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SOCIAL IDENTIFICATION IN MULTITEAM SYSTEMS: THE ROLE OF DEPLETION AND TASK COMPLEXITY

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Organizations construct multiteam systems to address complex challenges that require the joint efforts of multiple teams. Taking an uncertainty perspective and integrating social identity theory with depletion research, we theoretically and empirically examine the role of social identification in multiteam system performance. In contrast to general assumptions in the literature regarding the need to develop identity at the highest level of a system, we argue that within a multiteam system, identification with that system negatively relates to multiteam system performance, whereas identification with the component team positively relates to multiteam system performance. Our uncertainty perspective suggests that identification with the multiteam system introduces uncertainty regarding the appropriate norms and interdependencies in the system, which leads to more depletion, and consequently lower system performance. Conversely, identification with the component team offers less uncertainty, resulting in less depletion and higher multiteam system performance. Thus, our integrated theoretical framework suggests that depletion mediates the negative effects of multiteam system identification and the positive effects of component team identification on multiteam system performance. Moreover, consistent with our uncertainty perspective, the indirect effect of identification on multiteam system performance via depletion is stronger when task complexity is high and weaker when task complexity is low.

Many critical tasks in business and society have increased in scope and complexity to such an extent that they are beyond the managing capacity of a single team, resulting in an increased use of multiteam systems (Mathieu, Hollenbeck, van Knippenberg, & Ilgen, 2017). Multiteam systems are tightly coupled

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networks of two or more interdependent component teams that pursue at least one collective superordinate goal in addition to their component team goals (Mathieu, Marks, & Zaccaro, 2001). Most existing empirical research on multiteam systems has been on systems composed of functionally specialized teams that uniquely contribute to achieving the system's superordinate goal (Luciano, DeChurch, & Mathieu, 2018). Although multiteam systems are similar in many ways to traditional teams and organizations, the large size and functional specialization of multiteam systems provide more resource capacity compared to stand-alone teams, while still providing more flexibility relative to traditional organizations (Davison, Hollenbeck, Barnes, Sleesman, & Ilgen, 2012). As such, multiteam systems are exceptionally well suited for dealing with complex environments (Zaccaro, Marks, & DeChurch, 2012).

Because multiteam systems take on tasks that are novel, highly complex, and involve reciprocal interdependence, planning for these tasks is often difficult; thus, task execution takes place in contexts characterized by high levels of uncertainty (Lanaj, Hollenbeck, Ilgen, Barnes, & Harmon, 2013). Although the role of different degrees of task complexity has so far not been studied in multiteam systems (Luciano et al., 2018), it is likely that higher task complexity exacerbates uncertainty. This uncertainty results from the lack of predictability in the external task environment, as well as the high interdependence within and between component teams that comprise the multiteam system (Zaccaro et al., 2012). Thus, in order to manage these complex tasks, it is imperative that members of multiteam systems allocate their resources efficiently to the demands of their own component team, while at the same time allocating resources to the interdependent needs of the higher-order multiteam system (DeChurch & Zaccaro, 2010). As such, there is need for theory that addresses the puzzle "of building strong teams that must simultaneously function effectively as part of larger systems" (Luciano et al., 2018: 1066).

In general, the literature on traditional stand-alone teams has typically extolled the virtues of high levels of identification for building strong teams (Ashforth, Harrison, & Corley, 2008; Riketta & van Dick, 2005; see also Brewer, 1991; Roccas & Brewer, 2002). Considering the pervasive presence of uncertainty in the multiteam system context, social identification may be a particularly important phenomenon to understand in such systems. Indeed, social identification is an effective way to reduce people's uncertainty in organizational settings, because belonging to a group provides an "identity prototype" that helps one predict how others may react and behave, thereby prescribing what one should think, feel, and do (Chattopadhyay, George, & Lawrence, 2004; Chattopadhyay, Tluchowska, & George, 2004; George & Chattopadhyay, 2005). Strong identification with a social group leads members to adopt the norms and values of that social group and motivates members to invest their resources and effort toward making sure their group fulfills its tasks successfully (Ashforth & Mael, 1989). As such, the typical prescription in the literature on stand-alone teams is that people should identify with their team.

There has been very little theoretical or empirical work on the role of social identity in multiteam systems (Connaughton, Williams, & Shuffler, 2012). However, a natural generalization of the stand-alone team literature to multiteam systems would suggest that system members should identify with the higher-order entity—which in this case is the multiteam system (as proposed by Connaughton et al., 2012; DeChurch & Zaccaro, 2010; Luciano et al., 2018). This would insure that members are willing to invest their resources and effort toward making sure that their multiteam system fulfills its complex mission successfully. On the other hand, extant work has suggested that team identification may promote in-group biases and preferences, which tend to harden the boundaries between teams (e.g., Ashforth & Mael, 1989; Hogg, van Knippenberg, & Rast, 2012). From this perspective, component team identification may hinder cooperation and coordination between the interdependent teams in a multiteam system, and could thus hinder efforts to fulfill the system's larger and complex mission (Connaughton et al., 2012).

There are three reasons, however, for challenging the validity of generalizing this principle from the literature on small stand-alone teams to the multiteam system context. First, multiteam systems provide two nested foci of identification—the team and the multiteam system—and, as others have noted, the literature on multiple identities is sparse and scattered (Ramarajan, 2014). Therefore, it is unclear how multiteam system performance may be impacted by these potential multiple identities. Second, although the multiteam system may serve as an appealing focus of identification, this is an abstract identity prototype that may introduce more uncertainty given the large scope of the system's task and mission. Indeed, the more complex the task of the system, the more system members have to manage multiple sets of norms and interdependencies in this context (Zhu, Tatachari, & Chattopadhyay, 2017). Coping with uncertainty takes up resources and has been shown to be highly depleting (Inzlicht & Schmeichel, 2012; Maranges & Baumeister, 2017), and depletion, in turn, has been found to impair performance (Baumeister & Vohs, 2007; Lanaj, Johnson, & Barnes, 2014). Third, several recent studies on multiteam systems have shown that desirable features of traditional stand-alone teams often turn out to be detrimental when applied to multiteam systems. For example, completely connected communication networks (Davison et al., 2012), team empowerment practices (Lanaj et al., 2013), and shared mental models (Lanaj, Foulk, & Hollenbeck, 2018), which typically benefit small-team performance, actually hurt multiteam system performance. Instead, multiteam system performance tends to benefit in contexts where leaders of component teams act as boundary spanners, when planning is centralized at the leadership team level, and when leadership and component teams have divergent strategic preferences at the outset of planning.

Thus, the purpose of this work is to develop and test a theoretical model that explains the role of social identity in the complex context of multiteam systems. Drawing from an uncertainty perspective (Chattopadhyay et al., 2004a, 2004b; Fielding & Hogg, 1997), we examine the implications that identification with the team and multiteam system have for depletion as well as multiteam system performance, and how task complexity moderates these effects. We argue that identifying with the rather abstract identity prototype of the multiteam system requires members to invest resources in dealing with uncertainty regarding appropriate norms and interdependencies, which draws on their limited cognitive resources (Muraven & Baumeister, 2000).

Indeed, although one of the primary goals of identification is to reduce uncertainty (Hogg & Abrams, 1993), uncertainty management theory suggests that relying on an uncertain target (e.g., using a multiteam system as a source of identification) to manage uncertainty in one's environment "would be simply to exchange one uncertainty for another, and this would not be a very effective way of resolving discomfort of the sort caused by uncertainty" (Lind & Van den Bos, 2002:199; see also Matta, Scott, Colquitt, Koopman, & Passantino, 2017). Thus, we posit that system members who identify strongly with the multiteam system are likely to experience more uncertainty-induced depletion, which ultimately—and unintentionally—may compromise the success of the system. In contrast, because component teams serve as a more concrete, less uncertain prototype for identification, we suggest that identifying with the component team allows system members to manage uncertainty and to apply their resources more fully to their team's specialized task, which is likely to drive the success of the system. Finally, we argue that higher task complexity introduces more uncertainty into the multiteam system context (e.g., Tushman & Nadler, 1978), which is likely to exacerbate the relationships between identification, depletion, and multiteam system performance.

Our work makes four key contributions to theory and research. First, we challenge the consensus within the emerging multiteam system literature suggesting that multiteam system identification may help, and team identification may hurt, system performance (see Connaughton et al., 2012; DeChurch & Zaccaro, 2010). In contrast, we theoretically and empirically demonstrate that the opposite is true. That is, it is better for the performance of the overall system if members identify strongly with their component team rather than with the multiteam system. These findings are aligned with recent others showing that knowledge from team-level research may not always generalize to multiteam systems (Davison et al., 2012; de Vries, Hollenbeck, Davison, Walter, & Van der Vegt, 2016; Lanaj et al., 2013). Second, by taking an uncertainty perspective and integrating research on depletion, we extend the social identity literature by increasing our understanding of the intergroup relationships found within multiteam systems (cf. Hogg et al., 2012; Richter, West, van Dick, & Dawson, 2006). Third, by applying an uncertainty perspective to the multiteam system context (Chattopadhyay et al., 2004a; Wagoner & Hogg, 2017), we respond to the recent call to explicate the role that task complexity plays in the multiteam system context (Luciano et al., 2018). Finally, our study is the first to recognize the role of resource depletion in multiteam systems, documenting how the depletion of members' resources can have a profound impact on the performance of the system (Alquist, Baumeister, McGregor, Core, Benjamin, & Tice, 2018; Baumeister, Bratslavsky, Muraven, & Tice, 1998; Baumeister & Vohs, 2007).

