A Learning Perspective on Enterprise Architecture Management

Completed Research Paper

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Abstract

Enterprise architecture management (EAM) has long been propagated in research and practice as an approach for keeping local information systems projects in line with enterprise-wide, long-term objectives. EAM literature predominantly promotes strictly governed and centralized coordination mechanisms to achieve the promised alignment contributions. Notwithstanding the increasing maturity levels in practice, organizations still struggle with the successful establishment of EAM, mainly due to the inherent challenges of a firmly centralized approach in complex organizational settings. This study opts for cooperative learning as a theoretical lens to afford a distinctive, non-centralized conceptualization of EAM. We empirically demonstrate EAM as a stage-wise learning process in which knowledge acquisition and cooperative interactions among individuals contribute to project performance on the local level. Projects that benefit from this particular learning process, in turn, are found to significantly leverage enterprise-wide performance.

Keywords: Enterprise architecture management (EAM), project performance, enterprise-wide performance, cooperative learning, knowledge acquisition

Introduction

Over the past decades, increasing investments in corporate information systems (IS) have contributed to superior performance of organizations (Brynjolfsson and Hitt 2000; Melville et al. 2004). However, these increasing investments have also brought about an ever-growing number and diversity of technological solutions, which are costly to maintain and to integrate (Peterson 2004). This unbounded growth, among other reasons, has mainly resulted from allocating development budgets and project ownerships to local business units. Even though the latter fosters IS investments' alignment with business needs, it disregards an *enterprise-wide perspective* on the dependencies among local projects. Hence, for today's organizations, it has become vital to complement local project perspectives with enterprise-wide considerations in order to align diverse IS endeavors.

As a solution, scholars and practitioners have broadly propagated enterprise architecture management (EAM) as an organizing logic for business processes and their technological infrastructure to eventually align local projects with enterprise-wide objectives (Ross et al. 2006). Despite its prominence in IS research and notwithstanding the overall increasing maturity levels in practice (Ross and Quaadgras 2012), organizations still struggle with the successful establishment of EAM (Tamm et al. 2011). This is mainly due to the predominant approach to EAM as a strict and centralized governance practice to guide local IS investments (Aier et al. 2011; Boh and Yellin 2007). This centralized, top-down driven approach to EAM has been substantially promoted in Ross' (2003) reflection of EAM maturity levels (i.e., the more centralized, the more mature). Owing to the inherent challenges of a firmly centralized approach in complex organizational settings, it turned out that many organizations experience huge difficulties in establishing EAM (Haki et al. 2012), as it has been reflected in many failures of EAM endeavors (Löhe and Legner 2014). As such, the centralized approach to EAM has been subject to criticism and a complementary, non-centralized approach to EAM has recently been introduced through the notion of *architectural thinking* (Aier et al. 2015; Ross and Quaadgras 2012; Winter 2014). Architectural thinking targets local decision-makers, non-architects, and diverse (non-technical) stakeholders. It aims at applying enterprise-wide considerations in local design decisions, thus aligning local solutions with enterprise-wide, long-term objectives.

After studying the evolvement of EAM as a maturity process in over 40 case studies (Ross 2003), Jeanne Ross and her colleagues at the Massachusetts Institute of Technology, one decade later, found that superior performance rather results from promoting architectural thinking (Ross and Quaadgras 2012). As an implication of their new findings, they motivated the study of EAM as a learning process through which individuals conjointly learn to consider enterprise-wide objectives in their local design decisions (Ross and Quaadgras 2012). Inspired by these recent insights, in this research we seek to empirically demonstrate the realization of EAM success through a non-centralized, non-governance-based learning process. Particularly, we aim at answering the following research question: *How does cooperative learning contribute to EAM success?*

Building on cooperative learning, as a theoretical lens, as well as EAM's extant body of knowledge, we derive a research model that hypothesizes the impact of knowledge acquisition and cooperative learning on both project and enterprise-wide performance contributions of EAM. We test the research model following a partial least squares (PLS) approach to structural equation modeling (SEM). Our resulted insights prove stage-wise performance contributions of cooperative learning on project and on enterprise-wide levels. We hence demonstrate the realization of EAM success through a non-governance-based learning process in which project-concerned stakeholders interact and cooperatively learn from each other in aligning local solutions with enterprise-wide objectives.

The remainder of this paper is structured as follows: first, we lay out the state of research and motivate learning as a lens to study EAM. Second, we derive our research model based on extant learning literature, and particularly where this literature applies to EAM performance contributions. Having operationalized constructs, collected data, and conducted validity tests, we finally present our results and conclude by a discussion on the resulted insights.

Literature Review

Since the 1980s (Zachman 1987), enterprise architecture (EA) has developed a steadily growing discourse in IS research (Simon et al. 2013). According to Niemann (2006, p. 21), EA refers to a structured, harmonized, and dynamic collection of plans for the development of an enterprise's information technology (IT) landscape that illustrates different aspects of IT systems and their alignment with the business. EA primarily aims at catering an *enterprise-wide perspective* to IS investments—extending the focus of management beyond a single information system to achieve strategic, long-term objectives (Lange et al. 2015). As such, aligning different projects and stakeholders, with diverse and locally-oriented interests, and keeping their efforts in line with enterprise-wide objectives has become the *raison d'être* for EA management (EAM) (Boh and Yellin 2007). Consequently, expected contributions of EAM, such as IS effectiveness and efficiency, have often been measured at the enterprise-wide level (Lange et al. 2015; Schmidt and Buxmann 2011; Tamm et al. 2011).

To achieve these expected contributions, IS research has largely promoted EAM as a governance means, which exercises its efforts mainly from a centralized position in the hierarchy of an organization (Boh and Yellin 2007; Schmidt and Buxmann 2011). Following a top-down driven approach, EAM links and guides diverse project stakeholders through architecture artifacts, such as EA meta-models and modeling techniques (Jonkers et al. 2003; Lankhorst 2005), as well as through coordination mechanisms, such as EA standards and principles (Boh and Yellin 2007; Richardson et al. 1990). Nevertheless, EAM has often lacked flexibility in guiding organizational transitions that require considerable IS and organizational developments and transformations (Dietz and Hoogervorst 2008). More precisely, the centralized guidance of projects and stakeholders has often fallen short in adapting to organizational complexity as well as to the complexity of the IS landscape, which maintains thousands of applications to support various depending and interrelated business processes (Boh and Yellin 2007; Murer et al. 2010; Schmidt and Buxmann 2011). Shortcomings have also resulted from EAM's limited reach and impact on those stakeholders who are not directly related to IT (Gardner et al. 2012).

