How Ability, Motivation and Opportunity Drive Individual Performance Behaviors in Projects: A Test of Competing Models

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Abstract

Organizations performance assessment is one of the critical aspects in today's project management research. The performance of organizations can be affected by various factors beyond financial measures. Construction organizations faces difficulty in performance assessment stemming from the uncertain fragmented unique nature of the construction industry. Only few research focused on the non-financial factors that impact the organizations performance. Although many research works have been done to study organization success factors, most of the conducted research was only focusing on the construction project level rather than the organizational level. In addition, most of the research neglected the different perspectives of construction organizations functional units when assessing the performance. The goal of this research is to study the effect of different functional units on the company performance through identifying, ranking a set of critical success factors (CSFs) and build comprehensive performance construction organizations assessment models. Analytical Hierarchy Process (AHP) technique has been used for the data analysis and the models' development. The research findings indicated that the CSFs factors in construction organizations have different priorities and weights according to the different functional units. Four assessment models are eventually developed to reflect the unique perspective of four functional units in construction organizations. The developed models have been validated with satisfactory results ranging 80% to 90%. This research will benefit organizations managers to accurately assess their performance according to the different functional units.

Keywords

ability to perform (A), constraining-factor model (CFM), limiting-factor model (LFM), motivation to perform (M), opportunity to perform (O), performance behaviors

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Introduction

Performance is now accepted as a function of *ability* (A, i.e. capacity to perform), *motivation* (M, i.e. willingness to perform) and *opportunity* (O, i.e. opportunity to perform) (Marin-Garcia and Martinez Tomas, 2016, Blumberg and Pringle, 1982). But this has not always been the case and there are still disagreements regarding how the AMO variables relate in driving performance behaviors. Performance was long viewed as a function of motivation and ability (Vroom, 1964, Maier, 1955). This view reigned until Peters and O'Connor (1980) and subsequently Blumberg and Pringles (1982) contended that an often overlooked additional function of performance is "*opportunity to perform*", "the particular configuration of the field of forces surrounding a person and his or her task that enables or constrains that person's task performance and that are beyond the person's direct control" (Blumberg and Pringle, 1982, p. 565). While support for the role of ability and motivation in performance is particularly profound, that of opportunity is often less explicit. In many work situations however, persons who are both motivated and capable of successfully accomplishing tasks, may either be inhibited in or prevented from doing so due to situational constraints beyond their control (Peters and O'Connor, 1980). This assertion is supported by the findings of Ford *et al.,* (1992) that lack of opportunity to perform tasks is related to performance decrements. Opportunity to perform is therefore often described under the label of situational or operational constraints (Peters and O'Connor, 1980, Mathieu et al., 1992, Bendoly and Hur, 2007).

The AMO framework has since become an established theoretical basis for explaining behavior (Blumberg and Pringle, 1982, Boudreau et al., 2003, Marin-Garcia and Martinez Tomas, 2016). It has been used previously for example to explain behaviors such as consumer choice (MacInnis et al., 1991), firm-level decision making (Wu et al., 2004), social capital activation (Adler and Kwon, 2002, Binney et al., 2006), knowledge-management practices (Argote et al., 2003), task and contextual performance (Tuuli and Rowlinson, 2009) and more recently knowledge sharing behviors (Siemsen et al., 2008, Kettinger et al., 2015). Although using ability, motivation and opportunity to explain behavior abound, no consensus exists on how ability, motivation and opportunity jointly determine behavior (Van Rhee and Dul, 2017, Marin-Garcia and Martinez Tomas, 2016). Marin-Garcia and Martinez Tomas (2016) also recently concluded from a systematic review of the AMO framework that although many investigations mention the AMO model in their theoretical framework, 'it seems that little research has been conducted to verify the AMO model directly" (p. 1041).

From a work performance theory perspective, ability, motivation and opportunity (AMO) are predicted to play complementary roles in influencing behavior (Cummings and Schwab, 1973). Hence, without ability or opportunity, motivation alone should not lead to performance behavior (Blumberg and Pringle, 1982, Siemsen et al., 2008). Yet, there is little empirical evidence supporting the existence of such complementarity (Terborg, 1977). The key question that arises therefore is: if, as work performance theories predict, there is complementarity among motivation, opportunity, and ability in driving behavior, why have existing empirical tests of the AMO framework often fail to reveal this complementarity? (Siemsen et al., 2008). Siemsen *et al.* (2008) grappled with this puzzle and subsequently proposed and tested a constraining-factor model (CFM) as an alternative to the traditional additive/linear or multiplicative models in explaining the link between AMO and knowledge sharing. The CFM captures the notion that in the absence of any of the AMO variables no action takes place, but further that it is the minimum among the three factors (i.e. motivation, opportunity and ability) that ultimately determines behavior (Siemsen et al., 2008). More recently, van Rhee and Dul (2017) took further this notion of the minimum factor limiting behavior, and argued that an implicit and explicit logic exist that ability, motivation and opportunity are individually necessary and jointly sufficient for behavior. They further contend that, prior attempts to model how the AMO variables influence behavior inadequately incorporate the individually necessary and jointly sufficient principle.

Taken together, there are five types of theories on how ability, motivation and opportunity influence behavior: the multiplicative theory (Terborg, 1977, Bell and Kozlowski, 2002, Kim et al., 2015a, Kim et al., 2015b), the additive or linear theory (Boselie, 2010, Chang et al., 2012, De Wind et al., 2015, Gould-Williams et al., 2014, Shih et al., 2013, Wang et al., 2013), various interaction theories (Bos-Nehles et al., 2013, Clark et al., 2005, Gruen et al., 2007, MacInnis et al., 1991, Minbaeva, 2013, Gaurav Sabnis et al., 2013, Schmitz, 2013), the constraining-factor theory (Johnson, 2013, Kettinger et al., 2015, Siemsen et al., 2008) and the limiting factor model (i.e. individually-necessary-and-jointly-sufficient logic) (Van Rhee and Dul, 2017). While the first four theories have traditionally been used to study the influence of AMO on behavior from a correlational view on causality, van Rhee and Dul (2017) proposes that the jointly sufficient component of the limiting-factor theory can be tested by regressing behavior on the minimum of A, M and O while the individually necessary component of the limiting-factor theory is better tested using methods such as necessary condition analysis (NCA) as outlined by Dul (2016). To a large extent then, empirical explication of the first four theories and part of the last (i.e. individually necessary component of the limiting-factor theory) are not necessarily comparable as the methods for testing them are different (Delbridge and Fiss, 2013). Also, since interaction theories are mainly about mediation and moderation analysis, interaction theories are beyond the scope of this study, since this study seeks to assess direct links of the AMO variables to behavior. This study will thus focus on how the first 3 theories and the jointly sufficient component of Van Rhee and Dul's (2017) limiting-factor theory explain behavior.

