explore ($\chi^2 = 95.41$, $p < 0.01$). H3 stated that team empowerment climate would positively moderate the effect of team learning climate on user intention to explore. As the results in Table 2 (model 2) indicate, the interaction between team learning climate and team empowerment climate is positive and significant ($\gamma = 0.13$, $p < 0.05$), providing preliminary support for the hypothesis. To further probe the interaction effect, we plotted the relationship between team learning climate and user intention to

Table 2. Results of Models Predicting Intention to Explore

Variables	Intention to explore Model 1	Model 2
Individual-level controls		
Intercept	3.08***	2.88***
Company	0.35**	0.37*
Age	–0.03**	–0.03**
Education	0.03	0.06
Organizational tenure	0.12*	0.13*
Perceived usefulness	0.30***	0.30***
Usage scope (T_1)	0.07*	0.07*
Team-level controls		
Team size	–0.01	–0.01
Proportion of women	0.51	0.76
Individual-level main effects		
Gender	0.24*	0.23*
Team-level main effects		
Learning climate	0.50**	0.48*
Empowerment climate	–0.47**	–0.41*
Interaction effects (cross-level)		
Learning climate × gender		0.00
Empowerment climate × gender		0.25*
Learning climate × empowerment climate		0.13*
χ^2	106.73***	95.41**
$R^2_{between}$	0.31	0.40
R^2_{within}	0.21	0.30
R^2_{total}	0.22	0.31
Deviance	1,076.63	1,073.82

Notes: Individual-level n = 268; team-level n = 56. Gender is dummy coded (0 = women, 1 = men); company is dummy coded 0 = retail firm, 1 = banking firm. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

explore at one standard deviation above and below the mean for team empowerment climate [3]. As the interaction plot in Figure 2 shows, the positive relationship between team learning climate and user intention to explore is stronger when team empowerment climate is high than when it is low. Thus, H3 receives support. H4 suggested that men would have a stronger intention to explore compared to women. This hypothesis receives support ($\beta = 0.24$, $p < 0.05$). In H5, we predicted that the positive effect of team learning climate on user intention to explore would be stronger for women than for men. However, as the results indicate, the interaction effect between team learning climate and gender is nonsignificant ($\gamma = 0.00$, p = ns). Finally, H6, which posited that the effect of team empowerment climate on user intention to explore would be different between women and men, is partially supported. The overall coefficient for the interaction is statistically significant ($\gamma = 0.25$, $p < 0.05$). A simple slopes test indi-

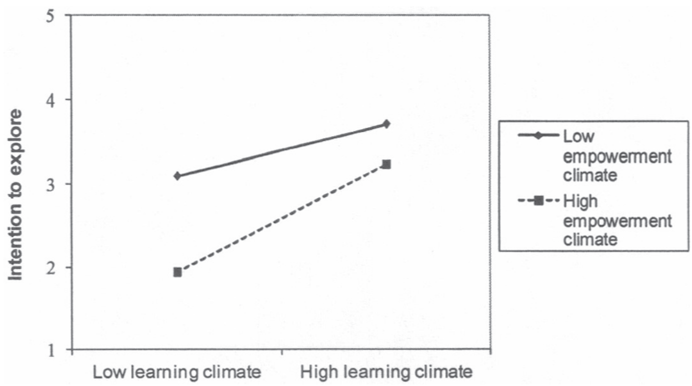

Figure 2. Plot of Cross-Level Interaction Between Team Learning Climate and Team Empowerment Climate

cates that the effect of empowerment climate on intention to explore is not significant for men ($b = -0.06$, p = ns), thus not supporting H6a. However, the simple slope test corroborates H6b, indicating that the relationship between empowerment climate and intention to explore is negative and significant for women ($b = -0.23$, $p < 0.05$). A plot of the interaction corroborated these results as shown in Figure 3.