In order to tackle the above-mentioned challenges, EAM literature has recently started to promote non-centralized, light-weight approaches to EAM (Ross and Quaadgras 2012; Winter 2014). Nonetheless, extant literature lacks a systematic research to investigate and demonstrate the impact of such non-centralized (and mainly non-governed) approaches for achieving the expected contributions that have long been promised in the EAM literature. To fill this research gap, and by following Ross and Quaadgras' (2012) view on EAM as a learning process, this study opts for organizational learning in general, and cooperative learning in particular, as a theoretical lens to examine EAM's contribution to enterprise-wide performance.

Organizational learning is defined as a process of improving performance due to increased knowledge (Fiol and Lyles 1985). It has been widely favored as a lens for studying various organizational and IS phenomena. In order to stay competitive, organizations constantly attempt to improve their work practices (Huber 1991). Consequently, a coherent understanding of individuals and decision-makers that link and drive an organization's work practices becomes necessary (Brown and Duguid 1991). Therefore, learning literature has often laid emphasis on capturing work systems as interrelated social constructions generally, as well as understanding information exchange practices, collaboration and interaction among individuals particularly (Brown and Duguid 1991; 2001). By the same token, in IS research, organizational learning has found extensive application as a lens, for instance in studying the performance of cross-unit work practices or investigating individuals' performance in collaborative work practices (e.g. Cha et al. 2008; Leonardi and Bailey 2008). One of the main approaches to organizational learning is cooperative learning, which refers to a non-centralized, highly personalized, and collaborative form of organizational learning (Janz and Prasarnphanich 2003). Thereby, cooperative learning particularly focuses on personal interaction, interdependencies and social relations mechanisms for studying the realization of superior performance from a non-centralized perspective (Janz and Prasarnphanich 2003; Miller 1996). Similarly, in IS research, cooperative learning has often been applied for investigating collaborative interaction, task and goal dependencies among individuals (e.g. Leidner and Jarvenpaa 1995; Majchrzak et al. 2005).

In the next section, we derive the research model and its constitutive hypotheses based on the selected theoretical lens as well as its implications for EAM.

Hypotheses Development

In order to study how learning supports EAM's expected contributions, the research model consists of two blocks: (i) the *learning process* and (ii) the resulted *performance* from learning. (i) The process of learning is represented by two constitutive elements: the acquisition of knowledge and the cooperative behavior of individuals, being enabled and willing to share and apply knowledge in making decisions or in influencing others' decisions (Miller 1996). (ii) Performance evolves as a dynamic process, starting in fragmented stages at the individual level, increasing more and more to the project (team), and ultimately to the enterprise-wide level (Janz and Prasarnphanich 2003; Power and Waddell 2004). For studying EAM performance, as the main focus is on guiding projects to achieve enterprise-wide objectives (Lange et al. 2015), the constitutive elements are both project and enterprise-wide performance effects (see Figure 1).

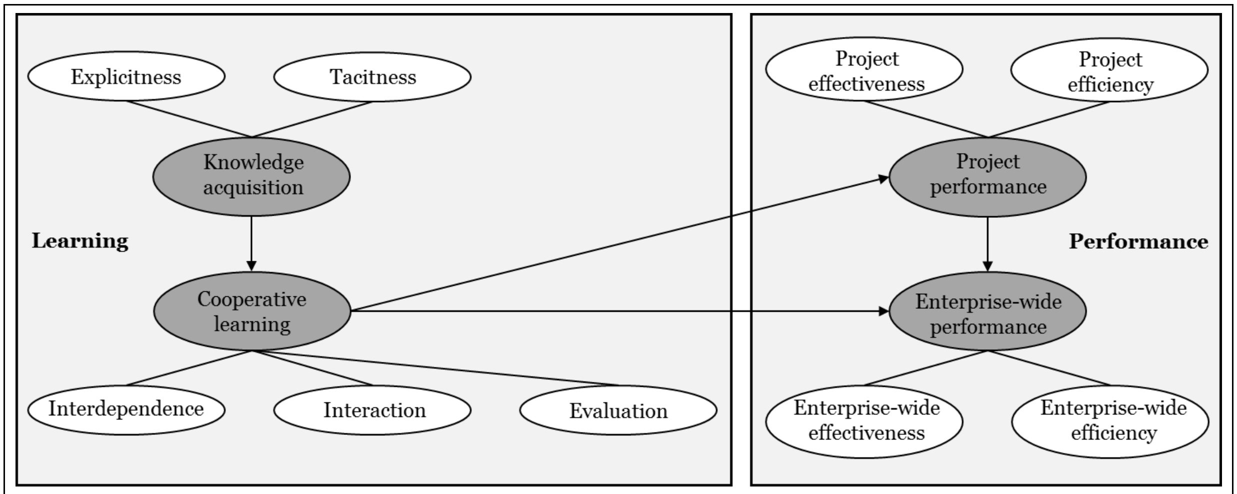

Figure 1. Research Model

Knowledge Acquisition and Cooperative Learning

Knowledge acquisition is the fundamental basis for organizational learning. Knowledge occurs in two forms namely, tacit and explicit knowledge (Nonaka 1994). *Tacit knowledge*, also referred to as highly personalized knowledge, is hard to formalize and to communicate (Polanyi 1966). It becomes visible to others when being actioned in commitment, involvement, or in behavior (Nonaka et al. 1994). Tacit knowledge becomes acquired by individuals through shared experience, observation or personalized interaction (Nonaka et al. 1994). *Explicit knowledge*, in turn, is a form of codified knowledge, containing information "that is transmittable in formal, systematic language" (Nonaka 1994, p. 16). It becomes acquired by individuals in rather formalized ways, for instance via shared documents, through enactive liaisoning, or by communication (Nonaka et al. 1994).

