**Big data, technology capability, and construction project quality: A cross-level investigation**

**Abstract**

**Purpose –** Embracing big data has been at the forefront of research for project management. Although there is a consensus that the adoption of big data has significantly positive impact on project performance, far less is known about how this innovative information technology becomes an effective driver of construction project quality improvement. This study aims to better understand the mechanism and conditions under which big data can effectively improve project quality performance.

**Design/methodology/approach –** Adopting Chinese construction enterprises as samples, the theoretical framework proposed in this paper is verified by the empirical results of the two-level hierarchical linear model. The moderated mediation analysis is also conducted to test the hypotheses. Finally, the empirical findings are validated by a comparative case study.

**Findings –** The results show that big data facilitates the development of technology capability, which further produces remarkable quality performance. That is, a project team’s technology capability acts as a mediator in the relationship between organizational adaptability of big data and predictive analytics and project quality performance. It is also observed that two types of project team interdependence (goal and task interdependence) positively moderate the mediation effect.

**Research limitations/implications –** The questionnaire study from China only represents the relationship within a short time interval in the current context. Future studies should apply longitudinal designs to properly test the causality and use multiple data sources to ensure the validity and robustness of the conclusions.

**Practical implications –** The value of big data in terms of quality improvement could not be determined in a vacuum, it also depends on the internal capability development and elaborate design of project governance.

**Originality/value –** This study provides an extension of the existing big data studies and fuels the ongoing debate on its actual outcomes in project management. It not only clarifies the direct effect of big data on project quality improvement, but also identifies the mechanism and conditions under which the adoption of big data can play an effective role.

**Paper type** Research paper

**Keywords:** Big data, Project quality, Hierarchical linear model, Technology capability, Team governance

1. **Introduction**

As the most valuable asset in the information era, big data is innovatively shaping people’s life quality and changing social progresses nowadays (Bilal and Oyedele, 2020; Dubey et al., 2019; El-Kassar et al., 2019; King, 2011; Sivarajah et al., 2017). The term big data refers to volumes of complex and linkable information, such as environmental, financial, geographic, social media information and so on (Bilal and Oyedele, 2020; Khoury and Ioannidis, 2014). Combined with the techniques, systems, practices, methodologies, and applications of data analysis, this kind of artefact, in essence, can document, measure, and digitally capture anything virtual (Sivarajah et al., 2017; Su et al., 2012). The overwhelming amount of data is pouring from anywhere, anytime, and any device, which has brought unprecedented opportunities for diverse individuals or organizations to better understand the world and make timely decisions (Chen et al., 2012). The potential of big data techniques is considerable and tangible to move forward the field of project management. Embracing big data could appropriately meet the immediate needs of developing solutions to complex problems that require the collaborative efforts involving multi-disciplinary knowledge and extensive resources (Shi et al., 2017).

Bringing big data to bear on project management is where the rubber meets the road (Levitt, 2011). The increasing datafication and technological advancements have proven fundamental building blocks for the continuing advancements of construction projects, while the use of big data is heavily shaping the current evolution of project management (Lu et al., 2015; Shi et al., 2017; Su et al., 2014). As the most important issue of project management (Lin et al., 2017; Zeng et al., 2015), project quality can benefit from building valuable information by analyzing extremely complex and heterogeneous data. Theoretically, the implementation of big data and predictive analytics (BDPA) is becoming a critical factor in achieving and maintaining high-quality results. It could promote product, process, and organization quality. Specifically, BDPA could more accurately describe customer expectations, the ultimate definition of project quality (Basu, 2014), and drive teams to meet the requirements (El-Kassar et al., 2019). It could also extract and analyze quality data multidimensionally, then easily discover defects and explore root causes for quality issues, which enables project managers to timely predict the key points of quality management and refrain from high-cost post-event inspections (Lu et al., 2019). The best-informed project managers with more profound understandings of data are inclined to use zipped information in big data to create benchmarks and achieve better quality performance throughout the whole project lifecycle (Bilal and Oyedele, 2020; Shi et al., 2017). The integrated data even breaks down the gaps between designing and constructing, and then effectively reduces the incidence of quality problems (Bilal and Oyedele, 2020; Whyte et al., 2016). For example, building information modelling (BIM) platforms, as a significant source for construction of big data, has attracted mounting attention worldwide, covering project quality improvement (Jin et al., 2017; Kim et al., 2016; Lu et al., 2017). Although an extensive body of literature on big data adoption in project quality improvement exists, far less is known about how and when BDPA becomes effective drivers of project quality.

On this basis, the objective of this paper is to develop a better understanding of the mechanisms by which, and the conditions under which, big data can efficiently and effectively improve project quality performance. Through undertaking a cross-level examination of Chinese construction firms’ data, two research questions are initiated. Firstly, does the adaption of BDPA actually lead to better project quality by building technology capability? Secondly, how do work team characteristics influence the path from ties with big data to project quality performance? Through the lens of capacity-based view, our theoretical model proposes that the adaption of BDPA can lead to better quality performance, and that this relationship is mediated by the project team’s technology capability. This mechanism is also moderated by goal interdependence and task interdependence. The intriguing and robust empirical results support the hypotheses and show that BDPA has positive effects on project quality, and that the successful conversion of information advantage to quality improvement requires project teams to be able to develop technology capability by absorbing useful information from redundant data (El-Kassar et al., 2019). Additionally, the elaborate design of project team governance (i.e. team goal and task interdependence) could promote this kind of transformation.

The rest of this paper is organized as follows: in the second section, the relevant literature is briefly reviewed and the hypotheses are derived. The research methodology is described in Section 3 while the empirical results are presented in the fourth section. Then, a comparative case study is conducted to validate the empirical findings in Section 5 as well as the discussions. Finally, conclusions, contributions, limitations, and implications for future study are given in the last section.

1. **Theory development and hypotheses**

To answer the research questions mentioned above, this study tries to paint a panorama by developing a cross-level framework including BDPA as the independent variable, project quality performance as the dependent variable, technology capability as the mediator, and project team governance (team reward, goal, and task interdependence) as the moderator. Figure 1 shows the conceptual model that indicates the relationships among the variables.