The results of the HLM models predicting usage scope are presented in Table 3.[1] As the results of model 1 indicate, the main effects explained 38 percent of the total variance in individual usage scope ($\chi^2 = 94.26$, $p < 0.01$). In H7, we predicted a positive relationship between intention to explore and usage scope. Consistent with this hypothesis, the coefficient for intention to explore is positive and significant in predicting usage scope ($\beta = 0.87$, $p < 0.05$), whereas team learning climate and team empowerment climate do not have a direct positive cross-level influence on usage scope. Following Mathieu and Taylor's [59] meso-mediation test, we conducted a Sobel test to determine the extent to which the cross-level effects of team learning climate and team empowerment climate on usage scope are carried through individual intention to explore. Results of the Sobel test show that the cross-level effects of team learning climate ($z = 1.65$, $p < 0.05$) and team empowerment climate ($z = -1.66$, $p < 0.01$) on usage scope are indeed carried through individual user intention to explore.

Robustness Checks

To check the robustness of our results, we ran post hoc tests to determine whether our observations about gender and intention to explore varied across individuals of different ages and levels of education. It is possible that the attitudes of younger women, or women with advanced degrees, toward technology in the workplace are not reflective of those shown in the extant technology adoption literature (e.g., [84, 86]). Recent literature has started to suggest that attitudes toward technology may indeed differ among women and men of younger versus older age [65]. Therefore, a post hoc test

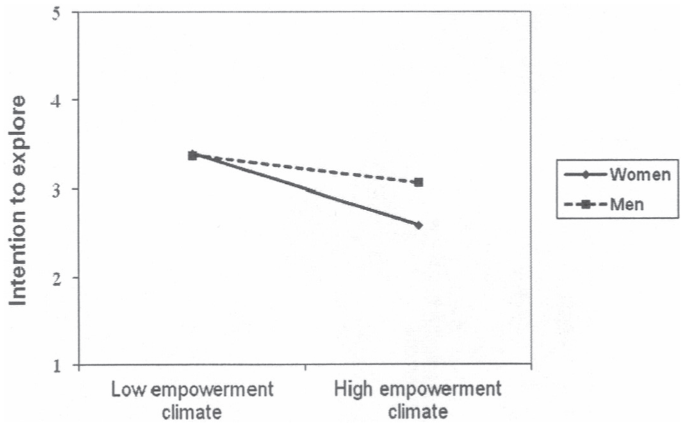

Figure 3. Plot of Cross-Level Interaction Between Team Empowerment Climate and Gender

Table 3. Results of Models Predicting Usage Scope

Variables	Usage scope (T_2)
Individual-level controls	
Intercept	30.87***
Company	–2.55
Age	0.01
Gender	–0.58
Education	0.05
Organizational tenure	0.30
Perceived usefulness	0.73†
Usage scope (T_1)	0.41*
Team-level controls	
Team size	–0.02
Proportion of women	1.82
Individual-level main effects	
Intention to explore	0.87*
Team-level main effects	
Team learning climate	1.89
Team empowerment climate	–2.24
χ^2	85.86**
$R^2_{between}$	0.40
R^2_{within}	0.24
R^2_{total}	0.38
Deviance	824.13

Notes: Individual-level $n = 268$; team-level $n = 56$. Gender is dummy coded 0 = women, 1 = men; company is dummy coded 0 = retail firm, 1 = banking firm. † $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

is helpful to understand whether gender differences in intention to explore technology could be contingent on individual age and education. To account for these factors, we estimated a model that included a three-way interaction (as well as all associated two-way interactions) between gender, age, and education. The results of our tests show that the three-way interaction does not affect individual intention to explore ($\beta = 0.06$, p = ns), thus corroborating the robustness of our results. We also tested the effect of a three-way cross-level interaction between gender, learning climate, and empowerment climate on individual intention to explore. Results show that the three-way interaction does not have a significant effect on individual intention to explore ($\gamma = -0.14$, p = ns). Taken together, these results corroborate the robustness of our model.