Cooperative learning builds on the acquisition of explicit and particularly tacit knowledge among individuals for the purpose of increasing their work performance (Janz and Prasarnphanich 2003). In its essence, the sharing and application of knowledge depends on the enablement and the willingness of individuals. Regarding the enablement, work in teams is typically structured in such a way that individuals depend on each other, and that no individual team member can successfully accomplish tasks without others being successful (Janz and Prasarnphanich 2003). In the process of learning, *interdependencies* hence become a personalized linkage for individuals and teams to structure their knowledge, make it sharable (explicit) and thus applicable for others (Alavi and Leidner 2001). Furthermore, cooperative learning builds on team members' willingness in making knowledge acquirable, and in interacting with one another for accomplishing tasks (Janz and Prasarnphanich 2003). This *interaction* also relies on a personalized linkage between individuals for the purpose of externalizing, sharing and applying knowledge. In addition, cooperative learning aims at performance enhancements by evaluation, where the sharing and application of knowledge, toward expected purposes and outcomes, is reflected (Janz and Prasarnphanich 2003). This *evaluation* is necessary to detect and correct shortcomings in the process of learning, and is essential for maintaining a coherent knowledge base of the team in order to realize superior work performance. Maintaining a coherent knowledge base becomes especially relevant due to the fact that learning represents an unlasting effort. For instance, team members may fluctuate, project goals or task requirements change (Grant 1996; Janz and Prasarnphanich 2003), which requires individuals to continuously acquire, share and apply knowledge among one another.

One of the key functions associated with the EA is that it serves as a communication instrument among diverse stakeholder groups with different, however complementary, knowledge and expertise (Abraham et al. 2015; Jonkers et al. 2006). EA consequently links project-concerned stakeholders (who mainly follow local interests) with enterprise architects (who represent cross-project, enterprise-wide interests) and fosters effective interaction among them (Foorthuis et al. 2010). Having involved diverse groups of stakeholders, an active EA practice enables knowledge acquisition and integration (van Steenbergen and Brinkkemper 2009) and eventually leverages a cooperative learning process.

We hence assume that work conducted on behalf of EAM is required to become a cooperative process of interaction, which is essentially dependent on the mutual acquisition of knowledge. We therefore hypothesize:

H1: In EAM efforts, knowledge acquisition is positively related to cooperative learning.

Effects of Learning on Project and Enterprise-wide Performance

In the literature, the effects of learning have been investigated from two complementary perspectives namely, process and outcome perspectives (Janz and Prasarnphanich 2003; Power and Waddell 2004). On the one side, literature promotes a "process perspective", concerning the way learning as a process impacts performance. The process perspective reflects the stage-wise evolvement of performance throughout the organization, i.e., from the individual level to the project, and from the project to the enterprise-wide level. On the other side, research has focused an "outcome perspective", shedding light on the effects of learning at each process level i.e., project and enterprise-wide levels. Cooperative learning promotes aligning outcomes at different process levels through interdependencies and interaction that extends the impact of learning processes beyond single projects and toward the enterprise-wide scope (Grover and Davenport 2001; Janz and Prasarnphanich 2003). Having captured "cooperative learning as a process", EAM performance contributions will be investigated from an "outcome perspective" at project and enterprise-wide levels.

EAM's prevalence as an approach is grounded on improving both project and enterprise-wide performance by guiding individuals in local IS project endeavors on behalf of enterprise-wide intentions (Lankhorst 2005). At the **project level**, EAM guides and specifies the project scope in order to further scale work activities (Bucher et al. 2006). As such, EAM enables knowledge integration among enterprise architects and their related project stakeholders, as well as among project stakeholders (van Steenbergen and Brinkkemper 2009). Linking complementary knowledge holders to effectively interact with each other is hence expected to leverage work performance (Foorthuis et al. 2010). Therefore, local IS change and development projects achieve superior performance, reflected prevalently in *effectiveness* outcomes, such as delivering in higher quality or functionality, and in *efficiency* measures, such as delivering by reduced costs or by mitigated complexity (Lange et al. 2015; Schmidt and Buxmann 2011). We thus assume a positive relation between cooperative learning and project performance in EAM efforts:

H2: In EAM efforts, cooperative learning is positively related to project performance.

The central promise of EAM is to guide multiple, interrelated projects (Boh et al. 2003) that without this guidance would favor local IS solutions at the expense of **enterprise-wide level** objectives. For effective cross-project guidance, EAM maintains architecture artifacts, such as models or meta-models, which act as boundaries objects among project stakeholders with complementary knowledge and heterogeneous requirements (Abraham 2013; Abraham et al. 2015; Lankhorst 2005). These artifacts help to overcome knowledge boundaries and thus foster learning among enterprise architects and project stakeholders across the horizon of local endeavors, toward enterprise-wide and long-term objectives (van Steenbergen and Brinkkemper 2009). Initializing projects under EA guidance is shown to realize performance benefits enterprise-widely, prevalently by *effectiveness* outcomes, such as the achievement of business goals or business-IT alignment, and *efficiency* outcomes such as mitigated organizational landscape complexity or harmonized IS solutions (Lange et al. 2015; Schmidt and Buxmann 2011). Hence, we hypothesize cooperative learning as being positively related to enterprise-wide performance in EAM efforts:

> *H3: In EAM efforts, cooperative learning is positively related to enterprise-wide performance.*

Building on the dynamic process of learning and its contributions to performance (Grover and Davenport 2001; Janz and Prasarnphanich 2003; Power and Waddell 2004), which evolves stage-wise from the individual to project and to enterprise-wide level, we expect a mediation of project performance on the relation between cooperative learning and enterprise-wide performance. As EAM-guided projects are locally focused on the one side, and their success is measured based on the contribution to enterprise-wide outcomes on the other side, there is considerable evidence in literature revealing a trade-off between the achievement of local versus enterprise-wide benefits (Ross and Quaadgras 2012; Weiss et al. 2013). EAM efforts aim at waiving this trade-off primarily by targeting IS project decision-makers, aligning them with enterprise-wide intentions, and hence guiding projects on behalf of enterprise-wide purposes (Lankhorst 2005; Schmidt and Buxmann 2011). Consequently, project performance enhancements are expected to mediate the relationship between cooperative learning and enterprise-wide performance. We hypothesize this relation as follows:

> *H4: In EAM efforts, project performance is positively related to enterprise-wide performance, reflecting a mediation of the relation between cooperative learning and enterprise-wide performance.*

Research Method

As motivated in the previous section, our research model comprises two major blocks, derived from knowledge acquisition and cooperative learning as well as from project and enterprise-wide performance. The model hypothesizes the relation between the constitutive constructs of these two blocks. In Figure 2, lines reflect the category of measures for each construct, while arrows[1] represent the hypothesized (*H*) relations between the constructs.