<Insert Figure 1 here>

*Top-down influences of big data on project quality performance*

As a dimension in the ‘iron triangle of cost, time and quality’, project quality not only directly concerns the project itself but also closely relates to the life and property security of people (Flyvbjerg, 2013; Lu and Liu, 2014; Wanberg et al., 2013). The improvement of quality often leads to stronger organizational competitive advantages, e.g., larger sale and increased market share or alternatively, smaller demand elasticity and higher price (Lu et al., 2019). Although the level of project quality management is continuously improving, quality problems are still lingeringworldwide, especially in emerging countries (Arditi and Gunaydin, 1997; Tam and Le, 2007). The closely intertwined challenge over the quality of projects often becomes a *cause célèbre* and attracts widespread concerns (Lin et al., 2017; Zeng et al., 2015). There is an urgent necessity of achieving and maintaining high-quality through resorting to all sorts of critical activities and practical applications in project management (Dow et al., 1999; Lu et al., 2019).

The extant literature has identified a number of factors that contribute to the desired quality level or adversely affect the project quality (Larsen et al., 2015). For example, at the corporate level, top management commitment, total quality management (TQM) system, and knowledge management could exert considerable influence on project quality (Jha and Iyer, 2006; Larsen et al., 2015; Reich et al., 2014). At the project level, project manager’s competence, efficient communication and teamwork, quality training of all personnel, project governance, and project characteristics are also related to quality performance (Basu, 2014; Jha and Iyer, 2006; Lu et al., 2019). While the information era has changed the core values and key resources needed to create competitive advantage (Chen et al., 2012), the innovative information technology which is closely related to the building of organizational capabilities and provides new ideas for project quality improvement should not be ignored (Bilal and Oyedele, 2020; Su et al., 2012).

Big data is now considered as a game changer enabling improved organizational efficiency and effectiveness in both strategy and operation (El-Kassar, et al., 2019; Khoury and Ioannidis, 2014). As a data-centric approach, big data can be defined as large quantities or volumes of datasets coming from numerous and independent sources and cannot be dealt with traditional methods (Gunasekaran et al., 2017; King, 2011). In response to the rapidly changing technological landscape and the increasing complexity of project itself, organizations are raising their entrepreneurial profile to embrace the excitement generated by the potential of big data analytics (Dubey et al., 2019). Towards the three-dimensional model of quality (Basu, 2014), specifically, BDPA could significantly improve design, process, and organization quality.

Firstly, the adoption of BDPA could broaden organizational information scope to promote design quality. Design quality refers to the defined attributes of a project that contain both numeric specifications and perceived dimensions (Basu, 2014). Mostly grounded in data mining and statistical analysis, BDPA could obtain new science, discovery, and insights from the highly detailed, contextualized, and rich contents hiding in the overwhelming amount of web-based, mobile, and sensor generated data (Chen et al., 2012). The new information helps organizations and project teams clearly specify the definition of project quality and share the distinct specifications or common objectives among departments. Comprehensive design quality is the core basis for the convenience of reconfiguring resources in ways adapting to dynamic conditions and building better alignment with their partners (Tam and Le, 2007). Thus, BDPA contributes to the betterment of design quality, leading to the improvement of quality performance.

Secondly, the adoption of BDPA could help monitor project process in real time to ameliorate process quality. The process quality is the acceptable level criteria which the final output of project should be validated against (Basu, 2014). To ensure the quality throughout all processes, a unified planning and control system is requisite. However, in a considerable sum of projects, the internal links have been cut down, and the consequent disruption of the information flow often leads to information-isolated island phenomena (Chen et al., 2018). The presence of BDPA creates limitless opportunities to eliminate information isolation and guarantees the conformity to quality criteria. It could not only offer complete data of the project, but also help comprehend the full spectrum of factors that are relevant (Whyte et al., 2016). This advantage enables project staff to predict the key points of quality management and promptly address the drawbacks (Dubey et al., 2019). Thus, the new quality management based on BDPA could transcend the traditional one which is mainly dominated by post-event inspections and further contribute to the realization of concept of “prevention first.”

Thirdly, the adoption of BDPA could predict managerial risks beforehand to advance organization quality. The quality of organization relates to a holistic culture which emphasizes transparent measurement and communication with key stakeholders (Basu, 2014). Extracting value residing inside big data, firms and project teams could more easily grasp manifold expectations of various stakeholders and balance their interests (Sivarajah et al., 2017). Moreover, BDPA is instrumental in constructing a borderless organization and encourages cross functional communications and teamwork. It conduces to foster sustainable culture that is good at identifying the possible perils and recommending mitigating strategies far ahead in time.

In sum, with the help of BDPA based on searching, analyzing, and predicting technology, firms and project teams could benefit from a systematic, refined, intelligent, and informative management model and conveniently improve the quality of design, execution processes, and the communications between stakeholders. Therefore, we propose that:

H1. The organizational adoption of big data and predictive analytics (BDPA) positively influences project quality performance.

*The mediating role of technology capability*

Although big data can broaden organizational information scope, monitor project process in real time, and predict risks beforehand, the success of big data implementation depends not only on technological resources, but also on the capability of technology use and quality control (El-Kassar et al., 2019).

Being considered the focus of utilization, technology capability demonstrates the way in which a firm or a team mobilizes resources to maximize benefits from the adoption of new technologies (Gold et al., 2001). Nowadays, the increasing adoption of advanced technologies has given prominence to consanguineous relationship between technology capability and organizational or project performance. This capability is often achieved by providing suitable and capable technologies, including hardware systems and soft power involving human and organizational aspects. Early engagement in project design, construction modularization, and stakeholder (e.g. suppliers) involvement are all considered as the key dimensions (Arana-Solares et al., 2019). Logically, higher technology capability is associated with better quality performance, i.e. design, process, and organization quality, because design engagement produces explicit specifications, modularization guarantees conformance, and stakeholder involvement germinates sustainability.

