How motivation, opportunity, and ability drive knowledge sharing: The constraining-factor model

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Abstract

We introduce and empirically test a theoretical metamodel that explains knowledge-sharing behavior among employees. Building on the well-established motivation–opportunity–ability (MOA) framework, we posit that knowledge sharing among employees is a function of their MOA to do so. Existing literature suggests that the interaction among motivation, opportunity, and ability drives knowledge-sharing behavior. In contrast, we specify a new model in which the “bottleneck” or constraining factor among the MOA variables determines the degree of knowledge sharing that occurs. This constraining-factor model (CFM) fits the data better than the traditional multiplicative model and reveals a new, qualitatively different portrait of knowledge sharing that resolves some of the puzzles in the previous literature. The CFM provides macro-level insights with respect to how operations managers can improve employee knowledge sharing by focusing on the bottleneck MOA variable. As a result, the CFM can help set strategic directions of related policies. The model emphasizes that, counter to conventional wisdom, the MOA variables should not be addressed independently, but rather in a dynamic and coordinated way.

Keywords: Knowledge sharing; MOA framework; Constraining-factor model; Bottleneck; Behavioral operations

1. Introduction

The notion of resource constraints has been extensively investigated in the operations management (OM) literature, in part because the identification of constraints enables managers to plan more effective interventions. Bottleneck analysis, for example, identifies constraining resources in a process, so that the capacity of the process can be increased by adding capacity at the bottleneck (Chase et al., 2004). Critical path analysis identifies the set of activities taking the longest time in a project, so that the project can be shortened by crashing activities on the critical path. Although OM-based knowledge of physical resource and time constraints is extensive, much less is understood about how behavioral constraints act in OM contexts. Yet, such constraints can severely limit the effectiveness of managerial interventions (Boudreau et al., 2003). For example, process improvement and just-in-time (JIT) programs can be fruitless without the full participation and motivation of employees (Hackman and Wageman, 1995; Shah and Ward, 2003). Similarly, behavioral responses can offset the advantages of worker flexibility programs (Schultz et al., 2003; Siemsen et al., 2007a).

In this study, we present a metamodel that can be used to identify behavioral constraints, and we
empirically test this meta-model within the operational context of inter-employee knowledge sharing. Our research provides a way of conceptually and empirically identifying and addressing such behavioral constraints. The foundation for our research is the well-known motivation–opportunity–ability (MOA) framework, which has been applied in various management disciplines. Broadly speaking, motivation captures the individual’s willingness to act; opportunity represents the environmental or contextual mechanisms that enable action. Ability represents the individual’s skills or knowledge base related to the action (Rothschild, 1999). Providing a novel perspective, our research posits that it is the constraining factor among these three MOA variables that ultimately determines behavior. Thus, changes in motivation only affect behavior and outcomes if motivation is the constraining factor; they have little or no impact if either opportunity or ability is constraining. We develop a new modeling approach, which we call the “constraining factor model” (CFM), that embodies this bottleneck perspective. We then empirically test this model’s ability to explain knowledge-sharing behavior and evaluate how the CFM performs compared to alternative, existing specifications of the MOA framework in the literature.

Our study focuses on the specific context of one-way employee knowledge sharing in a dyadic work relationship. There are four reasons for choosing this context. First, OM researchers have emphasized the importance of better understanding the dissemination of operational know-how and learning (Hayes et al., 1988; Leonard-Barton, 1992; Roth et al., 1994; Roth, 1996; Mukherjee et al., 1998; Ferdows, 2006). Previous studies have highlighted that employees on the shop floor do not always share their knowledge with their peers (Aeppel, 2002), which makes this context particularly interesting to OM. Second, practitioners have employed many different approaches to the management of knowledge in their organizations (Hansen et al., 1999), but approaches that neglect behavioral constraints are not always successful (Dixon, 2000). Third, existing research has questioned the role of motivation in knowledge sharing (Szulanski, 1996). The CFM enables us to clearly state under what conditions motivation plays a less of a role in promoting employee knowledge sharing, thereby clarifying conflicting perspectives in the literature. Finally, the perceptions of individual employees about their intentions to share work-related knowledge with a coworker can be considered a primary building block in this area. Practically speaking, it is usually only known to the employee whether or not she chooses not to share. Even in cases where an employee attempts to share, it is not always clear whether the coworker involved always picks up the knowledge being shared. Arguably, understanding the barriers to an individual’s propensity to share knowledge is an important, but understudied area in OM.

To illustrate the managerial implications of our research, consider the following three real-life examples of knowledge-sharing initiatives. A large public utility was facing a brain drain, as the old guard of engineers was close to retiring. There was a generational gap between these experienced engineers and the junior employees that were hired to replace them. Operations, quality and human resource managers attempted to increase knowledge sharing between the experienced workers and the new recruits, but were stymied. Due to the urgency of the situation, a corporate initiative was put into place to consider what knowledge management initiatives should be prioritized. Should they focus on training, on changing their incentive system, or on providing the time and infrastructure for knowledge sharing to occur? Clearly, the corporate management team needed a guiding framework and empirical data to further their strategic planning process and set directions. Our research provided the firm with both the framework and concrete suggestions that were employed in their strategy.

Consider a second example. A management consultancy suffered from high employee turnover. The partners felt that their organization constantly generated and lost important knowledge. To address this situation, they implemented a large-scale corporate intranet, providing instant intranet access for consultants to document and share the lessons they learned from projects. Further, the company employed communication and information experts to help consultants document their knowledge. However, when the system went online, consultants only contributed knowledge of little importance. Even though the system provided an easy opportunity to share knowledge, and experts were readily available to support consultants who lacked the ability to codify their knowledge, the consultants simply had little motivation to share their important knowledge with a broader community. Thus, the managerial intervention did not address the real behavioral bottleneck, resulting in overall failure.

The third example has a slightly different context, and pertains to a credit union that desired to improve its overall customer satisfaction levels. Customer satisfaction ratings had reached a plateau at 85%. The former CEO spent precious resources trying to motivate tellers, loan officers, and customer service representatives with
various types of monetary and other incentives. Motivational signs and slogans were visible in the break room. The CEO and her management team provided time and space for customer contact employees to meet and have a dialogue. There was very little turnover, since working conditions were good. Yet none of these efforts moved the bar, despite top management commitment. A new CEO was brought in and given the same goal by the Board of Directors to improve customer satisfaction. Soon after his arrival, he made staff development and training his top priority. He brought in external consultants, who actually provided formal training in service quality, teamwork, and process improvement over a 2-year period. Not surprisingly, customer satisfaction rose to 96%—the best in the industry. In this case, whereas ability was the bottleneck, it was not detected because the credit union’s employees were technically very competent and experienced—and the former CEO did not realize that service quality training was as important as technical competence. This scenario is consistent with the extensive quality management literature that highlights the importance of training employees in the use of process improvement tools and customer requirements.

The MOA framework is well established as a theoretical basis for the explanation of work performance (Blumberg and Pringle, 1982; Boudreau et al., 2003). It has been successfully employed to explain a wide array of behaviors such as consumer choice (MacInnis et al., 1991), firm-level decision making (Wu et al., 2004), and social capital activation (Adler and Kwon, 2002; Binney et al., 2006). More recently, it has been used as a conceptual organizing framework for knowledge-management practices (Argote et al., 2003). Despite the popularity of the MOA framework, there are two important puzzles that endure in the related literature. Our research addresses these puzzles.

First, the MOA framework highlights the importance of motivation as a driver of behavior (action), or more specifically in the context of this research, an employee’s propensity to share knowledge. Clearly, many operations’ infrastructural policies take the importance of motivation for granted. Yet, some empirical research on the dissemination of best practices has questioned the importance of motivation in explaining the successful sharing of knowledge (Szulanski, 1996, 2000). The puzzle, therefore, is this: if motivation is a construct of theoretical importance in the context of inter-employee knowledge sharing, why does the empirical evidence raise questions about its role as a major driver of knowledge sharing?

Second, work performance theory indicates that motivation, opportunity, and ability should play complementary1 roles in influencing behavior (Cummings and Schwab, 1973). In this view, without ability or opportunity, motivation alone should not lead to knowledge-sharing behavior. Yet again, there is little empirical evidence supporting the existence of such complementarity (Terborg, 1977). This inconsistency leads us to the second puzzle: if, as work performance theories predict, there is complementarity among motivation, opportunity, and ability in driving behavior, why have existing empirical tests of the MOA framework often failed to reveal this complementarity?

