PROJECTS AS DYNAMIC, MULTI-LEVEL TEMPORARY ORGANIZATIONS: ADVANTAGES OF AN AGENT-BASED MODELING APPROACH

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Abstract: Projects are complex systems. They are dynamic, uncertain, heterogeneous entities embedded within social, organizational, and broader contexts. Agent-based modeling (ABM) is a computational method that allows for the modeling of autonomous, heterogeneous, and interacting agents in a multi-level system. The re-conceptualized view of projects discussed in the literature supports the notion of projects as dynamic, multi-level temporary organizations. Through this lens, we argue that an ABM approach provides key advantages for understanding and exploring relevant topics in project management. The features that make temporary organizations challenging to understand and explore, including temporality, behavioral considerations, and embeddedness, are also areas where ABM could prove advantageous. We also address the difficulties associated with using ABM in this context and do not claim that ABM is the only method for addressing these challenges. The goal of this paper is to provide a computational perspective from which to think about and further explore research in project management.

1. INTRODUCTION

Traditionally, projects have been viewed as a "tool" for achieving some goal (Packendorff, 1995). Projects are rational, normative, and controllable (Williams, 2005; Turner et al., 2013). Projects are, therefore, a system that can be optimized (Turner et al., 2013). This characterization overlooks the unique motives, commitments, and relationships of individuals on a project (Packendorff, 1995). Projects are influenced by social, longitudinal, and organizational context (Engwall, 2003; Lundin & Soderholm, 1995; Packendorff, 1995). Moreover, the increasing complexity, uncertainty, and time sensitivity of projects placed an additional burden on researchers and practitioners to re-conceptualize the traditional notion of the project (William, 2002; Svejvig & Andersen, 2015). Through the lens of projects as temporary organizations, projects are for instance: uncertain, unique, transient (dynamic), composed of a collection of individuals, and task-oriented (Lundin & Soderholm, 1995; Packendorff, 1995; Turner et al., 2013). Described as a "project ecology," temporary organizations are also embedded within a multi-level system – the community, the (permanent) organization, the team, and the personal network (Grabher, 2002b). Understanding all levels of this system is vital for better performance (Gareis & Huemann, 2007).

In this vein, projects are complex systems – a system composed of numerous interacting components (individuals, projects, teams) whose aggregate behavior is nonlinear. Generating these macro-behaviors requires that we model the individual components of the system (Miller & Page, 2007; Schelling, 2006). Agent-based modeling (ABM) is a computational method that allows for the modeling of autonomous, heterogeneous, and interacting agents (Gilbert & Troitzsch, 2005). Within an "artificial" society, agents interact with each other and the environment (Macal & North, 2010). These interactions, which can be implemented at a degree of sophistication selected by the modeler, make ABM appropriate for creating dynamic models of projects, teams, and organizations.

In addition, ABM has been promoted as particularly useful for understanding social context within organizations (National Research Council, 2014).

The goal of this paper is to demonstrate that an ABM approach is well suited for exploring and understanding various aspects of project management. This is in line with the re-conceptualization of projects as dynamic, uncertain, and complex entities composed of individuals with unique attributes and behaviors. We argue that there are key advantages to using ABM to model such a system. We do not claim, however, that ABM is the only method for addressing all questions, or even most questions, in project management. Moreover, hybrid approaches that integrate ABM with system dynamics, discrete-event simulation, or statistical approaches, may be more appropriate in certain cases. While there is some discussion of these models in our review of the literature, the topic of hybrid modeling is beyond the scope of this paper. This paper seeks to show the advantages and existing challenges associated with using an ABM approach in the field of project management. The re-conceptualized notion of projects (discussed in Section 2) combined with the growing, but limited, research applying ABM in the context of projects makes this an opportune time to address ABMs role in potentially advancing research in project management.