Since technology is multifaceted, the characteristics of BDPA, such as business intelligence, opportunity generation, and knowledge application support the building of technology capability (Sivarajah et al., 2017). Through the linkage of information and communication systems, BDPA could integrate previously fragmented flows of information and knowledge intra- and inter-organization. These linkages are helpful to eliminate communication barriers that naturally occur among different individuals, units, or organizations. Specifically, BDPA could intelligently combine and interpret complex information derived from various sources, and further enable firms and project teams to eliminate structural or geographical impediments, and generate knowledge regarding competition and external environments. It further allows users to ensure the appropriate application of the technology and track information about its customers, partners, employees, or suppliers (Arana-Solares et al., 2019). This synthesized information would significantly reduce uncertainties from demands, capacities, and supply availability (Lu et al., 2019; Whyte et al., 2016). As a result, BDPA offers the continuous improvement for project design engagement, construction modularization, and stakeholder involvement, consequently guarantees project quality through statistical control and the training of people in the principles of technology management.

Therefore, it is proposed that:

H2: Team technology capability mediates the positive relationship between BDPA and project quality performance.

Although technology capability could mediate the relationship between BDPA and project quality performance, this effect may appear under certain conditions. While the project execution relies on project teams, and the structural property of teams could significantly exert contingent influence on the association. Interdependence is a central aspect of team design that reflects the degree to which team members interact in performing tasks (Courtright et al., 2015). This study provides a unique lens to investigate the role of different forms of interdependence (reward, goal, and task interdependence) on the outcomes of technology capability development.

*The moderating role of reward interdependence*

Reward interdependencerefers to the extent to which an individual’s rewards depend upon the performance of coworkers (Campion et al., 1993; Courtright et al., 2015). It is a function of the distribution of final outcomes. Theoretically, the interdependence of rewards combines team and individual performance to provide incentives for collaboration. However, if an individual cannot heavily affect the outcomes of the entire team, free-riding behaviors will arise. Schemes that take into account peer pressure and mutual supervision are effective in preventing free-rides and heightening individual incentives (Wageman and Baker, 1997).

When team rewards are highly interdependent, members will have a greater sense of shared “ownership” and tend to work together to find solutions to project problems (De Clercq et al., 2015). Also, team managers will focus less on their personal turf and horizon if their rewards are connected to the whole performance of colleagues. Instead, they will become more receptive to the suggestions and expertise from others as well as sensitive to innovative technology, such as big data. They could more easily synchronize team members’ behavior to focus on capability development and final quality performance. Therefore, it is proposed that:

H3: The mediating effect of technology capability on the relationship between BDPA and project quality performance is stronger when team reward interdependence is higher.

*The moderating role of goal interdependence*

Goal interdependence refers to the interconnectedness among group members, which is driven by the way performance is measured (Courtright et al., 2015). It reflects the cooperative relationship between employees towards their goal, which means that individuals move towards their goal attainment depending on others’ goal-achieving movements (Leung et al., 2015). The alignment of interests among individuals often promotes collaborative behaviors. When one person acquaints the perception of goal relationship with others, positive interpersonal interactions, e.g. mutually beneficial exchange, will reinforce the perception that colleagues are working towards a joint goal. Thus, a clearly defined goal relationship is thought to be critical to team effectiveness (Courtright et al., 2015). Not only should goals exist within project teams, but also individual members’ goals must be concatenated to projects’ goals for maximum efficiency (Campion et al., 1993).

When project goal setting is well documented at the individual level , team goal interdependence is higher. Employees are motivated to display mutually supportive assistance or helping behaviors (Campion et al., 1993; Courtright et al., 2015). Like reward interdependence, the conglutination of interests and cooperation for goal achievement facilitates the synergy among project teams and helps project managers lead members to adopt innovative technologies and ideas to optimize project quality . Therefore, it is proposed that:

H4: The mediating effect of technology capability on the relationship between BDPA and project quality performance is stronger when team goal interdependence is higher.

*The moderating role of task interdependence*

Task interdependence refers to the interconnectedness guiding the work process and the distribution of resources among team members (Courtright et al., 2015). It reflects the extent to which a project team member’s task performance depends upon the efforts or skills of other colleagues. Whether tasks are highly interdependent or not depends on how the project team leaders define team’s tasks and how the process of getting the work done is indicated (Wageman and Baker, 1997). Task interdependence could also promote collaborative behaviors by enhancing the individual sense of responsibility. Motivation to act together increases when team members recognize the value of other people's work to the team's achievements (Courtright et al., 2015).

Task interdependence often varies across project teams, and becomes higher as work flow goes from pooled to sequential to reciprocal (Campion et al., 1993). Tasks become highly dependent if other project team members need extensive interaction in order to access critical resources and operate in an interdependent workflow structure. A strong coordination is expected to be built and substantial collaboration is encouraged. Consequently, clear task definition related to high interdependence could arouse lofty responsibility for new technology adoption and better project quality.

Therefore, it is proposed that:

H5: The mediating effect of technology capability on the relationship between BDPA and project quality performance is stronger when team task interdependence is higher.

1. **Methodology**

*3.1 Sample and data collection*

To investigate these hypotheses, a questionnaire survey towards construction industry was conducted. The standard procedure for research designing was employed to ensure validity and to avoid cultural bias (Lin et al., 2018; Yu et al., 2019). While all scales were adopted in English, the surveys were translated into Chinese and then back-translated by two scholars with substantial research experience in relevant subjects. Moreover, *ex ante* procedural remedies were used to reduce the common method bias (Podsakoff et al. 2003).The questionnaire consisted of two parts. One top manager completed Part 1 that contained variables related to firms. Several project managers in the same firm were asked to complete Part 2 that contained variables related to projects. Informant anonymity was guaranteed, and it was also clearly stated that there were no right or wrong choices.