THEORY AND LITERATURE REVIEW

Multiteam systems are increasingly popular in organizational contexts because they are able to meet the demands of complex, uncertain, and highly turbulent environments (Zaccaro et al., 2012). The fundamental attributes of multiteam systems are their large scope, their modular structure, and the coordination required among multiple functionally specialized component teams in the pursuit of a common goal (Luciano et al., 2018; Marks, DeChurch, Mathieu, Panzer, & Alonso, 2005). Although the goals of component teams inform the multiteam system goal hierarchy, at times component teams may pursue different team-level goals (Lanaj et al., 2018; Marks et al., 2005). Typically, the boundary-spanning team (e.g., the leadership team) has the specific task of managing coordination and conflict via boundary-spanning efforts, while the other functionally interdependent component teams each have unique and specialized roles. Thus, performance in multiteam systems is often nonadditive in nature, and failure on the part of one component team threatens the success of other component teams and the system as a whole (Davison et al., 2012). This interdependence of teams within multiteam systems becomes an important boundary condition when it comes to generalizing theoretical conclusions from stand-alone teams to multiteam systems (Davison et al., 2012; de Vries et al., 2016), and may also extend to the role of social identification.

Social Identity Theory

Social identity theory, the dominant theoretical perspective in research on intergroup dynamics, is based on the idea that people perceive themselves and others in terms of their membership in a social group (or groups)—their social identity (Tajfel & Turner, 1979; Turner, Hogg, Oakes, Reicher, & Wetherell, 1987). People tend to categorize themselves and others into groups based on group prototypes (fuzzy sets of attributes, perceptions, attitudes, and behaviors) that render groups distinctive. Identification occurs through the incorporation of these group prototypes into one's social identity (Chattopadhyay et al., 2004b; Fielding & Hogg, 1997). The stronger members' degree of identification with a particular social group, the more they define and categorize themselves in terms of the prototype of that social group. One of the major reasons people are motivated to identify with groups is because it reduces uncertainty. That is, the group that people identify with provides them with guidance on the appropriate values, attitudes, and behaviors that they should display in a certain context (Hogg & Abrams, 1993; Hornsey & Hogg, 2000). Accordingly, higher levels of group identification make people want to adhere more to the norms and values of that group (Ashforth & Mael, 1989).

Whether people actually act in terms of a given social identity depends on identity salience; that is, the probability that a given identity will be invoked (Ashforth & Johnson, 2001). Certain contexts prime a certain identity via conscious or unconscious cues congruent with the activated identity (Ashforth et al., 2008). Activation of an identity is critical because people often belong to several different groups at the same time (professional roles, workgroups, regions, or organizations). Accordingly, "current research is moving away from the idea of a single salient identity" toward multiple identities paradigms (Ramarajan, 2014: 599). Indeed, dual identity research introduced the idea that two identities can be salient simultaneously. This research examined the influence of an (external) emphasis on a subgroup identity (e.g., Black or White, male or female), on a shared, superordinate identity (e.g., nation of origin, university affiliation), or on both of these identities (Gaertner et al., 1999; Gaertner, Dovidio, & Bachman, 1996). However, little is known about what happens when multiple identities are both naturally in place, and hence simultaneously salient (Ashforth et al., 2008; Ramarajan, 2014).

Social Identification in Multiteam Systems

Although typically considered an individual psychological state, over time in collective settings, the identification tendencies of individuals tend to converge (see Dietz, van Knippenberg, Hirst, & Restubog, 2015; Van Der Vegt & Bunderson, 2005), thus setting the stage for multiteam system-level identification. This convergence is facilitated by a shared understanding of the collective reality that members develop as part of their multiteam system life (Mael & Ashforth, 1992; Morgeson & Hofmann, 1999). Repeated interactions, shared experiences, and collective incentives then reinforce this convergence even further. Based on this convergence, and in line with common practice in social identity research (Dietz et al., 2015; Somech, Desivilya, & Lidogoster, 2009; Van Der Vegt & Bunderson, 2005), we consider both the influence of team and multiteam system identification on multiteam system performance from the perspective of psychological states that are shared at the multiteam system level.

Multiteam systems offer multiple foci of identification, and both the component team and multiteam system may be simultaneously salient, as they meet the three requirements that trigger simultaneous salience as identified by Ashforth and Johnson (2001). First, identities in a multiteam system form a means–end chain between the higher-order multiteam system identity and the lower-order group identity, where the team is "nested" in the multiteam system (Roccas & Brewer, 2002). Due to the nested structure and means–end chain, members' efforts simultaneously contribute to both the component team goals and the overall goal of the multiteam system, which makes it more likely that working in the system will make both identities simultaneously salient. Second, in the interdependent context of the multiteam system, both the team and the multiteam system identities are important, which makes both identities relevant to the multiteam system context. Third, the process of working closely together cues both team and multiteam system identities—either sequentially or simultaneously in such systems.

Still, although both the component team and the multiteam system identity may be simultaneously salient in the multiteam system context, members of different systems can differ in the degree to which they come to see the component team and multiteam system as a basis for self-definition. Strong identification with the (higher-order) multiteam system may emerge because members of a multiteam system share responsibility for outcomes or because the task environment requires members to work together interdependently. Indeed, the social identity and work design literatures have demonstrated that people want to be part of something larger than themselves, and the large scope of the system's mission is likely to have a strong appeal (Hackman & Oldham, 1976; Reid & Hogg, 2005; Zhu et al., 2017). Despite being a plausible target of identification, however, the multiteam system may offer a rather impersonal base of identification because its impact on its members tends to be indirect and defined in relatively general terms (e.g., Ashforth, Rogers, & Corley, 2011; George & Chattopadhyay, 2005). Moreover, although individuals use social identification to mitigate uncertainty (Hogg, 2009), which should be a particularly salient objective in the uncertain multiteam system context, identifying with the abstract prototype of the system may ironically introduce uncertainty.

Strong component team identification may emerge because all component teams hold specialized skills, capabilities, and functions that uniquely contribute to achieving the overarching mission of the system, with the leadership team managing coordination between these functionally interdependent teams (Davison et al., 2012). Generally, lower-order foci of identification offer a more concrete base of identification because the team has specialized concrete objectives and affects the individual more directly and immediately. The interactions with other members of the component team provide people with clarity, structure, and contextual meaning, as well as a sense of belonging (Mael & Ashforth, 1992). Strongly identifying with the component team reduces uncertainty about who one is, how one should behave as a member of the component team, and how others in the component team will likely behave.

Examining the strengths of these multiple, simultaneously salient identities in a multiteam system context is important because social identity research in organizational settings has largely focused on within-group processes and outcomes (Ashforth et al., 2008; Riketta & van Dick, 2005). The scarce conceptual work that has discussed the role of identification in multiteam systems has generalized from team-level social identification research to multiteam systems, implying that the higher-order identity is always more important when it comes to system performance. That is, just as team identity prevents individuals embedded in stand-alone teams from focusing on individual instead of team interests (Ashforth & Mael, 1989; Riketta & van Dick, 2005), it has generally been argued that multiteam system identity will prevent individuals embedded in multiteam systems from focusing on team instead of system interests (Connaughton et al., 2012; DeChurch & Zaccaro, 2010).

In contrast to these generalizations, we integrate social identity theory with an uncertainty perspective to explicate how component and multiteam system identity impact system performance via depletion. We propose that system members should identify most strongly with the smaller collective (i.e., the component team) for the multiteam system to be most effective. In the following sections we lay out our hypotheses, focusing on depletion as a mechanism that mediates, and task complexity of the system as a contextual feature that moderates, the relationships between both foci of identification and multiteam system performance.

Identification, Multiteam System Performance, and the Mediating Effects of Depletion

The social identity literature has shown that higher levels of identification in a collective make people want to adhere to the norms and values of that collective (Ashforth & Mael, 1989; Riketta & van

Dick, 2005). When system members identify strongly with the system, it is likely that they are motivated to work on the system's tasks, making it a norm in the system that everyone thinks and acts in accordance with the system. In contrast, when system members identify strongly with their component team, it is likely that all members of the system are motivated to pursue the tasks of their component team, making it a norm in the system that everyone thinks and acts in accordance with their respective component team. These differences in attention, motivation, and effort are critical because individuals have a limited set of cognitive resources that can be depleted (Baumeister et al., 1998; Kruglanski, Bélanger, Chen, Köpetz, Pierro, & Mannetti, 2012). Depletion tends to be harmful, because once attention and energy are depleted, individuals find complex work activities more demanding, are more susceptible to nontask distractions, and perform worse (Baumeister & Vohs, 2007; Lanaj et al., 2014).

When it comes to depletion, we propose that the process of identification with a multiteam system is likely more cognitively taxing compared to identification with a component team, for two reasons. First, although a multiteam system is an appealing focus of identification due to its large scoped goals, it offers a rather abstract identity prototype, because the system is large with specialized teams, but has very little standardization, institutionalized procedures, norms, or formal rules (Davison et al., 2012). As such, this prototype provides only a general sense of why and how to perform certain tasks, compared to the proximal and specialized task of the component team, and thereby introduces, or at least leaves, uncertainty regarding both appropriate norms and goals and knowledge of other system members' activities and skills (George & Chattopadhyay, 2005). Accordingly, members have to invest significant resources into gathering and processing information to flesh out the specifics of identity-prototypical behavior, coordination demands, and intense interdependencies. Such uncertainty-reduction work is likely to take its toll on system members' information processing capabilities, and is likely to be resource depleting (Kruglanski et al., 2012; Schmeichel, Vohs, & Baumeister, 2003).

Second, strong multiteam system identification makes members more attuned to the system's uncertainty. Although one of the primary goals of identification is to reduce uncertainty (Hogg & Abrams, 1993), identifying with a multiteam system is likely to leave or even exacerbate depletion-inducing uncertainty. Indeed, uncertainty management theory has noted that relying on an uncertain target (e.g., using a multiteam system as a source of identification) to manage uncertainty in one's environment would simply be exchanging one uncertainty for another (Lind & Van den Bos, 2002; Matta et al., 2017), exacerbating (rather than mitigating) the deleterious effects of uncertainty. Importantly, one of the harmful effects of uncertainty is that coping with it is cognitively effortful and depleting (Alquist et al., 2018; Welsh & Ordóñez, 2014).