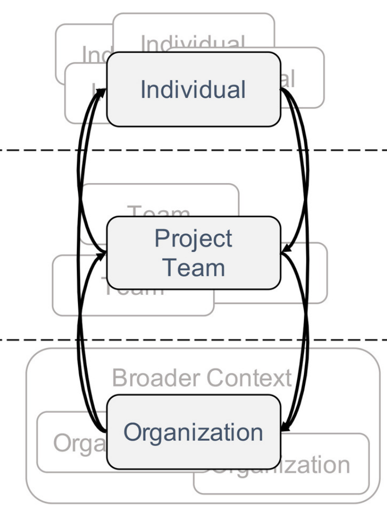
2 Projects as Dynamic, Multi-level temporary Organizations

Projects represent complex systems in that they are comprised of dynamic networks of interactions of individuals that change and adapt over physical and social space. Projects do not exist in isolation, they interact with the larger organization for which they are embedded and are made-up of a collection of individuals (Engwall, 2003; Grabher, 2002a, b; Lundin & Soderholm, 1995; Packendorff, 1995). Moreover, projects consist of both formal and informal structures. Formal structures are prescribed based on the organizational and project structure. Informal structures include things that occur outside of these prescribed structures. They are the emergent, social structures that arise from individual-level interactions of project members (De Long & Fahey, 2000; Soda & Zaheer, 2012; Tichy et al., 1979; Weiss & Jacobson, 1955). Formal and informal structures can interact as projects progress and adapt to the individuals, teams, and broader context.

Projects are also temporary and must deliver some desired outcome under some (often) prescribed timetable (Lundin & Soderholm, 1995; Packendorff, 1995; Turner & Muller, 2003).

From this perspective, we can think of projects as dynamic, multi-level temporary organizations consisting of both formal and informal structures. **Figure 1** illustrates the multi-level nature of projects and its interactions with both micro (individual) and macro (organization and broader context) constructs. Such a view of project management supports the shift in the field; from the classical approach that emphasizes optimization and rationalistic agents to one that considers issues of complexity, uncertainty, and social and organizational context (Williams, 2005; Winter et al., 2006; Svejvig & Andersen, 2015). This is evidenced when we consider both the various "schools" of thought that have emerged (Turner et al., 2013) and the re-conceptualization known as rethinking project management (RPM) (Svejvig & Andersen, 2015; Winter et al., 2006).

The traditional or classical view is largely rooted in operations research (Turner et al., 2013). Projects are viewed as a system that can be optimized (Cleland et al., 1975). This hard systems approach, however, leaves out behavioral factors and other social components of project management. This led to a growing interest in modeling projects from a complex systems perspective. The modeling school (William, 2002) discerned that increasing complexity and uncertainty in projects warrants an approach that accounts for the total project management system. The focus is placed on capturing the project and its interactions with its surrounding context. This is in contrast to the traditional view which argues that project management is rational, linear, and predictable (Williams, 2005; Turner et al., 2013). While the methodology of choice has largely been a systems dynamics (SD) approach (Turner et al., 2013), there is a growing interest in agent-based modeling (see Section 3).



	Formal	Informal
Micro	Individual tasks and responsibilities; performance metrics and evaluation procedures	Cognitive (e.g., knowledge, skills, abilities) and non-cognitive (e.g., motivation) attributes; behavior (e.g., performance); individual interactions; informal/social ties
Meso	Team, project, and department structures; performance metrics and evaluation procedures; project objectives; knowledge sharing through formal means	Interactions within and between projects, teams, and departments; team cohesiveness, morale; project adaptation to changes in resources, staffing, leadership, etc.; knowledge sharing through informal networks; project culture
Macro	Organizational chart/hierarchy, performance objectives; knowledge sharing through formal means	Informal networks; organizational adaptation to changes in resources, staffing, leadership, project objectives; knowledge sharing through informal networks; organizational culture

Figure 1: Projects as multi-level temporary organizations with formal and informal structures. The rows represent the micro, meso, and macro layers of a project. Listed are examples of formal and informal constructs within each layer.

Two other closely related schools are the governance and behavior schools (Turner et al., 2013). With attention to organization theory and organizational behavioral approaches, the governance school highlights the need for a "theory of the temporary organization" (Lundin & Soderholm, 1995; Packendorff, 1995), stressing the distinction between the role of time on a project (defined as a temporary organization) and a permanent firm. The behavior school (Jay R., 1973; Youker, 1977) takes this a step further in that it views the temporary organization as a social system. It focuses on the human component of the project, particularly teamwork behaviors such as collaboration, leadership, and communication (Turner et al., 2013). While the focus on the social component overlaps with the complex systems perspective, attention to human behavior in this school puts the individual at the forefront. Moreover, it places additional consideration on the dynamic, temporal limitations of the project, which has important implications for areas such as knowledge management and knowledge sharing. In line with this, the success school (Andersen et al., 2009; Jugdev & Muller, 2005) recognizes that project success is a function of a wide range of considerations from external stakeholders to team communication and collaboration. Another school worth noting is the contingency school, which views each project as its own unique entity. This school stresses the need to adapt project management processes to account for the heterogeneous nature of projects (Turner et al., 2013).