We attempt to resolve these two puzzles using the CFM. Importantly, our research is part of a larger research effort that investigates the theory and practice of interemployee knowledge sharing from analytical and empirical perspectives. We view the CFM as a meta-model of employee knowledge-sharing behavior that provides a strategic perspective. We therefore focus on the meta-model of employee knowledge-sharing propensity, in order to address this first-order question: how do motivation, opportunity, and ability influence employee knowledge-sharing behavior? The answer to this question indicates where operations managers should prioritize their investments and scarce resources to achieve desired knowledge sharing behaviors. Thus, we do not explicitly study antecedents of motivation, opportunity, or ability in this research. Other related work delves into the complexities of the antecedents of motivation, especially by exploring the impact of individual and group incentives associated with different job designs (Siemsen et al., in press), the impact of social identity and competence similarity (Siemsen et al., 2007a), and the effects of psychological safety and codifiability of knowledge (Siemsen et al., 2007b).

We identify three key findings in this study. First, our results show that the CFM provides a superior explanation of knowledge-sharing behavior compared to the traditional multiplicative model. This finding clarifies the appropriate functional form for the MOA framework. It helps resolve the first puzzle by suggesting that the lack of empirical evidence for complementarity among the MOA variables may be due to the nature of the models of complementarity employed

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1 In this research, complementarity is defined as the degree to which the effect of one variable depends on the presence of other variables. Moderate complementarity implies that the effect of one variable depends on another variable; extreme complementarity implies that one variable has no effect unless the other variable is present.
in prior research. Second, our analysis suggests that extreme complementarity exists among motivation, opportunity, and ability to share, such that the degree to which knowledge is shared strongly depends on which of these three variables is the constraining factor. This result has important managerial implications. For example, managerial interventions that aim to improve ability, such as training workers to better communicate and document their “tricks of the trade,” will only be effective in enhancing employee knowledge sharing if ability is the constraining factor in that setting. Third, we find that motivation plays a pivotal role in explaining successful knowledge sharing between individuals. This helps resolve the second puzzle we referred to earlier, as it shows that motivation is indeed an important factor explaining successful knowledge sharing—but only when it is the constraining factor (i.e., the minimum among the three MOA variables).

In Section 2, we develop the theory behind the CFM model. The research methods, data, and measurement issues are discussed in Section 3; the empirical tests and results are described in Section 4. In Section 5, we conclude with a discussion of the contributions of this paper, its limitations, and directions for future research.

2. Theory development

2.1. The MOA framework

The origins of the MOA framework lie in the theoretical discourse between industrial psychologists, who have traditionally viewed performance as a function of training and selection that sharpen employees’ ability to perform (e.g., Lawshe, 1945), and research by social psychologists, who have emphasized the motivational component to performance (e.g., Wyatt, 1934). Opportunity was later added into this framework to capture all those exogenous factors that prevent employees from performing well (Peters and O’Connor, 1980; Blumberg and Pringle, 1982). Opportunity has also often been described under the label of situational or operational constraints (Mathieu et al., 1992; Bendoly and Hur, 2007).

Motivation, opportunity, and ability are related constructs (Blumberg and Pringle, 1982). For example, from an efficacy perspective, employees who are less able to share knowledge may also be less motivated to do so, because they may perceive that sharing knowledge will be more difficult for them, or they may have a lower likelihood of success, and/or they may feel that coworkers will not be willing to learn from them (Gist and Mitchell, 1992). However, the precise direction of all causal relationships among MOA is difficult to justify theoretically; therefore, we conceptualize them as correlated but distinct constructs.

Of the MOA variables, motivation has evoked the greatest debate and discussion in the literature (Mitchell and Daniels, 2003). There is an extensive body of knowledge on motivation (Latham, 2006). However, as Ambrose and Kulik (1999, pp. 278–279) report, research in organizational behavior has “largely abandoned the general concept of ‘motivation’ and replaced it with more specific measures of employee behavior.” Motivational theories provide a framework for predicting individual behaviors, but researchers rarely measure or model motivation as a distinct construct. Ambrose and Kulik (1999, p. 279) emphasize that this development circumvents “the biggest difficulties with motivational research: defining motivation and measuring the mediating effects of motivation.” Our research addresses this important issue by explicitly measuring and modeling the way that motivation affects knowledge-sharing behavior.

However, we wish to emphasize that we are not proposing a theory of motivation. Theories of motivation discuss what drives motivation, and not how motivation affects behavior and performance. Rather, we add to the general theory of knowledge-sharing behavior by exploring when and how employee motivation leads to such behavior. The next subsection presents four competing models for this purpose.

2.2. Competing models

Classic work-performance theories hypothesize moderate complementarity among the MOA variables by projecting that action is a multiplicative function of motivation, opportunity, and ability (Maier, 1955; Vroom, 1964; Blumberg and Pringle, 1982). In this perspective, motivation (M), opportunity (O), and ability (A) must all be present to some degree for an action to occur, and lower values of any one of these factors are hypothesized to strongly reduce action (Blumberg and Pringle, 1982). This notion of complementarity leads to the following specification, termed the “multiplicative model”:

\[
\text{Action} = a_0 + a_1 M + a_2 O + a_3 A + a_4 M \times O + a_5 M \times A + a_6 O \times A + a_7 M \times O \times A + \varepsilon
\]

(1)

Whereas the multiplicative model has been subjected to empirical scrutiny (see Cummings and Schwab, 1973 for a review), there is scant empirical evidence that the
multiplicative terms explain significantly more variance than the linear terms alone (Campbell and Pritchard, 1976; Terborg, 1977). Interestingly, even though this multiplicative model has never been empirically validated, it is still frequently applied in conjunction with the MOA framework. In fact, Bell and Kozlowski (2002, p. 497) refer to it as a “truism.” An extensive literature search on constructs such as motivation and ability typically yields numerous applications of this multiplicative formulation of the MOA model. The common understanding is that moderate complementarity among motivation, opportunity, and ability ought to exist, even if such complementarity has never been empirically established in a rigorous manner. This situation and the corresponding implications are aptly summarized by Cummings and Schwab (1973, p. 46):

Certainly at the extremes of either ability or motivation some interaction must take place. Someone with no ability to complete a task cannot successfully perform no matter how highly motivated he may be to do so. Likewise, at least some modest amount of motivation is required, regardless of one’s ability to do a task, before we can expect successful performance. It is, however, much less clear that the notion of interaction contributes to the predictability of employee performance in applied settings where employees may be assumed to possess some minimal amount of both ability and motivation. A simple additive approach will probably enable us to predict performance just about as well.

This quote captures the insight that at the extremes, where there is either no motivation or no ability, little or no action is expected to take place. As Cummings and Schwab suggest, however, performance could be predicted equally well by a model that does not capture potential complementarity between MOA variables at all, yielding the following “linear model” specification:

$$\text{Action} = a_0 + a_1M + a_2O + a_3A + \varepsilon$$

(2)

Some researchers have examined the effect of the interaction between goal-setting (as a proxy for motivation) and ability on performance in learning tasks. Kanfer and Ackerman (1989) have developed a complex model describing how performance is driven by (a) the attention people put into tasks, (b) the division of attention among on-task, off-task, and self-regulating activities, and (c) motivation. Experimental results revealed that goal setting can have a detrimental impact on the effect of ability in determining performance, especially during early stages of training. Intuitively, individuals engage in self-monitoring activities when assigned specific goals. Such self-monitoring reduces the attention devoted to on-task activities, thereby reducing task performance. This effect is especially salient for workers with lower ability as such people are less confident about achieving their goals. Following this reasoning, Campbell et al. (1993) posit that work-performance theories should distinguish between declarative knowledge and procedural knowledge when determining ability, and that work performance is a result of the interaction between declarative knowledge, procedural knowledge, and motivation. However, even though Campbell et al. propose an interaction model, they conclude that “the precise functional form . . . is obviously not known and perhaps not even knowable” (pp. 44–45).

In a related stream of empirical research, researchers have examined how valence, instrumentality, and expectancy interact in Vroom’s classical expectancy theory (Vroom, 1964). Note that Vroom’s work presents a theory of motivation, and not of behavior or performance. Thus, this stream of research does not represent a direct alternative to the MOA framework. There is, however, substantial variation with respect to how Vroom’s three central variables have been operationalized, as well as in the dependent variable used to test the functional form the control variables take in determining motivation (van Eerde and Thierry, 1996). In many studies, performance or behavior is measured instead of motivation, and valence and expectancy are operationalized as desirability and ability. In this case, testing whether the interaction between valence and expectancy enhances performance is similar to testing whether the interaction between motivation and ability leads to action. Interestingly, the results of these empirical studies parallel those of the tests of the multiplicative model described earlier: a meta-analysis of expectancy theory research suggests that the multiplicative relationship does not explain significantly more variance in motivation than does a simple linear model (van Eerde and Thierry, 1996).