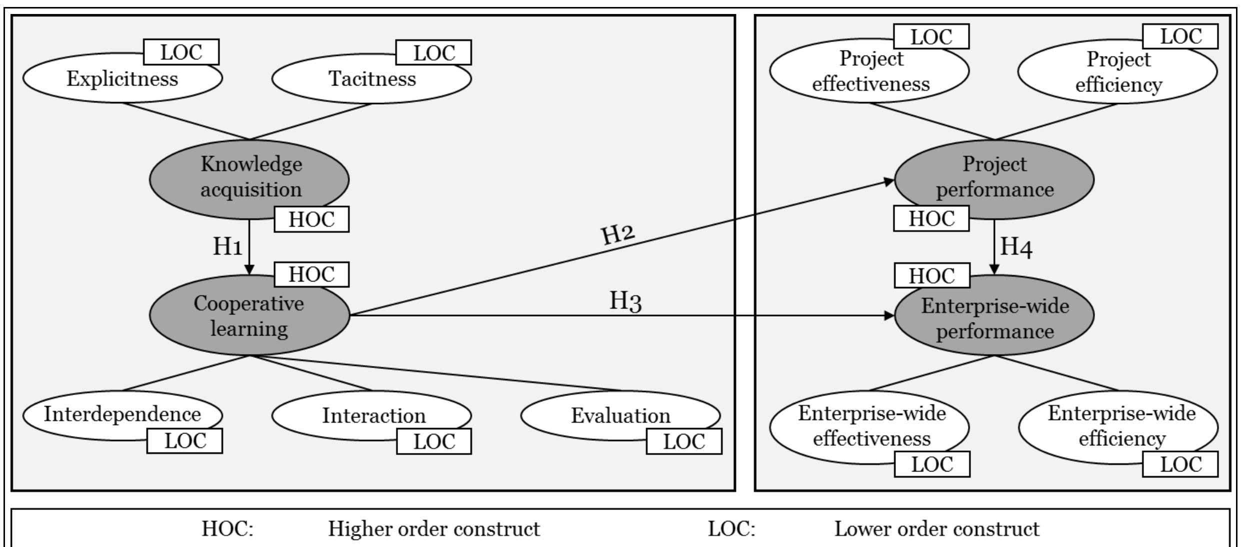

Figure 2. Research Model as a Higher-order Model

In effect, the research model is designed at a higher level of abstraction, i.e., as "higher-order model" (Chin 1998; Hair Jr et al. 2014; Lohmöller 1989). As such, the described higher-order model comprises four

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[1] There is a discussion in IS research on causal reasoning (Gregor and Hovorka 2011). In the research model, we do not address causality in the hypothesized relations.

higher-order constructs (HOC), relevant for testing the derived hypotheses, as well as of nine lower-order constructs (LOC), representing the reflected measures of the HOCs (Wilson and Henseler 2007).

Knowledge acquisition represents the fundamental basis for cooperative learning (*H1*). It is reflected by the two forms through which knowledge is formulated, namely, *tacitness* and *explicitness*. Cooperative learning enables the integration of acquired knowledge in projects (*H2*), and for aligning diverse projects and their stakeholders toward enterprise-wide considerations (*H3*). Cooperative learning is reflected by its three constitutive constructs, i.e. *interdependence*, *interaction*, and *evaluation*. As EAM performance contributions have often been measured through IS *effectiveness* and *efficiency* (e.g., Lange et al. 2015; Schmidt and Buxmann 2011), both project and enterprise-wide levels have been reflected by these two constructs. Drawing from projects' local focus and their ultimate evaluation in terms of their contribution to enterprise-wide performance, our research model reflects *H4* primarily as a mediation of project performance on the relation between cooperative learning and enterprise-wide performance, and secondarily as the relation between project and enterprise-wide performance.

In order to test the derived research model, the method of this research is designed in three steps, starting with the operationalization of constructs, followed by the collection of data, and finally the analysis of data.

Construct Operationalization

For the operationalization of constructs, we chose to adopt existing measurement items identified from the reviewed literature.

We measured *knowledge acquisition* with nine items, adopted from Lee and Choi (2003): five items thereby focusing on tacitness, and four items measuring the explicitness of the acquirable knowledge (see also Nonaka et al. 1994; Nonaka and Takeuchi 1995). *Cooperative learning* was measured by 19 items, adopted from Janz and Prasarnphanich (2003): ten items for interdependence (enablement to share and apply knowledge), six items for interaction (willingness to share and apply knowledge), and three items for the evaluation of shared and applied knowledge (see also Hult 1998; Johnson et al. 1988).

To fit to the purpose of our research, the originally extracted measurement items for both project and enterprise-wide performance (see Lange et al. 2015) were slightly adjusted in formulation, so that items explicitly focused performance contributions of EAM rather than EAM as a means for performance. Adapted from Lange et al. (2015), we employed eight items to reflect *project performance*, three of which measuring project effectiveness, and five of which measuring project efficiency. Finally, *enterprise-wide performance* was reflected by twelve items, also formulated based on Lange et al. (2015). Enterprise-wide effectiveness was measured by five items, while for enterprise-wide efficiency we employed seven measurement items.

In sum, we included a total of 48 items and measured them on a 5-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (5). As the models' measurement items are not a complete, exhaustive representation of the respective constructs, the constitutive constructs of the model are measured in a reflective, rather than formative, mode. This is due to the selection of measurement items for the specific objectives of our research.

Data Collection

We collected data by an online survey as well as by paper-based questionnaires. The paper-based collection took place between October and November 2015. Questionnaires were distributed at a workshop within an IS practitioner community and at two larger IS practitioner events. We used the practitioner workshop not only for collecting data, but also for testing face validity. Regarding face validity, we probed for clarity, wording and validity of the formulated measurement items in the questionnaire. Based on the successful pre-test, we continued data collection at two larger events and included the collected data from the questionnaire's pre-test step. We collected 118 responses in total by our paper-based questionnaires, having a response rate of approximately 71%.

We further launched an online survey from January to April 2016 for measuring exactly the same items. The survey was sent out to 581 contacts, to the large extent IT managers and enterprise architects. For the online survey, we collected 70 answers in total, having a response rate of approximately 12%. Of these 70 answers, we considered only those responses that covered at least 50% the measurement items (excluding demographic questions), which led to a reduced number of 33 responses. Together with the paper-based questionnaires, we totally collected 151 responses for further analysis. Missing values for measurement items in the responses were treated by mean replacement.

Besides the discussed measurement items, our survey also included five additional questions on demographics as well as on the functional and professional background of the respondents. Table 1 provides an overview on demographics, illustrating the industry as well as the staff size of the organizations to which respondents are affiliated.