The trend from a hard systems to a soft systems (or integrative) approach is largely in line with the re-conceptualization of project management under the RPM paradigm (Winter et al., 2006). The emphasis shifted from the project as rational, linear, and controllable to one that is complex, uncertain, social, heterogeneous, dynamic, and situated in a broader context. This re-conceptualization takes a more holistic view of project management, therefore building on, rather than rejecting, the tools, techniques, and research of the classical view. RPM further provides an opportunity to engage in using new methods and approaches for understanding and exploring the field of project management (Winter et al., 2006). Multiple research paradigms (e.g., governance school, behavior school, RPM) have supported the notion of projects as temporary organizations (Jacobsson et al., 2016). Agent-based modeling, which takes a "bottom-up" approach to simulate complex systems, is well suited to account for the project features emphasized in this re-conceptualized view of project management. By modeling individual project members as agents with unique attributes and behaviors that interact within a multi-level space, we can observe a diverse set of project, team, and organizational-level outcomes.

3 Relevant Prior Work

Agent-based modeling has been applied across a variety of business and management-related topics, including manufacturing (e.g., Deen, 2013; Shen et al., 2006), supply chain management (e.g., Giannakis & Louis, 2016; Costas et al., 2015), and consumer preferences (e.g., Noori & Tatari, 2016; Stummer et al., 2015). The closely related field of organization science, in particular, has seen a growing acceptance of ABM approaches to understand organization and team dynamics and performance (e.g., Kozlowski et al., 2013; Kozlowski & Chao, 2012; Levine & Prietula, 2012; Pires et al., 2017). ABMs in project management have simulated projects, teams, resources, tasks, and the interactions between these and other project-related components. While most ABMs in project management pertain to the construction industry, likely due to project management's roots in engineering and construction (Turner et al, 2013), other sectors modeled include research (e.g., Robinette et al., 2009), software development (e.g., de Medeiros Baia, 2015), and firms (e.g., Hsu et al., 2016).

One area of research explores teamwork behaviors such as communication, collaboration, task allocation, and helping behaviors within and across teams. These models have a common focus on the social environment and how human behavior and individual interactions impact project and team-level outcomes (Fan & Yen, 2004). Agents represent individual project or team members. Hsu et al. (2016), for example, evaluate the impact of team composition on performance. Accounting for constraints in work capacity, the individual skills of team members, the interdependence (contributions) between team members, and the characteristics of project tasks, they find that higher functional diversity across team members results in better firm performance. While Robinette et al. (2009) similarly examine team composition and performance, they allow the team members (researchers in this case) to select their projects based on factors such as skills, interest, and project duration. This strategy of self-organization is found to perform better than traditional approaches. ABMs have also explored the concept of team cognition – the emergence of collective knowledge in a team (Cannon-Bowers & Salas, 1990) – and its relationship to leadership, communication strategies, and team performance (e.g., Grand et al., 2016; Dionne et al., 2010). These models, which are largely grounded in theory from organization science, consider the dynamic nature of team processes as an important contributor to shared knowledge in teams. Son & Rojas (2010), on the other hand, explore collaboration (i.e., information sharing) in temporary teams in large-scale construction projects from a game theoretic perspective. Results demonstrate the impact that social network structures have on knowledge creation processes on teams.

ABMs have also been used to study workflow design, which includes the flow of information, deliverables, and resources. A factor shown to improve performance on construction projects. Al Hattab & Hamzeh (2016) developed an ABM to explore workflow management where team members are connected through a social network. Information diffuses through these networks as agents move through different states, such as designing, coordinating, and sharing deliverables. Watkins et al. (2009) represent agents as workers and tasks examining the role of crew member interactions and workflow design on productivity and congestion on construction sites. Similarly, Kim & Kim (2010) develop an ABM to explore traffic congestion and its impact on construction planning. These models highlight the necessity of accounting for the dynamic and decentralized nature of project management.