Some studies have tested the AMO within the context of some of the theories above. Siemsen *et al.'s* (2008) and more recently Kettinger et al. (2015) assessed the validity of the first three competing AMO theories with regards to knowledge sharing while Johnson (2013) replicated same within the context of marketing strategies. The competing theories of AMO however are yet to be tested with regards to performance behaviors specifically and the limiting-factor theory is yet to be empirically tested. This omission is curious, given that the AMO framework was originally developed within the context of work performance. Indeed, Peters and O'Connor (1980) speculated on the development of competing models for explaining performance variance when they stated that "While substantive progress has been made in accounting for performance variance in terms of ability and motivation variables, it may be that a more complete understanding of performance variance must await the specification and measurement of additional variables that either directly affect performance or indirectly contribute to explained variance in performance through their interactions with measures of ability and motivation." (p. 391). Siemsen *et al.* (2008) also called for a replication of their CFM results in multi-respondent context that employs a broader measure of opportunity. Drawing on Siemsen *et al.* (2008) and Van Rhee and Dul (2017) therefore, the three competing theories of focus in this study are, the multiplicative, the additive or linear, the constraining-factor model (CFM) and limiting-factor model (LFM), reflecting different levels of complementarity and interactions among motivation, opportunity and ability and their link to performance behaviors.

The focus here is on two performance behaviors, task performance behaviors which are valuable behaviors that contribute to the core technical activities of the organization/project, and contextual performance behaviors, those behaviors that maintain and enhance the psychological, social and organizational context of the work (Borman and Motowidlo, 1993). Task performance behaviors are thus formally recognized as part of an individual's job description, whereas contextual performance behaviors are generally discretionary (Borman and Motowidlo, 1993). Yet, discretionary behaviors are often necessary in many work contexts especially project settings, where due to the dynamic and uncertain work environment it is often impossible to anticipate and specify all possible desirable behaviors in job descriptions (Tuuli and Rowlinson, 2009).

In the sections that follow, four competing models are developed reflecting four theoretical basis of how the AMO variables influence behavior, leading to the postulation of 10 hypotheses. Subsequently, methods for comparing the competing models are proposed and used to test the hypotheses as they relate to the models' ability to predict task and contextual performance behaviors. The results and findings are subsequently discussed and implications for theory and practice outlined.

Theoretical Development of Competing Models and Hypotheses

The AMO Framework

Motivation, opportunity, and ability (AMO) are related constructs (Blumberg and Pringle, 1982). The precise inter-relationships among the AMO variables is however often difficult to justify theoretically, hence, they can be viewed as correlated but distinct constructs (Siemsen et al., 2008). How the AMO variables interact to influence performance behaviors is the subject of this paper. The issue of complementarity of the AMO variables is therefore central to the development of the competing models. Complementarity is defined as the degree to which the effect of one variable depends on the presence of other variables (Siemsen et al., 2008). Moderate complementarity implies that the effect of one variable depends on another variable while extreme complementarity implies that one variable has no effect unless the other variable is present (Siemsen et al., 2008). Four competing models, a multiplicative, linear/additive, constraining-factor model (CFM) and limiting-factor model (LFM), reflecting different levels of complementarity and interactions among motivation, opportunity and ability, and their impact on performance behaviors are specified next.

Competing Models

Multiplicative Model

In classic work-performance theories, it is assumed that the AMO variables display moderate complementarity in influencing action in the form of a multiplicative function of motivation, opportunity and ability (Maier, 1955, Vroom, 1964, Blumberg and Pringle, 1982). From this perspective, motivation, opportunity, and ability must all be present to some degree for an action to occur, but the level of action is strongly reduced by lower values for any of the AMO variables (Blumberg and Pringle, 1982, Siemsen et al., 2008, Van Rhee and Dul, 2017, Kim et al., 2015b). Therefore, if "ability has a low value, increments in motivation [or opportunity] will result in smaller increases in performance than when ability has a high value" (Vroom, 1964, p. 237) while when one of the factors is absent (i.e. zero), there will be no behavior irrespective of the level of the other factors (Van Rhee and Dul, 2017). The logical reasoning here is that the AMO variables interact (Delery, 1998). Thus, the first competing model, the "*multiplicative model*", can be specified as follows;

$$\text{Performance Behaviors} = \beta_o + \beta_1 M + \beta_2 O + \beta_3 A + \beta_4 M \times O + \beta_5 M \times A + \beta_6 O \times A + \beta_7 M \times O \times A + \varepsilon \qquad (1)$$

Linear/Additive Model

While the multiplicative model has been subjected to empirical scrutiny (Cummings and Schwab, 1973), there is little empirical evidence that the multiplicative terms (i.e. $\beta_4 M \times O$, $\beta_5 M \times A$, $\beta_6 O \times A$ and $\beta_7 M \times O \times A$) explain significantly more variance than the linear/additive terms (i.e. $\beta_1 M$, $\beta_2 O$ and $\beta_3 A$) alone (Campbell and Pritchard, 1976, Terborg, 1977), yet, Bell and Kozlowski (2002, p. 497) refer to the multiplicative model as a "truism". This truism logic suggests that, moderate complementarity among motivation, opportunity, and ability is something that ought to exist, even if such complementarity has never been empirically established in a rigorous manner (Siemsen et al., 2008). Cummings and Schwab (1973, p. 46) aptly summed up this perspective when they state that:

"*…….. It is, ….. much less clear that the notion of interaction contributes to the predictability of employee performance in applied settings where employees may be assumed to possess some* *minimal amount of both ability and motivation. A simple additive approach will probably enable us to predict performance just about as well.*"

Cummings and Schwab (1973) therefore appear to suggest that performance behavior can be predicted equally well by a model that does not capture potential complementarity between the AMO variables at all. Boxall and Purcell (2003) also assert that performance is better described by an additive function. According to the additive function, behaviour will only be absent if all factors are zero (Van Rhee and Dul, 2017). The second competing model, "*linear or additive model*", can therefore be specified as follows;

Performance Behaviors =

$$\beta_0 + \beta_1 M + \beta_2 O + \beta_3 A + \varepsilon \qquad (2)$$

Based on the above discussion therefore and more recent empirical evidence (Siemsen et al., 2008, Johnson, 2013, Kettinger et al., 2015, Bello-Pintado, 2015, Terborg, 1977), it is posited that;

Hypothesis 1: A linear/additive model linking AMO to performance behavior is a better-fit model and will explain as much or more variance in (a) task and (b) contextual performance behaviors than their multiplicative model counterparts.

Constraining-Factor Model (CFM)

Since little explanatory power is gained by adding interaction terms, Siemsen et al. (2008) suggest that a different model of complementarity is called for, the constraining-factor model (CFM), which captures the notion that in the absence of any of the AMO variables no action takes place, but that the level of action is dependent on the lowest value of the AMO variables (Blumberg and Pringle, 1982, Siemsen et al., 2008, Van Rhee and Dul, 2017, Kim et al., 2015b). Mathematically, the CFM emphasizes extreme complementarity instead of the moderate complementarity emphasized by the traditional multiplicative model. The constraining-factor model captures the notion "that it is the constraining factor among these three AMO variables that ultimately determines behavior. Thus, changes in motivation only affect behavior and outcomes if motivation is the constraining factor; they have little or no impact if either opportunity or ability is constraining" (Siemsen et al., 2008, p. 427). The CFM is specified as follows:

Performance Behaviors =

$$\beta_0 + \beta_1 M + \beta_2 O + \beta_3 A +$$

$$\delta_O(\beta_4 + \beta_5 M + \beta_6 O + \beta_7 A) +$$

$$\delta_A(\beta_8 + \beta_9 M + \beta_{10} O + \beta_{11} A) + \varepsilon \qquad (3)$$

Where the variables δ_O and δ_A are dummy variables that are defined to be 1 if O (or A, respectively) is the minimum of A, M and O, and 0 otherwise. Theoretically, the CFM is similar to the notion of bottleneck, or a limiting resource perspective (Schmenner and Swink, 1998, Chase et al., 2004), where the minimum among the three factors of motivation, opportunity, and ability ultimately determines behavior (Siemsen et al., 2008). Other theoretical analogies for CFM can be found in the theory of constraints (Goldratt, 1999) and the theory of queuing networks (Kulkarni, 1995) and factory physics (Hopp and Spearman, 2000).