Discussion

THE OBJECTIVE OF THIS RESEARCH WAS TO UNDERSTAND the role of team climate as a potential factor influencing employee exploration and expanded feature use of new collaboration technologies in the workplace. To this end, we drew on the team climate literature to examine how team learning climate and team empowerment climate affect user exploration of system features. This was driven by the recognition that, increasingly, organizations are moving toward a team-based structure for complex knowledge work. Table 4 summarizes the hypotheses and results.

Theoretical Contributions and Implications for Research

Taken together, our model and results contribute to the literature in several important ways. First, our research contributes to the technology use literature by identifying and incorporating the role of team climate as a driver of employee innovation with technology. Although prior research has hinted at the importance of teammates in shaping each other's reactions to technologies in the workplace [27, 29], limited consideration has been given to the mechanisms through which managers can foster desirable behaviors [51]. We drew on the team climate literature and identified team learning climate and team empowerment climate as two levers that come into play in molding technology exploration. The results of our empirical study revealed that these two types of team climate differ in their effects on intention to explore. Specifically, team learning climate promoted greater intention to explore, whereas team empowerment climate reduced employees' propensity to explore the technology—primarily among women. Consequently, team learning climate emerges as an important mechanism through which innovative behavior with technology can be reinforced. This view of learning climate, as a shared perceptual lens through which team members can interpret events, such as new technology implementation, advances and complements prior literature that underscores the value of social contagion in shaping reactions to technology (e.g., [26, 29]). Counter to our expectations, our results showed that team empowerment climate seemed to discourage employees from innovating with the new technology. One possible explanation is that employees with greater autonomy in task

Table 4. Summary of Hypotheses and Results

Hypothesis	Test	Result
H1: Team learning climate → intention to explore	Positive cross-level main effect of team learning climate	Supported
H2: Team empowerment climate → intention to explore	Positive cross-level main effect of team empowerment climate	Not supported
H3: Team learning climate × team empowerment climate → intention to explore	Interaction of team learning climate and empowerment climate	Supported
H4: Gender → intention to explore	Individual-level main effect of gender (higher intention to explore for men)	Supported
H5: Team learning climate × gender → intention to explore	Cross-level interaction of team learning climate and gender (stronger positive effect of team learning climate for women)	Not supported
H6: Team empowerment climate × gender → intention to explore	Cross-level interaction of team empowerment climate and gender (negative for women)	Partially supported
H7: Intention to explore → usage scope	Positive individual-level main effect of intention to explore	Supported

accomplishment are prone to cognitive distraction [50] as they attempt to maintain a balance between accomplishing the tasks for which they are responsible while also exploring the technology's features. Employees may opt to focus on accomplishing their work tasks because the cognitive distraction associated with exploring the technology's features can lead to the erosion of task performance [6, 50]. It is also possible that the dual focus on task-related decision making and execution may reduce the amount of available slack time during which innovation-oriented behaviors might otherwise be enacted [2, 30, 77]. This interesting result is consistent with emerging literature underscoring the unintended effects of a team environment characterized by autonomy. For example, Langfred [50] has argued that the autonomy facet can negatively influence task performance by increasing the amount of cognitive load placed on individuals to simultaneously make task-related decisions and execute assigned tasks. Individuals with autonomy have the added burden of considering past task-related decisions and considering future consequences of current ones, while also managing current tasks. Therefore, our result could be explained in light of this emerging theoretical stream. The introduction of new technologies in organizations often changes employees' work processes [13, 32, 64]. This could place significant strain on employees to maintain their pre-implementation level of work productivity as they come to terms with the new system [5, 64]. Team empowerment climate places additional demands on team members as they are given greater latitude in making decisions about how to incorporate the technology into their work while also being accountable for any effects on their task performance. While exploration of technology has the potential to enhance task performance, it is essentially an experimental process that may not yield gains for some time [2, 66]. Thus, when individuals are given autonomy to decide how to use the technology, they are likely to focus on the functionality with which they are familiar and comfortable [81]. However, our results show that a high team learning climate compensates for the effect of empowerment climate. Indeed, the presence of a climate that favors interaction and information exchange is more effective when individuals have a high degree of autonomy. Collectively, our results indicate that the content of team climate (i.e., what the climate actually supports/promotes) matters significantly in motivating innovation with technology. More broadly, the results of this research shed light on how team-level factors motivate individual-level cognitions and behavior in the technology domain.