Aritua et al. (2009) stress the importance of a complex systems approach in modeling multi-project environments, arguing that projects exist as part of a larger system that includes the organization and external environment. ABMs along this research thread largely seek to better manage project portfolios and allocate resources in a multi-project environment. Here agents represent projects, which are said to be complex, uncertain, dynamic entities (Arauzo et al., 2009) that interact with other projects, resources, and the organization. Farshchian et al. (2017), for instance, simulate budget allocation in a portfolio of construction projects as projects dynamically change states (e.g., not started, in progress). In an ABM by Arau´zo et al. (2010) projects bid for resources while an agent plays the role of "auctioneer" and centralized decision-maker. Similarly, Taghaddos et al. (2011) model projects as bidders to simulate resource scheduling in large-scale construction projects.

While limited, the growing interest in applying agent-based approaches to understand a variety of topics in project management, and in related business areas more broadly, demonstrates the versatility of the approach in the field of project management. Moreover, the recognition that individuals, teams, and projects exhibit heterogenous behaviors and attributes and function on dynamic, uncertain environments paves a path for ABM to become an important methodology for understanding relevant topics in project management.

4 Opportunities and Challenges

In this section, we discuss the advantages and potential limitations of using an ABM approach in project management. This discussion is not meant to be exhaustive but is instead meant to highlight certain key advantages of using ABMs to explore and better understand projects. We also describe areas where ABM could be used to potentially help advance research in project management.

4.1 Modeling complex systems

The most important advantage of ABM is its ability to model complex systems. In a complex system, understanding perfectly the behavior of the component parts of a system does not imply understanding the system as the whole (Manson et al., 2012; Miller & Page, 2007). Complexity arises in projects because projects are made-up of many dependent and inter-related components; projects and project members do not exist in pure isolation. Simply observing the aggregate, we cannot always discern the underlying behaviors of individual team members and the interdependencies between project components. A complex systems approach allows us to take a holistic approach to projects that considers multiple levels of interactions, including the micro (individual), meso (project and teams), and macro (organization and broader context) levels (see **Figure 1**).

Researchers have re-conceptualized projects as complex systems and have argued that a complexity approach is fruitful for explaining project behavior in that it can account for the non-linear, non-intuitive nature of projects (Pundir et al., 2007; Winter et al., 2006). For instance, the decisions and actions of a project member, project manager, or stakeholder may depend on others decisions and actions (Root, 2013; Schelling, 2006). Uncertainties, particularly those inherent in the informal structures of a project, can exacerbate these decisions and actions as individuals become closely coupled to one another. Such behavior can be reinforcing, thus creating a situation of positive feedback and instability (Schelling, 2006).

The re-thinking of projects as complex systems has largely followed a systems dynamics approach (Turner et al., 2013), which emphasizes the non-linear, complex nature of projects, but models' entities as collectives. An "agent" in a SD model may be a project, a collection of project members, or even a portfolio of projects for example (Pundir et al., 2007). We cannot decompose or simplify beyond any defined subpopulation in such models (Gilbert & Troitzsch, 2005). ABMs, on the other hand, have the ability to model autonomous, heterogeneous, and interacting agents (Gilbert & Troitzsch, 2005).

SD approaches potentially provide a nice departure point into an agent-based approach, which takes many of the same principles from systems modeling. Researchers applying SD models already appreciate the non-linear, non-intuitive aspects of the system they are modeling and by taking a systems approach, view a project holistically, as one part of a bigger organizational context that interacts with the project itself. These are key considerations in any ABM. The more common use of SD approaches over agent-based approaches, however, may mean that re-conceptualizing projects from the individual perspective and appreciating the stochasticity inherent in ABMs may be a challenge.. Having said that, RPM and several schools of thought discussed in Section 2, appreciate the behavioral component of projects. This combined with the growing interest in using ABM in project management (discussed in Section 3) could help motivate this trend. ABM approaches would allow us to further explore the behavioral component of projects.

Despite such challenges, an approach that allows us to account for the heterogeneity of individuals, teams, projects and their behaviors cannot be underscored. Researchers have discussed the importance of these features in project management (see Section 2).