Table 1. Demographics of Survey Respondents

Industry	Percent	Company Staff Size	Percent
Education	2.65%	< 10 employees	3.31%
Financial Services	17.88%	10 - 49 employees	3.97%
Healthcare	9.27%	50 - 99 employees	3.31%
Retail	1.99%	100 - 249 employees	1.99%
Information and Communication	7.95%	250 - 499 employees	4.64%
Insurance	7.28%	500 - 999 employees	6.62%
Manufacturing and Processing	10.60%	1000 - 4999 employees	18.54%
Public Administration	7.95%	>= 5000 employees	27.15%
Transport and Logistics	3.97%	No indication	30.47%
No indication	30.46%		

Since the focus of this research was on cooperative learning from both a process and outcome perspective, we opted for a diversified sample of EA audience. From the process perspective, and regarding respondents' hierarchical positions, we did not only survey managers and executives (as representative of enterprise-wide objectives), but also employees (as representative of local objectives) to provide an exhaustive analysis of learning as a non-centralized, stage-wise process. Likewise, the professional diversity of respondents allowed an analysis of learning outcomes throughout different organizational levels, focusing performance contributions at the local project and enterprise-wide level. The hierarchical positions, held by the surveyed respondents, were reported as employees (9.93%), team leaders (12.58%), unit leaders (21.19%), department leaders (10.60%), and executive managers (7.28%) (38.42% no indication). Regarding the professional background, 2.65% of the survey participants reported to have been working for less than one year, 3.97% between one and two years, 19.21% between three to five years, 21.85% between six and ten years, and 20.53% for more than ten years in their organization (31.79% no indication).

Furthermore, analyzing responses from both business and IT departments substantiated traditional EA performance measures, which mainly focuses on IT staff, toward an aligned perspective on performance measures. In their respective organizations, 35.76% of the respondents were primarily affiliated to IT units and 20.53% to business units (43.71% no indication).

In order to test for systematic measurement errors and bias in the estimates of the "true relations" among constructs (common methods bias), we considered *Harman's single-factor test* as supplemental analysis (Ringle et al. 2012). The results led to 25.35% of the variance explained, hence indicating that no single factor accounted for the majority (>50%) of covariance among the measures (Podsakoff et al. 2003).

Data Analysis

For analyzing data, we used PLS-SEM. We chose SEM in favor of other linear regression models in order to cope with the number of diverse indicators reflecting, rather than directly measuring, our constructs of interest (Gefen et al. 2011). We performed the test of the model by the PLS method, using the PLS implementation in SmartPLS, version 2.0.M3 (Ringle et al. 2005). We chose the PLS-SEM approach, contrary to other covariance-based approaches (e.g., LISREL, AMOS), as it has only soft distributional assumptions and modest sample size requirements (Chin 2010).

The bootstrapping resampling procedure, with a total number of 5,000 resamples, was applied in order to evaluate the stability of the estimates. The significances were determined by the (two-tailed) *t*-value.

Results

Measurement Model and Validity Tests

We evaluated the measurement model regarding *content validity*, *indicator reliability*, *construct reliability*, *convergent validity*, and *discriminant validity*. We further measured the model's *predictive accuracy* as well as its *predictive validity*.

Content validity refers to a subjective evaluation of the constructs' domain content, captured by their respective indicators. To ensure the content validity, the constructs and their constitutive measurement items are theory-driven, adopted from the respective literature (both learning and EA), and adapted to our context of interest.

Indicator reliability explains to which degree the variance of an indicator is explained by the underlying construct. To be reliable, indicators should have a factor loading of 0.7 or higher, while indicators below a value of 0.4 should always be removed from the model (Hair Jr et al. 2014). After a pre-test of the model, 3 indicators were removed (2 items from interdependence and 1 item from project efficiency) due to a factor loading of below 0.4. In the final measurement model, indicators had an average loading value 0.7, and no indicator was below 0.4. As shown in Appendix A, all indicator loadings are highly significant at the 0.01 significance-level (t-value > 2.576).

Construct reliability specifies whether a construct is appropriately measured by its indicators. Commonly, construct reliability is evaluated by the composite reliability (CR) and Cronbach's alpha (CA). Desirable values for both CR and CA are above 0.6 (Hair Jr et al. 2014). For both CR and CA, all constructs in our model reach value beyond this threshold (see Appendix B), which illustrates their reliability.

Convergent validity aims at analyzing to which degree a construct is explained by its indicators rather than by error terms (Gefen and Straub 2005). Following Hair Jr. et al. (2014), the average variance extracted (AVE) should be greater than 0.5. For most of the constructs, this is the case, however, 5 constructs remain with lower values (see Appendix B). Nevertheless, a convergent validity with an AVE value below 0.5 can still be acceptable, if the CR of the respective construct is higher than 0.6 (Fornell and Larcker 1981). As for all of these 5 constructs the CR is above the desired value of 0.6 (see Appendix B), no construct was withdrawn from the model.

Discriminant validity is assessed in order to evaluate the dissimilarity of the research model's constructs (Gefen and Straub 2005). It is especially necessary for the test of higher-order models (Hair Jr et al. 2014), such as applied in our research. For testing the discriminant validity, we applied the Fornell-Larcker criterion, comparing the square roots of a construct's AVE with the other constructs' correlations. Specifically, when the square root of each construct's AVE is greater than the highest correlation with any other construct, discriminant validity is sufficient. In the case of higher-order models, the discriminant validity criteria do not apply for comparisons between higher level and lower level constructs, and neither between lower level constructs (Hair Jr et al. 2014). Comparing the square root of AVE (main diagonal) in all rows and columns (see Appendix C), we find the discriminant validity criterion met.

Compared to the Fornell-Larcker criterion, a more sensitive approach to uncover potential lacks of discriminant validity has been recently introduced to variance-based SEM: the heterotrait-monotrait (HTMT) ratio of correlations (Henseler et al. 2015). Measuring the average of the heterotrait-heteromethod (item correlations across constructs) relative to the average of the monotrait-heteromethod (item correlations within the same construct) correlations, HTMT ratios below a threshold of 0.9 ($HTMT_{.90}$) are desirable. In our data, we found discriminant validity thoroughly established (see Appendix D).

The determination coefficient R^2 represents an important coefficient for measuring the model's *predictive accuracy*. The interpretation of R^2 is dependent on the broadness and complexity of the investigated constructs, however, there is no general recommendation of acceptable values (Hair Jr et al. 2014). In our model, 23% of cooperative learning is explained by knowledge acquisition, 6% of project performance by cooperative learning, and finally 27% of enterprise-wide performance by both project performance and cooperative learning (see Appendix B).