A pretest was conducted by carrying out in-depth interviews with four experienced scholars and four senior professional managers to verify the content, phraseology, and clarity of the draft. All problematic items were revised or eliminated to produce the final version. Then, two hundred sets of questionnaires were distributed on-site to participants from randomly chosen construction firms located in the Yangtze Delta in China. This area is one of the most developed regions in China, with well-established institutional and technological infrastructure (Lin et al., 2020). The regional construction industry is also at the leading level in China. Therefore, the sample could capture corporations progressing various degree of digitalization, which is necessary to test the theoretical model. Finally, 99 sets (302 respondents from 48 firms) were collected. After deleting invalid and mismatch questionnaires, 92 responses were obtained. Of these 92 project samples, 78.26% of project managers were male; 6.52% of managers held a middle school degree, 15.22% held a college degree, 58.68% held a bachelor degree, and 8.70% held master degree; 4.35% of project managers were below 29 years old, 15.22% were above 30 and below 34 years old, 46.74 were above 35 and below 39 years old, 33.70 were above 40 years old; the mean of project tenure is 6.45 years (S.D. = 5.04 ); the mean of company tenure is 9.22 years (S.D. = 4.51 ); the mean of team size is 15.74 members (S.D. = 15.27); the mean of project age is 4.74 years (S.D. = 3.52).

*3.2 Measurements*

All perceptual items were assessed on 5-point Likert-type scales ranging from 1 (strongly disagree) to 5 (strongly agree) unless otherwise noted. For multi-item constructs, average scores were calculated to measure the variable.

*Big data and predictive analytics*

In line with El-Kassar et al. (2018), *Big Data and Predictive Analytics* (*BDPA*) was measured from three dimensions: *big data adoption (BDAD), big data routinization (BDRT),* and *big data assimilation (BDAS)*. Three items were used to measure BDAD by inquiring about the incorporation of big data into the organizational structure and its effect on the respondents’ job performance after their associations with BDPA (Hazen et al., 2012). Five items were used to measure BDRT by reflecting whether organizational procedures provided technical support, aided in hiring qualified people, and offered BDPA training opportunities. Four items adapted from Hazen et al. (2012) and Liang et al. (2007) were used to measure BDAS by inquiring about the BDPA’s volume being used as a tool in every department, its diversity being allocated for decision making, and its depth being functional in both managerial and operational areas. Cronbach’s alpha coefficients for BDPA was 0.89.

*Technology capability*

A twelve-item scale adopted from Gold et al. (2001) was used to measure the technology capability of project knowledge management. The sample items are *“*My project team has clear rules for formatting or categorizing its product knowledge” and “My project team uses technology that allows it to monitor its competition and business partners”. Cronbach’s alpha coefficient for technology capability was 0.90.

*Team Interdependence.*

Following toCampion et al. (1993), team Interdependence was measured from three dimensions: *reward interdependence*, *goal interdependence*, and *task interdependence*. Each dimension consisted of three items. The sample item of reward interdependence is “Many rewards from my job (e.g., pay, promotion, etc.) are determined in large part by my contributions as a project team member”, the sample item of goal interdependence is “My work goals come directly from the goals of my project team”, and the sample item of task interdependence is “Within my project team, jobs performed by team members are related to one another”. Cronbach’s alpha coefficient for reward interdependence, goal interdependence and task interdependence were 0.74, .84, .79, respectively.

*Project quality performance*

A four-item scale developed byDow et al. (1999) was used to measure project quality performance. The four items include: (1) the percentage of defects at final assembly, (2) the cost of warranty claims, (3) the total cost of quality, and (4) an assessment of the defect rate relative to competitors. Cronbach’s alpha coefficient for project quality performance was 0.74

*Control variables*

To rule out alternative explanations and considering the potential effects of project manager’s demographics (e.g., age, gender, and education, company tenure and project tenure) and project characteristics (e.g., project size and age), a total of seven control variables were included in this study. Gender is represented by dummy variables (1= male, 0 = female), age was defined by integer values ranging from 1 to 4 (1= “below 29 years old”, 2 = “above 30 and below 34 years old”, 3 = “above 35 and below 39 years old”, 4 = “above 40 years old”). Project managers’ education experience is represented by numerical variables (1= “high school or technical secondary school degree”, 2 = “college degree”, 3 = “bachelor degree”, 4 = “master degree”, 5 = “doctor degree”). Company tenure, project tenure, and project age were reported by managers in years, and project size was reported in number of project members.

1. **Results**
	1. *Confirmatory Factor Analysis (CFA)*

A set of CFAs is conducted to assess the construct validity (Yu et al., 2019). Firstly, the approach of item parceling was adopted to reduce parameters that need to be estimated because of the baseline model with full items exceeding the ratio (sample size/parameters is more than 1:5, Bentler and Chou, 1987) for estimation. Item parcels for technology capability were created based on factor loading in exploratory factor analysis (EFA) (Landis et al., 2000). For technology capability, the item with highest factor loading and the item with the lowest factor loading are parceled to one item, the item with second highest factor loading and the item with the second lowest factor loading are parceled to one item, and so forth to create parceled items until this construct has three parceling items.

After item parceling, a set of CFAs were conducted to test the construct validity, the results are shown in Table 1. The model fitting of the six-factor model (baseline model, Model 1) was compared with the other seven alternative models. Compared with the seven alternative models (Model 2-8), the assumed six-factor model has the best fitting degree with the sample data (*χ*2/d*f* = 1.54, IFI = .93, TLI = .92, CFI = .93, RMSEA = .08, SRMR = .07). However, each alternative measurement mode would significantly increase the *χ*2 value (comparing to baseline model, all alternative models’ ∆*χ*2/∆d*f* are significant, *p* < .001). These results support that the construct validity of measurement model in this study is acceptable.

<Insert Table 1 here>

* 1. *Hierarchical linear modeling (HLM) analysis*

Table 2 summarizes descriptive statistics and Pearson correlations among variables. The correlation between independent variables is not larger than 0.75 and is within a reasonable scope.