In summary, while there is some theoretical evidence to suggest that motivation, opportunity, and ability are complementary in driving behavior, existing empirical evidence from work-performance theories suggests that little explanatory power is gained by adding interaction terms. This paradox leads us to the second puzzle mentioned earlier. Whereas theory predicts that there should be considerable complementarity among the MOA variables in driving behavior, why does empirical research not consistently support the existence of such complementarity? Some researchers suggest this situa-
tion could be a result of measurement scaling issues (Schmidt, 1973). However, given good measures, we argue in this paper that a different model of complementarity is called for. Note first that Eq. (1) proposes a moderate form of complementarity, such that:

\[ \partial_M E [\text{Action}] = a_1 + a_4 O + a_5 A + a_7 O \times A \]  

Eq. (3) predicts that the effect of \( M \) in the multiplicative model continuously changes in the other two variables. Work-performance theories (e.g., Cummings and Schwab, 1973) provide little justification for this continuous change. As suggested by Cummings and Schwab (1973), the multiplicative model was proposed mostly to emphasize that in the extremes—in the absence of motivation, opportunity, or ability—no action should take place. This effect is certainly captured in Eq. (1). However, Eq. (1) also predicts a continuous change in the size of the effect.

To address this issue, we propose an alternative model referred to in this research as the constraining-factor model (CFM). The CFM captures the notion that in the absence of any of the MOA variables no action takes place, but it does not additionally impose a continuous change in the size of the effect. To be more precise, the CFM allows for an intercept and for linear effects of MOA, and it also allows both the intercept and the linear effects to change, depending upon which variable of the three is the lowest. Mathematically, the CFM emphasizes extreme complementarity instead of the moderate complementarity emphasized by the traditional multiplicative model. The CFM is specified as follows:

\[
\text{Action} = a_0 + a_1 M + a_2 O + a_3 A \\
+ \theta_0 (a_4 + a_5 M + a_6 O + a_7 A) \\
+ \theta_A (a_8 + a_9 M + a_{10} O + a_{11} A) + \varepsilon
\]  

The variables \( \theta_0 \) and \( \theta_A \) are dummy variables that are defined to be 1 if OS (or AS, respectively) is the minimum of MS, OS, and AS, and 0 otherwise. An alternative interpretation of CFM is that of a multiple group model with three groups (see, for example, Griffiths et al., 1993), where group membership is determined based on whether motivation, opportunity, or ability is the minimum. Since one of these groups has to be ‘omitted’, parameters in the CFM have to be interpreted with care. For example, the effect of motivation if motivation is the minimum is given by \( a_1 \), but the effect of ability if ability is the minimum is given by \( a_3 + a_{11} \). Similarly, the intercept is given by \( a_0 \) if motivation is the minimum, but the intercept is given by \( a_0 + a_8 \) if ability is the minimum.

The theoretical perspective of the CFM captures that of a bottleneck, or a limiting resource (Schmenner and Swink, 1998; Chase et al., 2004). It is the minimum among the three factors of motivation, opportunity, and ability that ultimately determines behavior. To use a metaphor, one can think of motivation as a flow of energy that has to pass through the neck of a “bottle” in order to result in a particular action. But there are two potential bottlenecks: one defined through opportunity, the other through ability. If the flow of energy (motivation) is less than the capacity defined by the two potential bottlenecks, the flow itself is the constraining factor and increased motivation leads to stronger and/or more frequent action. If, however, it is either opportunity or ability that constrains the flow, then that factor becomes the bottleneck and determines the degree to which motivation can flow through the bottle—and therefore to what degree an action takes place.

Other theoretical analogies for CFM can be found in the theory of constraints (Goldratt, 1999) and the theory of queuing networks (e.g., Kulkarni, 1995), and factory physics (Hopp and Spearman, 2000). Consider an assembly line with three serial, dependent workstations. The throughput rate of the production line is the minimum of the processing rates of the three workstations. The CFM reflects a similar logic. In that sense, the proposed CFM represents a new “bottleneck” metamodel of behavior.

The CFM allows for the effects of the constraining factor to differ depending upon which variable is the constraining factor (e.g., \( a_1 \neq a_6 \neq a_{11} \)), and for the intercepts to differ depending upon which variable is the constraining factor (\( a_4 \neq a_8 \neq 0 \)). There is no theoretical reason to allow for these additional parameters, but in the absence of a strong theoretical basis to the contrary, we do not constrain these parameters a priori. It is preferable to estimate unconstrained models and test whether the implicit assumptions implied by the theory are supported by the data (Edwards, 1995).

Eq. (2) is nested in Eqs. (1) and (4). Similarly, Eqs. (1) and (4) are nested in the following more general, “combined” model that includes both moderate and extreme complementarity:

\[
\text{Action} = a_0 + a_1 M + a_2 O + a_3 A \\
+ \theta_0 (a_4 + a_5 M + a_6 O + a_7 A) \\
+ \theta_A (a_8 + a_9 M + a_{10} O + a_{11} A) \\
+ a_{12} M \times O + a_{13} M \times A + a_{14} O \times A \\
+ a_{15} M \times O \times A + \varepsilon
\]  

(5)
This combined model is only introduced to allow a comparison of the multiplicative model and the CFM.

2.3. The knowledge-sharing context

Having discussed the MOA framework in detail, we now briefly discuss the particular context wherein we apply this framework. Our research focuses specifically on individual work-related knowledge, which is generated from the experiences of employees engaged in organizational tasks (Dixon, 2000). Such knowledge has both tacit and explicit components. It is often declarative but can contain procedural elements. Dixon emphasizes the critical nature of common knowledge at the lowest levels of the organization, which she refers to as ‘coal face’ knowledge. In practice, Six Sigma engineers refer to it as “tribal knowledge”—the undocumented tricks of the trade that make experienced workers so valuable. We do not study a formal knowledge-sharing context, like Six Sigma improvement projects (Choo et al., 2007), but rather focus on informal knowledge sharing within a workgroup.

Knowledge sharing involves at least two people: a sender (here, an employee who attempts to share knowledge); and a recipient (the coworker who is intended to acquire it). Our research focuses on the sender and explores his/her MOA to share knowledge. Arguably, this one-way sharing in a dyadic relationship is a fundamental building block—a behavioral kernel—of knowledge-sharing behavior. We do not explicitly consider the recipient’s actions in acquiring this knowledge. This is not to downplay the value of studying the recipient’s perspective; it is well known that the recipient can suffer from the “not invented here” phenomenon (Katz and Allen, 1982). We leave it to future research to explore this perspective.

Within the context of our research, knowledge sharing is the informal communication process underlying the sharing of tribal knowledge between members of a workgroup. The knowledge sender will hereafter be referred to as the employee (she/her). The receiver will be referred to as the coworker (he/him). As a proxy for the employee’s knowledge-sharing (KS) behavior, we operationally define knowledge-sharing attempt (KSA) as the degree to which the employee actively tries to share some aspect of her job-related knowledge with a coworker in the same workgroup.

The topic of knowledge sharing has received considerable attention in diverse academic fields (see Cabrera and Cabrera, 2005 for a recent review), as have antecedents associated with each of the MOA variables. Motivation is a construct that reflects the dynamic, personal energy with which an action is performed (Cummings and Schwab, 1973). Based on Boudreau et al. (2003), an employee’s motivation to share (MS) is defined as her inner drive to share knowledge with a coworker. Although much recent research has focused on exploring the perspective of knowledge recipients and seekers (Levin and Cross, 2004; Menon et al., 2006), many antecedents of a person’s motivation to share knowledge are already well known. These include trust and norms of reciprocity (Dirks and Ferrin, 2001; Szulanski et al., 2004); the effort involved in sharing knowledge (Darr and Kurtzberg, 2000); the perception that knowledge sharing is a way to build one’s reputation (Wasko and Faraj, 2005); belief in the organizational ownership of knowledge (Constant et al., 1994; Jarvenpaa and Staples, 2001); proper incentive structures (Ferrin and Dirks, 2003; Siemsen et al., in press); and leadership, internal competition, and competence similarity (Siemsen et al., 2007a).