A second contribution of this work is the incorporation of gender as a cross-level moderator of the effects of team climate on intention to explore. Although prior research has acknowledged that people of different gender vary in their reactions to new technology in the workplace (e.g., [2, 84, 86]), our understanding of how these gender differences manifest in the face of team climate—which represents a social context for interacting with technology—was limited. This research contributes to the extant literature by showing how men and women are affected by team climate in different ways. We found that for men team empowerment climate had no influence on intention to explore, whereas for women there was a significant negative effect. This finding is counterintuitive when compared to prior literature, which has generally viewed empowerment climate positively (e.g., [76]). According to Seibert et al. [76], empowerment climate places greater work-related responsibility and accountability in the hands of employees, enabling them to perform their work more effectively. As outlined earlier, it is possible that through an expanded set of responsibilities and expectations fostered by such climate, employees may be experiencing work overload. Indeed, Ahuja and Thatcher [2] found that women's propensity to innovate with IT in the workplace is negatively affected by higher workload. Moreover, Morris and Venkatesh [64] recently found that changes in job responsibilities—such as work autonomy—in the context of new technology implementation have negative implications for employee outcomes. This result shows how a seemingly beneficial intervention can have unintended consequences for employee behavior. While we theorized that learning climate would have a stronger effect on intention to explore among women, this was not borne out in our results. This suggests that women and men are equally receptive to learning-oriented interventions.

Finally, we contribute to the research on individual system usage in answering a call by Burton-Jones and Straub [18] and Jasperson et al. [44] to adopt a technology-feature perspective. Previous research treated usage as a black box without taking into consideration the organizational context in which the technology is embedded. Individuals' willingness to explore a technology has not been explicitly incorporated into existing theorizing on users' likelihood of taking advantage of a broader set of technology features for accomplishing their tasks. As such, there was a need for research to shed light on the implications that such exploratory intentions would have for individual usage of the technology. In our theorizing on the role of intention to explore, we reasoned that increasing levels of individual intention to explore would affect individual usage. The underlying logic was that the process of appropriation of a wide array of features requires a planned and active role on the part of users as they attempt to find new ways to use the system in their work [32]. The results of our study provided support for this argument, and we found that user intention to explore positively affects usage scope.

Strengths and Limitations

Our research study has several strengths that should be noted. First, our study design involved data collection from multiple sources within participating teams. This is particularly noteworthy given the difficulty of obtaining such data in a field setting. Second, our treatment of climate does not rely on a single source but reflects the shared perception of team members, offering a more accurate representation of the climate concept. Third, all of the participants in our study used the same new system. Therefore, we were able to capture the entire set of features embedded in the system. This allowed for a meaningful comparison of feature usage scope across participants. Fourth, our field study involved 268 participants in 56 different teams. This team-level sample size compares favorably with other field studies of teams, especially considering the multiple waves of measurement (e.g., [24]).

The strengths of our study notwithstanding, as with any research, our findings need to be interpreted in light of a few limitations. One limitation is the use of a survey method in the study. Such a design raises the potential for common method bias because participants can engage in hypothesis guessing and social desirability while completing the questionnaire [70]. However, this concern is allayed since we followed recommendations by Podsakoff et al. [70]. Specifically, we aimed to reduce concerns of common method bias by using multiple respondents within each team, and by collecting intention to explore and usage scope data at two different points in time. Further, our research model included moderation relationships between factors at different levels of analysis. Finally, we also tested for common method variance and found no indication that it was a concern in our analysis. Although the system we examined embodied characteristics that are common to other systems, future research should validate our results in other settings in order to increase the generalizability of our findings.