4.2 Modeling formal and informal structures in a multi-level system

ABM allows us to model a complex system from the bottom up (Miller & Page, 2007; Schelling, 2006). By modeling the individual, localized behavior of agents, we have the ability to account for heterogeneous attributes and behaviors across individuals, projects, and teams. As shown in **Figure 1**, projects are embedded in a multi-level system consisting of both formal (explicit/prescribed) and informal (emergent) structures. An agent-based modeling approach allows us to start at the micro, or individual level. We can easily aggregate from the individual to create collectives, e.g., project teams, departments, informal networks, an organization. This is not to say that the lowest aggregate modeled cannot, or should not, be the project, team, department or another collective of individuals and things. In the case of a large-scale multi-project environment, for example, the project (rather than the individual person) may be better suited to represent the lowest level agent (see Section 3). The purpose of the study in conjunction with other considerations (e.g., data, modeling environment) should dictate the agents modeled.

At the micro level, we have the individual team members. Individuals in a project may have different roles (e.g., project manager, engineer, administrative assistant) with unique skill sets and knowledge and as such may be assigned different tasks and responsibilities. Non-cognitive attributes such as attitudes and motivations may be heterogeneous across project members. Social interactions through personal networks can influence both the cognitive and non-cognitive attributes of an individual. These influences may be reinforcing within and across teams and could potentially create environments of low team morale, limited sharing of knowledge, or poor team performance for instance. Individuals sharing a project, team, physical space, etc. form connections through these interactions. These informal (social) ties strengthen and dissolve over time depending on the interactions of the individuals and factors such as physical proximity, homophily (similarity), and social influence (Tobler, 1970; Centola et al., 2007; Friedkin, 2006; McPherson et al., 2001).

At the meso level exists projects, project teams, departments, and other collectives below the level of the organization. Individuals may belong to multiple collectives – they may be members of multiple teams on multiple projects that span different departments in an organization. Individual, local level interactions generate meso- and macro-level informal structures (e.g., social networks). Due to social influence, there is continued feedback between the informal networks at the meso level and cognitive and non-cognitive individual attributes at the micro level (Friedkin, 2006; McPherson et al., 2001; Centola et al., 2007). The dynamic, temporary nature of projects means that informal structures may be unstable or continually evolving as projects form and disband upon completion. These connections can impact important aspects of project success. For example, Lee et al. (2004) found that on-the-job embeddedness via motivational effects is a predictor of job performance, where embeddedness includes the formal and informal ties to other individuals, teams, and the general community.

At the macro level, we have one or more organizations and the relevant broader context. Formal and informal structures at this level, such as the organizational hierarchy, performance objectives, organizational culture, and communication strategies, have an important influence on the behaviors and outcomes at the micro and meso levels. There is continuous feedback across these levels. This feedback can result in the reinforcement of organizational structures such as norms, culture, and performance standards. It can also highlight certain challenges. For instance, individuals may have organizational roles that differ from their project roles, organizations may have cultures that clash with a project's objectives, or within team networks may be cohesive but individuals across teams may be disconnected. The organization provides a top-down view of the formation and creation of projects, informal structures, and adaptive responses. We can observe how micro- and meso-level interactions impact organizational-level outcomes such as performance, knowledge sharing, and culture.

While ABM affords us the opportunity to model at the individual level, there remain challenges around whether we can and/or should model the individual and to what extent. Every model is some abstraction of reality, and the degree to which we have to abstract in an ABM is often less than in mathematics and other computational techniques such as systems dynamics (Axtell, 2000; Gilbert & Troitzsch, 2005; Taber & Timpone, 1996). If we abstract too much, however, we may build a model that is too simple, that may miss key variables, and that may be an oversimplification of the system being modeled. On the other hand, too much detail can make the model unnecessarily complicated (Crooks & Castle, 2012). Limitations such as data, computational resources, and our own understanding of a system may also stipulate how much we abstract (discussed further in Section 4.4).

4.3 The human component

Humans do not behave randomly; our actions and decision are based on our individual characteristics, our interactions, and our environments (Kennedy, 2012). Moreover, our cognitive abilities are bounded, and we seldom behave in ways that mimic the perfectly rational, profit-maximizing agent (Simon, 1996). Modeling human behavior is not a simple task (Kennedy, 2012). Agent-based models allow us to model the boundedly rational agent, which interacts and makes decisions based on imperfect cognitive knowledge.