In contrast, the component team offers a less abstract, more specialized, and differentiated prototype that aligns well with the specialized task of the team. This prototype is also reinforced over time by repeated intrateam interactions (e.g., Ashforth et al., 2011; George & Chattopadhyay, 2005). The component team prototype can serve as an effective means for managing uncertainty in this context, mitigating the detrimental outcomes associated with uncertainty—such as depletion. Indeed, communication and interpersonal interactions in the component teams involve people who are more proximally located, who share the same specialization, and who engage in similar tasks, all of which make fleshing out the prescribed component team's prototypical behavior, coordination demands, and interdependencies more certain and less depleting (e.g., Chattopadhyay et al., 2004a; Wagoner & Hogg, 2017). In addition, the component teams are embedded in a larger structure that includes a leadership team whose specific function is to absorb uncertainty and to coordinate efforts across the component teams (Davison et al., 2012). As a result, strong identification with the component team is less depleting, allowing system members to focus their attention and effort on executing their teams' specialized role that contributes to the overarching goal of the system.

It is important to point out that we are not arguing that team members with high multiteam system identification purposefully deplete their *own* resources or intentionally act to *harm* the multiteam system. Rather, as members identify more strongly with an entity, the norms of prototypical behavior become stronger, regardless of whether these norms are most productive (Fielding & Hogg, 1997). Additionally, recent research has suggested that multiteam systems struggle with learning because they may not reflect sufficiently (Lanaj et al., 2018). Moreover, despite their best intentions, system members may not always know the "big picture" that is known by the leadership team, and may thus be in a poor position to recognize all the coordination and sequencing requirements at the multiteam system level (Bunderson & Boumgarden, 2010).

Accordingly, we hypothesize that when members of the system identify strongly with the multiteam system, they are likely to experience resource depletion, thereby unwittingly harming the performance of the larger multiteam system that they are trying to support. Depletion due to identification with the system hurts multiteam system performance because depletion makes it more difficult for members to maintain effort and adequately perform their tasks (Baumeister & Vohs, 2007; Lanaj et al., 2014). In addition, it limits the resources available for accomplishment of the component team's own specialized and nonsubstitutable task (e.g., Baumeister et al., 1998; Kanfer & Ackerman, 1989; Kruglanski et al., 2012). In contrast, we hypothesize that when members of the multiteam system identify strongly with their component team, this will ensure that they have more resources available for their component team tasks and consequently improve the performance of the multiteam system. We hypothesize the following:

Hypothesis 1a. There is a negative relationship between multiteam system identification and multiteam system performance.

Hypothesis 1b. There is a positive relationship between component team identification and multiteam system performance.

Hypothesis 2a. Depletion mediates the negative relationship between multiteam system identification and multiteam system performance.

Hypothesis 2b. Depletion mediates the positive relationship between component team identification and multiteam system performance.

The Moderating Effects of Task Complexity

Our integrated theoretical perspective informed by uncertainty management theory and research on multiteam systems suggests that the effects of both types of identification—identifying with the multiteam system and the component team—on multiteam system performance (in terms of both the total effects and the indirect effects via depletion) may be contingent upon the complexity of the system task. As we noted earlier, multiteam systems deal with tasks that are more complex and larger in scope relative to the tasks traditionally assigned to standalone teams (Zaccaro et al., 2012). Still, as Luciano et al. (2018) noted, multiteam system tasks vary in complexity from system to system. Yet, to date, no multiteam system study has investigated the role of task complexity or directly manipulated task complexity as part of its research design. This is a surprising omission, particularly given the important yet varied nature of missions undertaken by multiteam systems (e.g., Lanaj et al., 2018). In this study, we examine task complexity directly because our integrated theoretical framework suggests that it may moderate the effects of identity on performance (both the total effects and the indirect effects via depletion).

Generally, scholars have treated task complexity as a unidimensional construct that originates from three distinct but related task demands: (a) component complexity, (b) coordination complexity, and (c) dynamic complexity (Horwitz & Horwitz, 2007; Vashdi, Bamberger, & Erez, 2013; Wood, Mento, & Locke, 1987). *Component complexity* refers to the number of different information cues or activities that make up a task. *Coordinative complexity* refers to the types of relationships between task inputs and products, such that tasks low in coordinative complexity require sequential interdependence rather than reciprocal interdependence. Finally, *dynamic complexity* refers to tasks where the skills or knowledge required for task execution vary due to changes in the required activities, information cues, or relationships between task inputs and products. Together, these three task demands combine to distinguish simple from complex tasks.

When task complexity of the multiteam system increases, this introduces more uncertainty to members because it becomes harder for them to predict (a) the information cues that are likely to be most relevant, (b) the precise relationship between task inputs and products, and (c) potential changes in the task environment over time. Our integrated theoretical framework suggests that although social identification serves to mitigate uncertainty (Hogg, 2009), complex tasks introduce uncertainty for subunits that work together because complex tasks pose greater information processing requirements and cognitive work on members of interdependent units (Tushman & Nadler, 1978). Hence, the greater uncertainty associated with an increasingly complex multiteam system task is likely to enhance the effects of each focus of identification on depletion, and ultimately multiteam system performance.

When multiteam system identification in the system is high, members will invest significant resources and information processing capabilities to flesh out the specifics of identity-prototypical behavior, coordination demands, and interdependencies *within* *the system.* Here, members' information processing will likely focus on the many different information cues *in the system*, changes in the task environment *of the system,* and the reciprocal relationship between task inputs and products *within the system.* This is likely to take its toll on members' information processing capabilities (e.g., Tushman & Nadler, 1978) and will likely be highly depleting. Thus, the increased complexity of the system is likely to enhance the depletion drawbacks of high multiteam system identification for system performance.

In contrast, when component team identification in the system is high, members will focus on fleshing out the specifics of identity-prototypical behavior, coordination demands, and interdependencies *in their component team*. Here, members' information processing will likely focus on the different information cues *in their team*, changes in the task environment *of their team*, and the reciprocal relationship between task inputs and products *within their team.* As such, members are likely to focus their attention and effort on executing their team's proximal and specialized role, where the leadership team will focus on its own specialized responsibilities of coordinating efforts across component teams (Davison et al., 2012). Thus, the benefits of high component team identification for system performance will increase when complexity is high.

Alternatively, when task complexity is low, this reduces the cognitive burden associated with the task itself, making the role of identification in managing uncertainty and the detrimental outcomes associated with uncertainty—in our case, resource depletion—less critical. That is, when task complexity is relatively low, team members are far from approaching the limits of their resources and information processing capabilities, and thus less likely to experience high levels of performance-inhibiting depletion (Schmeichel et al., 2003). Consequently, the downside of strong multiteam system identification (and the upside of strong component team identification) are less pronounced (in terms of depletion and subsequent multiteam system performance) when the task of the multiteam system is low in complexity. We hypothesize that:

Hypothesis 3a. Task complexity moderates the negative relationship between multiteam system identification and multiteam system performance, such that the negative total effect of multiteam system identification on multiteam system performance is stronger when the task is more complex and weaker when the task is less complex.

Hypothesis 3b. Task complexity moderates the positive relationship between component team identification and multiteam system performance, such that the positive total effect of team identification on multiteam system performance is stronger when the task is more complex and weaker when the task is less complex.

Hypothesis 4a. Task complexity moderates the mediated relationship between multiteam system identification and multiteam system performance, such that the negative indirect effect of multiteam system identification on multiteam system performance via depletion is stronger when the task is more complex and weaker when the task is less complex.

Hypothesis 4b. Task complexity moderates the mediated relationship between component team identification and multiteam system performance, such that the positive indirect effect of team identification on multiteam system performance via depletion is stronger when the task is more complex and weaker when the task is less complex.

METHOD

Participants and Procedures

We collected data from a sample of 289 undergraduate students attending a large university in the United States. The students we recruited were part of a select group given the opportunity to be involved in activities within the business college early in their college career. Participants were enrolled in a class on teamwork and competed in a series of highly interactive, team-based computer simulations throughout the year as part of this program. In year one of the program 155 of the students participated, and in year two of the program 134 students participated. The average participant age was 18.08 years (SD = .37), and 49.1% of the sample was male (50.9% was female).

The simulation in which the students participated was called Leadership Development Exercise (LDX), which is a team-based exercise widely used in the multiteam systems literature. We composed teams and multiteam systems in a manner that followed the proposed temporal sequencing suggested for programs or interventions designed to increase the salience of multiple identities (see the ASPIRe model by Haslam, Eggins, and Reynolds [2003]). This sequence is used to, first, allow members to engage in activities that promote (sub)group identity, and then bring different groups together for activities in which they can build a superordinate identity. We did this by initially assigning participants of each year to a four- to five-person autonomous team and training these teams to play the LDX simulation as a stand-alone team. Each team engaged in the same task, received the same training and engaged in the same two simulations as a stand-alone team over the course of two months. During these team activities, teams knew that they were working toward becoming and working as a multiteam system. Only after these two months did each team sign up for a date to participate with two other teams in a multiteam system performance episode. At this time, the teams informally knew members of other teams because they interacted with them in several classes, their university program, volunteering activities, and the dorm where all participants lived during the year in which they participated in this study.

The multiteam system roles for each team were assigned based upon their relative performance during their training sessions, with the highest scoring team performing as the Leadership Team (leadership roles), the second highest scoring team performing as the Support Team (intelligence roles), and the lowest scoring team performing as the Point Team (operations roles). We held the method for assigning teams to roles constant across the entire study and across conditions so that this would not confound the results of the study in any way. Over the course of four months, the teams that started as stand-alone teams came back three more times to the laboratory to perform as part of their multiteam system. Thus, each of the 22 multiteam systems participated in three 10-round LDX simulations over the course of approximately four months. Each performance episode lasted about two hours and the task required that the multiteam system members make a large number (over 5,000) of structured decisions, all of which were time-stamped and captured by the software. In terms of the Multidimensional Model of Team Types proposed by Hollenbeck, Beersma, and Schouten (2012), these teams were moderate in temporal stability, and high in authority differentiation and skill differentiation.