Practical Implications

Amabile et al. [7] suggest that managers generally have not received much guidance on how to promote innovative endeavors in the workplace. Motivating such behavior is particularly challenging because monetary incentives may prove to be ineffective since managers cannot easily monitor the breadth of features used by their employees. The findings in this research have several key implications for managers. First, the results related to team learning climate point to one potential lever that managers can use to promote innovation with technology in the workplace. Through team learning climate, managers can intrinsically encourage employees to engage in innovative use of technology and team members can mutually reinforce such behaviors. In fostering such a team environment, managers need to exercise patience with employees and recognize that gains from technology exploration are unlikely to be realized in the short term. As Edmondson [23] suggests, this means that any efforts to foster innovation with technology must dispel fear of failure among employees. Rather, managers should recognize that employees need time to engage in ongoing experimentation with the system, in the hopes that gains will be realized over time. Failure is a natural part of innovation, and thus emphasis must be placed on experimentation, risk taking, and mutual sharing of lessons learned [23]. Learning climate creates an environment that promotes such activities. The good news is that men and women alike seem to be receptive to the behavior promoted by learning climate, therefore eliminating the need for gender-tailored interventions. Second, managers are cautioned against adding to employees' existing responsibilities during the early stages of exploration and experimentation with system features. Although empowering employees is generally a positive gesture, there are times when it may yield undesirable outcomes. Amabile et al. [7] argue that timing is an important factor in the innovation process. Employees need time to engage in the innovation process. Consequently, this may be the time when managers should hold back on expanding employees' work responsibilities as well as place less emphasis on accountability for work performance. Exploring technology features takes time away from task accomplishment and, as a result, affects performance. Finally, our findings indicate that men and women are affected differently by team empowerment climate. As women make up a larger proportion of the workforce, it is important for managers to create a work environment that enables them to innovate effectively.

Directions for Future Research

Future research would benefit from studies that uncover the specific behaviors through which managers can shape team climate when new systems are being deployed. Leadership theories may provide a particularly useful lens for understanding relevant behaviors. For instance, the literature on transformational leadership might shed light on the activities through which managers can encourage the development of team learning climate. Alternatively, the role of coaching can be incorporated into future studies of technology use in teams. Specifically, future research could focus on understanding how team members and team leaders mutually reinforce each other's exploration and use of the technology so as to maximize its benefits.

In this research, we only focused on gender as a demographic factor that affects the efficacy of team climate in motivating exploration of technology features. Although we included age as a control variable in our model, we did not theorize about its role and effects with regard to team climate and intention to explore. However, prior research has found that age does affect how people react to new technology (e.g., [21, 63, 85]). Future research should examine the extent to which individuals of different age groups are reliant on team climate to motivate exploration of new technology at work, especially since new technologies are likely to exert more demands on fluid versus crystallized learning capabilities [34, 69].

Given the limited amount of research adopting a multilevel lens, future research could help advance this work by examining learning climate, individual exploration intentions, and task performance over time. In particular, it would be valuable to examine the existence of a feedback loop between learning climate, exploration intention, and individual (and, consequently, team) task performance. If individual exploration of a technology's features yields new insights, the extent to which those insights are shared among team members over time might inform the long-term viability of the team's climate while also yielding task performance gains. It would be worthwhile to observe such phenomena in the context of dispersed teams, where communication patterns and information flow is constrained by distance between team members [4, 8]. Moreover, it would be interesting to take a social network perspective to observe the internal communication structure of the team because it may affect the efficacy of the feedback loop such that the degree of centrality, the density, and the presence of bridging links in the team social networks may drive the diffusion of insights (among team members) gained from individual exploration [9, 16].