Common sense would argue that if a person does not want to share knowledge, knowledge sharing will not occur. From an empirical standpoint, however, the evidence on the role that motivation plays is mixed. Some prior empirical research on the sharing of best practices has questioned the importance of motivation (Szulanski, 1996, 2000), and these findings have been quite influential (see e.g., O’Dell and Grayson, 1998). Other conceptual research has highlighted the pivotal role of motivation as a determinant of successful knowledge sharing (Argote et al., 2003). This leaves us with the first puzzle mentioned in the introduction. While there is a clear theoretical justification for motivation as a driver of knowledge sharing, it is surprising that the empirical evidence is not strongly and uniformly supportive of this role. As noted above, our research offers a possible explanation.

In this research, the employee’s ability to share (AS) is defined as the extent of her skills and proficiencies required to share knowledge with her coworker (MacInnis et al., 1991; Rothschild, 1999). The factors that influence a person’s ability to share knowledge, including the tacitness of the knowledge being shared (Nonaka and Takeuchi, 1995), are also well established. Ability is a construct that reflects an individual’s general capacity to perform in specific types of situations.
Organizations may aim to improve employees’ abilities by following certain hiring standards or by investing in mentoring and training procedures.

Based on Blumberg and Pringle (1982), we define an employee’s opportunity to share (OS) as the combination of direct and, at least in the short run, uncontrollable factors surrounding the employee and the task environment that inhibit or enable her sharing of knowledge with her coworker. Opportunity is generally used as a construct to capture the remaining, exogenous elements that are posited to either inhibit or enable a person to act (Rothschild, 1999). Organizations can establish work conditions that facilitate knowledge sharing. In operations management, these are realized through the proximity of employees at work, job designs, process layouts, benchmarking, and investments in information and knowledge management systems (Roth et al., 1994; Borgatti and Cross, 2003).

The concept of opportunity is somewhat vaguer than the constructs of motivation and ability. Peters and O’Connor (1980), for example, identify eight different possible situational constraints at work. One of the most important operational constraints among coworkers is time. We therefore define time availability (TA) as the degree to which an employee has slack time available at work, and we use TA as a proxy for OS. Knowledge sharing between coworkers can be an informal process, requiring few other resources – such as finance or material – from the organization. Further, coworkers within a workgroup usually are in proximity to each other and at least occasionally meet in the course of their daily work or during common workgroup meetings. However, due to the informal nature of knowledge sharing, employees will likely only be able to engage in sharing if they have sufficient slack time available. Consequently, time is posited to be a major constraint on knowledge-sharing behavior if employees are fully utilized by their regular tasks at work.

Having now clarified the context and provided the operational definitions of the MOA framework constructs for this study, we devote the remainder of the paper to a comparison of the models developed in the previous subsection using the constructs defined by the knowledge-sharing context of this research: action = knowledge-sharing attempt (KSA); motivation (M) = motivation to share (MS); opportunity (O) = time availability (TA); and ability (A) = ability to share (AS).

3. Methods

3.1. Data

Our database was developed from survey data that were obtained from employees in four different companies. The first company, a large public utility company, served as the pilot site. The pilot dataset comprised 140 observations, with most respondents being design engineers. This pilot study dataset was used to calibrate and refine our measures and was not included in any of the subsequent empirical analyses, unless specifically noted otherwise. Data from the three remaining companies (2, 3 and 4) served as validation samples and were used for model testing.

The unit of analysis for our study is a “knowledge-sharing incident,” which involves two individuals (the employee and the coworker). We measured the employee’s perceptions related to this incident. In the survey instrument, respondents were presented with a general definition and an example of what we meant by a knowledge-sharing incident and were then asked to recall the most recent incident that they had encountered. In order to ground the responses, each respondent was asked to provide specific details about their particular incident. Appendix A contains the precise wording of the survey question as well as illustrative examples of the types of knowledge that respondents referred to in their responses. In companies 3 and 4, we asked respondents some standardized questions to further characterize these knowledge-sharing incidents. About 71% of respondents indicated that they had been aware of this knowledge for some time, implying that respondents mostly based their response on so-called “tricks of the trade.” Only about 22% of respondents indicated that this knowledge was based on an idea for improvement that they had. This suggests that the shared knowledge captured by the survey may be less innovative in nature, and based more on personal knowledge and experience. Also, only 15% of the respondents indicated that the knowledge was based on an error or mistake they had observed. We measured the degree of codifiability of this knowledge. The average score for codifiability was 5.63 (standard deviation 1.35), indicating that most of the knowledge was explicit in nature.

After describing their knowledge-sharing incidents qualitatively, respondents answered a series of questions pertaining to those specific incidents, their work,
their perceptions of their coworker, their workgroup, and their organization. We randomized the position of scale items throughout the survey, and took care to avoid placing items from the same scale in the direct vicinity of each other.

In the pilot study, we initially asked respondents to report on their most recent KS incident, regardless of whether its outcome was positive (reflecting their belief that knowledge was shared) or negative (reflecting their belief that knowledge was not shared). This resulted in an over-reporting of positive incidents. We therefore redesigned the survey for the subsequent data collection efforts by randomly assigning questionnaires that asked with equal probability for respondents to report on either a positive or a negative incident.³ Previous researchers in knowledge management have faced similar issues (Levin and Cross, 2004).

The survey was administered in both a web-based version (company 2) and a traditional pen-and-paper version (companies 3 and 4). Both media have strengths and weaknesses. Web-based surveys allow the quick collection of detailed information in an interactive format and are inexpensive to administer (Rosenzweig et al., 2007). In addition, the time and effort involved in coding the data are significantly reduced. However, the impact of web-based surveys on the response rate is not clear (Boyer et al., 2002). Companies 3 and 4 were shop-floor environments. It was not obvious if employees there had easy access to Internet resources. In the pilot survey, data for some items used in the final survey (KSA1, KSA3, AS1, TA1 and TA2) were collected using both methods. An overall test of means in a multivariate regression revealed no significant differences \( (p = .31) \) between the data collected through the Web and the data collected via the pen-and-paper survey.

A description of the three companies (2, 3, and 4) used in the validation sample is given in Table 1. Company 2 consisted of a group of IT professionals who provided Web services for educational purposes. Much of their work was organized in projects, but some elements of work were routed to individuals in a job-shop fashion. Employees in company 3 assembled complex aircraft components. The shop floor represented a mixture of job-shop and assembly line manufacturing operations. Respondents were mostly technicians and quality engineers. Company 4 was a food-manufacturing operation that featured continuous-flow processing. Respondents were mostly line workers and machine technicians. This was the only unionized organization represented in the three samples. In each location, management allowed us to collect data from their employees and encouraged them to participate in the survey; however, great care was taken to assure the anonymity of respondents. Respondents were reminded three times to take the survey, either via email or via a company blackboard.

In order to encourage response, participants received $2 with the survey, and after the successful completion of the survey, respondents were entered into a raffle. The survey was long, and took respondents half an hour to complete. Response rates ranged from 11 to 16%, which is low, but not atypical for this type of research when long surveys are used and access to respondents is limited (Frohlich, 2002). To test for response bias, population demographic data was available for company 4. No overall significant differences at the .05 level were found between the group of respondents and the company population with respect to job tenure, age, or gender.

As we have discussed earlier, the dataset used in this study has been used in other research as well (see e.g., Siemsen et al., in press). However, the measure of MS is

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³ To comply with academic affairs institutional review requirements, we had to allow respondents to report on the other type of incident if they were unable to think of an incident of the type they were asked to report on.
the only overlapping variable (besides control variables). In this research, MS is an independent predictor variable, whereas it is the dependent variable in these other studies.

We collected data from a single respondent for each incident. This created the possibility that some of our variables were influenced by common-method variance. Note that common-method variance generally increases the univariate linear relationship between variables. Our research compares different multivariate, nonlinear models. Common-method variance is less likely to introduce bias into this comparison and favor one nonlinear model over another, especially as common-method variance is less troublesome in testing models with interactions (Evans, 1985).

In the pilot survey, we considered collecting data regarding KS incidents from both employees and coworkers. Such a survey design, however, requires the identification of the coworker. This, in turn, could compromise the anonymity of the employee and might reduce her willingness to provide accurate responses or to participate in the study at all. This situation greatly increases the potential for response bias, because the characteristics of the knowledge-sharing process may affect whether the employee wants to identify the coworker. Particularly for incidents in which the employee did not share knowledge, she would be less inclined to identify the recipient and report on this incident. We asked respondents whether they would be willing to identify the recipient and let us ask him about the incident, and only 21% of respondents indicated their willingness to do so. This result presented us with the dilemma of having to choose between reducing common-method bias and increasing potential non-response bias is not uncommon in survey research and has been discussed previously (Podsakoff et al., 2003).