<Insert Table 2 here>

A two-level hierarchical linear modeling (HLM) is used to analyze project-level outcomes (*Project Quality Performance*) nested in firms. It can simultaneously investigate relationships within and between hierarchical levels of grouped data and offer more accurate estimation of higher-level implementation (e.g., organizational level) on lower-level outcomes (e.g., project level). By specifying firm-level differences as a higher-level variable in analysis models, we also control for the fixed effects owing to between-firm differences. The results are shown in Table 3.

As presented in Models 2 and 4, BDPA is positively correlated to both technology capability (Model 2, *γ* = .21, *p* < .05) and project quality performance (Model 4, *γ* = .15, *p* < .05), thus H1 is empirically supported. H2 predicts that technology capability mediates the relationship between BDPA and project quality performance. To test H2, both BDPA and technology capability were incorporated into the multi-level analysis model. It was found that the coefficient of BDPA change from .15 (Model 4, *p* < .05) to .07 (Model 5, *p* > .05), and the coefficient of technology capability is still significant (Model 5, *γ* = .34, *p* < .001), thus H2 is also supported.

To test H3, H4, and H5, technology capability, reward interdependence, goal interdependence, and task interdependence were firstly centralized, and then interactive terms were produced through multiplying technology capability by the three dimensions of team interdependence respectively. The results show that interactive term between technology capability and reward interdependence is insignificantly positively related to project quality performance (Model 8, *γ* = .17, *p* > .05), thus H3 is not supported. As for construction projects, the quality responsibility is often hard to split intensively. Project manager is the first responsible person, thus, reward interdependence might not create enough incentives. In line with the prediction of H4, the interactive term between technology capability and goal interdependence is positively related to project quality performance (Model 10, *γ* = .18, *p* < .05). In order to further demonstrate this interactive effect on project quality performance, the relationships between technology capability and project quality performance were plotted under the case of high and low level of goal interdependence in project team, according to the procedure proposed by Stone and Hollenbeck (1989),. Figure 2 shows that goal interdependence strengthens the positive relationship between perceived technology capability and project quality performance. Specifically, the positive association between technology capability and project quality performance is stronger when goal interdependence is higher. We also conduct a bootstrap procedure, drawing on 5,000 random samples to calculate the indirect effect and its confidence intervals in the case of high level and low level of goal interdependence. The results show that the indirect effect of big data and predictive analytics on project quality performance through technology capability is .08 (.01, .16) in the case of high level goal interdependence, at the 95% confidence intervals. It means that such indirect effect is significant; and the indirect effect of big data and predictive analytics on project quality performance through technology capability is .03 (-.03, .08) in the case of low level goal interdependence, and the 95% confidence intervals including zero, it means that such indirect effect is insignificant. Therefore, H4 is supported.

<Insert Figure 2 here>

As predicted in H5, the interactive term between technology capability and task interdependence is positively related to project quality performance (Model 12, *γ* = .19, *p* < .05). Similar to H4 testing, the relationships between technology capability and project quality performance were also plotted under the case of high and low level of task interdependence in project team. Figure 3 shows that task interdependence strengthens the positive association between technology capability and project quality performance. Specifically, the positive association between technology capability and project quality performance is stronger when task interdependence is higher. A bootstrap procedure was also conducted, drawing on 5,000 random samples to calculate the indirect effect and its confidence intervals in the case of high level and low level of task interdependence. The results show that the indirect effect of big data and predictive analytics on project quality performance through technology capability is .11 (.01, .22) in the case of high level task interdependence, the 95% confidence intervals excluding zero, it means that such indirect effect is significant; and the indirect effect of big data and predictive analytics on project quality performance through technology capability is .04 (-.01, .09) in the case of low level task interdependence, and the 95% confidence intervals including zero, it means that such indirect effect is insignificant. Therefore, H5 is supported.

<Insert Figure 3 here>

1. **A comparative case study**

To validate the empirical findings, Zhongyifeng Construction Group (ZYF), a large-scale construction contractor in Jiangsu Province, was selected as a comparative case study. ZYF is a 60-year-old firm dedicated to providing first-class services for megaprojects construction and comprehensive operation, and has been on the lists including Top 500 private enterprises in China, ENR Top 80 Contractors in China, and Top five construction enterprises with strong comprehensive strength of Jiangsu province. In the process of its development, ZYF has always regarded innovation as an important source of excellent project quality and competitive advantage. Empowered by the application of emerging technologies, the firm has successfully executed a great deal of influential megaprojects, such as Suzhou Center, 524 National Road Reconstruction and expansion project, Suzhou rail transit Line S1, Nanjing Youth Olympic Stadium, Haiyang power plant in Vietnam, Imitated Tang-style hall project in Canada, etc. These accomplished high-quality megaprojects have brought about a series of honors including Zhan Tianyou Award, Luban Award, National Quality Engineering Award, Huaxia Construction Science and Technology Award, China Municipal Gold Cup Award, China Installation Star, and so on. One senior manager (SM) and four project managers (PM1-4) of ZYF group who did not participate in the questionnaire survey, were invited to the in-depth interview, thus reducing the potential biases of the validation results.

Generally, all the experts unanimously agree with the opinion that the application of information technology, including big data and predictive analytics, has greatly contributed to project quality control and improvement. Constantly innovating based on new information technologies, the firm has deeply integrated lean management into the whole life cycle of projects and significantly speeded up the transformation of the construction mode. At the organizational level, the SM reiterated the importance of technology innovation during the firm’s development. ZYF has set up a Science and Technology Commission to be responsible for top-level design of science and technology-driven development strategy and annual science and technology development plan. A series of initiatives has been taken to focus on cutting-edge technology and activate employees’ creative thinking. As a very popular technology growing at ever-increasing rates, BDPA is occupying the center of corporate science and technology strategies. A wholly-owned subsidiary company, Zhongheng Digital Construction, was founded to cultivate new fields of emerging information technology and offer technical supports for the group development. Towards the goal of optimal quality, the implementation of BDPA has brought about fundamental changes in digital construction and intelligent construction For example, a people-oriented job behavior supervision system was set up to prevent the risks of unsafe acts based on the combination of face recognition, two-dimensional code, big data checking technology, and real-time dynamic analysis of construction progress. Meanwhile, the operation status data of machinery and equipment was embedded in the BDPA to monitor idle operating and safety risks. In terms of supply chain, the technology of Internet of Things (IoT) was adopted and its data was used to identify the potential cost wastage, resource waste, and other misconducts (e.g. dereliction, fraud, and corruption). The real-time multi-level big data analysis and revisualization provided a fine-grained panorama of enterprise production and management that significantly facilitated the total quality management.