Thus, following on Siemsen et al. (2008) it is also posited that;

Hypothesis 2: A CFM linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behaviors than their multiplicative model counterparts.

Hypothesis 3: A CFM linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behaviors than their linear/additive model counterparts.

From the specifications above, it can be deduced that equation (2) is nested in equations (1) and (3). Similarly, equations (1) and (3) are nested in the following more general, "combined" model that includes both moderate and extreme complementarity:

Performance Behaviors =

$$\beta_o + \beta_1 M + \beta_2 O + \beta_3 A + \delta_O(\beta_4 + \beta_5 M + \beta_6 O + \beta_7 A)$$

$$+ \delta_A(\beta_8 + \beta_9 M + \beta_{10} O + \beta_{11} A) + \beta_{12} M \text{ x } O$$

$$+ \beta_{13} M \text{ x } A + \beta_{14} O \text{ x } A + \beta_{15} M \text{ x } O \text{ x } A + \varepsilon \quad (4)$$

This combined model enables a comparison of the multiplicative model and the CFM. Thus, it is further posited that;

Hypothesis 4: A CFM linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behaviors than their combined model counterparts.

Hypothesis 5: A combined model linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behaviors than their multiplicative model counterparts.

Hypothesis 6: A combined model linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behaviors than their linear/additive model counterparts.

Limiting-Factor Model (LFM)

The limiting-factor model (LFM) captures the logic that the three AMO variables are individually-necessary-and-jointly-sufficient for behaviour (Van Rhee and Dul, 2017). According to Van Rhee and Dul (2017), there can be one, two or three factors simultaneously limiting behavior or there can be no limiting factor depending on which factor(s) is the minimum. The individually necessary component of the limiting-factor theory is better tested using methods such as necessary condition analysis (NCA) as outlined by Dul (2016) to determine ceiling lines of each factor (Dul, 2015). Mathematically, the LFM showing that the AMO variables are jointly sufficient for behavior can be specified as follows;

Performance Behaviors =

$$\beta_o + \beta_{16}(\min M, O, A) + \varepsilon \quad (5)$$

To allow for comparison between the LFM and the previously specified models, equation (5) is re-specified as follows by adding the additive/linear terms;

Performance Behaviors =

$$\beta_o + \beta_1 M + \beta_2 O + \beta_3 A + \beta_{16}(\min M, O, A) + \varepsilon \quad (6)$$

Since, Van Rhee and Dul (2017) assert that prior models depicting how the AMO variables drive behavior, inadequately captures the individually-necessary-and-jointly-sufficient logic for behavior, the following hypotheses are postulated.

Hypothesis 7: An LFM linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behaviors than their linear/additive model counterparts.

Hypothesis 8: An LFM linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behaviors than their multiplicative model counterparts.

Hypothesis 9: An LFM linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behaviors than their CFM counterparts.

Hypothesis 10: An LFM linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behaviors than their combined model counterparts.

Research Method

Sample

To test the competing models and the hypotheses specified above, a quantitative methodology was employed. The AMO variables as well as the task and contextual performance behavior variables are measured through a quantitative questionnaire survey. The data was collected through 526 key contact persons in 526 organizations (105 client, 158 consultant and 263 contractor organizations) in Hong Kong. The first administration of the questionnaire yielded 232 responses (104 from contractors, 50 from consultants and 78 from clients). A second administration to contact persons from whom one or no questionnaire was received in the first administration, yielded a further 150 responses (70 from contractors, 44 from consultants and 36 from clients), giving a total of 382 individual responses from 115 organizations (52 contractor, 34 client and 29 consultant), giving a 23% response rate.

A missing data pattern analysis resulted in the exclusion of 2 responses for excessive missing data (>50%) (c.f. Hair et al. 1998). The effective sample size for the analysis was therefore 380.

A non-response bias test, following Armstrong and Overton's (1977) time trend extrapolation procedure, and based on a comparison of the first and second administration respondents showed no significant differences in age ($\chi^2 = 3.75$, $df = 4$, $p > .441$), gender ($\chi^2 = .050$, $df = 1$, $p > .824$), education ($\chi^2 = 7.46$, $df = 4$, $p > .113$), nationality ($\chi^2 = 7.64$, $df = 6$, $p > .266$) and organizational rank ($\chi^2 = 3.50$, $df = 3$, $p > .321$). While the presence of non-response bias cannot be completely ruled out, it can be inferred from the above results that the sample is representative of the population.

Overall, 53% of the respondents are older than 40 years and 94% fall under the ranks of middle-management (40%), senior management (41%) and director level (13%). This distribution corresponds favorably to the target population of management-level staff. Males make up 89% of the sample, nationals of Hong Kong and China combined make up 82% and persons of Chinese ethnicity make up 87%. Average tenure in the construction industry is 17 years. In terms of education, 89% have a Bachelors degree or higher. Regarding organizational characteristics, 82% employ 50 or more people.

Measures

Opportunity to perform was measured by adapting the 11-item organizational constraints scale ($\alpha = .85$) developed by Spector and Jex (1998), which covers each of the situational constraint areas proposed by Peters and O'Connor (1980). Two potential constraint areas specific to the operational circumstance of construction projects were also added; the need to comply with safety requirements and statutory regulations.

Intrinsic motivation was assessed with Hackman and Oldham's (1976) 6-item internal work motivation scale ($\alpha = .75$). A sample item is "I feel a great sense of personal satisfaction when I do my job well".

Ability to perform was operationalized with a 7-item subscale ($\alpha = .76$) of ability, experience, training and knowledge (AETK) developed by Podsakoff et al. (1993). A sample item reads, "My job knowledge is sufficient enough that I do not have to depend on my supervisor to get my work accomplished".

Task performance behaviors were measured with a 6-item scale ($\alpha = .91$) of employee in-role behaviors (IRB) developed by Williams and Anderson (1991). A sample item reads, "I adequately complete assigned duties".

Contextual performance behaviors were assessed with an adapted version of Van Scotter and Motowidlo's (1996) 15-item scale [*interpersonal facilitation* (7 items; $\alpha = .93$) and *job dedication* (8 items; $\alpha = .95$)]. Respondents indicated the likelihood of engaging in discretionary performance behaviors ranging from cooperative acts to self discipline acts in the course of performing their work role.

All the above measures were anchored with a 5-point Likert scale. A number of control and demographic variables were also measured. At the individual level, g*ender*, *age*, e*ducational*, *ethnicity*, *nationality* and *tenure* were measured using single item questions. Organizational characteristics such as *firm age* and *size* were also measured.