The human component in project management is associated with behaviors such as knowledge sharing, coordination, individual performance, and task initiation and completion (Du & El-Gafy, 2012; Jin & Levitt, 1996; Grabher, 2004). Decision processes underlying these behaviors can range from simple, reactive processes (e.g., certain routine work tasks) to more complex, deliberative processes (e.g., decision to share knowledge, decision to collaborate). Such deliberate behaviors may necessitate construction of the agent's internal model (Schmidt, 2000). Theoretical and empirical studies have looked at the association of individual differences, motivational factors, and social and environmental contextual influences on workplace behaviors (Sackett et al., 2017). Development of an agent's internal model may necessitate accounting for one or more of these factors and how they interact with the environment. In contrast to other social systems where simpler, reactive behaviors may suffice (e.g., certain models of transportation, spread of certain infections), modeling the human component in project management may not be straightforward.

Given the importance of cognitive attributes (knowledge, skills, abilities) and non-cognitive processes, such as motivation, attitudes, and trust, on project-related behaviors, there is an opportunity to integrate project management with approaches from fields such as organization science, sociology, and psychology. Researchers have acknowledged the importance of considering the cognitive, emotional, and social (interactions) processes of human behavior when modeling social systems (e.g., Epstein, 2014). Furthermore, some progress has been made on developing ABMs with more sophisticated agents (e.g., Pires et al., 2017; Pires & Crooks, 2017). A recent line of research takes this a step further by assessing the feasibility of integrating social systems with cognitive and neurophysical systems at scale (Orr et al., 2018). This not to say, however, that every model need include all aspects of the social, cognitive, and emotional components of behavior. Many successful implementations of ABMs have included simple rules of behavior. Just as an ABM is some abstraction of a social system, the agent and its corresponding behavior is some abstraction of individuals and their behaviors. One must consider the purpose of the model in concert with other considerations (see Section 4.2) when making such modeling decisions.

The focus on human behavior in project management (see Sections 2 and 3) underscores the importance of the human component and the advantage that ABM brings over traditional approaches. We have an opportunity to integrate the progress being made on developing computational formulations of human behavior with models in the field of project management.

4.4 Creating "artificial" societies

Within an "artificial" society, agent interactions can occur over both physical space and social space (social networks) (Axtell, 2000). ABM offers the unique ability to rerun this "artificial" society multiple times and observe the varying set of outcomes (Axtell, 2000; Gilbert & Troitzsch, 2005; Taber & Timpone, 1996). By rerunning the model, we can evaluate a multitude of "what if" scenarios (Taber & Timpone, 1996). Thus, we not only have the advantage of re-creating current conditions and observing its outcomes, but we can also make changes to our world and observe those outcomes against different sets of initial conditions. We can test the current theory, theoretical assumptions, and empirical findings (Taber & Timpone, 1996).

Through scenario analysis, we can observe the impact that varying changes to a system have on meso- and macro-level outcomes. Examples of such changes are personnel attrition and hiring, changes to individual schedules, changes to organizational policies or strategies, and exposure to new knowledge through formal training or informal means. Because ABMs account for the inter-dependencies and feedback in a system, such scenarios may, in fact, result in unintended consequences. The removal of a poor performing employee may hinder communication because of their position in the informal network; starting knowledge with the most prominent employees (e.g., the project manager) may hinder information flows across teams; or placing the best performing employees on one team may not optimize team performance.

There are certain challenges however, associated with creating these "artificial" societies. Given the stochasticity inherent in ABMs, one run of the model does not provide any information regarding its robustness. We must perform multiple runs while systematically varying parameter values (Axtell, 2000), which may be difficult in situations of limited computing power, especially when modeling large systems (Crooks & Castle, 2012). Limitations around available data to build and populate ABMs can further pose a challenge (Watts, 2013; Weinberger, 2011). At times, these limitations may require adjustments to the model, such as the degree to which we abstract and the scale to which we build the model.

Validation means ensuring that the model provides an accurate representation of the phenomena being modeled (Gilbert & Troitzsch, 2005) – i.e., measuring the model's goodness of fit to empirical evidence (Crooks et al., 2008). Validating ABMs is particularly challenging because they are stochastic and computationally demanding. Existing guidance on the best validation strategy given certain features of the model may help overcome some of these challenges (Axtell & Epstein, 1994; Crooks & Castle, 2012; Crooks et al., 2008). For instance, validation may simply involve qualitative (versus quantitative) goodness-of-fit assessments, which can include visual inspection of model results to spatial-level data or distributional plots of agent properties. In addition, by calibrating parameter values to best represent the real world, we find that calibration and validation may go hand in hand. In essence, calibrating the model allows us to best fit the model to empirical results (Crooks et al., 2008). Progress has also been made in handling the stochastic and computational challenges of ABM calibration. Fadikar et al. (2017) developed a statistical methodology using a Bayesian framework to calibrate parameters and quantify prediction uncertainty in an ABM.