At the project level, four project managers confirmed the effectiveness of BDPA in the project quality management progress and further highlighted its specific applications across various projects. For safe construction, Moreover, BDPA facilitated virtual construction, multi technology collision, and mass concrete temperature, foundation pit, and high formwork monitoring. It could automatically issue early warning and execute problem positioning when comprehensive data analysis captured an exception. Consequently, a large number of quality defects would be detected and handled timely. Unsafe behaviors were also identified, for instance, a worker entering the construction site without wearing safety helmet or broke into the forbidden area. Especially, the big data system played a significant role against the COVID-19 pandemic due to the combination with the integrated body temperature sensors. It could quickly identify the health status of workers and differentiate suspected feverish ones. In terms of material and metering management, files and reports are all automatically generated and analyzed. This method displaced the handicrafts, restricted fabrications, and enforced the whole process quality tracing. In general, they agreed with the results of the empirical findings from this study, which indicated that BDPA did matter in the aspect of project quality. Admittedly, there were distinct differences among projects. Firstly, imbalance existed due to the staffing and resources. Skilled employees who are familiar with computer or data science are still in shortage, and most of them were often dispatched to the priority projects. Secondly, judgment based on personal experience was given the priority in many cases. The analytical models for project quality were not quite fully relied on. Concerns about the effectiveness regularly appeared in practice. Thirdly, incentives for frontline employees were insufficient. The training on big data technology has just covered the mid-level management but not the whole firm. Initiatives for arousing spontaneous learning are imperative as well as the team designing and building.

1. **Discussion and contribution**

Within the era of “big data,” the innovative information technologies are assuring a constant supply of novel solutions for conquering quality challenges (Bilal and Oyedele, 2020; Levitt, 2011; Lu et al., 2019; Shi et al., 2017). Despite of the increasing importance of this phenomenon, insufficient efforts have been devoted thus far to clearly identify the mechanisms and conditions underlying big data’s significant role. To reveal the black box, this study tries to paint an interesting picture of the associations among big data and predictive analytics, technology capability, project team governance (team reward, goal, and task interdependence), and project quality performance. More particularly, the research examines the mechanism beyond the relationship between big data and project quality performance, from the perspective of technology capability as a mediator, and the three dimensions of project team interdependence as moderators. Based upon a sample of Chinese construction firms, the cross-level empirical analysis demonstrates that the organizational adoption of BDPA has a significant positive impact on project quality performance. Furthermore, team technology capability, focusing on the utilization of innovative information technologies, acts as a mediator in the relationship between BDPA and project quality performance. It is also observed that both team goal interdependence and task interdependence could positively moderate the mediation effect of team technology capability on the relationship between BDPA and project quality performance. In other words, the mediation effect is stronger when team goal interdependence (task interdependence) is higher. These results not only highlight that the value of innovative information technologies in quality improvement could not be determined in a vacuum, but also reveal the mechanism by which the effects are taken through the elaborate design of project governance.

*Theoretical contributions*

The current research offers several contributions which can deepen the theoretical and managerial understanding of big data’s impacts on project quality management.

Firstly, this study provides an extension of existing big data studies and fuels the ongoing debate on its real outcomes in project management. Through the plethora of sources, there is an ever-growing discourse about big data in project management offering both Big Opportunities and Big Challenges extending from organizations to sciences (Sivarajah et al., 2017). Despite of the importance of understanding this phenomenon, gaps still exist whether a firm could really obtain deeper insights and benefit from becoming increasingly digital (Dubey et al., 2019). To fill the gaps, a theoretical framework is proposed to offer empirical evidence for a better understanding of the outputs of big data implementation by theorizing and testing the cross-level association between BDPA and project quality performance. This study extends from the common linear perspective to the cross-level hierarchical linear model to describe complex relationships between organizational strategic progress and heterogeneous project performance. Firms could embrace innovative information technologies to collect intra- and inter-organizational data, and then excavate a tremendous amount of valuable information from the rapidly expanding data (Sivarajah et al., 2017). This kind of information finding helps firms scan inside and outside boundaries in real time, acquire disembodied knowledge, fully comprehend customer expectations, and catch sight of best practices with lower costs (Dubey et al., 2019; Kim et al., 2016). Thus, connections with big data not only provide organizations with a new manner for quality control, but also promote them to renew their stocks of capabilities that enable firms or teams to achieve better quality. Firms are recommended to invest in big data to unleash new organizational capabilities and value. For example, the system for data crating, calculating, managing, applying and sharing is essential. Focusing on quality improvement, this study sheds light on the nature and role of the development of data collection capacities, storage technologies and analysis methods in the contemporary project management (Whyte et al., 2019; Yang et al., 2012).

Secondly, this study identifies the mechanisms and contextual conditions for successful BDPA implementation by investigating the mediating role of technology capacity and the moderating role of team interdependence governance on the relationship BDPA between and project quality performance. It is unanimously agreed that there is great business value of big data investments (Gunasekaran et al., 2017; King, 2011). Firms could innovatively implement advanced technological strategy to embody information elements in their business activities. However, the consequences are not constantly significant. How and when could big data become effective drivers of project quality remains to be explored. A lucrative transformation of these investments into substantive performance improvements requires adequate and appropriate team capabilities to leverage inputs (Lin et al., 2020). For example, firms as well as project teams need to foster their technology capability to acquire valuable know-how, reasonably apply new technology, and continually increase operational efficiency. Furthermore, the mechanism is context-dependent and the link between big data and quality improvement through capability building cannot be studied in isolation from the team characteristics. Because project quality is a kind of collective outputs rather than individual contributions, interconnectedness among team members would heavily constrain the utilization of new technology and the development of capability (Arana-Solares et al., 2019; Parolia et al., 2011). The presence of interdependent tasks and goals for project teams is necessary for cooperation (Leung et al., 2015). Careful design for team governance should be employed to trigger the motivations of corporative behaviors and curb managerial bias. In this respect, this study provides a fine-grained and panoramic picture for the understanding of project quality management by revealing latent mechanisms and restrained conditions. It also explains why firms or projects benefit from innovative technologies widely and differently although they may all claim to attach importance to big data.