If we were to change the concreteness of our constructs (for example, by asking respondents about generic knowledge-sharing attitudes rather than about a specific situation), we would be able to collect data from the recipients. However, as Doty and Glick (1998) have shown in their meta-analysis, increasing the concreteness of constructs decreases common-method variance, whereas having multiple respondents does not decrease common-method variance in a statistically significant way. Therefore, solely on an empirical basis, reducing the concreteness of constructs in order to be able to collect data from multiple respondents is not a recommended design.

To test whether common method variance influences the correlations between our constructs, we estimated a confirmatory factor analysis model that allows for a methods factor to load onto all observed items (Podsakoff et al., 2003). For identification purposes, the factor loadings for this methods factor were constrained to be equal. We then compared the latent variable correlations from this analysis to latent variable correlations obtained from a regular confirmatory factor analysis (see Appendix B). No large differences were observed between the two sets of latent variable correlations.

### 3.2. Measurement properties

We now address the validity and reliability of the measurement scales used in this research. Items related to each construct are described in Appendix C. Prior to the pilot data collection, scales were pretested in up to six rounds of item-sorting exercises (Anderson and Gerbing, 1991; Roth et al., 2008). Respondents in the item-sorting exercises were graduate and undergraduate students. They were given randomized lists of items and construct definitions and were asked to sort items to constructs. After each round, confusing and ambiguous items were identified, revised, and subjected to further item sorting.

Each of our scales was designed to be unidimensional because the underlying constructs are distinct, singular theoretical concepts, rather than separate but related dimensions treated as a single theoretical concept (Edwards, 2001). Therefore, the questions within each scale are homogeneous in terms of their content, but they substantially vary the language used to test this content ( DeVellis, 1991). To provide statistical tests of unidimensionality, we subjected our scales to a confirmatory factor analysis (CFA) using the validation sample (companies 2–4) to look for evidence of correlations among the unique variance components of the scale items (Gerbing and Anderson, 1988). Accordingly, the initial factor structure of our CFA was specified by allowing factor loadings of indicators on their associated constructs but constraining all cross-loadings on other constructs to zero (see Bollen, 1989). Similarly, all measurement errors were assumed to be uncorrelated. The first item of each scale served as the scaling indicator. This model is identified according to the three-indicator rule (Bollen, 1989).

All items belonging to the MOA framework loaded significantly ($p < .01$) on their predicted factors. We proceeded to examine the modification indices (MIs) on the cross-loadings and on the measurement-error correlations. When testing the MI indices, we applied a Bonferroni correction for the MIs on the cross-loadings and measurement-error correlations, as
required by the significance level ($\alpha = .05$). MS4 in the validation sample had a significant MI index ($p \leq .01$) on the cross-loading with KSA, even with the Bonferroni correction. To retain validity and maintain the theoretical interpretability of our results, we therefore removed MS4 from the MS scale (Edwards, 2003). We then re-estimated the CFA model and assessed overall model fit. No significant MIs remained on either cross-loadings or measurement-error correlations. The re-estimated model fit well and had a non-significant $\chi^2$ (Bollen, 1989):

$$\chi^2_{d.f=48} = 44.94 \quad (p = .60), \quad \chi^2/d.f. = .94, \quad \text{RMSEA} = .00 \quad (p = .98)$$

We also examined scale reliability using Cronbach’s alpha and the average variance extracted (AVE). An $\alpha$ estimate greater than .70 constitutes evidence of adequate reliability (Nunally, 1967), as does an AVE greater than .50 (Fornell and Larcker, 1981). All our scales satisfy these criteria. A summary of the standardized factor loadings is provided in Appendix C.

Having obtained evidence for the convergent validity and reliability of our measurement scales, we investigated their discriminant validity. We conducted a confirmatory factor analysis in which we constrained the correlation between pairs of latent variables to unity and estimated the decrease in model fit due to that constraint. For all pairs of latent variables, the model $\chi^2$ decreased significantly ($p \leq .05$) upon imposing the constraint, thus establishing the discriminant validity of the scales (see Table 2).

We conducted a measurement invariance analysis to test whether or not the measurement properties of our scales differ among the three companies used in the validation analysis (Vandenbreg and Lance, 2000). Using listwise deletion to deal with missing data, we first estimated a multi-group CFA model constraining all parameter matrices between groups to be equal ($\chi^2_{d.f=144} = 209.76, \ p \leq .01$). Freeing the $\Lambda$ matrix (factor loadings) resulted in a non-significant change in model fit ($\Delta \chi^2_{d.f=16} = 17.47 \ p = .36$). After this, we removed the constraints from the $\Theta_A$ matrix (measurement error correlations), which increased model fit significantly ($\Delta \chi^2_{d.f=24} = 70.23, \ p \leq .01$). Finally, freeing the $\Phi$ matrix (latent variable correlations) did not increase model fit significantly ($\Delta \chi^2_{d.f=20} = 15.71, \ p = .73$). There is, therefore, evidence of factorial invariance between companies. However, there is also evidence that the reliabilities of the scales change slightly in the different samples. We compare standardized factor loadings across samples in Appendix C. As can be seen, the scales are somewhat less reliable in company 3, but the standardized factor loadings are not reduced to a degree that would call into question the reliability of these scales.

### 4. Analysis and results

Having demonstrated that our measures are reliable and valid, we constructed latent variable scores by creating scale averages for each scale. We then standardized these scores. We operationally defined the lowest standardized score on MS, TA, and AS as the minimum of the three variables for each respondent, and we further defined $\Theta_{TA}$ to be a dummy variable that is set to 1 if TA is the minimum (0 if not), and $\Theta_{AS}$ to be a dummy variable that is set to 1 if AS is the minimum (0 if not).

#### 4.1. Testing the constraining factor model

To test our hypothesis, we estimated four different models. Model 1 corresponds to the linear model (Eq. (2)) and only allows for the basic linear effects of the MOA variables. Model 2 corresponds to the constraining-factor model (Eq. (4)) and allows for all linear terms to change, depending upon whether MS, OS, or AS is the minimum. Model 3 corresponds to the multiplicative model (Eq. (1)) and includes the interaction effects in addition to the linear terms. Finally, model 4 corresponds to the combined model (Eq. (5)). In addition, each model contains dummy variables to control for company fixed effects. Further, we added controls for age, gender (0 = female, 1 = male), education (1 = some high school, 2 = completed high school, 3 = some college, 4 = BA/BS, 5 = graduate degree; note that in the subsequent analysis, we pooled and then omitted categories 1 and 2), job tenure (years with company), and management responsibility (0 = no employees reporting to respondent, 1 = employees reporting to respondent). Age and job tenure were also standardized prior to analysis.
All models were estimated using ordinary least squares estimation in Stata 9.2 with Huber-White standard errors. We conducted a comprehensive outlier analysis in order to test whether the estimates were driven by influential cases. For every observation, we calculated the DFBeta values for all (non-control) variables of interest. To reduce the effect of outliers on our estimates, we identified influential cases on the basis of the DFBeta statistics and dropped those outliers for which the maximum of the absolute value of all DFBeta scores (DF_{max}) was greater than .30. In other words, to be conservative, we eliminated only those observations that influenced the effect estimate of one of our variables of interest by more than .30 standard errors, which is twice as large as the recommended cutoff (Bollen and Jackman, 1990). A total of 16 observations fit this criterion and were dropped from the sample.

Some of the tests of our hypothesis are based on the acceptance of the null hypothesis. Therefore, we gauged the power of these tests (Cortina and Folger, 1998) by reporting two $\beta$ values (probability of making a type II error) for such tests. The first $\beta$ value represents the probability of missing a moderate effect ($f^2 = .10$, which is similar to a change in $R^2$ by 3.4 percentage points); the second $\beta$ represents the probability of missing a small effect ($f^2 = .05$, which is similar to a change in $R^2$ by 1.7 percentage points). Both these $\beta$s assume $\alpha = .10$ (probability of making a type I error), the minimum level of significance required to falsify our hypotheses.