4.5 Projects as temporary organizations

Earlier we introduced the notion of a project as a temporary organization, largely due to the dynamic, temporal nature of projects. Here we delve a bit further into this idea and how viewing projects as temporary organizations lends itself to certain opportunities for using an ABM approach.

4.5.1 Approaches from organization science

While the notion of projects as temporary organizations is not new (e.g., Miles, 1964), the idea really came into prominence in the 1990s with the emergence of the "Scandinavian schools of thought" within the governance school (Burke & Morley, 2016; Turner et al., 2013). Temporary organizations are said to have several key features. Projects are for instance: subject to uncertainty, composed of an organized collection of individuals (team), task-oriented, time-related or transient (i.e., have a beginning and end), complex and unique (Turner & Muller, 2003; Packendorff, 1995; Lundin & Soderholm, 1995).
Permanent organizations, for which the temporary organization (project in this case) is embedded, are generally thought of as static entities (Lundin & Soderholm, 1995). While organizations also have elements of complexity, uncertainty, and uniqueness (Gareis, 2006), the additional pressures placed on projects due to their temporary (urgent) nature, adds to the challenges associated with these features.
The view of projects as temporary organizations centers largely around applying approaches from organization theory and organizational behavior approaches (Jacobsson et al., 2016). This view allows us to draw on the field of organization science where there is a growing acceptance of agent-based modeling approaches to understand organization dynamics. Furthermore, the shift in project management towards addressing the human component (see Section 2) helps merge some of the interests in the two fields. In particular, researchers in organization science have used ABM to explore topics such as team dynamics, team cognition, and knowledge sharing and management, which are relevant themes to project management (e.g., Grand et al., 2016; Jamshidnezhad & Carley, 2015; Levine & Prietula, 2012; Pires et al., 2017; Sanchez-Marono et al., 2014; Vazquez & López, 2007). The focus on individual interactions and behaviors in these models provides a fruitful building block for further research in project management. This is not to say that organization theory cannot also leverage the research in project management. Organization theory is often based on the assumption that organizations are unchanging (Burke & Morley, 2016; Lundin & Soderholm, 1995). As businesses adapt to new environments, studies are beginning to view organizations as changing entities that are also dynamic, fluid, and flexible (Schreyogg & Sydow, 2010).

4.5.2 The distinguishing features of temporary organizations

In viewing projects as temporary organizations, we must consider the features of projects that distinguish them from the (permanent) organization. Burke & Morley (2016) in their review of current research in temporary organization discuss these features and outline several opportunities for future research in the field.
First, projects and their parent organization operate on different timescales. It is largely agreed that projects have three phases: development, implementation, and termination (Packendorff, 1995). Meanwhile, during the time that a project exists, the parent organization will be generally stable with its structures given (Turner & Mu¨ller, 2003). This may pose a challenge when seeking to build on the research in team dynamics, for instance (Burke & Morley, 2016). Research has shown that team cohesiveness and performance improve over time (Marks et al., 2001), and that teams in the earlier stages are fundamentally different from those in their later stages (Kozlowski et al., 1999). Teams on projects, however, are constrained by the limited duration of the project. It is not well understood how this temporal limitation impacts such group-level processes (Burke & Morley, 2016). This temporal feature also has implications for knowledge transfer and learning, whereby the collective knowledge of a project becomes dispersed at project completion (Lampel et al., 2008).
Second, projects are embedded within one or more larger, parent organizations. As shown in Figure 1, projects must interact with both micro (individual) and macro level (organization/broader context) processes. They do not exist in isolation and are affected by the larger organization for which they exist (Engwall, 2003). Temporary organizations are highly dependent on the larger organization for resources for example (Lundin & Soderholm, 1995). Organizational culture may also influence projects, as project teams and project members develop their own norms, attitudes, and commitments. The concept of social embeddedness, which is composed of the micro-level relationships and interaction patterns within and across projects, has also been shown to influence project dynamics (Jones & Lichtenstein, 2008; Sydow, 2009). Lundin & Soderholm (1995) notes that individuals on projects have other "homes" before, during, and after involvement in a temporary organization. These connections result in larger "project networks" that dynamically evolve as projects begin and end (Sydow, 2009). Grabher (2002b) envisions a project's embeddedness in social and organizational structures as the "project ecology". An individual's simultaneous embeddedness in multiple layers is also said to influence other social processes such obligation and loyalty to the organization and the project (Grabher & Ibert, 2006). It is generally not well understood, however, how projects as temporary structures interact with the permanent, macro structures and how that interaction might evolve over the life of a project (Burke & Morley, 2016).
Third, teams on a project are always formed around the task (Lundin & Soderholm, 1995). The task thus influences the social interactions on a project, as individuals work together to complete some task (Packendorff, 1995). The task focus of projects also has implications on learning and knowledge transfer. Knowledge is important given its ability to execute some immediate task rather than for some larger context (Grabher, 2004) – a perspective that may impact how we model learning, knowledge sharing, and knowledge management in a temporary organization versus a permanent organization or enduring team.