Thirdly, this study makes contributions to project management research in emerging economies. The ongoing progress and unprecedented expansion of megaprojects increasingly call for the stricter quality management, especially in China (Lin et al. 2017; Ma et al., 2020; Zeng et al., 2015). Although big data is a differentiator of project performance (Whyte et al., 2016), the source of competitive advantage (Gunasekaran et al., 2017), or new frontier of competition (Chen et al., 2012), Chinese construction industry now is still suffering from frequent accidents and quality problems probably on account of neglecting the big data of construction. In reality, employing big data generates advantages not only for high-tech firms, but also for construction firms which are staying in low technical level, labor intensive and low-efficiency. This study finds a way out of this impasse *via* an empirical attempt in the emerging and transforming economy. Quintessential information from big data throughout the entire project life cycle represents a relevant strategy for project management and should be given emphasis to promote technology abilities in diverse industries.

*Managerial implications*

From above findings, this study also draws important guidance and practical implications for practicing managers and policymakers. As for construction firms, managers need to be motivated to think about and integrate innovative technologies (e.g. big data) on operational and managerial activities. On one hand, firms need to reacquaint the system of project management based on data-driven insights. Big data is breaking the mold of established approaches and enabling radically new, rapid, and flexible decision-makings (Whyte et al., 2016). Managers should delve into the changed way how information is generated, collected, analyzed and used. On the other hand, the potential benefits of big data are substantially influenced by the degree of team collaboration. Developing and maintaining team capability and cohesion is critical to the project success. Project teams should not only focus on meeting the written requirements for the project, but also carefully think over other stakeholder needs and expectations from the projects (Tam and Le, 2007). Both advanced technologies and managerial methods are indispensable to facilitate the team integration which would help project teams deliver value in their own distinctive way and be agile and adaptive enough to restructure their value proposition when circumstances change.

Meanwhile, policymakers should place greater emphasis on creating effective institutional arrangements or policies to facilitate the application of innovative information technologies for improving people’s wellbeing. On one hand, it is necessary to accelerate the construction of digital information infrastructure. While the high-speed, ubiquitous infrastructure is fundamental for the cultivation of an independent and controllable big data eco-system, policies must focus on the need to target cutting-edge technology and mobilize prime resources. On the other hand, forward-looking deployment schemes are of utmost urgency to overcome potential adoption obstacles. For example, initiatives should be taken to speed up relevant legislation, encourage data opening and sharing and reinforce privacy protection. In particular, policy intervention needs to take into account what can attract small-scale organizations without hesitation.

1. **Limitation and conclusion**

*Limitations and future research directions*

There are a few limitations to be addressed in future research. Firstly, this study employs a questionnaire survey which is a cross-sectional design and restricted to only one point in time. Despite the support from mediation analysis, the direction of causality might be a potential problem. Future studies should apply longitudinal designs to properly test the causal relationship and use multiple data sources to ensure the validation and robustness of the conclusions. Secondly, the perceptual scales are used to measure the variables. It is highly recommended to use objective data to measure these constructs in the future. Especially, more scale development is also required with respect to some quality practice constructs. Thirdly, the findings only reflect the current situation in China. It is significant and meaningful to explore the impacts of more contextual factors and replicate the findings in other countries.

While existing research has highlighted the function of big data, scholars have devoted far less attention to explore how and when big data and predictive analytics become effective factors in improving project quality. To this end, this study has taken an initial step by identifying the mechanisms by which, and the conditions under which, big data and predictive analytics can efficiently and effectively influence project quality. It is expected that these efforts could provide a better understanding of how emerging technology contribute to project quality management.

**Conflict of interests**

The authors have declared that no conflict of interest exists.

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Table 1. Comparison of Measurement Models

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Model | *χ*2 | d*f* | *χ*2/d*f* | Δ*χ*2/Δd*f* | IFI | TLI | CFI | RMSEA | SRMR |
| Baseline model | 210.33 | 137 | 1.54 | - | .93 | .92 | .93 | .08 | .07 |
| Five factors-BDPA and TC were combined | 348.10 | 142 | 2.45 | 27.55\*\*\* | .81 | .77 | .81 | .13 | .11 |
| Five factors-TC and PQP were combined | 349.79 | 142 | 2.46 | 27.89\*\*\* | .81 | .77 | .81 | .13 | .11 |
| Five factors-RD and GD were combined | 241.80 | 142 | 1.70 | 6.29\* | .91 | .89 | .91 | .09 | .07 |
| Five factors-RD and TD were combined | 239.32 | 142 | 1.69 | 5.80\* | .91 | .89 | .91 | .09 | .07 |
| Five factors-GD and TD were combined | 235.99 | 142 | 1.66 | 5.13\* | .92 | .89 | .91 | .09 | .07 |
| Four factors-RD, GD and TD were combined | 250.90 | 146 | 1.72 | 4.51\* | .90 | .89 | .90 | .09 | .07 |
| One factor | 686.55 | 152 | 4.52 | 31.75\*\*\* | .51 | .44 | .40 | .20 | .14 |
| Note: \* p < .05, \*\*\* p < 0.001; BDPA= Big Data and Predictive Analytics, TC = Technology Capability, RD= Reward Interdependence, GD = Goal Interdependence, TD = Task Interdependence |