In addition to the predictive accuracy, we tested the *predictive validity* of our research model by the non-parametric Stone-Geisser test (Geisser 1974; Stone 1974). For conducting the Stone-Geisser test, we used a blindfolding procedure with an omission distance of 7 in SmartPLS (Hair Jr et al. 2014). All resulting Q^2 values, indicating the predictive relevance, had a value of larger than 0 (see Appendix B), which proves predictive validity for our model, meaning that our collected empirical data can be reconstructed using our research model and the PLS parameters (Götz et al. 2010).

Testing of Hypotheses

In Figure 3, we provide the final SEM. Arrows include the path coefficients between the constructs. To every arrow we added the value of the path coefficient as well as the significance level (based on two-tailed *t*-tests). The significant levels (***: α < 0.01; **: α < 0.05; *: α < 0.1) were calculated by a bootstrap run in SmartPLS (Hair Jr. et al. 2014), calculated with 5000 samples. Based on the results provided in Figure 3, we present the test of hypotheses in the following (see Table 2).

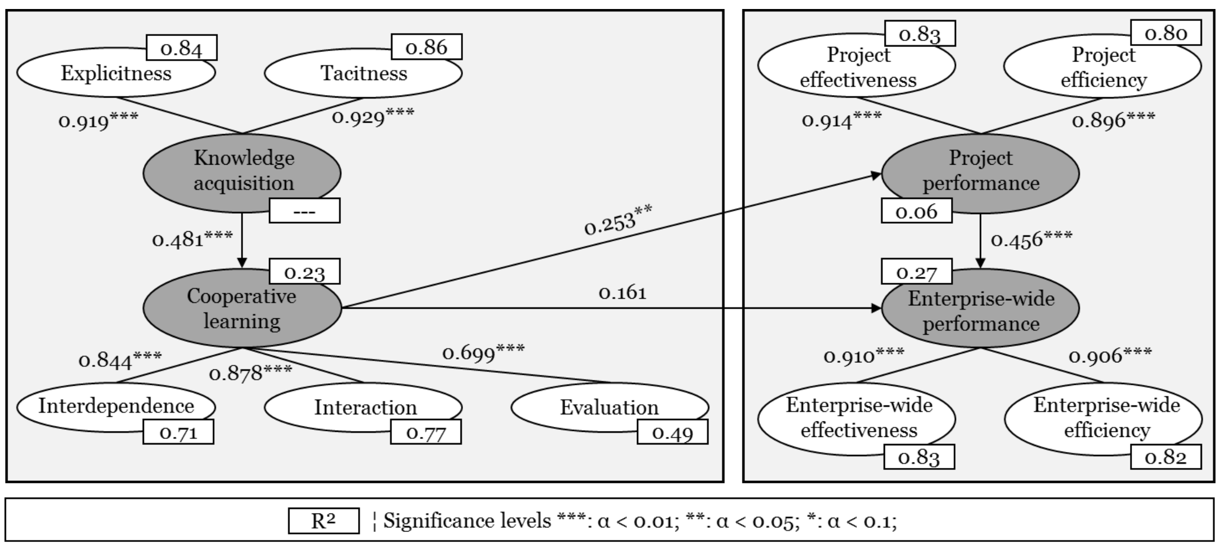

Figure 3. Research Model Results

We found a positive and significant relation between knowledge acquisition and cooperative learning, which supports *H1*. For the relation between cooperative learning and project performance, we also found a positive and significant relation, thus supporting *H2*. Between cooperative learning and enterprise-wide performance, we found a small positive relation, however, this relation was not found to be significant. Thus, *H3* is not supported by our data.

Table 2. Test of Hypotheses

Hypothesis	Path description	Path coefficient and significance	*t*-value (two-tailed)	Result
H1	Knowledge creation → Cooperative learning	0.481***	5.838	Supported
H2	Cooperative learning → Project performance	0.253**	2.528	Supported
H3	Cooperative learning → Enterprise-wide performance	0.161	1.612	Not supported
H4	Project performance → Enterprise-wide performance	0.456***	4.555	Supported

For the relation between project performance and enterprise-wide performance, we found a positive and significant relation, which supports *H4*. This hypothesis further assumes that project performance is not only positively related to enterprise-wide performance, but also mediates the relation between cooperative learning and enterprise-wide performance. We performed the Sobel test statistic in order to analyze whether project performance is a mediator that significantly carries the relation between cooperative learning and enterprise-wide performance. We used an online calculator for measuring the significance of the mediation by two-tailed probability values (Soper 2016). The test returned a highly significant mediation of project performance at a two-tailed *t*-value of 2.076. Hence, *H4* is also significantly supported as mediating the relation between cooperative learning and enterprise-wide performance in the form of a mediation effect.

Discussion and Conclusion

Summary

Through going beyond established views on EAM as a centralized governance means in the extant literature, we empirically demonstrate how cooperative learning, as a non-centralized process, leverages EAM's expected performance contributions. This brings us to a distinctive conceptualization of EAM endeavors, in which knowledge acquisition, cooperative and personalized interactions among individuals facilitate both project and enterprise-wide objectives. We hence contribute to the recently promoted non-centralized and learning view on EAM (Ross and Quaadgras 2012) through empirically illustrating EAM as a stage-wise learning process, reflecting enterprise-wide considerations at both project and individual levels.

Instead of taking either a process or outcome perspective to learning, which is dominant in the extant literature on learning, this study opts for a concerted view. This concerted view examines outcomes at different process levels through different mechanisms of cooperative learning. Building on this theoretically grounded basis and a statistically valid research model, we illustrate that performance enhancements evolve stage-wise from the individual to the enterprise-wide level. As such, the process of cooperative knowledge sharing and personalized interaction among individuals explains direct performance contributions at the level of local projects, while those projects with enhanced performance become in turn an impact means to enterprise-wide performance. This insight is in line with the essential assumption of architectural thinking, that concerns local decision-makers in the organization for guiding their endeavors in such a way that the realization of project outcomes becomes beneficial to the organization as a whole (Ross and Quaadgras 2012; Winter 2014). The achievement of superior enterprise-wide performance thereby becomes the success criterion for evaluating project performance, to which individuals are aligned by the means of learning. In this learning process, performance evaluation is an essential construct in which purposes and expected outcomes of learning are reflected. This explains that cooperative learning is unlikely to have very direct relations to enterprise-wide performance effects, as enterprise-wide objectives are expected to be reflected in project performance measures, and that project performance therefore is the mediator to achieve enterprise-wide objectives.