Given the tendency for individuals to "fake good" in self-report surveys, *social desirability* was also measured using the 10-item short version of the Marlowe-Crowne 33-item scale of social desirability (Crowne and Marlowe, 1960), proposed by Strahan and Gerbasi (1972). Reliabilities of between .73 and .88 have been reported (Robinson et al., 1991). Respondents indicated "True" or "False" to five positively worded statements and five negatively worded statements, measuring two streams of behavior; desirable but uncommon behaviors (e.g. practicing what one preaches) and undesirable but common behaviors (e.g. taking advantage of others). The full questionnaire containing the measures of the key constructs described above are shown in Appendix 1

Data Analysis Strategy

The data collection procedure as described earlier resulted in non-independence of the observations, the degree to which responses of individuals are influenced by, depend on, or cluster by group membership due to social interaction or their arrangement spatially or sequentially in time (Kenny and Judd, 1986, Kenny and Judd, 1996). Non-independence renders statistical analysis techniques such as Analysis of Variance (ANOVA) and Ordinary Least Square (OLS) Regression inappropriate. This stems from their fundamental assumption that observations are independent (Baron and Kenny, 1986, Raudenbush and Bryk, 2002). Ignoring non-independence leads to bias in significance tests (Kenny and Judd, 1986) and loss of power (Bliese and Hanges, 2004). A suitable method of analysis for overcoming the impact of non-independence is Hierarchical Linear Modeling (HLM) (Bliese and Hanges, 2004, Raudenbush and Bryk, 2002).

A key difference between HLM and OLS regression is that HLM decomposes the variance in the outcome variable into its within-team and between-team components (i.e. σ^2 and τ_{00} respectively), through the estimation of a *null model,* a model without predictors. Generally, lower-level predictors explain the within-team variance (σ^2) while higher-level predictors explain the between-team variance (τ_{00}). The parameters σ^2 and τ_{00} are also used to estimate the Intraclass Correlation Coefficient (ICC) which is a measure of non-independence (Bliese, 2000). ICC is calculated as a ratio of the between-team variance (τ_{00}) and the total variance ($\sigma^2 + \tau_{00}$). An ICC of .15 for e.g. task performance behaviors means that 15% of the variance in an individual's rating of task performance behaviors is attributable to his group membership. Barcikowski (1981) has shown that relatively low levels of non-independence (e.g., an ICC of .05) combined with a relatively large group size of 25, results in an observed Type I error rate of .19. This means that applying OLS regression in a situation like that will mean that significance tests assumed to be at .05 are actually being tested at .19. It is to avoid misspecifications of this nature and the subsequent misinterpretations that, HLM instead of OLS regression is employed in testing the relationships and models as outlined in Hypotheses H1 to H10.

With regards to empirically comparing the competing models and testing Hypotheses H1 to H10, an analysis strategy outlined by Siemsen *et al.* (2008) is adopted. Based on models and hypotheses specified, the linear/additive model will be expected to explain significantly more variance in the performance behaviors (i.e. task and contextual) than the multiplicative model (i.e. Hypotheses 1a & 1b). Also, the CFM will be expected to explain significantly more variance in the performance behaviors (i.e. task and contextual) than the multiplicative model (i.e. Hypotheses 2a & 2b), the linear/additive model (i.e. Hypotheses 3a & 3b) as well as the combined model (i.e. adding the linear/additive, multiplicative and CFM models; Hypotheses 4a & 4b). Lastly, the combined model (adding the linear, multiplicative and CFM models) will be expected to explain more variance in performance behaviors (i.e. task and contextual) than the multiplicative model (i.e. Hypotheses 5a & 5b) as well as the linear/additive model (i.e. Hypotheses 6a & 6b).

Further, the LFM will be expected to explain significantly more variance in the performance behaviors (i.e. task and contextual) than the linear/additive model (i.e. Hypotheses 7a & 7b), the multiplicative model (i.e. Hypotheses 8a & 8b), the CFM model (i.e. Hypotheses 9a & 9b), as well as the combined model (i.e. Hypotheses 10a & 10b).

In addition to the variance explained, two fit statistics are employed to assess which model is a better fit (Bickel, 2007). First, the Akaike Information Criterion (AIC) is a goodness of fit statistics that operates on the basis of small is better (Field, 2013, Bickel, 2007) and enables us to compare both nested and non-nested models (Bickel, 2007). Second, the Deviance (i.e. minus twice the log-likelihood, -2LL) is also employed, which is a chi-square likelihood ratio test where the smaller the value, the better the model (Field, 2013, Bickel) and the change in -2LL enables us to compare nested models (Bickel, 2007).

Results

Descriptive Statistics

The reliabilities and dimensionality of all multi-item measures were assessed by exploratory factor analysis. The scale items loaded as hypothesized or meaningfully and the measures also exhibited acceptable reliabilities as shown by their Cronbach's alphas in the diagonal of Table 1. Table 1 also shows the descriptive statistics and zero-order correlations. The interrelationships among the AMO variables and performance behaviors are as expected, all positive and

Table 1: Descriptive Statistics and Correlations

	Variables	**Mean**	**SD**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1	Age	0.53	0.50	-										
2	Gender	0.89	0.31	.09	-									
3	Education	0.43	0.50	.21*	-.08	-								
4	Nationality	0.82	0.39	-.10	.02	-.09	-							
5	Ethnicity	0.87	0.34	.11†	-.03	-.03	.66*	-						
6	Firm Size	0.77	0.42	.03	.01	-.02	.07	.03	-					
7	Firm age	35.49	18.88	.07	.01	.07	-.08	-.02	.19*	-				
8	Team Type 1 (Cont.)	0.46	0.50	-.16†	.22*	-.25*	.03	-.05	.02	.03	-			
9	Team Type 2 (Client)	0.20	0.40	.14†	-.01	.20*	-.04	-.03	.11~	.06	-.46*	-		
10	Team Type 3 (Dual)	0.10	0.30	.07	-.02	.07	.09	.08	.18*	.08	-.31*	-.17*	-	
11	Tenure	16.89	8.46	.79*	.04	.18*	-.17†	.07	-.01	.09	-.09	.06	.09	-
12	Cont. Behaviors	3.66	0.73	.12~	.10	-.02	.03	-.03	.04	-.02	-.11~	.05	.10~	.09
13	Task Behaviors	3.90	0.80	.18†	.12~	.04	.00	-.05	.01	.07	-.14†	.07	.12~	.17*
15	Intrinsic Motivation	3.54	0.68	.04	.11~	-.05	.01	-.06	.01	.03	-.10~	.02	.05	.04
15	Opportunity	3.57	0.84	.08	.09	-.05	.02	-.05	.04	-.02	-.03	.02	.00	.03
16	Ability	3.40	0.75	.23*	.17*	.03	-.10	-.13†	-.08	.01	-.01	-.05	.05	.27*
17	Social Desirability	5.95	1.56	.17*	-.10~	.17*	.07	.03	.07	-.04	-.29*	.20*	.04	.13†
				12	**13**	**14**	**15**	**16**	**17**					
12	Cont. Behaviors			(.95)										
13	Task Behaviors			.67*	(.94)									
14	Intrinsic Motivation			.70*	.70*	(.84)								
15	Opportunity			.62*	.50*	.55*	(.95)							
16	Ability			.57*	.59*	.57*	.37*	(.89)						
17	Social Desirability			.20*	.19*	.07	.16*	.13†	-					

NOTE: ~p < 0.05; †p < 0.01; *p < 0.001.