Our central hypothesis involves a comparison of two non-nested models. In order to compare these models nevertheless: (1) the CFM must explain more variance than the linear model, (2) the multiplicative model must not explain more variance than the linear model, (3) adding the multiplicative terms to the CFM must not explain more variance than the linear model, and (4) adding the CFM terms to the multiplicative model must explain more variance than the multiplicative model. In addition, fit statistics to compare non nested models like the adjusted $R^2$ and the Akaike Information Criterion (AIC) must indicate that the CFM provides better fit.

We provide a summary of the results of the regression analysis in Table 3. The constraining-factor model (CFM) fits significantly better than the linear model ($F_{133}^8 = 1.99, p < .05$). The multiplicative model, in contrast, does not fit significantly better than the linear model ($F_{142}^4 = .63, p = .64, \beta = .06/30$). Comparing the CFM and the multiplicative model to the combined model, we find that the combined model does not significantly increase fit over the CFM ($F_{134}^4 = .47, p = .75, \beta = .06/30$); however, model 4 does significantly increase model fit over model 3 ($F_{134}^3 = 2.28, p < .05$). These tests provide evidence in support of our hypothesis. A comparison of the models’ adjusted $R^2$ values (the higher the $R^2$, the better the fit) and AIC (the lower the AIC, the better the fit) also indicates that the CFM dominates all other models. These results provide support for H1.

The CFM delivers an increase in $R^2$ of 6% compared to the linear model. This is a statistically significant increase, but arguably one that is small. Two important caveats are applicable here. First, the small magnitude of the improvement in $R^2$ is not surprising, because the functional form of the constraining-factor model is not much different from that of the linear model. Second, and more importantly, the qualitative insights are very different across the models. In the CFM, the linear effect of the variables is conditional on the identity of the constraining factor.

Consider the effect of motivation: in the linear model, motivation has an effect size of .50 ($p < .01$). In the CFM, this effect is conditional on the factor that is the bottleneck. If motivation is the minimum of the three factors, the effect of motivation is .81 ($p < .01$), which is even higher than in the linear model. If, however, ability is the minimum, the effect of motivation is .81 – .64 = .17, which is not significantly different from 0 ($p = .34, \beta = .01/30$). Similarly, if TA is the constraining factor, the effect of MS is .81 – .58 = .23, which also is not significantly different from 0 ($p = .19, \beta = .01/30$). Whereas, MS has a strong effect on KSA if it is the constraining factor, changes in MS have little or no effect on KSA if MS is not the constraining factor. We illustrate these effects in Fig. 1a.

A similar argument holds for ability. If ability is the minimum of the three factors, it has an effect of .49 – .09 = .40 ($p < .01$). This effect of AS is stronger than the effect of ability as estimated in the linear model. If motivation is the minimum, as predicted, the effect of ability is $-0.09$ ($p = .56, \beta = .01/13$), which is not statistically different from 0. If, instead, opportunity (TA) is the constraining factor, the effect of ability is $-0.09 + .23 = .14$, which is not statistically different from 0 ($p = .27, \beta = .01/13$). In support of H1, these results show that a purely linear interpretation of the way that ability drives knowledge-sharing attempts may be misleading. We illustrate these different effects in Fig. 1b. AS has an impact on KSA if AS is the constraining factor. However, the effect of changes in AS on KSA disappear if either MS or TA is the constraining factor.
So far, we have empirically demonstrated that motivation (MS) and ability (AS) drive KSA exactly as predicted in the CFM. However, in model 2, TA appears to have little or no effect at all, irrespective of whether motivation (MS) \((b = 0.05, t = 0.53, p = 0.60)\), TA \((b = -0.21, F_{138}^1 = 3.07, p = 0.08)\), or ability (AS) \((b = 0.03, F_{138}^1 = 0.27, p = 0.61)\) is the constraining factor. This seems somewhat contrary to previous research, which has established that situational constraints can affect behavior (Villanova and Roman, 1993; Villanova, 1996). It should be noted, however, that TA has an implicit effect on behavior. When TA is the constraining factor, changes in TA do not influence KSA, but they do reduce the effect sizes of MS and AS to zero. In other words, the data show that not providing time to share is a barrier to motivation and ability. This provides an important managerial insight: if workers feel that they have no time to share knowledge, it does not matter how much they want to share what they know, nor how much they are able to do so; they simply do not share. In such cases, resource investments in motivation or ability may have virtually no knowledge-sharing payoffs.

4.2. Robustness

We performed robustness tests to determine whether our analysis would yield different insights if we did not drop the outliers. We ran a multigroup analysis, including the observations originally excluded as outliers but allowing different parameter estimates for....

Table 3
Parameter estimates (dependent variable: Knowledge Sharing Attempt (KSA))

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1 (linear)</th>
<th>Model 2 (constraining factor)</th>
<th>Model 3 (multiplicative)</th>
<th>Model 4 (combined)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Est.</td>
<td>S.E.</td>
<td>Est.</td>
<td>S.E.</td>
</tr>
<tr>
<td>Constant</td>
<td>-.01</td>
<td>.09</td>
<td>.45</td>
<td>***</td>
</tr>
<tr>
<td>Company 2</td>
<td>-.04</td>
<td>.15</td>
<td>-.09</td>
<td>.15</td>
</tr>
<tr>
<td>Company 4</td>
<td>-.04</td>
<td>.14</td>
<td>-.09</td>
<td>.13</td>
</tr>
<tr>
<td>Male</td>
<td>.24</td>
<td>**</td>
<td>.21</td>
<td>***</td>
</tr>
<tr>
<td>Age</td>
<td>.01</td>
<td>.07</td>
<td>.00</td>
<td>.06</td>
</tr>
<tr>
<td>Management</td>
<td>-.04</td>
<td>.13</td>
<td>-.01</td>
<td>.13</td>
</tr>
<tr>
<td>Tenure</td>
<td>.02</td>
<td>.05</td>
<td>.02</td>
<td>.05</td>
</tr>
<tr>
<td>Education</td>
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<td>.10</td>
<td>-.09</td>
<td>.10</td>
</tr>
<tr>
<td>Education</td>
<td>.01</td>
<td>.12</td>
<td>-.05</td>
<td>.13</td>
</tr>
<tr>
<td>Education</td>
<td>-.19</td>
<td>.23</td>
<td>-.25</td>
<td>.24</td>
</tr>
<tr>
<td>Motivation (MS)</td>
<td>.50</td>
<td>***</td>
<td>.81</td>
<td>***</td>
</tr>
<tr>
<td>Time Avail. (TA)</td>
<td>.00</td>
<td>.03</td>
<td>-.05</td>
<td>.09</td>
</tr>
<tr>
<td>Ability (AS)</td>
<td>.21</td>
<td>***</td>
<td>-.09</td>
<td>.16</td>
</tr>
<tr>
<td>MS × TA</td>
<td>.00</td>
<td>.06</td>
<td>.01</td>
<td>.09</td>
</tr>
<tr>
<td>MS × AS</td>
<td>.03</td>
<td>.07</td>
<td>.09</td>
<td>.07</td>
</tr>
<tr>
<td>TA × AS</td>
<td>-.05</td>
<td>.07</td>
<td>-.07</td>
<td>.07</td>
</tr>
<tr>
<td>MS × TA × AS</td>
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<td>.09</td>
<td>.10</td>
<td>.09</td>
</tr>
<tr>
<td>θTA</td>
<td>-.33</td>
<td>*</td>
<td>.20</td>
<td>.20</td>
</tr>
<tr>
<td>θTA × MS</td>
<td>-.58</td>
<td>**</td>
<td>.21</td>
<td>.26</td>
</tr>
<tr>
<td>θTA × TA</td>
<td>-.16</td>
<td>.15</td>
<td>.16</td>
<td>.18</td>
</tr>
<tr>
<td>θTA × AS</td>
<td>.23</td>
<td>.21</td>
<td>.20</td>
<td>.24</td>
</tr>
<tr>
<td>θAS</td>
<td>-.17</td>
<td></td>
<td>.16</td>
<td>.19</td>
</tr>
<tr>
<td>θAS × MS</td>
<td>-.64</td>
<td>**</td>
<td>.21</td>
<td>.26</td>
</tr>
<tr>
<td>θAS × TA</td>
<td>.08</td>
<td>.11</td>
<td>.02</td>
<td>.17</td>
</tr>
<tr>
<td>θAS × AS</td>
<td>.49</td>
<td>***</td>
<td>.18</td>
<td>.20</td>
</tr>
</tbody>
</table>

N | 159 | 159 | 159 | 159
F | 22.27 | 28.24 | 19.98 | 34.32
R² (adj. R²) | .55 (.52) | .61 (.56) | .56 (.51) | .62 (.55)
AIC | 1.69 | 1.64 | 1.72 | 1.68

Notes. S.E. = Huber-White standard errors. Estimates for continuous variables are standardized regression coefficients. Note that Education3 = some college; Education4 = BA/BS; Education5 = graduate degree. The omitted Education category variable represents the combined categories “some high school/completed high school.” Company 3 is the omitted company.