Discussion

Our findings complement, and to some extent call for reconsidering the traditional approach to EAM as a highly centralized, governance-based means. In effect, EAM's notion roots in a control-oriented practice that is concerned with the direct reach of enterprise-wide outcomes. Therefore, in line with Ross and Quaadgras' (2012) perception of architectural thinking, our study entails a need for future EAM practice to be less focused on controlling the achievement of outcomes rather than on supporting the processes for achieving these outcomes. This can be reflected in "self-control" for local (especially non-IT) stakeholders and their associated projects to apply enterprise-wide considerations in their decisions. According to Henderson and Lee (1992), self-control reconsiders centralized, top-down driven means as "the extent to which an individual exercises freedom or autonomy to determine both what actions are required and how to execute these activities". Janz and Prasarnphanich (2003) propose autonomy as a relevant factor for supporting cooperative learning. As such, autonomy refers to a degree of decision-freedom for individuals to make decisions on their own and to determine necessary actions. In cooperative learning, individuals evaluate their performance autonomously to detect and correct errors in working toward expected outcomes (Janz and Prasarnphanich 2003), and hence learn how to guide their decisions on behalf of enterprise-wide objectives.

Even though our study spotlights the impact of cooperative learning on EAM performance contributions, there are a number of factors that vitally support and influence knowledge integration, personalized interaction, and collaborative work among individuals. Among these factors is the degree of centralization in the structure of the work environment. A decentralized structure flattens communication and cross-project contact, thus extending the reach of interaction and cooperative relations, and further enabling organizational members' spontaneous involvement in work and tasks (Hopper 1990; Lee and Choi 2003). Furthermore, a low degree of formalization is supported by learning literature for achieving more flexibility (Lee and Choi 2003). More precisely, knowledge integration and learning lay less emphasis on formalized rules, standards or procedures (Ichijo et al. 1998). Since one of EAM's shortcomings results from the high degree of formalization (e.g., highly sophisticated tools, meta-models, and coordination mechanisms) (Aier et al. 2015), scholars explicitly promote architectural thinking as a "lightweight" approach to support individuals' consideration of enterprise-wide objectives in less formalized, less sophisticated ways (Winter 2014). Moreover, organizational culture represents an important antecedent to knowledge integration and cooperative interactions (e.g., see Aier 2014; Niemietz et al. 2013; van Steenbergen 2011). We consider culture as a mechanism that is being adopted both consciously (e.g., visible structure in work environment) and unconsciously (e.g., assumptions on espoused goals of the organization) by individuals as a way of perceiving and ultimately working in their environment (Schein 2010). In cooperative learning, Janz and Prasarnphanich (2003) suggest culture (i.e., "climate") as an encouraging mechanism for personal interaction, social relations, and as a result, cooperative learning (see also Cohen 1998; Davenport and Prusak 1998). Culture supports the integration of individuals in thoughts and actions (Schein 2010), which is favored by architectural thinking, promoting the application of enterprise-wide considerations among local stakeholders (Ross and Quaadgras 2012; Winter 2014), and thereby raising a reconsideration of centralized EAM means in cultural dimensions.

As today's organizations constantly attempt to improve their work processes by the means of learning, there is an ever-present need to maintain and develop organizational learning capabilities (Janz and Prasarnphanich 2003). Over the past decades, organizations have predominantly developed these capabilities by firmly centralized approaches to knowledge management (Lee and Choi 2003). Nevertheless, organizations have also become highly dependent on decentralized learning capabilities, such as collaborative efforts, heterogeneous expertise, and complementary knowledge levels that enable and realize superior performance contributions from local levels (Brown and Duguid 1991; 2001). Further, learning as a process is not necessarily reliant on formal or systematic capabilities. It is often less structural and becomes collocated as a collaborative and interactive process that raises impact to an organization's overall knowledge capabilities (Miller 1996). These findings commonly suggest a complementary understanding of learning capabilities that draw from centralized approaches on the one side, and simultaneously rely on decentralized, more local considerations of organizational learning mechanisms on the other side.

While this study demonstrates the achievement of EAM performance by the means of a non-centralized learning process, we do not promote this non-governance-based approach as an alternative to traditional EAM. We rather consider it as a complementary view—as another side of the same coin. As illustrated in the extant literature, centralized procedures are required to institutionalize the reflection of enterprise-wide objectives in local and project-based endeavors. Simultaneously, as demonstrated in this study, the consideration of enterprise-wide objectives in local design decisions is a step-wise learning process that occurs in a non-centralized and bottom-up fashion. As such, depending on the context in which EAM is established, organizations try to reach an effective balance between giving autonomy to or strictly controlling local IS endeavors (Haki and Legner 2013; Haki et al. 2012).

Limitations and Implications

This research has some limitations. Although we employ a theory-driven measurement model, we note a construct that might have been addressed with more appropriate indicators: interdependence. We found all indicators of interdependence with loadings below the common standard of 0.7 (Urbach and Ahlemann 2010). According to Hair Jr. et al. (2014), indicators of a value between 0.4 and 0.7 should only be considered for exclusion, if this exclusion leads to an increased AVE value. However, the step-wise exclusion of indicators led to a decrease in interdependence's AVE values, thus weakening convergent validity. Facing this comparable weak indicator reliability, we raise a reconsideration of interdependence' indicators.

Another limitation reconciles with this research's employed static approach. Specifically, the mediation of project performance on the relation between cooperative learning and enterprise-wide levels raises a consideration of timeliness in realizing enterprise-wide performance effects. Likewise, the discussed reconsideration of traditional, centralized EAM neglects further insights into development or evolvement of underlying mechanisms. These limitations all share the same implication, that is, an outline for future research to apply more longitudinal perspectives on the phenomenon of interest. Existing studies mainly take a static approach and investigate architecture endeavors in a specific point in time (Haki and Legner 2013). Centralized approaches, described by traditional EAM, are less often followed as organizations and their individuals are shaped by their cultural backgrounds (Schmidt and Buxmann 2011), which are not static in nature and evolve over time. Hjort-Madsen (2007) attests that the organizational adoption of EAM should be examined as an emergent, evolving, and social process, being shaped by cultural and structural forces in organizations. The same holds for the concept of architectural thinking as well as our discovered performance contributions of learning. This requires the investigation of non-centralized EAM performance contributions in a long journey. Prospective research may conduct a series of chronological analyses (instead of taking short-time, static grasp), for instance through longitudinal case studies, to eventually better understand the longitudinal dynamics and effects of learning on EAM performance contributions to project and enterprise-wide levels.