[a]Sample size = 380 individuals (nested in 115 project teams).

[b]Control variables are coded as follows: Gender is coded 1 = Male, 0 = Female; Age is coded 1 = Old (over 40 years old), 0 = Young (under 40 years old); Education is coded 1 = Graduate degree or higher, 0 = Bachelors degree or lower; Nationality is coded 1 = Hong Kong or China National, 0 = Other; Ethnicity is coded 1 = Chinese, 0 = Other; Firm size is coded 1 = Large (100 or more employees), 0 = Small (less than 100 employees); Team Type 1 (CM) is coded 1 = Contractor, 0 = Others; Team Type 2 (Client) is coded 1 = Client, 0 = Others and Team Type 3 (Dual) is coded 1 = Dual (Client + Consultant), 0 = Others, thus, Consultant is the reference in all cases

significantly related. All correlations are also below .80, the threshold of very high correlations when multicollinearity is obvious (Field, 2013). To further reduce the effect of multicollinearity, all variables were grand-mean centered in the analysis (Hofmann, 1997). The correlations between the social desirability measure and team type 1 dummy variable (r = -.29, p < .001) is higher than the threshold of between -.20 and +.20 suggested by Mitchell and Jolley (2001) while that for team type 2 dummy (r = .20, p < .001), contextual behaviors (r = .20, p < .001) and task behaviors (r = .19, p < .001) are also high. Social desirability bias therefore appears to have a moderate influence on the outcome measures and thus warrants controlling for in the analysis.

Tests of Hypotheses

Hypotheses H1 to H10 were tested through a series of HLM regression analyses. Age, gender, education, nationality, ethnicity, firm size and age, tenure and organization type as well as social desirability were included as control variables in all the analyses due to their possible confounding effect on the relationships examined (Dimitriades and Kufidu, 2004, Kanter, 1977, Spreitzer, 1995, Spreitzer et al., 1997). It was particularly important to control for nationality and ethnicity, given the predominantly Chinese sample and the impact of cultural differences on empowerment (Eylon and Au, 1999). Given the large number of control variables, the shared variance between the predictor variables of interest and the control variables were assessed in accord with Breaugh (2008), to check over control of predictor variance. The results show that 13% of the variance in ability to perform and less than 1% for opportunity to perform and intrinsic motivation are shared with the control variables. This suggests that on average 93% of the original construct is still reflected in the residual predictors. Thus, lack of construct validity resulting from over control should not be an issue in the analysis.

Tests of Hypotheses H1a and H1b

Hypothesis 1 posited that a linear/additive model linking AMO to performance behavior is a better-fit model and will explain as much or more variance in (a) task and (b) contextual performance behavior than a multiplicative model. Prior to testing Hypothesis 1, two null models (i.e. a model without predictors) with task and contextual behaviors as the dependent variables, (i.e. models *1a* and *2a* respectively in Table 2) were run. The results provide evidence of significant within-team and between-team variance in both task performance behaviors (σ^2 = .55, p < .001; τ_{00} = .08, p < .01) and contextual performance behaviors (σ^2 = .45, p < .001; τ_{00} = .09, p < .01). This also gives an interclass correlation coefficient (ICC) of .12 (or 12% of variance) for task behaviors and .17 (or 17% of variance) for contextual behaviors, confirming the presence of non-independence in the observations and justifying the use of HLM to overcome the associated problems discussed earlier.

Models *1b* and *2b* (Table 2) are then run with only the control variables as predictors. In model *1b*, gender (B = -.36, p < .01), team type 2-client (B = -.38, p < .05) and social desirability (B = .08, p < .01) significantly predict task behaviors. Similarly, gender (B = -.32, p < .01) and social desirability (B = .08, p < .01) are significant predictors of contextual behaviors in model *2b*. The results also show that the control variables together account for 8% of the variance in task behaviors and 9% in contextual behaviors (lower part of Table 2).

Finally, models *3a* and *3b (Linear/Additive Models)* and models *4a* and *4b (Multiplicative Models)* were estimated to directly test Hypotheses H1a and H1b. For the Linear/Additive Models, the results indicate highly significant relationships between the AMO variables and both task and contextual performance behaviors. The Linear/Additive Models also explain 56% of the variance in task behaviors and 61% in contextual behaviors (lower part of Table 2). For the Multiplicative Models, the results indicate none of the multiplicative terms is significantly related to both task and contextual performance behaviors. The models however also explain 56% of the variance in task behaviors and 61% in contextual behaviors (lower part of Table 2). The model fit statistics (i.e. AIC and -2LL) results are however mixed. While AIC supports that the linear/additive models (i.e. *3a & 3b*) are better-fit models than their multiplicative counterparts (i.e. *4a & 4b*), the

Table 2: HLM Analyses of MOA and Performance Behaviors Direct Relationships (Hypotheses H1 to H10)