We chose to have each of the 22 multiteam systems participate in three performance episodes for three reasons. The first and primary reason was our manipulation of task complexity. In the first two sessions we used two different, low-complexity simulation grids to create a stable baseline.[1] Then, in the third session, we used another, high-complexity simulation grid (Wood, 1986). Second, an added benefit of this repeated measures approach is that each multiteam system serves as its own control when testing for the effects of manipulated task complexity, thus increasing the precision of our design. The third reason is that this approach tripled the number of observations. This is critical considering the widely recognized difficulty in attaining an adequate sample size in multiteam systems research (Davison et al., 2012). As we note in more detail below, we statistically accounted for the non-independence in observations created by our research design. Overall, we nested the 289 research participants in 66 four- to five-person component teams, and then further nested these 66 component teams in 22 multiteam systems. Those 22 multiteam systems (level 2 observations) each participated in three simulations, resulting in 66 performance episodes (level 1 observations).[2]

Our method of creating teams and multiteam systems employed all four methods used in the literature to increase the salience of an identity (Hogg & Turner, 1985; Turner et al., 1987; van Dick, Wagner, Stellmacher, & Christ, 2005). First, we highlighted both identity categories in the instructions preceding and during each of the three simulations, and in the surveys participants filled out pre- and post-performance episode (cf. Hogg & Turner, 1985). Second, we ensured that both the team and multiteam system were engaged in a context with other relevant and comparable teams and systems (cf. Turner et al., 1987). To do so, we discussed the progress of all multiteam systems and component teams in the related teamwork class. Third, we created some competition between multiteam systems and between component teams of the same type across multiteam systems by providing specific rank order comparisons in performance levels as part of

[1] The mean difference in performance between sessions 1 and 2 was not significant (mean difference = 21.45, $t[42] = 1.69$, n.s.), which alleviates concerns regarding learning or carryover effects of practice with our within-subject design.

[2] Due to the level 1 ($n = 66$) and level 2 ($n = 22$) sample sizes, some may have concerns over the statistical power of our analyses. To address this concern, we estimated the power of our tests in the primary model, using the program PinT (Power in Two-Level Designs) (based on calculations derived by Snijders & Bosker, 1993). This program provides specifically tailored guidance on the choice of sample sizes in two-level multilevel research. These tests revealed that the average power for detecting the effects examined here was .74 (range = .51 −.91), which is near the typical recommended level of power of .80. Given our interest in level 1 regression parameters and standard errors, our sample size is unlikely to result in bias in terms of the estimation of our models or Type I error rate (e.g., Hox, 2013; Maas & Hox, 2005).

the teamwork class following each session. Fourth, we provided nominal prize money for being the best component team type or the best multiteam system. These cash prizes were small, and consistent with monetary rewards in other identification studies (e.g., Dovidio, Gaertner, & Validzic, 1998; Gaertner et al., 1999; Gleibs, Täuber, Viki, & Giessner, 2013).

Task

As noted earlier, we used the LDX, a computer-based simulation that was codeveloped by the United States Air Force and a large research-oriented university, to test our study hypotheses (see Davison et al., 2012; Lanaj et al., 2013; Lanaj et al., 2018). LDX involves managing remotely piloted aircrafts (RPAs) to search for, identify, and engage eight different enemy targets. The dynamic LDX environment used in our study required teams to discover and engage both hidden and unhidden targets on a 16×16 game grid. The simulation included a series of 10 rounds, consisting of five phases—*staff planning*, *director planning*, *commander planning*, *execution*, and *critique or analyze*.

The objective of the multiteam system in the simulation was to maximize points by deploying operational RPAs and intelligence assets to find and destroy all types of targets without losing RPAs or having the multiteam system's base attacked. After each decision round, the multiteam system received performance feedback as members were engaged in the task, as they saw and heard when they hit targets, or as they were attacked (both visible and audible cues were provided), so that they could act on those cues in the next decision round. During the simulation, members could see how many points they had scored as a system but did not know their relative performance for that session compared to other multiteam systems or other component teams. It was not until after all multiteam systems had participated in a full session of the simulation that it could be determined (both by us and by the participants) who was the best multiteam system and who were the best component teams in that session.

Although new to the context of identity salience research, LDX offers an engaging, complex, and interactive setting that is suitable for the study of social identity in a laboratory setting (cf. Dovidio et al., 1998; Gaertner et al., 1999; Hornsey & Hogg, 2000). First, the simulation, although laboratory-like, has face validity because it involves counterterrorism efforts and RPAs that are constantly in the news, as well as television and motion pictures (see Gavin Hood's 2015 movie *Eye in the Sky*). Second, individuals and teams must collaborate for at least two hours in the same room where there is interdependence both within and between teams. Third, as Davison and colleagues (2012) noted, this task mirrors the activities and processes described in the Marks, Mathieu, & Zaccaro (2001) episodic model of team processes.[3]

Multiteam System Structure and Team Roles

Each multiteam system was composed of three component teams: (a) the Support Team (intelligence), (b) the Point Team (operations), and (c) the Leadership Team. The Support Team used four different types of intelligence assets to gather and provide information about the location of all enemy targets. The Point Team used four different types of RPAs to find and engage enemy targets across the game grid. Multiteam systems earned points for successfully engaging targets, but lost points if RPAs were destroyed or the base was hit. Each of the four or five staff members in a Support and Point team was responsible for their own specialized role. All operations and intelligence assets were deployed during the *staff planning phase*.

The Leadership Team consisted of four roles (commander, vice commander, director of operations, director of intelligence) and was responsible for overviewing all activities in the multiteam system. During the *director planning phase*, the director of operations and director of intelligence had responsibility to adjust or edit the asset deployments made by the Point and Support Teams. In the *commander planning phase*, the commander was responsible for final changes to all RPA and intelligence asset deployments. The actual deployments and results of all of those decisions were shown in the *execution phase.* Finally, in the *critique or analyze phase,* the vice commander transferred new information to, and updated, the Common

[3] That is, "teams were given an initial intelligence briefing at the start of the performance episode and were allowed 10 minutes to formulate a strategy (i.e., a transition phase) prior to engaging in the 10-round preprogrammed scenario. Each round consisted of a sub-episode during which assets were deployed and missions enacted (i.e., activities fitting Marks et al.'s definitions of coordination, team monitoring, and backup) and a sub-episode during which feedback was received and the environmental situation analyzed (i.e., activities fitting Marks et al.'s definitions of system monitoring and monitoring progress toward goals)" (Davison et al., 2012: 814).

Operational Picture (COP). The COP recorded information provided by the intelligence staff members to track enemy target movements and to record destroyed targets.

Task Complexity Manipulation

Drawing from Wood's (1986) definition of task complexity, we manipulated task complexity by changing the game grid in the third and final simulation. We used a manipulation that had implications for all three demands that determine task complexity: component complexity, coordinative complexity, and dynamic complexity. Specifically, instead of having the typical fixed set of eight defined enemy targets, in the high-complexity condition we introduced four new unknown enemy target categories. In total, we added 22 unknown enemy targets (from four different unknown enemy target categories) to the game grid, thus increasing task complexity. Determining the correct classification of an unknown enemy target required team members to (a) track the target over time to determine whether it was mobile or fixed, (b) identify what it took to successfully engage the target, and (c) track the points gained for successfully engaging the target. In terms of the conceptual definition of complexity, this operationalization increased (a) the number of acts needed to successfully execute the task (component complexity), (b) the collaboration requirements across component teams (coordinative complexity), and (c) the need to respond to changes in the task environment (dynamic complexity).

Because we were interested in objective task complexity (rather than participant perceptions of task complexity), we had four LDX experts rate the task complexity of the three game grids used in the three performance episodes (the two low-complexity baseline game grids and the one high-complexity game grid with unknown targets). Specifically, the experts examined each game grid and rated each of Wood's (1986) dimensions of task complexity (i.e., component complexity, coordinative complexity, and dynamic complexity) using the Vashdi, Bamberger, and Erez (2013) assessment of task complexity. The three items were "Relative to other LDX game grids, how complex would you rate this LDX game grid in terms of the number of acts and information cues involved?" "Relative to other LDX game grids, how complex would you rate this LDX game grid in terms of the type and number of relationships among acts and cues?" and "Relative to other LDX game grids, how complex would you rate this LDX game grid in terms of changes in acts and cues and the relationships among them?"

The coefficient α for the three-item measure (averaged across the three game grids) was .98, and a factor analysis revealed that these items all loaded on one factor that explained 98% of the variance in the three items. This evidence supports the consensus that it is best to operationalize task complexity as one unidimensional variable (rather than three separate factors) (e.g., Horwitz & Horwitz, 2007; Vashdi et al., 2013; Wood et al., 1987). It is also consistent with recommendations by Judge and Kammeyer-Mueller (2012) to rely on generalized predictors (e.g., aggregate task complexity) when the dependent variable is a generalized outcome.

The results of the expert ratings showed that the two low-complexity game grids had mean task complexity scores of 2.50 ($SD = 1.00$) and 2.75 ($SD = 1.00$), and the high-complexity game grid (with the unknown targets) had a mean task complexity score of 4.75 ($SD = .50$). Paired-samples t-tests demonstrated that the differences in the means between the high-complexity and the low-complexity game grids were significant ($t[3] = 9.00$, $p < .05$ and $t[3] = 5.55$, $p < .05$, respectively), and no significant difference existed between the means of the two low-complexity game grids ($t[3] = .68$, n.s.). Thus, the results of the paired samples t-tests demonstrated that we successfully manipulated task complexity.

Measures

In line with our theoretical arguments, the central constructs under investigation in this study all reside at the multiteam system level of analysis. Although team identification, multiteam system identification, and depletion were completed by individual team members, in line with past multiteam systems research (DeChurch & Marks, 2006) we provide empirical justification for aggregating individual scores to the multiteam system level for each performance episode. Specifically, following the recommendations of Klein and Kozlowski (2000), we rely on the intraclass correlation $ICC_{(1)}$ and $ICC_{(2)}$ to justify aggregation to the multiteam system level. We also report the interrater agreement index, $r_{wg(j)}$. We assessed team identification, multiteam system identification, and pre-session depletion prior to each multiteam system performance episode and depletion after each performance episode.