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Appendix A: Measurement Scales

Table 3. Measurement Items included in the Final Model

Construct		Measurement item	Ld.	*t*-val.
Explicitness	Exp1	Our organization values enactive liaisoning for cross-functional activities.	0.79	19.48
	Exp2	Our organization values forming teams for conducting experiments, and sharing results with other departments.	0.72	11.38
	Exp3	Our organization values developing and sharing new values and thoughts.	0.86	30.07
	Exp4	Our organization values sharing and trying to understand management visions through communications with fellows.	0.80	16.88
Tacitness	Tac1	Our organization values gathering information from different internal units/departments.	0.72	10.45
	Tac2	Our organization values sharing information with external stakeholders.	0.72	11.12
	Tac3	Our organization values engaging in dialogue with competitors.	0.68	9.04
	Tac4	Our organization values discussing new plans and future opportunities within the organization.	0.77	15.82
	Tac5	Our organization values creating a work environment that allows peers to understand the craftsmanship and expertise.	0.77	17.74
Interdependence	Intd1	In our teamwork, we make sure that everyone learns from each other.	0.59	6.46
	Intd2	In our teamwork, our job is not finished until every team member has finished his or her job.	0.59	5.16
	Intd3	In our teamwork, our performance evaluations depend in part on how much all team members learn.	0.49	4.16
	Intd4	In our teamwork, I make sure that all other team members learn.	0.64	7.35
	Intd5	In our teamwork, the work steps are divided up so that everyone has a part to contribute.	0.46	3.73
	Intd6	In our teamwork, we have to share work material in order to complete the project.	0.49	3.25
	Intd7	In our teamwork, everyone's ideas are needed if we are going to be working successfully.	0.66	8.61
	Intd8	In our teamwork, I am dependent on other team members' knowledge for completing my part of the project.	0.57	6.12
Interaction	Inta1	In our team, I like to share my ideas and work material with other members of the team.	0.74	6.52
	Inta2	In our team, I can learn important things from other team members.	0.82	14.68
	Inta3	In our team, I like to help my team members.	0.79	9.71
	Inta4	In our team, it is useful to help other team members learn.	0.74	12.25
	Inta5	In our team, I like to cooperate with my team members.	0.83	14.41
	Inta6	Members of our team learn a lot of important things from each other.	0.69	13.94

Evaluation	Eva1	In our team, we take time to examine areas in which we can deepen our skills and experience.	0.84	23.17
	Eva2	We rarely stop to consider how we can work better as a team.	0.87	29.78
	Eva3	We have recently discussed the strengths and weaknesses of our work on a particular project/job.	0.71	7.44
Project Effective-ness	Pefft1	The quality of the project deliverables in our organization is high.	0.91	46.89
	Pefft2	The projects in our organization meet the desired requirements.	0.90	41.45
	Pefft3	Project scopes can be changed effectively.	0.77	14.51
Project Efficiency	Peffc1	The projects in our organization meet their budgets.	0.70	9.04
	Peffc2	The projects in our organization meet their deadlines.	0.82	21.39
	Peffc3	The complexity of the projects in our organization are manageable.	0.59	6.13
	Peffc4	Project scopes can be changed efficiently.	0.71	10.26
Enterprise-wide Effectiveness	Eweffct1	The optimization of our organization's information systems often leads to organization-wide (instead of local) benefits.	0.75	13.03
	Eweffct2	Our organization's information systems landscape supports the operational alignment of business and IT.	0.82	25.01
	Eweffct3	Our organization's information systems landscape effectively fosters communication across organizational units.	0.89	42.65
	Eweffct4	Our organization's information systems landscape supports the strategic alignment of business and IT.	0.86	26.62
	Eweffct5	Our organization's information systems landscape enables effective cooperation.	0.79	16.11
Enterprise-wide Efficiency	Eweffc1	Our organization's information systems fulfill business requirements.	0.58	5.57
	Eweffc2	Our organization's information systems follow set standards.	0.64	7.95
	Eweffc3	Our organization's information systems are consolidated enterprise-widely.	0.78	19.55
	Eweffc4	The complexity of our organization's information systems landscape is low.	0.51	4.61
	Eweffc5	The cost of our organization's information systems landscape are low.	0.68	8.93
	Eweffc6	Our organization's information systems landscape is cost-efficient.	0.79	17.19
	Eweffc7	Our organization's information systems landscape enables efficient cooperation.	0.78	16.11

Appendix B: Construct Statistics

Table 4. Overview of Constructs

Construct Order	Construct	Construct-ID	Composite Reliability (CR)	Cronbach's Alpha (CA)	AVE	R Squared (R^2)	Q Squared (Q^2)
LOC	Explicitness	Exp	0.87	0.80	0.63	0.84	0.51
LOC	Tacitness	Tac	0.85	0.78	0.54	0.86	0.46
LOC	Interdependence	Intd	0.79	0.69	0.32	0.71	0.23
LOC	Interaction	Inta	0.90	0.86	0.59	0.77	0.45
LOC	Evaluation	Eva	0.85	0.74	0.66	0.49	0.32
LOC	Project effectiveness	Pefft	0.90	0.83	0.74	0.83	0.46
LOC	Project efficiency	Peffc	0.80	0.67	0.50	0.80	0.25
LOC	Enterprise-wide effectiveness	Ewefft	0.91	0.88	0.68	0.83	0.55
LOC	Enterprise-wide efficiency	Eweffc	0.86	0.81	0.47	0.82	0.38
HOC	Knowledge acquisition	Ka	0.90	0.87	0.49	---	---
HOC	Cooperative learning	Cl	0.88	0.86	0.32	0.23	0.07
HOC	Project performance	Pp	0.87	0.82	0.50	0.06	0.03
HOC	Enterprise-wide performance	Ewp	0.91	0.89	0.46	0.27	0.12

Appendix C: Constructs Correlations

Table 5. Constructs Correlations

$\sqrt{AVE}$	Cl	Ewp	Ka	Pp
Cl	*0.57*			
Ewp	0.28	*0.68*		
Ka	0.48	0.44	*0.70*	
Pp	0.25	0.50	0.44	*0.71*

Appendix D: Heterotrait-Monotrait Ratio

Table 6. Heterotrait-Monotrait Ratio

	Cl	Ewp	Ka	Pp
Cl				
Ewp	0.35			
Ka	0.55	0.50		
Pp	0.31	0.59	0.53	

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