* p ≤ .10.
** p ≤ .05.
*** p ≤ .01.
all noncontrol variables for the outlier group. This test confirmed our suspicion that the outliers are influential, as the parameter estimates for the group of outliers are significantly different from those of the nonoutlier group ($F_{12}^{141} = 22.14, p < .01$). Reassuringly, most of our substantive results continue to hold even if the outliers are retained in the dataset. Most importantly, the CFM continues to dominate the multiplicative model when the outliers are included. The only substantive difference relates to the role of motivation. In contrast to the results reported in Table 3, if we include the outliers in the analysis, motivation has a reduced but positive effect, even when ability or opportunity is the constraining factor.

We also conducted a multigroup analysis to test whether the parameter estimates differed among the samples. We freed the slopes of our non-control variables in both the CFM and the multiplicative model for each sample and then tested whether these additional parameters resulted in a significant increase in model fit. Company 2 cannot be distinguished by these means from companies 3 and 4, neither in the CFM model ($F_{127}^{11} = 1.03, p = .43$) or the multiplicative model ($F_{135}^{7} = 1.53, p = .16$). In company 4, no significant increase in model fit can be established for the CFM model ($F_{127}^{11} = 1.02, p = .43$), but the multiplicative model shows a significant increase in fit when the parameters are freed up ($F_{135}^{7} = 3.84, p < .01$). A regression of the multiplicative model in company 4 shows that both the three-way interaction ($b = .53, p = .03$) and the interaction between opportunity and ability ($b = -.42, p = .04$) become significant.

As noted above, we defined the constraining factor as the lowest standardized score on the three MOA scales. Some observations were “close calls,” where the difference between the constraining factor and the next highest score is not large. To test whether our results depend in any way on these close calls, we ran an analysis eliminating all observations for which the difference between the minimum standardized score and the next highest score is less than .10 standard deviations. Fifteen observations fit this criterion; however, dropping these observations revealed no substantive differences compared to our analysis reported in Table 3. We also conducted a bootstrap analysis with bias-corrected and accelerated confidence intervals and 1000 replications to test whether the normality assumptions inherent in our regression affected our results. Whereas the bootstrap standard errors were generally higher than those in the standard regression estimates, all estimates reported in Table 3 remained statistically significant.

5. Discussion and conclusion

In this paper, we have presented a theoretical model and an empirical test of the way that motivation, opportunity, and ability together drive knowledge-sharing behavior. Drawing from theory, observations in practice, and conceptual arguments, we specified four competing models: the linear, multiplicative, constraining-factor, and combined models. Of these, the constraining factor model (CFM) captures a new perspective introduced in this paper—a bottleneck theory of knowledge sharing. We developed and administered a survey to collect data on employee KS behaviors in four companies and established the reliability and validity of the newly developed measures. The results from the empirical estimation support the superiority of our proposed constraining-factor model over the linear and multiplicative models.
Our analysis and findings have implications for both research and practice.

5.1. Research implications

We argue from an examination of the literature and discussions with practitioners that there were still conceptual difficulties with the MOA framework that needed to be understood if it is to be useful for operations management. For example, as solely an organizing framework, MOA makes no assumptions about how to prioritize investments in motivation, opportunity or ability. Interventions regarding motivation may be very different than those providing opportunities to share, such as improving workgroup leadership versus making time available to workers. Moreover, the functional form of how MOA drive behavior is left unspecified. This severely weakens the explanatory elements of the framework. This weakness is bothersome, as it has already led some research to call the framework a truism (Bell and Kozlowski, 2002), something that ought to be true but lacks proper empirical evidence. Our research helps to clarify these issues. As a result, the theoretical aspects of the MOA framework are strengthened.

Secondly, our results highlight the pivotal role that motivation plays in explaining successful knowledge sharing. While casual reasoning and straightforward logic suggest that nothing would happen in the absence of motivation, some past studies have found only limited support for the role of motivation in explaining successful knowledge sharing. The constraining-factor model and the empirical findings in this paper resurrect the strategic importance of motivation, while simultaneously providing a deeper understanding of the conditions under which motivation fails to play a role in explaining successful knowledge sharing. Specifically, extreme complementarity is shown to be empirically valid in that if either opportunity or ability is the constraining factor, changes in motivation have no impact on behavior. This empirical result reveals a possible explanation for the low importance attributed to motivation in other studies.

A further contribution of our research is the establishment of a new functional form that describes the multiplicative models presented in the prior literature. This finding strengthens the MOA framework as a metamodel.

Finally, in the methodological context, the CFM proposed in this paper expands the tool set of researchers by providing an alternative approach to the conceptualization and modeling of interactions that emphasizes extreme complementarity among the variables. We have shown how the CFM can be empirically tested and compared to standard multiplicative models. Specifically, it would be interesting to apply the CFM in other OM research settings where complementarity among variables could theoretically be expected to exist, but empirical findings have had difficulty establishing it. A particular example of such a setting in operations management would be the study of JIT practices. Researchers might investigate to what
degree practices in the JIT bundle have to be applied together, and whether a lack of implementation of any of the typical JIT practices would reduce the overall effectiveness of the program (Shah and Ward, 2003). In the field of organizational behavior, one could apply the CFM to Vroom’s expectancy model. In general, the CFM offers a viable alternative to existing ways of modeling interactions.

5.2. Managerial implications

Many organizations are currently engaged in knowledge management and knowledge sharing initiatives. Our model offers a strategic view of the knowledge-sharing landscape from the employees’ perspective. It also provides broad-scale guidance about what interventions in terms of programs, practices and tools will advance knowledge sharing for the particular business entity. First, our CFM results suggest that before expending significant resources on designing knowledge-sharing initiatives, managers must carefully study the workplace to identify whether motivation, opportunity, or ability, or some combination of these variables, represents the bottleneck in the knowledge-sharing process. This will be an ongoing process, as these bottlenecks might shift over time, or go unnoticed.

Discovering and widening the bottlenecks is important for two reasons. In the presence of a bottleneck, resources allocated to enhancing the levels of the other variables are likely to be unproductive. Managerial interventions aimed at MOA factors that are not constraining in the organization are less likely to be effective. Also, the nature of investments to be made will vary widely depending on which variable or combination of variables constitutes the bottleneck that needs to be addressed. For example, training people on how to communicate their knowledge may improve their ability to share knowledge. Providing proper incentives to share (Siemsen et al., in press) or improving psychological safety in teams (Edmondson, 1999) can improve employee motivation to share knowledge. However, neither of these interventions will result in tangible benefits if they do not address a constraining factor.

Second, our analysis provides insights into the kinds of metrics and measurement systems that can be used in the implementation of knowledge-sharing initiatives and in assessing their relative benefits versus costs. Managers can periodically measure levels of employee motivation, opportunity, and ability to share knowledge within a well-defined context and empirically relate those measurements to the actual knowledge sharing that occurs. Then, utilizing insights from this analysis, managers can identify which variable constitutes a bottleneck, and direct their scarce resources and efforts at improving this variable. The multi-item measurement scales developed in this paper serve as a practical first step towards the creation of an assessment tool that would support such an undertaking.

Take, for example, company 2: For 40% of respondents, motivation was the constraining factor; for 32% of respondents, ability was the constraining factor, and for 28% of respondents, the constraining factor was opportunity. The managerial advice for this company would be to redirect their knowledge-management efforts on the provision of proper incentives (Siemsen et al., in press) and an environment that is psychologically safe (Siemsen et al., 2007b) in order to enhance their employees’ motivation to share. In company 3, in contrast, 53% of respondents showed opportunity to be the constraining factor, while 30% of respondents in that sample reported ability and only 17% reported motivation as the constraining factor. A recommendation for this company would be to prioritize their efforts on interventions that increase employees’ opportunities for knowledge sharing and increase employees’ ability to share. For example, they can reduce employee utilization and specifically integrate knowledge sharing into the regular workflow (Roth et al., 1994); and they can train employees to better communicate and document their tricks of the trade. In company 4, 24% of respondents indicated that motivation was the constraining factor; 50% reported the constraining factor of opportunity; and 26% showed ability to be the constraining factor. Again, employees in this company seem to be severely time-constrained at work, and a prerequisite for any other knowledge management activity would be either to free up time and space for workers to share their knowledge or to explicitly make the sharing of “lessons learned” a part of regular work processes.