Team identification and multiteam system identification. We measured component team identity and multiteam system identity with a modified 8-item version of the Identification with Group Scale from

Roccas Sagiv, Schwartz, Halevy, and Eidelson (2008), including item content that focused on importance of the component team or multiteam system, and on commitment to the component team or multiteam system. Each team member was asked to indicate how closely he or she identified with the component team and the multiteam system to which he or she was assigned prior to beginning each 10-round performance episode. Items used to measure team identification included "I feel strongly affiliated with this subteam" and "It is important to me that others see me as a member of this subteam." Items used to measure multiteam system identification included "I feel strongly affiliated with this organization" and "It is important to me that others see me as a member of this organization," where it was clarified that "organization" in this context meant the multiteam system. All items were measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The coefficient α for component team identification and multiteam system identification was .94 and .95, respectively. Responses were then averaged to create a multiteam system-level variable describing the mean level of team identification and multiteam system identification. We conducted interrater agreement analyses to support aggregation of both identification variables. This is consistent with past work aggregating identification to a higher level (e.g., Dietz et al., 2015; Somech et al., 2009; Van Der Vegt & Bunderson, 2005).

For team identification, because there were three component teams, we first aggregated members' scores to the team level and then took the average of the three team identification scores in the multiteam system as the multiteam system-level variable. The results showed acceptable levels of agreement, allowing us to proceed with the aggregation. More specifically, the evidence suggested (a) agreement on team identification ($ICC_{(1)} = .33$; $ICC_{(2)} = .48$; F-ratio = 1.91, $p < .05$; median $r_{wg(j)} = .94$), and (b) agreement on multiteam system identification ($ICC_{(1)} = .46$; $ICC_{(2)} = .89$; F-ratio = 9.34, $p < .05$; median $r_{wg(j)} = .92$). Agreement on these measures was not surprising considering that the component team and multiteam system members knew each other well (i.e., lived in the same dormitory), were trained together as a team and multiteam system, and experienced working together as a multiteam system (except for the first session).

Multiteam system performance. We used the total number of points earned during the 10-round simulation as the measure of multiteam system performance. We standardized these scores within each of the three performance episodes.

Depletion. Multiteam system depletion was measured using Johnson, Lanaj, and Barnes' (2014) five-item scale (which drew from the Twenge, Muraven, and Tice [2004] measure) prior to each 10-round session (pre-session) and following each 10-round session (end of session). In our depletion model, we controlled for pre-session depletion to assess change in depletion over the performance episode, to assuage concerns over the causal order of the relationship between team and multiteam system identification, and to potentially rule out alternative explanations not attributable to the task (e.g., Glomb, Bhave, Miner, & Wall, 2011; Scott & Barnes, 2011).

At each time point, team members responded to the items using a 5-point scale ranging from 1 = very slightly or not at all to 5 = very much. Example items are "Right now, my mind feels unfocused" and "Right now, it would take a lot of effort for me to concentrate on something." The coefficient α for pre-session and end of session depletion was .95 and .97, respectively. Team member responses were averaged to create a multiteam system-level variable describing the mean level of depletion within the multiteam system. Interrater agreement analyses suggested support for aggregation, allowing us to proceed with aggregation to the multiteam system level ($ICC_{(1)} = .30$; $ICC_{(2)} = .81$; F-ratio = 5.16, $p < .05$; median $r_{wg(j)} = .77$).[4]

Control variable. We controlled for the year of the program because there were slight variations in the program from year to year when it came to recruitment procedures.

Analysis

Due to the multilevel nature of our data (i.e., performance scenarios nested within multiteam systems), we used multilevel path analysis with Mplus 7 (Muthén & Muthén, 2010), although we should note that the inferences regarding all of our hypothesis tests are the same when tested using hierarchical linear modeling (Raudenbush & Bryk, 2002). In our Mplus 7 model, we clustered by multiteam system and controlled for the year in which the multiteam

[4] Although depletion demonstrated strong levels of agreement in our data (LeBreton & Senter, 2008), one reason for some degree of within-multiteam systems disagreement on depletion was that leadership teams had significantly lower levels of depletion relative to the intelligence and operations teams across all multiteam systems (no differences existed between operations and intelligence teams).

system participated. Thus, the level 1 variables included the repeated multiteam system-level observations of team identification, multiteam system identification, multiteam system performance, depletion, and task complexity. The level 2 control variable was the year in which the multiteam system participated in the three performance episodes.

Specifying this model allowed us to account for the nested structure of our data (i.e., performance scenarios nested within multiteam systems). Statistically controlling for nonindependence in multilevel data is important in order to obtain the correct standard error estimates and avoid Type I (Bryk & Raudenbush, 1992; Heck & Thomas, 2000) as well as Type II (Bliese & Hanges, 2004) errors. Because "there is no statistical preference between these various centering options, but rather, the choice needs to be made based on theoretical and conceptual considerations" (Hofmann & Gavin, 1998: 633, see also Enders & Tofighi, 2007), we chose to center our level 1 data on the sample's mean. This was appropriate because our research centers on absolute rather than relative multiteam system social identification (for similar exemplars of this approach, see Joshi, Liao, & Jackson, 2006; Liao & Chuang, 2004; Lin, Law, & Zhou, 2017; Schaubroeck et al., 2012; Tangirala & Ramanujam, 2008). For indices of variance explained, we present a pseudo-R^2 ($\sim R^2$) statistic (Snijders & Bosker, 1999).

Following best practice (e.g., MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002), we included the direct effect when modeling mediation. To test moderated mediation, we followed the recommendations of Preacher, Zyphur, and Zhang (2010) and applied a parametric bootstrap to estimate the significance of the indirect effect at high and low levels of the moderator. Specifically, we tested the indirect effect where the magnitude of the first-stage coefficient was calculated at high (i.e., task complexity = 1; high-complexity manipulation) and low (i.e., task complexity = 0; low-complexity manipulation) levels for task complexity. We constructed bias-corrected confidence intervals (CIs) for the estimated indirect effect at high and low levels of the moderator using a Monte Carlo simulation with 20,000 replications (for examples of a similar procedure, see Koopman, Lanaj, & Scott, 2016; Lanaj et al., 2014). Support for moderated mediation was determined based upon whether the bias-corrected confidence interval (CI) for the index of moderated mediation excluded 0; which equates empirically to the difference between the two conditional indirect effects (Hayes, 2015).

RESULTS

We first conducted multilevel confirmatory factor analyses (CFA) to demonstrate that the substantive constructs in our model were distinguishable from one another. Although prior research has demonstrated that identifications across various levels (e.g., team and organizational identification) are distinct (even when highly correlated [e.g., van Dick, van Knippenberg, Kerschreiter, Hertel, & Wieseke, 2008]), it was important to empirically demonstrate the distinctiveness of team identification, multiteam system identification, and our other substantive constructs at the multiteam system level of analysis. We modeled pre-session depletion and post-session depletion at the within-multiteam system level using item-level indicators. Consistent with its operationalization (Roccas et al., 2008), we modeled each form of identification (team and multiteam system) by specifying two first-order latent constructs (importance of and commitment to the team or multiteam system) as indicators of a second-order identification factor at the within-multiteam system level. Following the recommendations of Cole, Ciesla, and Steiger (2007), we allowed the residuals of items with identical item content to covary.

The results of our multilevel CFA revealed that our proposed within-multiteam system model fit the data well. Specifically, χ^2 (276) = 506.83 ($p < .05$), the comparative fit index (CFI) = .91, the root mean square error of approximation (RMSEA) = .11, and the standardized root mean square residual (SRMR) [within] = .07. All items loaded significantly on their corresponding factor. Importantly, this model fit the data significantly better—$\Delta\chi^2$ (3) = 106.06 ($p < .05$)—than a comparison model that constrained the team identification and multiteam system identification factors to correlate at 1.0 (χ^2 [279] = 612.89, $p < .05$, CFI = .86, RMSEA = .14, and SRMR [within] = .25). Additionally, because of the relatively small sample size, we also reestimated our multilevel CFA model using item parcels to ensure the stability of our estimates (Marsh & Hocevar, 1988). We used three item parcels per construct using the distributed uniqueness strategy (Hall, Snell, & Foust, 1999). The results of our multilevel CFA using item parcels also revealed that our proposed within-multiteam system model fit the data well. Specifically, χ^2 (48) = 94.16 ($p < .05$), CFI = .96, RMSEA = .12, and SRMR [within] = .04. All items loaded significantly on their corresponding factor. Importantly, this model fit the data significantly better—$\Delta\chi^2$ (3) = 176.70 ($p < .05$)—than a comparison model that constrained the team identification and multiteam system identification factors to correlate at

1.0 (χ^2 [51] = 270.86, $p < .05$, CFI = .81, RMSEA = .26, and SRMR [within] = .22). In addition to demonstrating the dimensionality and discriminant validity of all of our measures, these analyses showed that it was best to operationalize team identification and multiteam system identification as distinct constructs.

Descriptive Statistics and Correlations

Table 1 presents the means, standard deviations, and within-multiteam system correlations among the focal study variables (reported at the multiteam system level). We averaged coefficient alphas for the survey variables across the three scenarios of data collection.

Test of Hypotheses

Figure 1 presents the results of the multilevel path analysis testing Hypotheses 1a and 1b. Hypothesis 1a predicted a negative relationship between multiteam system identification and multiteam system performance, and Hypothesis 1b predicted a positive relationship between component team identification and multiteam system performance. The path model results indicated that multiteam system identification was negatively associated with multiteam system performance at a marginal level of statistical significance ($\gamma = -1.25$, $p < .10$). Thus, we found partial support for Hypothesis 1a. Hypothesis 1b was supported, as component team identification was positively associated with multiteam system performance ($\gamma = 1.60$, $p < .05$).

Figure 2 presents the mediation framework for our multilevel path analyses and Table 2 presents the results of these analyses. Hypotheses 2a and 2b predicted that depletion would mediate the relationships expressed above. As shown in Table 2, at average task complexity, multiteam system identification was positively associated with depletion ($\gamma = .53$, $p < .05$), component team identification was negatively associated with depletion ($\gamma = -.50$, $p < .05$), and depletion was negatively associated with multiteam system performance ($\gamma = -.87$, $p < .05$).