Conclusion

Drawing on the team climate literature, we theorized relationships among team learning climate, team empowerment climate, gender, and their influence on intention to explore technology. We found that team learning and empowerment climate have a direct cross-level effect on individual intention to explore technology. In particular, we found that team learning climate has a positive cross-level effect on individual intention to explore technology, and that this relationship is invariant across individuals of different gender. Counter to our expectations, we found that team empowerment climate has a negative cross-level effect on individual intention to explore, such that an increase of employees' autonomy, responsibility, and accountability hampers their likelihood of engaging in exploratory behaviors with technology. Our results show that this negative effect is salient for women but not for men in affecting exploratory behaviors with technology. Further, our findings show that team empowerment climate and team learning climate have an interactive effect on individual intention to explore, such that the existence of high levels of team learning climate may compensate for the negative effects of team empowerment climate. Finally, intention to explore the technology is found to positively influence the usage scope, highlighting an important link between team climate, individual cognition, and the scope of features used by individual users.

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Note

1. HLM does not allow a multistage approach in testing the models and instead requires two separate analyses, much like regression analysis. Therefore, we tested the model by following the approach outlined by previous research (e.g., [45, 57, 76]).

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Appendix

Table A1. Factor Loadings for Study Variables

Construct/item	Factor loadings			
Team empowerment climate				
1. We have created structures and procedures that encourage and expect people to take initiative in improving team performance.	**0.80**	0.46	0.08	0.03
2. We have created team policies and practices that help individuals use their knowledge and motivation.	**0.80**	0.49	0.09	0.06
3. Team members provide direction and training to enhance members' freedom to experiment.	0.81	0.21	0.00	0.08
4. My team recognizes individuals for taking initiative.	**0.70**	0.39	0.13	0.12
5. The team is the focal point of accountability and responsibility.	**0.62**	0.35	0.04	0.03
6. In this team, there is room for initiative.	**0.73**	0.34	0.03	0.02
Team learning climate				
1. In this team, errors are considered a source of learning.	0.41	**0.70**	0.02	0.03
2. In the team, there is freedom to experiment.	0.14	**0.76**	0.02	0.01
3. My team makes its lessons learned available to all members.	0.21	**0.72**	0.01	0.07
4. In my team, individuals revise their thinking as a result of group discussion or information collected.	0.24	**0.72**	0.11	0.21
5. In the team, we are encouraged to take risks when trying new ideas.	0.26	**0.79**	0.08	0.03
Intention to explore				
1. I intend to explore how the (system) can be used for other tasks.	0.00	0.09	**0.92**	0.11
2. I intend to explore other ways that the (system) may enhance my effectiveness.	0.00	0.06	**0.95**	0.15
3. I intend to spend time and effort in exploring the (system) for potential applications.	0.04	0.04	**0.91**	0.13
Perceived usefulness				
1. The (system) is adequate for synchronizing tasks with my colleagues.	0.09	0.27	0.14	**0.89**
2. The (system) is effective for sharing information with my colleagues.	0.20	0.32	0.05	**0.79**
3. The (system) is effective for managing multiple communications.	0.14	–0.05	0.14	**0.73**
4. The (system) is effective for being readily available while traveling outside my office.	0.18	0.16	0.14	**0.64**
5. The (system) is effective for tracking and storing communication data.	0.08	0.10	0.28	**0.59**

Note: Boldface values indicate the factor on which an item has the highest loading.

Usage scope: Please indicate the extent to which you use each of the following (system) features in your job-related work (1 = “not at all”; 5 = “very extensively”):

Name of feature 1	1	2	3	4	5
Name of feature 2	1	2	3	4	5
Name of feature 3	1	2	3	4	5
Name of feature 4	1	2	3	4	5
Name of feature 5	1	2	3	4	5

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