4.5.3 Opportunities for agent-based modeling in future research

Through the lens of projects as temporary organizations, we believe that an ABM approach is well suited to tackle the challenges discussed above. The temporary, urgent nature of projects makes them dynamic – individuals and teams must quickly work to complete a task within some prescribed timetable. Using ABM, dynamic processes over both social space (informal networks) and physical space can be modeled with relative ease. We can simulate the localized behaviors of individuals in this dynamic environment and observe the group-level processes that emerge within and across projects. Because of these features, ABM may be able to help us understand the impact of the temporality of projects on a team- and organizational-level processes.
In this vein, projects are embedded within a multi-level system that too is dynamic. Individuals are part of both formal and informal structures generated by individual roles, relationships, and patterns of interactions. Within an ABM, we can assign formal roles and simulate these informal interactions. The networks generated can evolve over time as individuals interact within and across projects. We can observe how these micro-level processes result in a team- and organizational-level outcomes. We can test how changes at the individual level (e.g., voluntary attrition) and at the team or organization level (e.g., new communication strategy) might impact the system as a whole. We can also observe the feedback between individual- and group-level changes to social processes such as attitude formation and change, loyalty, and trust (e.g., Pires et al., 2017). This type of scenario analysis may help broaden our understanding of how structures at different levels interact over time.

The acquisition and recollection of knowledge on projects are fundamentally different in projects than in enduring teams. Cognitive architectures such as ACT-R can be used to simulate these individual-level processes on projects. ACT-R provides a framework for representing knowledge and skill acquisition and recollection within agents. While ACT-R was not originally designed for scaling to populations, notable progress has been made in modeling multiple cognitive agents (e.g., Lebiere et al., 2010; Petrov, 2006). ACTR-UP, for instance, applies what they term “Accountable Modeling” to model only those components of cognition that are specified and supported by theoretical and empirical evidence (Reitter & Lebiere, 2010). By coupling these architectures with an ABM, we can account for how learning and knowledge sharing occurs in a temporary environment and observe how these unique processes impact individual and organizational outcomes.

5 Conclusion

The re-conceptualized view of projects as complex, uncertain, heterogeneous entities situated in social and broader contexts, provides the field of project management with the opportunity to engage in using new methods and approaches. Agent-based modeling is well suited for modeling the project features emphasized in this re-conceptualized approach. This combined with the growing interest in using ABM in project management and other related fields provides a path for ABM to become a methodology of choice. In this paper, we argued that an ABM approach provides several key advantages for understanding and exploring relevant topics in project management. We further discussed how ABM may be able to help advance future research in the field of temporary organizations. ABM is a flexible and intuitive methodology for modeling complex systems such as projects. The features that make projects as temporary organizations challenging to understand and modal are also areas where ABM could prove advantageous

In this paper, we have attempted to illustrate how we might begin to tackle these challenges using an ABM approach. Many details would still need to be worked out, however, and one may encounter unforeseen challenges to using this approach. The purpose of this paper was to provide a (perhaps) new, computational perspective from which to think about and further explore research in project management.

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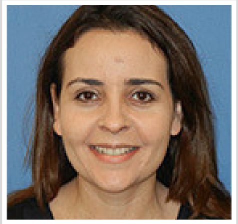

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