Variables	*Control Model*				*Linear Model*		*Multiplicative Model*		*CF Model*		*Combined Model*		*LF Model*	
	Task Behaviors		**Contextual Behaviors**		**Task Behaviors**	**Contextual Behaviors**	**Task Behaviors**	**Contextual Behaviors**	**Task Behaviors**	**Contextual Behaviors**	**Task Behaviors**	**Contextual Behaviors**	**Task Behaviors**	**Contextual Behaviors**
Control Variables	*1a* β(S.E)	*1b* β(S.E)	*2a* β(S.E)	*2b* β(S.E)	*3a* β(S.E)	*3b* β(S.E)	*4a* β(S.E)	*4b* β(S.E)	*6a* β(S.E)	*6b* β(S.E)	*6a* β(S.E)	*6b* β(S.E)	*7a* β(S.E)	*7b* β(S.E)
Gender		-.36(.14)†		-.34(.13)†	-.03(.09)	-.01(.07)	-.02(.09)	.02(.07)	-.03(.09)	.01(.07)	-.03(.09)	.01(.07)	-.04(.09)	-.01(.07)
Age		-.14(.14)		-.14(.13)	-.05(.09)	-.02(.07)	-.05(.09)	-.04(.07)	-.09(.09)	-.07(.07)	-.09(.09)	-.07(.07)	-.06(.09)	-.02(.07)
Education		.06(.09)		.12(.08)	-.02(.06)	.04(.05)	-.01(.06)	.05(.05)	-.01(.06)	.05(.05)	-.01(.06)	.05(.05)	-.02(.06)	.04(.05)
Nationality		-.15(.16)		-.08(.14)	-.02(.10)	.05(.07)	-.03(.10)	.06(.07)	-.05(.10)	.05(.08)	-.05(.10)	.05(.08)	-.03(.10)	.05(.07)
Ethnicity		.20(.18)		.08(.17)	-.00(.12)	-.08(.09)	.01(.12)	-.06(.09)	.02(.12)	-.06(.09)	.02(.12)	-.06(.09)	-.01(.12)	-.08(.09)
Tenure		.01(.01)		.00(.01)	.00(.01)	-.00(.00)	.00(.01)	-.00(.00)	.00(.01)	-.00(.00)	.00(.01)	-.00(.00)	.00(.01)	-.00(.00)
Firm Size		.05(.12)		-.05(.11)	.04(.09)	-.05(.09)	.04(.02)	-.05(.09)	.02(.09)	-.07(.09)	.02(.09)	-.07(.09)	.04(.09)	-.05(.09)
Firm Age		.00(.00)		-.00(.00)	.00(.00)	-.00(.00)	.00(.00)	-.00(.00)	.00(.00)	-.00(.00)	.00(.00)	-.00(.00)	.00(.00)	-.00(.00)
Team 1 (Cont.)		-.20(.18)		-.19(.18)	-.22(.15)	-.23(.14)	-.21(.15)	-.20(.14)	-.22(.15)	-.20(.14)	-.22(.15)	-.20(.14)	-.21(.15)	-.23(.14)
Team 2 Client)		-.38(.16)˜		-.31(.16)	-.23(.13)	-.22(.13)	-.22(.14)	-.20(.13)	-.21(.13)	-.19(.13)	-.21(.13)	-.19(.13)	-.21(.13)	-.21(.13)
Team 3 (Dual)		-.20(.18)		-.16(.18)	-.13(.15)	-.10(.14)	-.12(.15)	-.09(.14)	-.15(.15)	-.12(.14)	-.15(.15)	-.12(.14)	-.12(.14)	-.10(.14)
Social Desire.		.08(.03)†		.08(.03)†	.04(.02)˜	.03(.02)	.04(.02)	.03(.02)	.03(.02)	.03(.02)	.03(.02)	.03(.02)	.04(.02)˜	.03(.02)
MOA Variables														
Motivation (M)					**.57(.06)***	**.39(.05)***	**.56(.06)***	**.37(.05)***	**.54(.07)***	**.36(.06)***	**.54(.07)***	**.36(.06)***	**.56(.06)***	**.38(.05)***
Opportunity (O)					**.14(.04)***	**.29(.03)***	**.15(.05)†**	**.27(.04)***	**.28(.06)***	**.31(.06)***	**.28(.06)***	**.31(.06)***	**.21(.05)***	**-30(.04)***
Ability (A)					**.25(.05)***	**.25(.04)***	**.25(.05)***	**.24(.04)***	**.14(.07)˜**	**.22(.05)***	**.14(.07)˜**	**.22(.05)***	**.31(.06)***	**.27(.04)***
Min. (M, O, A)													**-.18(.08)˜**	**-.05(.07)**
M x O							**.02(.06)**	**-.01(.05)**	**-.03(.09)**	**-.05(.07)**	**-.03(.09)**	**-.05(.07)**		
M x A							**-.03(.06)**	**-.04(.05)**	**-.08(.09)**	**-.01(.07)**	**-.08(.09)**	**-.01(.07)**		
O x A							**-.02(.07)**	**-.01(.05)**	**.10(.09)**	**.01(.07)**	**.10(.09)**	**.01(.07)**		
M x O x A							**-.01(.05)**	**.03(.03)**	**.01(.05)**	**.03(.04)**	**.01(.05)**	**.03(.04)**		
$^{d}\delta_O$									**.13(.14)**	**.14(.11)**	**.13(.14)**	**.14(.11)**		
δ_O x M									**.22(.21)**	**.15(.17)**	**.22(.21)**	**.15(.17)**		
δ_O x O									**-.23(.20)**	**-.15(.16)**	**-.23(.20)**	**-.15(.16)**		
δ_O x A									**.04(.20)**	**-.05(.16)**	**.04(.20)**	**-.05(.16)**		
$^{d}\delta_A$									**-.11(.12)**	**.06(.10)**	**-.11(.12)**	**.06(.10)**		

Table 2: HLM Analyses of MOA and Performance Behaviors Direct Relationships (Hypotheses H1 to H10) (Continued)

Variables	*Control Model*				*Linear Model*		*Multiplicative Model*		*CF Model*		*Combined Model*		*LF Model*	
	Task Behaviors		**Contextual Behaviors**		**Task Behaviors**	**Contextual Behaviors**	**Task Behaviors**	**Contextual Behaviors**	**Task Behaviors**	**Contextual Behaviors**	**Task Behaviors**	**Contextual Behaviors**	**Task Behaviors**	**Contextual Behaviors**
Control Variables	*1a* β(S.E)	*1b* β(S.E)	*2a* β(S.E)	*2b* β(S.E)	*3a* β(S.E)	*3b* β(S.E)	*4a* β(S.E)	*4b* β(S.E)	*6a* β(S.E)	*6b* β(S.E)	*6a* β(S.E)	*6b* β(S.E)	*7a* β(S.E)	*7b* β(S.E)
$^{d}\delta_O$									**.13(.14)**	**.14(.11)**	**.13(.14)**	**.14(.11)**		
δ_O x M									**.22(.21)**	**.15(.17)**	**.22(.21)**	**.15(.17)**		
δ_O x O									**-.23(.20)**	**-.15(.16)**	**-.23(.20)**	**-.15(.16)**		
δ_O x A									**.04(.20)**	**-.05(.16)**	**.04(.20)**	**-.05(.16)**		
$^{d}\delta_A$									**-.11(.12)**	**.06(.10)**	**-.11(.12)**	**.06(.10)**		
δ_A x M									**.20(.21)**	**.31(.16)**	**.20(.21)**	**.31(.16)**		
δ_A x O									**.14(.17)**	**-.10(.14)**	**.14(.17)**	**-.10(.14)**		
δ_A x A									**-.27(.18)**	**-.16(.14)**	**-.27(.18)**	**-.16(.14)**		
Parameter Estimates														
σ^2	.55(.05)*	.55(.05)*	.45(.04)*	.43(.04)*	.19(.02)*	.10(.01)*	.19(.02)*	.10(.01)*	.18(.02)*	.10(.01)*	.18(.02)*	.10(.01)*	.19(.04)*	.10(.01)*
τ_{00}	.09(.03)†	.05(.04)	.09(.03)†	.09(.03)	.09(.02)*	.11(.02)*	.09(.02)*	.11(.02)*	.09(.02)*	.11(.02)*	.09(.02)*	.11(.02)*	.09(.03)*	.11(.02)*
R_1^2	-	.06	-	.04	.56	.61	.56	.61	.58	.61	.58	.61	.56	.61
Deviance (-2LL)	900.42	771.57	829.12	711.74	487.62	343.82	486.88	339.37	472.14	334.62	472.14	334.62	483.34	343.31
AIC	906.42	801.57	835.12	741.74	523.62	379.82	530.88	383.37	532.14	394.62	532.14	394.62	521.34	381.31

NOTE:

[a]~$p < 0.05$; †$p < 0.01$; *$p < 0.001$.

[b]Unstandardized coefficients are reported with standard errors in parenthesis.

[c]Sample size = 380 individuals (nested in 115 project teams).