5.3. Limitations and future research

Like all studies of this kind, our research has a number of limitations. First, given our research questions and study setting, it was difficult to survey multiple respondents per incident without risking substantial nonresponse bias (see Section 3). Other data collection contexts or experimental conditions might be able to overcome this limitation and attempt to
replicate our results in a multi-respondent setting. In addition, our measure of opportunity (time availability) is only a proxy for opportunity. There may be other opportunity-related considerations – such as space or resource availability – that would apply in our research setting. Future implementations of the CFM should keep this in mind and gather data on such alternative situational constraints if possible. For example, in contexts such as knowledge sharing among coworkers on globally dispersed new product development teams, other means for informal dialogue may be relevant proxies for opportunity.

Another limitation of our research is that we identify the constraining factor by comparing scale averages of standardized variables. This approach neglects both the measurement error inherent in these scales and the fact that standardizing the variables makes them only imperfectly comparable. We paid careful attention to the creation of reliable and valid scales, thus minimizing the impact of measurement error on parameter estimates. In addition, we also tested the robustness of our results to “close calls” to test whether the scaling mattered. Nevertheless, these limitations could potentially be overcome by a latent variable model that posits the constraining factor as the minimum among latent variables. Future methodological work is warranted that will develop a model of this type and establish procedures for identification and estimation using maximum likelihood techniques.

We have tested the constraining factor model within the context of inter-employee knowledge sharing. However, we believe that the CFM is applicable in other contexts as well. Since we only study one context, we cannot rule out the possibility that our test of the CFM is influenced by particularities of this particular setting. Further research applying the CFM in different contexts, such as assessing the propensity of employees to participate in formal process improvement programs and reporting errors, would test the generality of the model.

Getting employees to share knowledge is an enduring problem, one that has increased in relevance over time. Our aim in this study has been to provide a fresh perspective on knowledge sharing from both the research and managerial viewpoints. The proposed constraining-factor model developed here has potential as a tool for planning managerial interventions to improve knowledge sharing and may have applications in many other areas of organizational and operational research. We hope our thoughts in this paper will stimulate further research on, and use of, the CFM approach.

Acknowledgements

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Appendix A. Illustrative incident descriptions

A.1. Survey question

Please think about the most recent occasion where you had some work-related knowledge (“tricks of the trade”) that would have been of some potential use to one of your coworkers, and you (attempted/did not attempt\(^4\)) to share this knowledge with him or her—whether your coworker acquired it in the end or not. Think of a situation where, for example, you learned something new or you had a new idea for improvement, where you detected errors in regular work procedures or where it became obvious to you that some of your existing knowledge may be valuable to a coworker. If this knowledge would have been of some use to many of your coworkers, just pick one of them to refer to.

<table>
<thead>
<tr>
<th>Company</th>
<th>Respondent examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>“Design ideas for creating a system which would force more project requirement documentation before software engineers could begin programming”</td>
</tr>
<tr>
<td></td>
<td>“I discovered a compiler switch that potentially could increase the speed of execution of certain numerical codes”</td>
</tr>
<tr>
<td>3</td>
<td>“When building a . . . our day shift has a flow which allows us to get further on building the . . .”</td>
</tr>
<tr>
<td></td>
<td>“Installing a . . . (which has to be heated) prior to installing a seal in the forward shaft. This allows time for the remaining shaft to cool while installing the seal in the forward shaft”</td>
</tr>
<tr>
<td>4</td>
<td>“I discovered that if pallets of product were turned a certain way, more product could be put on the cars”</td>
</tr>
<tr>
<td></td>
<td>“Some containers were not being stacked properly. Thus, sometimes they would fall into each other and spill. Through my observations, I came up with a plan to properly align the containers”</td>
</tr>
</tbody>
</table>

\(^4\) Note that alternative forms of the survey were used for attempted/withheld knowledge sharing incidents.
Appendix B. Latent variable correlations correcting for common method variance

<table>
<thead>
<tr>
<th></th>
<th>Knowledge sharing attempt (KSA)</th>
<th>Motivation to share (MS)</th>
<th>Time availability (TA)</th>
<th>Ability to share (AS)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Not correcting for CMV</td>
<td>Correcting for CMV</td>
<td>Not correcting for CMV</td>
<td>Correcting for CMV</td>
</tr>
<tr>
<td>Knowledge sharing attempt (KSA)</td>
<td>1.00</td>
<td>1.00</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Motivation to share (MS)</td>
<td>.77*</td>
<td>.77*</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Time availability (TA)</td>
<td>.06</td>
<td>-.13</td>
<td>-.06</td>
<td>.05</td>
</tr>
<tr>
<td>Ability to share (AS)</td>
<td>.41*</td>
<td>.40*</td>
<td>.47*</td>
<td>.41*</td>
</tr>
</tbody>
</table>

* $p \leq .01$.

Appendix C. Scale descriptions and reliability statistics

<table>
<thead>
<tr>
<th>Scales and associated indicators</th>
<th>Scale anchor points</th>
<th>Standardized factor loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge sharing attempt (Mean = 5.63, S.D. = 1.59)</td>
<td>Strongly disagree (1)–Strongly agree (7)</td>
<td>Overall Company 2 Company 3 Company 4</td>
</tr>
<tr>
<td>KSA</td>
<td>Cronbach’s $\alpha$: .84; AVE: .76</td>
<td></td>
</tr>
<tr>
<td>I attempted to teach this knowledge to my coworker</td>
<td>KSA1 1–7</td>
<td>.90 .95 .84 .97</td>
</tr>
<tr>
<td>I made an effort to transfer this knowledge to my coworker</td>
<td>KSA2 1–7</td>
<td>.90 .92 .82 .90</td>
</tr>
<tr>
<td>I tried to share this knowledge with my coworker</td>
<td>KSA3 1–7</td>
<td>.82 .82 .75 .88</td>
</tr>
<tr>
<td>Motivation to share (Mean = 5.92, S.D. = 1.18)</td>
<td>Cronbach’s $\alpha$: .75; AVE: .56</td>
<td></td>
</tr>
<tr>
<td>I had no intention to share this knowledge with my coworker</td>
<td>MS1 1–7</td>
<td>.63 .64 .69 .70</td>
</tr>
<tr>
<td>I was motivated to share what I know with my coworker</td>
<td>MS2 1–7</td>
<td>.86 .87 .82 .95</td>
</tr>
<tr>
<td>I really wanted to share this knowledge with my coworker</td>
<td>MS3 1–7</td>
<td>.73 .72 .68 .71</td>
</tr>
<tr>
<td>I meant to share this knowledge with my coworker</td>
<td>MS4 1–7</td>
<td>– – – –</td>
</tr>
<tr>
<td>Time availability (Mean = 4.83, S.D. = 1.26)</td>
<td>Cronbach’s $\alpha$: .73; AVE: .50</td>
<td></td>
</tr>
<tr>
<td>I have little free time to allocate during work</td>
<td>TA1 1–7</td>
<td>.78 .85 .78 .83</td>
</tr>
<tr>
<td>I am usually under high time pressure at work</td>
<td>TA2 1–7</td>
<td>.52 .67 .54 .56</td>
</tr>
<tr>
<td>The extra time I have available at work is limited</td>
<td>TA3 1–7</td>
<td>.78 .73 .79 .81</td>
</tr>
<tr>
<td>Ability to share (Mean 6.19, S.D. = .99)</td>
<td>Cronbach’s $\alpha$: .72; AVE: .56</td>
<td></td>
</tr>
<tr>
<td>I had the ability to transfer this knowledge to my coworker</td>
<td>AS1 1–7</td>
<td>.63 .63 .61 .62</td>
</tr>
<tr>
<td>I had the means to share this knowledge with my coworker</td>
<td>AS2 1–7</td>
<td>.78 .82 .78 .81</td>
</tr>
<tr>
<td>I was capable of sharing this knowledge with my coworker</td>
<td>AS3 1–7</td>
<td>.83 .96 .80 .91</td>
</tr>
</tbody>
</table>

* Scores on this item were inverted $(8 - x)$ prior to analysis.

References


Siemsen, E., Balasubramanian, S., Roth, A.V., in press. Incentives that induce task-related effort, helping, and knowledge sharing in workgroups. Management Science.