Table 2. Means, Standard Deviants, and Correlations

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
| 1. Gender | 1.13  | .32  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| 2. Education | 2.65  | .71  | -.06 |  |  |  |  |  |  |  |  |  |  |  |  |
| 3. Age | 4.11  | .81  | -.01 | .14 |  |  |  |  |  |  |  |  |  |  |  |
| 4. Project Tenure | 6.45  | 5.04  | -.04 | .03 | .26\* |  |  |  |  |  |  |  |  |  |  |
| 5. Company Tenure | 9.22  | 4.51  | .15 | -.04 | .31\*\* | .30\*\* |  |  |  |  |  |  |  |  |  |
| 6. Project size | 15.74  | 15.27  | -.10 | .10 | -.06 | .22 | .13 |  |  |  |  |  |  |  |  |
| 7. Project age | 4.75  | 3.52  | -.15 | .00 | .13 | .30\*\* | .15 | .17 |  |  |  |  |  |  |  |
| 8. BDPA | 3.84  | .75  | -.18 | -.03 | .11 | .14 | -.15 | .04 | .14 | ***.89*** |  |  |  |  |  |
| 10. TC | 4.12  | .62  | .23\* | .02 | .08 | -.02 | .00 | -.14 | -.06 | .20 | ***.90*** |  |  |  |  |
| 11. RD | 4.07  | .78  | .14 | -.29\*\* | .10 | .02 | .00 | -.16 | -.06 | .08 | .35\*\*\* | ***.74*** |  |  |  |
| 12. GD | 4.17  | .74  | .19 | -.26\* | .12 | -.05 | .01 | -.23\* | -.20 | .15 | .47\*\*\* | .64\*\*\* | ***.84*** |  |  |
| 13. TD | 3.87  | .86  | .13 | -.22 | .05 | .04 | .02 | -.20 | -.07 | .15 | .51\*\*\* | .60\*\*\* | .70\*\*\* | ***.79*** |  |
| 14. PQP | 4.04  | .48  | .15 | -.19 | -.15 | .00 | -.08 | -.28 | -.08 | .18 | .48\*\*\* | .52\*\*\* | .49\*\*\* | .43\*\*\* | ***.74*** |
| Note: \* *p* < .05, \*\* *p* < .01, \*\*\* *p* < .001; BDPA= Big Data and Predictive Analytics, TC = Technology Capability, RD= Reward Interdependence, GD = Goal Interdependence, TD = Task Interdependence, PQP = Project Quality Performance |

Table 3. Results of HLM analysis.

|  |  |  |
| --- | --- | --- |
|  | Tech | PQP |
|  | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 | Model 9 | Model 10 | Model 11 | Model 12 |
| Cont. | 3.41\*\*\* | 2.57\*\*\* | 4.62\*\*\* | 4.03\*\*\* | 3.15\*\*\* | 3.36\*\*\* | 2.70 | 2.69\*\*\* | 2.89\*\*\* | 2.83\*\*\* | 3.20\*\*\* | 2.95\*\*\* |
| Gender | .44\* | .50\* | .17 | .22 | .05 | .02 | -.01 | -.01 | -.00 | -.04 | .02 | -.02 |
| Education | .03 | .04 | -.08 | -.08 | -.10 | -.11 | -.02 | -.02 | -.05 | -.05 | -.08 | -.09 |
| Age | .07 | .04 | .11 | -.11 | -.13\* | -.12\* | .14\*\* | .14\*\* | -.14\*\* | -.14\*\* | -.12\* | -.10 |
| Tenure 1 | .00 | -.00 | .01 | .01 | .01 | .01 | .01 | .02 | .01 | .02 | .01 | .02 |
| Tenure 2 | -.01 | .00 | -.00 | .00 | -.00 | -.00 | -.00 | -.00 | -.00 | -.01 | -.00 | -.01 |
| Size | -.01 | -.00 | -.01 | -.01 | -.00 | -.01\* | -.01\* | -.01\*\* | -.01\* | -.01\* | -.01\* | -.01\* |
| Time | -.00 | -.01 | -.00 | .01 | -.00 | -.00 | -.00 | -.01 | .00 | -.00 | -.00 | -.01 |
| BDPA |  | .21\* |  | .15\* | .07 |  |  |  |  |  |  |  |
| TC |  |  |  |  | .34\*\*\* | .37\*\*\* | .27\*\*\* | .25\*\*\* | .26\*\*\* | .24\*\*\* | .30\*\*\* | .34\*\*\* |
| RD |  |  |  |  |  |  | .23\*\*\* | .24\*\*\* |  |  |  |  |
| GD |  |  |  |  |  |  |  |  | .20\*\* | .23\*\*\* |  |  |
| TD |  |  |  |  |  |  |  |  |  |  | .09 | .09 |
| TC\*RD |  |  |  |  |  |  |  | .17 |  |  |  |  |
| TC\*GD |  |  |  |  |  |  |  |  |  | .18\* |  |  |
| TC\*TD |  |  |  |  |  |  |  |  |  |  |  | .19\* |
| Between | .12 | .08 | .17 | .15 | .15 | .15 | .14 | .14 | .15 | .15 | .15 | .15 |
| With | .59 | .57 | .41 | .42 | .38 | .38 | .35 | .34 | .36 | .35 | .38 | .38 |
| LR Chi2 | 7.30 | 13.35 | 15.53\* | 20.33 | 42.30 | 40.71 | 58.04 | 60.63 | 49.76 | 53.64 | 43.17 | 48.56 |
| Log Likelihood | -82.01 | -78.98 | -54.22 | -52.01 | -41.02 | -41.82 | -33.16 | -31.86 | -37.30 | -35.35 | -40.59 | -37.90 |
| Note: \* p < .05, \*\* p < .01, \*\*\* p < .001; BDPA= Big Data and Predictive Analytics, TC = Technology Capability, RD= Reward Interdependence, GD = Goal Interdependence, TD = Task Interdependence, PQP = Project Quality Performance |



Figure 1. The conceptual model.



Figure 2. The moderating role of goal interdependence on the relationship between technology capability and project quality performance.



Figure 3. The moderating role of task interdependence on the relationship between technology capability and project quality performance.