[d]δ_O and δ_A are dummy variables defined to be 1 if O (or A, respectively) is the minimum of MOA, and 0 otherwise (Siemsen et al 2008) (Siemsen et al., 2008)

-2LL indicates the opposite. Since the linear/additive and multiplicative models are nested, both AIC and -2LL statistics are relevant (Bickel, 2007). Therefore, hypotheses H1a and H1b are **partially supported.**

Tests of Hypotheses H2a and H2b

Hypothesis 2 stated that, a CFM linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behavior than a multiplicative model. CFM models *5a* and *5b* are estimated to directly test Hypotheses H2a and H2b. The results indicate none of the CFM terms is significantly related to task behaviors, however, one CFM term is significantly (B = .33, p < .05) related to contextual performance behaviors. The CFMs also explain more variance in both task (i.e. 2% more) and contextual (i.e. 2% more) behaviors than their multiplicative counterparts. The model fit statistics (i.e. AIC and -2LL) also confirm that the CFM for task behaviors (i.e. *5a*) is a better-fit model than its multiplicative model counterpart (i.e. *4a*) but the fit statistics (i.e. AIC and -2LL) for the CFM for contextual behaviors (i.e. *5b*) shows mixed results with regards to it being a better-fit model than its multiplicative model counterpart (i.e. *4b*). While the -2LL support it as a better model, the AIC doesn't. But since the CFM and multiplicative models are not nested, priority is given to the AIC statistic (Bickel, 2007). Thus, hypothesis H2a is **fully supported** but H2b is only **partially supported**.

Tests of Hypotheses H3a and H3b

Hypothesis 3 stated that, a CFM linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behavior than a linear/additive model. The CFMs explain more variance in both task (i.e. 2% more) and contextual (i.e. 2% more) behaviors than their linear counterparts. The model fit statistics (i.e. AIC and -2LL) however shows mixed results with regards to the CFMs (i.e. *5a* & *5b*) being better-fit models than their linear/additive model counterparts (i.e. *3a* & *3b*). While the -2LL support the CFMs as better models, the AIC indicate the opposite. But since the linear/additive and CFM models are nested, both AIC and -2LL statistics are relevant (Bickel, 2007). Thus, hypothesis H3a and H3b are both **partially supported**.

Tests of Hypotheses H4a and H4b

Hypothesis 4 stated that, a CFM linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behavior than a combined model. The Combined Models *6a* and *6b* are estimated to directly test Hypotheses H4a and H4b. The results indicate none of the CFM or Multiplicative terms is significantly related to both task and contextual performance behaviors. The CFMs (i.e. *5a & 5b*) also explain the same variance in task behaviors (i.e. 58%) but more variance in contextual behaviors (i.e. 2% more) than their combined model counterparts. The model fit statistics (i.e. AIC and -2LL) results are however mixed. While AIC supports that the CFMs (i.e. *5a & 5b*) are better-fit models than their combined model counterparts (i.e. *6a & 6b*), the -2LL indicates the opposite. Since the combined and CFM models are nested, both AIC and -2LL statistics are relevant (Bickel, 2007). Therefore, hypotheses H4a is **not supported** but H4b is **partially supported.**

Tests of Hypotheses H5a and H5b

Hypothesis 5 stated that, a combined model linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behavior than a multiplicative model. The results show that the combined models explain the same variance in contextual behaviors (i.e. 61%) but explain more variance in task behaviors (i.e. 2% more) than their multiplicative model counterparts. The model fit statistics (i.e. AIC and -2LL) results are however mixed. While the -2LL supports that the combined models (i.e. *6a & 6b*) are better-fit models than their multiplicative counterparts (i.e. *4a & 4b*), the AIC indicates the opposite. Since the combined and multiplicative models are nested, both AIC and -2LL statistics are relevant (Bickel, 2007). Therefore, hypotheses H5a is **partially supported** but H5b is **not supported.**

Tests of Hypotheses H6a and H6b

Hypothesis 6 stated that, a combined model linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behavior than a linear/additive model. The results show that the combined models explain the same variance in contextual behaviors (i.e. 61%) but explain more variance in task behaviors (i.e. 2% more) than its linear/additive model counterpart. The model fit statistics (i.e. AIC and -2LL) results are however mixed. While the -2LL supports that the combined models (i.e. *6a & 6b*) are better-fit models than their linear counterparts (i.e. *3a & 3b*), the AIC indicates the opposite. Since the combined and linear/additive models are nested, both AIC and -2LL statistics are relevant (Bickel, 2007). Therefore, hypotheses H6a is **partially supported** but H6b is **not supported.**

Tests of Hypotheses H7a and H7b

Hypothesis 7 stated that, a LFM linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behavior than a linear/additive model. The results show that the LFMs explain the same variance in task (i.e. 56%) and contextual behaviors (i.e. 61%) as their linear/additive model counterparts. The model fit statistics (i.e. AIC and -2LL) results however show that the LFMs (i.e. *7a & 7b*) are better-fit models than their linear/additive counterparts (i.e. *3a & 3b*). Therefore, hypotheses H7a and H7b are both **partially supported**.

Tests of Hypotheses H8a and H8b

Hypothesis 8 stated that, a LFM linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behavior than a multiplicative model. The results show that the LFMs explain the same variance in task (i.e. 56%) and contextual behaviors (i.e. 61%) as their multiplicative model counterparts. The model fit statistics (i.e. AIC and -2LL) results for task behaviors however show that the LFM (i.e. *7a*) is a better-fit model than its multiplicative counterpart (i.e. *4a*). The model fit statistics (i.e. AIC and -2LL) results for contextual behaviors are however mixed. While the AIC supports that the LFM (i.e. *7b*) is a better-fit model than its multiplicative counterpart (i.e. *4b*), the -2LL indicates the opposite. Since the LFMs and multiplicative models are nested, both AIC and -2LL statistics are relevant (Bickel, 2007). Therefore, hypotheses H8a is **partially supported** while H8b is **not supported**.

Tests of Hypotheses H9a and H9b

Hypothesis 9 stated that, a LFM linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behavior than a CFM. The results show that the LFM for contextual behaviors explain the same variance (i.e. 61%) as its CFM counterpart while the LFM for task behaviors explain 2% less variance than its CFM counterpart. The model fit statistics (i.e. AIC and -2LL) results are however mixed. While the AIC supports that the LFMs (i.e. *7a & 7b*) are better-fit models than their CFM counterparts (i.e. *5a & 5b*), the -2LL indicates the opposite. Since the LFMs and CFMs are not nested, priority is given to the AIC statistic (Bickel, 2007). Therefore, hypotheses H9a and H9b are both **partially supported**.

Tests of Hypotheses H10a and H10b

Hypothesis 10 stated that, a LFM linking AMO to performance behavior is a better-fit model and will explain more variance in (a) task and (b) contextual performance behavior than a combined model. The results show that the LFM for contextual behaviors explain the same variance (i.e. 61%) as its combined model counterpart while the LFM for task behaviors explain 2% less variance than its combined model counterpart. The model fit statistics (i.e. AIC and -2LL) results are however mixed. While the AIC supports that the LFMs (i.e. *7a & 7b*) are better-fit models than their combined model counterparts (i.e. *6a & 6b*), the -2LL indicates the opposite. Since the LFMs and combined models are not nested, priority is given to the AIC statistic (Bickel, 2007). Therefore, hypotheses H9a and H9b are both **partially supported**.