Importantly, the indirect effects at average task complexity supported mediation via depletion. The indirect effect between multiteam system identification and multiteam system performance via depletion was −.47, and the 95% CI [–.95, −.18] did not include zero, supporting Hypothesis 2a. In addition, the indirect effect between component team identification and multiteam system performance via depletion was .44 and the 95% CI [.16, .88] did not include zero, supporting Hypothesis 2b.

Turning to the moderating role of task complexity, Hypothesis 3a and 3b predicted that task complexity would moderate the total effect between each identification focus (i.e., multiteam system and component team) and multiteam system performance, such that these relationships would be stronger (weaker) for multiteam systems engaged in tasks that are high (low) in complexity. In support of Hypothesis 3a, the path model results in Figure 1 indicated that task complexity moderated the negative relationship between multiteam system identification and multiteam system performance ($\gamma = -6.11$, $p < .05$). Figure 3 presents the plot of this interaction, at conditional values of task complexity, and shows that, as predicted, the negative effect of multiteam system identification on multiteam system performance was stronger when the task was more complex (simple slope = −5.32, $p < .05$) and weaker when the task was less complex (simple slope = .78, n.s.). In support of Hypothesis 3b, the path model results indicated that task complexity moderated the positive

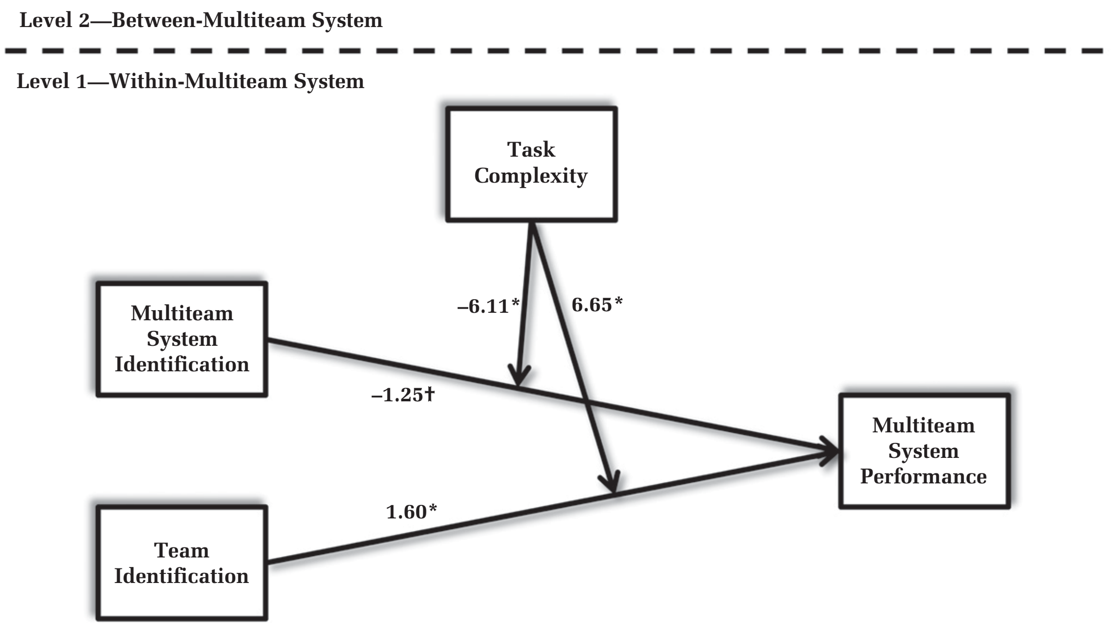
TABLE 1
Descriptive Statistics and Within-Multiteam System Correlations for the Study Variables at the Multiteam System Level

Variable	Mean	*SD* Within	1	2	3	4	5	6
1. Task Complexity	0.33	0.47	—					
2. Team Identification	3.64	0.18	–.14	(.94)				
3. Multiteam System Identification	3.52	0.19	.19	.61*	(.95)			
4. Depletion—Pre-Session	2.28	0.30	.07	–.18	–.31*	(.95)		
5. Depletion—Post-Session	2.06	0.37	.37*	–.21	–.07	.54*	(.97)	
6. Multiteam System Performance	0.00	0.93	.00	–.05	–.06	.11	–.35*	—

Notes: Within multiteam system $n = 66$. Between multiteam system $n = 22$. Coefficient alphas (averaged across scenarios) are on the diagonal. The mean of multiteam system performance was zero because the variable was standardized within each of the three performance episodes.

* $p < .05$

FIGURE 1
Multi-level Path Analyses Results for Baseline Model



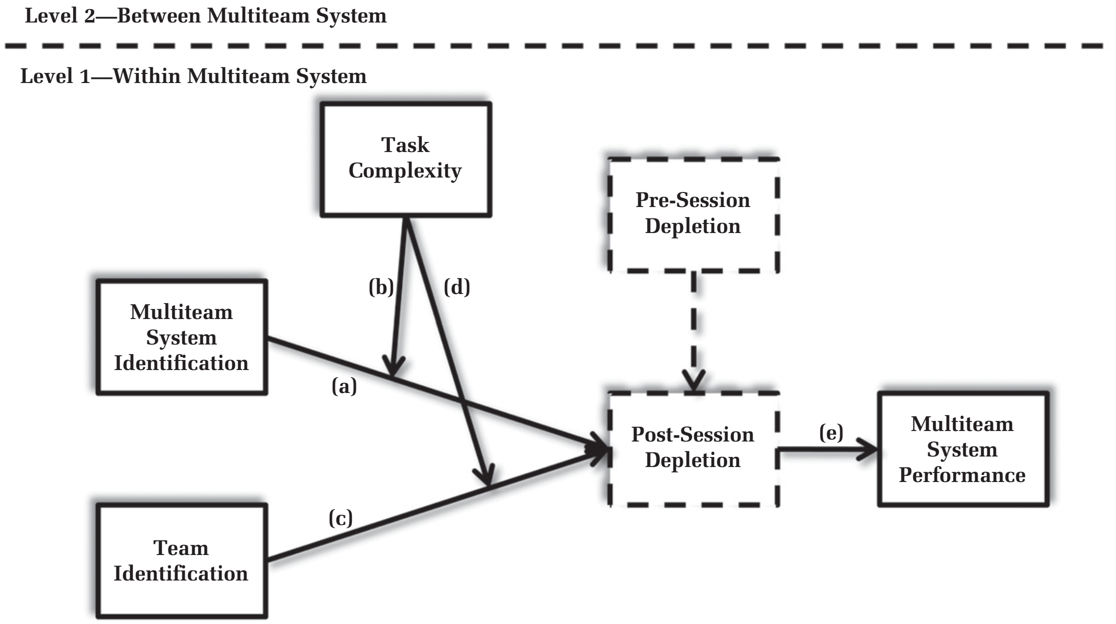
Notes: Within-multiteam system n = 66. Between-multiteam system n = 22. Multilevel path analysis conducted in Mplus 7. For clarity, only hypothesized paths are pictured. The control variables—i.e., direct effects of task complexity (γ = .47*) and year (γ = −.12) with multiteam systemperformance—are not pictured.
† $p < .10$
* $p < .05$

relationship between team identification and multiteam system performance ($\gamma = 6.65, p < .05$). Figure 4 presents the plot of this interaction and shows that, as predicted, the positive effect of team identification on multiteam system performance was stronger when the task was more complex (simple slope = 6.03, $p < .05$) and weaker when the task was less complex (simple slope = −.62, n.s.). Overall, the model presented in Figure 1 explained 21.0% of the level 1 variance in multiteam system performance.

Finally, Hypotheses 4a and 4b predicted that task complexity would moderate the relationships between each identification focus (i.e., multiteam system and component team) and multiteam system performance via depletion. As shown in Table 2, for multiteam system identification, task complexity moderated the positive relationship between multiteam system identification and depletion ($\gamma = 1.17, p < .05$). Depletion was negatively associated with multiteam system performance ($\gamma = -.87, p < .05$), and the 95% CI for the index of moderated mediation excluded zero (index of moderated mediation = −1.02, 95% CI [-2.46, −.21]; high complexity indirect effect = −1.15, 95% CI [-2.39, −.38]; low complexity indirect effect = −.13, 95% CI [–.51, .19]). In support of Hypothesis 4a, our results suggest that depletion mediated the interactive effect of multiteam system identification and task complexity on multiteam system performance, such that the negative indirect effect of multiteam system identification on multiteam system performance via depletion was stronger when the task was more complex.

For component team identification, task complexity moderated the negative relationship between team identification and depletion ($\gamma = -1.58, p < .05$). Depletion was negatively associated with multiteam system performance ($\gamma = -.87, p < .05$), and the 95% CI for the index of moderated mediation excluded zero (index of moderated mediation = 1.38, 95% CI [.31, 3.19]; high-complexity indirect effect = 1.36, 95% CI [.39, 2.78]; low-complexity indirect effect = −.02, 95% CI [–.54, .25]). In support of Hypothesis 4b, our results suggest that depletion mediated the interactive effect of component team identification and task complexity on multiteam system performance, such that the positive indirect effect of component team identification on multiteam system performance via depletion was stronger when the task was more complex and weaker when the task was less complex. Taken as a whole, the

FIGURE 2
Multi-level Path Analyses Framework for Depletion as a Mediator



Notes: Within multiteam system $n = 66$. Between multiteam system $n = 22$. Multilevel Path Analysis conducted in Mplus 7. For clarity, control variables (i.e., direct effect of task complexity and year with all endogenous variables) and direct effects of exogenous variables are not pictured. Full results presented in Table 2.

moderated mediation model explained 55.1% of the level 1 variance in depletion and 41.1% of the level 1 variance in multiteam system performance.