Discussion and Implications

This paper set out to specify and test competing models for examining how the AMO variables drive individual performance behaviors. Despite decades of research, the precise inter-relationships among the AMO variables and how they interact to drive performance behaviors still remain largely unclear. Four competing models, a multiplicative, linear/additive, constraining-factor model (CFM) and limiting-factor model, reflecting different levels of complementarity and interactions among motivation, opportunity and ability, and their impact on performance behaviors were specified and tested. These models offer fresh perspectives on how to promote performance in organizations. In so far as traditional AMO models make no assumptions about how to prioritize investments in motivation, opportunity or ability in organizations to engender performance (Siemsen et al., 2008), a test of computing models provides a promising path towards specifying such priorities for managerial interventions. More specifically, this study finds broad support that models that propose some form of the minimum of the AMO variables as driving behavior are better models, as shown by the confirmation of Siemsen et al's (2008) and Van Rhee and Dul's (2017) models being superior to previously specified models. This moves the modelling of AMO variables in driving behaviour beyond additive/linear and multiplicative models.

In general, the results support Siemsen et al's (2008) assertion that the constraining factor model (CFM) is a superior model of how motivation, opportunity and ability drive performance behavior compared with previously specified models. Of the 8 hypotheses comparing the CFM to other models, 2 hypotheses are fully supported, 4 are partially supported and only two hypotheses are not supported, confirming the superiority of the CFM. Thus, in the CFMs if opportunity or ability is the minimum of the AMO variables (i.e. the constraining factor), increasing motivation has no effect on performance behaviors. If ability is the minimum of the AMO variables, ability will have an effect of .14 - .30 = .16 (p = ns) on task behaviors and .23 - .18 = .05 (p = ns) on contextual behaviors. If motivation is the minimum, as predicted, the effect of ability on task behaviors is .14 ($p < .001$) and .23 ($p < .001$) on contextual behaviors. If, however, opportunity is the constraining factor, the effect of ability is .14 - .09 = .05 (p = ns) on task behaviors and .23 - .03 = .20 ($p < .001$) on contextual behaviors. This suggests that if ability is not the minimum, increasing the minimum of the AMO variables (i.e. the constraining factor – motivation or opportunity) will result in a change in the effect of opportunity on contextual behaviors but not task performance behaviors.

If opportunity is the minimum of the AMO variables, opportunity will have an effect of .27 - .16 = .11 (p = ns) on task behaviors and .33 - .19 = .14 (p = ns) on contextual behaviors. If motivation is the minimum, as predicted, the effect of opportunity on task behaviors is .27 ($p < .001$) and .33 ($p < .001$) on contextual behaviors. If, however, ability is the constraining factor, the effect of opportunity is .11 + .27 = .38 ($p < .001$) on task behaviors and .33 - .13 = .20 ($p < .001$) on contextual behaviors. This suggests that if opportunity is not the minimum, increasing the minimum of the AMO variables (i.e. the constraining factor – motivation or ability) will result in a change in the effect of opportunity on both task and contextual performance.

If motivation is the minimum of the three factors, the effect of motivation is .56 ($p < .001$) on task behaviors and .37 ($p < .001$) on contextual behaviors. If, however, ability is the minimum, the effect of motivation is 56 - .23 = .33 ($p < .001$) on task behaviors and .37 - .33 = .04 (p = ns) on contextual behaviors. Similarly, if opportunity is the constraining factor, the effect of motivation is 56 - .21 = .35 ($p < .001$) on task behaviors and .37 + .20 = .57 ($p < .001$) on contextual behaviors. Taken together, the results show that motivation has a strong effect on both task and contextual behaviors if it is the constraining factor, however, changes in motivation will have little or no effect on both task and contextual behaviors if motivation is not the constraining factor.

However, not withstanding the superior performance of the CFM against previously specified models, the recently specified LFMs perform equally as well as the CFMs and in comparison to each other the LFMs are actually better fitting models than their CFMs counterparts even though for tasks behaviours the CFM explains more variance than the LFM. Of the 8 hypotheses comparing the LFM to other models, 7 are partially supported and only one hypothesis is not supported, confirming partial validation of the LFM, given that this is one of the first attempts to empirically validate the LFM.

Overall, the multiplicative model emerged as the worse model, confirming the redundancy of the multiplicative terms in explaining behavior as predicted and confirmed in previous studies (Siemsen et al., 2008). Also, contrary to Siemsen et al (2008) and de Wind et al (2015), the results show that all the AMO factors have a direct impact on behavior in all the models examined. Motivation consistently had the highest direct impact on both task and contextual performance behaviors in all models. Opportunity was also a better predictor of contextual behaviors in all models than Ability confirming the assertion in previous research that opportunity to perform may be the forgotten hero in performance modeling (Tuuli and Rowlinson, 2009). These findings have implications for theory and practice.

Theoretical Implications

This paper adds to the growing interest in alternative views on interaction effects in organizational behavior (Siemsen et al., 2008, Casimir and Ng, 2010, Peters and O'Connor, 1980). While the topic of interactions remain particularly important as it affects issues of practice, theory and metatheory (Blalock, 1965, Cronbach, 1987), ample evidence from research conducted in diverse fields (e.g. management accounting and workplace motivation) indicate that the product-term or multiplicative term (which measures interaction) fail consistently to detect interactive effects even when there are sound theoretical reasons for expecting such effects (Paunonen and Jackson, 1988, Russell and Bobko, 1992). Competing models such as those specified and tested here should therefore go a long way to offering alternatives to examining interactions among variables of interest in organizational research.

This study has the potential to add to our understanding of the important determinants of task (in-role) and contextual (extra-role) performance behaviors in construction project settings. Indeed, the fundamental issues surrounding performance in construction have been identified as organizational and behavioral in nature (Courtney and Winch, 2003, Slevin and Pinto, 2004) and behavior in particular, still remains an area of management concern that has not received much focus in construction industry related research (Cox et al., 2005). Yet, the sparse research efforts in this direction continue to highlight the significant impact of behavior on project outcomes (e.g. Ahadzie et al., 2008, Anvuur, 2008, Phua, 2004).

Practical/Managerial Implications

These findings also have implications for managerial interventions aimed at improving individual performance behaviors and can be used to provide targets of concrete managerial interventions. In so far as the CFM and LFM are valid, they suggest that managerial attempts to improve performance should target increasing the minimum of the AMO variables as the constraining or limiting factor. Any resources dedicated to increasing any other variable other than the constraining or limiting factor is unproductive (Siemsen et al., 2008, Van Rhee and Dul, 2017).

Conclusion

Competing models for explaining the link between the AMO variables and performance behaviors have been specified and tested. This adds to the growing empirical evidence that the constraining-factor model (CFM) and limiting-factor Model (LFM) are superior models, providing better explanation of the variance in performance behaviors than the traditional multiplicative and linear/additive models. Further replication of the CFM and/or LFM is encouraged in different settings and in predicting different behaviors beyond performance and knowledge sharing.

Data Availability Statement

Data generated or analyzed during the study are available from the corresponding author by request.

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