Supplemental Analysis

Relative strength of team versus multiteam system identification. An anonymous reviewer also made the interesting suggestion that the *relative* strength of component team versus multiteam system identification may have been driving the effects of social identification on multiteam system performance. We followed the recommendations of Edwards (1994) to test this idea. Specifically, we operationalized relative (component team to multiteam system) identification by calculating the parameters for component team and multiteam system identification separately. We then tested the relative effect via the slope of the incongruence line of the response surface (i.e., by testing the significance of the linear combination of the estimated parameter for team identification minus the estimated parameter for multiteam system identification). The result of this analysis showed that relative identification had a significant positive relationship (incongruence line slope = 2.85, $p < .05$) with multiteam system performance. In other words, when system members' component team identification was greater than their multiteam system identification, this resulted in higher multiteam system performance. We also tested this same relative effect in the depletion model, and the result of this analysis showed that relative (component team to multiteam system) identification had a significant negative relationship (incongruence line slope = -1.04, $p < .05$) with depletion. Moreover, this effect was mediated through depletion onto multiteam system performance as the 95% CI for the indirect effect excluded zero (indirect effect = .91, 95% CI [.37, 1.81]. In all, these supplemental analyses underscore our original thinking that in multiteam systems it is better for members to identify strongly with their own component team instead of the overall system. Doing so reduces depletion and benefits overall system performance.

DISCUSSION

This study integrates theory from social identity, uncertainty, and depletion to advance our understanding of the role that team and multiteam system identification, depletion, and task complexity play

TABLE 2
Summary of Results for Mediator Analysis

	Mediator = Post-Session Depletion
Direct Effects and Controls	
Multiteam System Identification → Multiteam System Performance	−1.02
Multiteam System Identification × Task Complexity → Multiteam System Performance	−4.98*
Team Identification → Multiteam System Performance	1.12
Team Identification × Task Complexity → Multiteam System Performance	4.96*
Task Complexity → Mediator	0.14†
Task Complexity → Multiteam System Performance	0.62*
Pre-session Depletion → Mediator	0.68*
Substantive Paths	
(a) Multiteam System Identification → Mediator	0.53*
(b) Multiteam System Identification × Task Complexity → Mediator	1.17*
(c) Team Identification → Mediator	–0.50*
(d) Team Identification × Task Complexity → Mediator	−1.58*
(e) Mediator → Multiteam System Performance	–0.87*
Multiteam System Identification Indirect Effect	
Average	–0.47 (–0.95, −0.18)
High Task Complexity	−1.14 (-2.39, −0.38)
Low Task Complexity	–0.13 (–0.51, 0.19)
Index of Moderated Mediation	−1.02 (-2.46, −0.21)
Team Identification Indirect Effect	
Average	0.44 (0.16, 0.88)
High Task Complexity	1.36 (0.39, 2.78)
Low Task Complexity	–0.02 (–0.54, 0.25)
Index of Moderated Mediation	1.38 (0.31, 3.19)

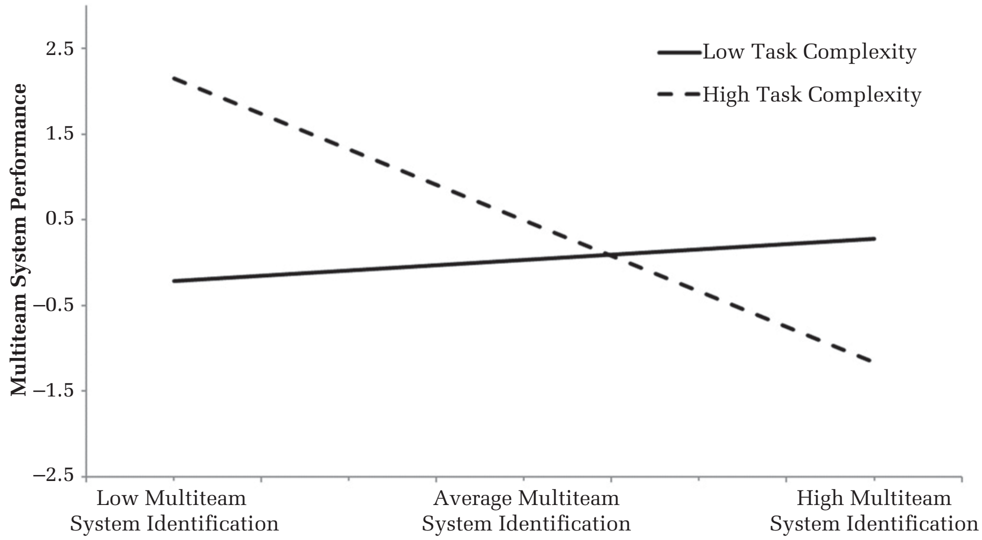
Note: Year had no effect on post-session depletion ($\gamma = .10$) or multiteam system performance ($\gamma = -.13$).
† $p < .10$
* $p < .05$

in affecting multiteam system performance. We showed that there is a positive relationship between component team identification and multiteam system performance when task complexity is high, whereas there is a negative relationship between multiteam system identification and multiteam system performance under the same conditions. In contrast, low task complexity mitigated these differential relationships. We also showed that depletion mediated these relationships, such that high multiteam system identification will result in more depletion, whereas high team identification will result in less depletion, with depletion being negatively related to multiteam system performance. The results from this study challenge the tendency to generalize from past theories regarding stand-alone teams to multiteam systems, and instead shows the value of developing a theoretically informed perspective on multiteam systems that explicitly recognizes the complexity of the tasks handled by these systems. More specifically, the evidence collected in this context leads to rejection of the widely held view that individuals nested in multiteam systems should identify most strongly with the multiteam system.

Theoretical Contributions

The primary theoretical contribution of this study is that we offered a social identity perspective on multiteam systems. Rather than generalizing from research on independent stand-alone teams, we took a structural approach, and developed our theoretical framework from theories of social identity, uncertainty management, and self-regulation. We went beyond what each of those literatures alone could offer, showing that the effects of multiteam system and team identification on performance differ from each other because the process of identification with the system is uncertain and depleting, whereas identification with the component team is less uncertain and less depleting. We also demonstrated that higher task complexity strengthens the effects of identification on performance, likely due to the

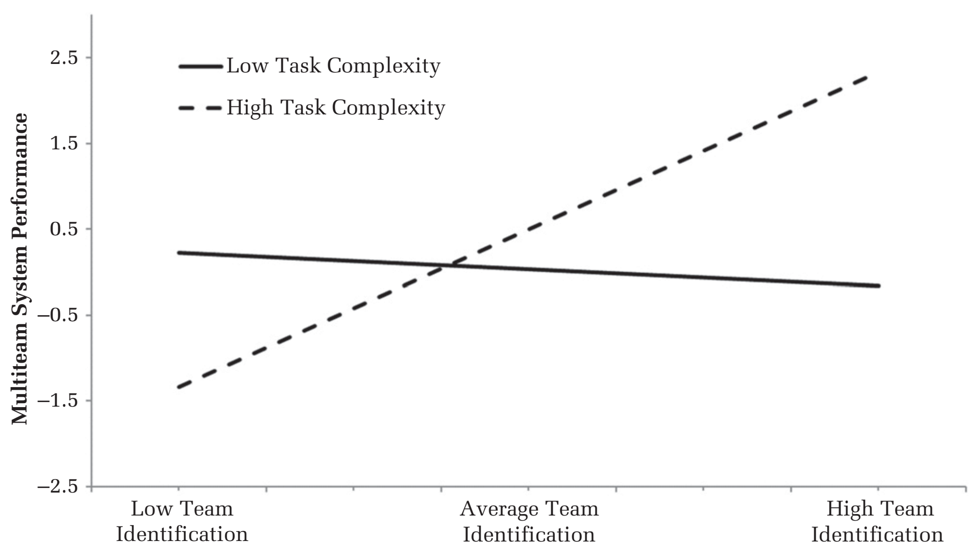
FIGURE 3
Moderating Effect of Task Complexity on the Relation between Multiteam System Identification and Multiteam System Performance



increased uncertainty that task complexity introduces to system members.

This study provides a meaningful extension to the burgeoning work on social identity in the management literature (e.g., Ashforth et al., 2011; Ramarajan, 2014). So far, this literature has had a strong focus on the intragroup effects of social identification, and paid less attention to intergroup effects (Hogg et al., 2012; van Knippenberg, 2003). In fact, outside of the management literature, the social identity perspective has been the primary framework used to understand many barriers that might hinder interdependent teams' coordination, such as intergroup bias and intergroup competition

FIGURE 4
Moderating Effect of Task Complexity on the Relation between Team Identification and Multiteam System Performance



(Dovidio et al., 1998; Gaertner et al., 1999). Typically, however, intergroup studies have not moved beyond individual-level evaluative biases favoring one's own team (Gaertner et al., 1996). In addition, although generalizations of small-team research on social identity would suggest that component team identification might lead to problems related to coordination and conflict, this is likely to be less of an issue in the context of the multiteam system. First, these assumed coordination issues stem from research where qualitatively similar teams are in direct competition with one another (Tajfel & Turner, 1979). Teams in multiteam systems, however, are not in direct competition with one another, and share important functional interdependencies that allow for mutual appreciation (instead of competition) (Ashforth & Mael, 1989). Second, in multiteam systems there is generally a specific boundary-spanning team (e.g., the leadership team), which has the specific task of managing coordination and conflict (Davison et al., 2012). The present study thus constitutes an important step forward in the development of the social identity perspective on intergroup relations as can be found in the specific and growing organizational form of multiteam systems.

Furthermore, our work advances present knowledge on the role of task complexity in multiteam systems, going beyond the notion that all multiteam systems are equal in this regard. Drawing from an uncertainty perspective, we found that, as predicted, when task complexity was high there were more pronounced effects in terms of (a) the negative total and indirect effects of strong multiteam system identification, and (b) the positive total and indirect effects of strong team identification on system performance. The results for low task complexity suggest that multiteam systems working on simple tasks do not encounter the same depletion effects owing to identification. These findings are important because the multiteam system literature has treated task complexity as a constant despite the fact that multiteam system task complexity is likely to vary from context to context (Luciano et al., 2018). Our findings that task complexity moderates the effects of social identification on depletion and multiteam system performance suggest that greater consideration is required for the role of task complexity in theoretical and empirical models of multiteam system performance. Hence, we believe that scholars investigating multiteam systems should provide sufficient information about the level of complexity of the system studied, in terms of component, coordinative, and dynamic complexity (see Luciano et al., 2018; Wood et al., 1987), to facilitate the accumulation of knowledge on multiteam systems.

Our research also advances knowledge on the role of depletion in multiteam systems, as our study is the first to take a self-regulation-based view of the multiteam system setting. Despite recent discussions on the mechanism underlying ego depletion (Inzlicht & Schmeichel, 2012), both theoretical and empirical research on self-regulation has suggested that people perceive depletion when they face challenging demands, and that this depletion matters for how they perform (Maranges & Baumeister, 2017; Milyavskaya & Inzlicht, 2017). Indeed, we argued and found that in the challenging setting of a multiteam system with a highly complex task, strong system identification among system members has a negative impact on system performance, because it is more depleting for those who identify strongly with the multiteam system. Although these findings go against popular belief about the role of multiteam system identification in the multiteam systems literature (Connaughton et al., 2012; DeChurch & Zaccaro, 2010), they are in line with the finding that motivated but depleted individuals struggle to perform well on complex and cognitively taxing tasks (Schmeichel et al., 2003; Vohs, Baumeister, Schmeichel, Twenge, Nelson, & Tice, 2008). Thus, our work not only tests the degree to which well-accepted theories derived for stand-alone teams generalize to multiteam systems, but also contributes to the literature on depletion and the negative effects this variable has on organizational outcomes (Lanaj et al., 2014; Mead, Baumeister, Gino, Schweitzer, & Ariely, 2009; Vohs et al., 2008).

Practical Implications

Our findings have two important implications for those tasked with setting up and leading multiteam systems. First, given the size and complexity of multiteam systems, it is not surprising that the general belief is that people in these systems should identify highly with the multiteam system. Our work, however, demonstrates that when the task of the multiteam system is highly complex, strong multiteam system identification brings along a risk of depletion, which in turn harms the performance of the system. Hence, we contradict the common prescription that managers should always aim to cultivate a shared identity at the highest possible level in complex systems. When the task is complex, the system is better off when members identify more strongly with their component team and focus on executing their component team's role. Only when the task of the multiteam system is low in complexity can high multiteam system identification potentially not harm the performance of the multiteam system.

Second, our findings demonstrate that for multiteam systems with high task complexity, high identification with one's component team is beneficial to the performance of the system. It is imperative that members understand that the *reason d'être* of a multiteam system is that the task is so complex that it cannot be performed by one team alone. Instead, component team tasks tie together and are interdependent to ensure the performance of the system as a whole. Thus, in such systems, members should be encouraged to identify with their component teams. In addition, the leadership team should manage members' uncertainty in the multiteam system context (Lind & Van den Bos, 2002) by providing confidence to the component teams that the system will reach its overarching goals if each team does their nonsubstitutable, specialized job, and that leadership can be trusted to coordinate between teams and to keep the "bigger picture" in mind.

Strengths and Limitations

The present research has several strengths. First, it relied on multiple sources of data collected at multiple periods, where we tracked teams over a period of six months on five different occasions; two occasions as a stand-alone team and three occasions as a multiteam system. Second, unlike some multiteam system laboratory studies, the members of component teams worked together on two occasions prior to placement within a multiteam system. Moreover, during the two months that the members worked as a team, they knew that they were working toward becoming a multiteam system and worked together and informally interacted with members of other component teams outside the confines of the LDX simulations during the entire period we conducted this study. Thus, component team members were likely familiar with one another and with members of the other component teams in their multiteam system. Finally, because we used a simulation commonly used in multiteam system research, our results can be compared with those other multiteam system studies (Davison et al., 2012; de Vries et al., 2016; DeChurch & Marks, 2006; Lanaj et al., 2013; Marks et al., 2005).

Still, as with any study, we need to note certain limitations associated with this work. First, despite all the advantages of our laboratory context, we recognize the limitations associated with laboratory research in terms of the generalizability of the findings. That is, we only studied university students in a stimulated environment; thus, we cannot know how well the current findings generalize to other contexts. Laboratory studies are and have been a vital component of theory-centered research (Anderson, Lindsay & Bushman, 1999; Berkowitz & Donnerstein, 1982). It is critical for research on multiteam systems, which is still in its infancy, to maximize internal validity at this stage of the research cycle (DeChurch & Marks, 2006). Indeed, our study met the criteria that are often suggested for laboratory studies, including the use of an objective behavioral measure of the multiteam system's performance via the simulation, and a task that offered psychological realism. We also created a situation where teams each had distinct team-level goals that related to the overall goal of their multiteam system in different ways, but the extent to which these goal hierarchies map to real-world goal hierarchies is subject to debate. Still, all our subjects were relatively young, and determining the degree to which these results would generalize to older and more experienced working adults would be a valuable avenue for future research.

Second, our level 1 sample size of 66 is relatively small. Still, our sample is large in relative terms for a multiteam system study, considering the widely recognized difficulty in attaining an adequate sample size in multiteam systems research (see Davison et al., 2012). Indeed, accruing a sample size of 66 multiteam system performance episodes required 660 hours of face-to-face laboratory time (i.e., 10 hours for each multiteam system)—and each of those 660 hours required involvement from 2–3 staff members from the research team. We believe that our within-subject design demonstrates resourcefulness in attaining an adequate sample, and is a way to increase the statistical power of multiteam system studies in a feasible way. Indeed, our power analyses (described in detail in note 2) suggest that our level of power was near typically recommended levels (average power = .74; range = .51 −.91). Moreover, because of our interest in level 1 regression parameters and standard errors, neither the estimation of our models nor the Type I error rate are likely to be biased. In fact, in a recent review, Hox (2013: 290; see also Maas & Hox, 2005) posited that "In multilevel regression modeling, a highest level sample size as low as 20 may be sufficient for accurate estimation, provided that the interest is in the regression coefficients and their standard errors." Similarly, Bell, Morgan, Schoeneberger, Kromrey, and Ferron's (2014: 9) provided simulation evidence that showed that:

> estimates of bias were not viewed as problematic regardless of sample size at each level ... across the many design factors included in the current study, these findings suggest that bias was minimal, and that 95% confidence interval coverage and Type I error rates tend to be slightly conservative but are fairly well controlled even when modeling hierarchically structured data with smaller sample sizes.

Finally, we note that we explained a large amount of the overall variance in objective multiteam system performance (21.0% in the baseline model and 41.1% in the moderated mediation model). This suggests that social identification is a substantive predictor of multiteam system performance—in line with past meta-analytic research on social identity (Riketta & van Dick, 2005). Regardless, future research should investigate the effects of social identification within multiteam systems in other contexts, with larger samples and with other multiteam systems of various levels of task complexity.

Future Research Avenues

Our research suggests several possibilities for future empirical studies on multiteam systems. For example, the social identity perspective is not limited to component team and multiteam system identification, and the current evidence for its validity in predicting multiteam system performance provides a good basis for the further development of this perspective. The social identity perspective, for instance, also speaks to precursors of identification that serve as angles for interventions to improve system performance. The uncertainty of the system may be an interesting precursor because uncertainty is generally considered to reduce identification (Chattopadhyay et al., 2004a), but the multiteam system offers a focus of identification that is both appealing, in terms of its overarching goal, and uncertain, in terms of its identity prototype. It would also be valuable to look at how the type of component team may influence the role of social identity in multiteam system phenomena. Indeed, considering that the leadership team crosses team boundaries and potentially can develop greater relational identification, it may be that the leadership team receives more of the benefits and bears more of the costs in a multiteam system context (see Hogg et al., 2012). We see this as a particularly fruitful area for future research.

Another important way to develop the social identity perspective on multiteam systems is to develop a more complex and comprehensive understanding of multiple salient identities in these systems. That is, in this study we accounted for the influence of each salient identity on multiteam system performance separately, in line with other social identity studies that have shown that multiple salient identifications with different foci operate independently of one another (Roccas & Brewer, 2002). Yet, we recognize the potential of examining the numerous ways in which multiple salient identities combine and interact to influence the dynamics in a multiteam system. Ways to accommodate these multiple identities might include, but are not limited to, being (a) nested or independent, or (b) sequential or simultaneous, or (c) conflicting, overlapping, or converging, or (d) stable or shifting (Gaertner et al., 1996; Richter et al., 2006; Roccas & Brewer, 2002). However, at least in a multiteam system context, the one thing that these combinations of multiple identities all have in common is that they are probably more cognitively depleting than the two simple identities we focused on here.

Finally, in line with our uncertainty perspective, we considered task complexity to be a very relevant moderator in the multiteam system context. Here, our work builds on the three task demands as identified by Wood (1986), but we developed hypotheses about the role of task complexity as an aggregate construct in line with other task complexity studies (e.g., Horwitz & Horwitz, 2007; Vashdi et al., 2013; Wood et al., 1987). We did not have different hypotheses about how these three subtly different task characteristics affect resources because all three demands make the task more taxing on cognitive resources. Still, in certain multiteam system contexts, a more detailed investigation of the role of task complexity might be valuable (see Luciano et al., 2018). Furthermore, we believe that several other moderators may also be relevant to further develop our understanding of the role of social identity in multiteam systems. These moderators include within- and between-team coordination (e.g., de Vries et al., 2016), multiteam system goal hierarchy characteristics (Mathieu et al., 2001; Zaccaro et al., 2012), and members' behavior (e.g., Lanaj et al., 2013). For instance, Lanaj and colleagues (2013) have shown the value of distinguishing between members' planned activities and their actual behavior to study goal-related behavior. This distinction may also be relevant when the focus is on how social identity increases the salience of certain goals in the multiteam system context.

CONCLUSION

The process of social identification has profound effects on organizational behavior, and individuals working in large organizations have multiple foci of potential identification available to them at work. Increasingly, in team-based organizations, two potent foci of identification are the component team and the larger multiteam system in which the team is nested. Our research shows that the strength of identification associated with the component team and the multiteam system are important for predicting performance in multiteam systems, and that the notion that it is always better for the system if all members strongly identify with the larger collective does not generalize when the task is highly complex. Instead, identification with the multiteam system interferes with multiteam system performance because it is more depleting, while identification with the component team is less depleting and thereby allows system members to work on their specialized component team tasks, which the system as a whole ultimately depends upon.

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