Using Advanced Statistical Methods to Identify the Drivers of Knowledge Sharing Intention among Construction Workers

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Abstract: Front-line construction workers possess the hands-on knowledge required to execute projects. However, insufficient research has been conducted on the drivers of workers' behavior with respect to knowledge sharing. This study aims to develop an integrative understanding of the factors affecting knowledge sharing intention among construction workers. Starting with factors from the literature, a survey was prepared to record the responses of construction workers to questions about their view of the work environment and the knowledge sharing process, and 137 usable responses were collected from 16 construction building sites. Advanced statistical methods—exploratory factor analysis (EFA) and structural equation modeling (SEM)—were used to identify the factors, among which are social and professional contributions, and study the links between them. The results indicate strong links among organizational climate factors, professional contributions, social contributions, and attitude. These results were used to propose methods to improve the working environment, enhance the knowledge sharing process, and, therefore, improve productivity and overall project performance. This study contributes to the body of knowledge on construction labor and, generally, knowledge management in construction by offering a data-driven framework to understand the drivers of workers' behavior with respect to knowledge sharing and propose techniques to enhance the knowledge sharing process. The results lay the foundation for sustaining knowledge on construction sites and develops the groundwork for future research on the link between construction workers' behavior and project performance. **DOI: 10.1061/(ASCE)CO.1943-7862.0002238.**

Author keywords: Behavior; Construction worker; Intention; Knowledge sharing.

Introduction

The major pillars of project performance are meeting schedule targets while maintaining budget and not compromising quality (Thamhain 1992). One major contributor to these pillars is labor productivity, which directly affects task durations and, hence, project schedules, as well as the amount of rework and, thus, project cost and quality. In practice, construction falls behind other industries in terms of labor productivity (Kiomjian et al. 2020); a study by Vereen et al. (2016) showed a consistent productivity decline in output per labor hour from 1990 to 2008. Thus, there is a need to analyze the drivers behind this decline and its impact on project performance. Such studies should be done on blue-collar workers since they are the major contributors to project progress. Despite their importance, these workers suffer from a lack of formal training and develop their skills from on-the-job training (Golden and Skibniewski 2009). They acquire their knowledge by learning from their senior coworkers. This social interactive learning process is referred to as knowledge sharing (Koskinen et al. 2003).

In construction, knowledge comes in two basic forms: (1) explicit knowledge, which can be documented in codes, reports, and maps and thus coded for transfer to other individuals, and (2) implicit or tacit knowledge, which develops from experience and practice and, hence, resides in the minds of its bearers, rendering it difficult to codify or document (Koskinen et al. 2003; Nonaka and Takeuchi 1995; Thomas et al. 1998). Nonaka and Takeuchi (1995) argued that the key to acquiring tacit knowledge is experience, which is what construction workers rely on. Implicit or tacit knowledge is very common among construction workers (Poleacovschi et al. 2018), who rely on informal verbal communication to discuss methods for carrying out tasks; thus, its distribution is dependent on the personalities and social traits of its sharers (Thomas et al. 1998). These discussions that aim to ensure progress on work are part of the knowledge transfer process that is based on a variety of interactions, one of which is knowledge sharing. To ensure that knowledge is transferred, know-how and know-where must be shared, which can happen from experienced worker to inexperienced workers or among junior workers themselves (Paulin and Suneson 2015). Thus, knowledge sharing is defined as the distribution of knowledge among individuals through informal verbal discussions, formal assemblies, or information management systems (Bock et al. 2005).

Hence, the inspiration for this study stems from two angles. First, labor productivity is directly related to informal on-the-job training that takes place on construction sites and is therefore highly dependent on human behavior. To improve this means of knowledge sharing, it is necessary to understand what affects workers' behavioral intentions to suggest coachable approaches to enhancement. Second, there is a need to implement efficient knowledge management strategies to maintain the flow of practical knowledge between generations of construction workers, which also happens by studying their intentions to share their knowledge as a first step toward transferring and preserving it.

Considering that construction projects are of a temporary nature and teams generally dissolve following project completion,

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knowledge sharing is important to allow workers to carry and transfer the knowledge they gained to other projects and have the chance to share with new team members. Thus, they will avoid reinventing the wheel and repeating mistakes, which are common drawbacks in cultures suffering from lack of vocational training such as the Middle East and North Africa (MENA) region (Srour et al. 2018), unlike European and North American countries that constantly seek out opportunities for vocational training, education, and skills development. A lack of training indicates that there is no technical-systematic way of preparing workers to perform their duties and, hence, no control over their behavior, implying more uncertainties in their performance. Thus, using Lebanon as a testbed, this paper helps understand personal and social factors impacted by workplace setting and environment, which drive the transfer of tacit knowledge among construction workers. A better understanding of these factors allows for creating strategies to (1) preserve construction knowledge capital; and (2) improve labor productivity and, therefore, achieve project performance goals.

The paper starts with a literature review on the knowledge sharing process, which is followed by the theoretical underpinning of the study. Next comes a description of research objectives and methodology, followed by model analysis and research hypotheses. Later, statistical analysis and results are presented, followed by a discussion of practical implications and conclusions.

Literature Review

This section discusses the knowledge sharing process in the construction industry highlighting the need to direct efforts on studying blue-collar workers as well as the main findings and gaps of previous studies.

Process of Knowledge Sharing among Construction Workers

Learning in construction typically refers to so-called learning on the job, which is how blue-collar workers develop their skills and knowledge (Golden and Skibniewski 2009). On-the-job learning has both individual and social aspects (Collin and Valleala 2005). The individual aspect is represented by workers' own effort of repeating tasks, which is driven by task characteristics, such as complexity and mechanization, along with workers' professional profiles, such as skills and previous experience (Srour et al. 2018). The social aspect of learning is resembled by the interaction and exchange of knowledge among crew members, which is driven by schedule structure, workers' previous experience, crew demographics, and workers' personal traits (Kiomjian et al. 2020). To better understand the dynamics of the social aspect of learning, knowledge must be clearly defined. Knowledge is a person's expertise and know-how that allow him or her to better carry out specialized jobs (Bock et al. 2005). The informal nature of the knowledge sharing process on construction sites makes it highly dependent on the interpersonal behavior of the knowledge sender and receiver (Thomas et al. 1998). This behavior, in turn, makes the knowledge sharer think of what he is gaining from this exercise, such as applying expertise in task execution while managing time and learning from mistakes or even creating new knowledge by cooperating to increase team efficiency. The results may include getting paid faster, obtaining referrals for jobs with other employers, and meeting new people. Nevertheless, it might seem like knowledge sharing comes at the expense of competitiveness. To preserve knowledge, supervisors need to find ways to motivate workers to share their tacit knowledge. Considering the social aspect of on-the-job learning and the practical nature of tacit knowledge, the knowledge sharing process among construction workers is expected to be driven by a number of social and personal factors (Sanboskani et al. 2020).

State of the Art of Knowledge Sharing in Construction Industry

Like Bock et al. (2005), who assessed the factors that affect Korean employees' intentions to share knowledge, Zhang and Ng (2013) studied the antecedents of knowledge sharing and their impact on knowledge sharing attitudes and intentions of Hong Kong construction professionals. Alashwal et al. (2011) determined the factors that obstruct and enable knowledge sharing among project teams of fragmented firms in the Malaysian construction industry by interviewing project managers, construction managers, project directors, and architects. Issa and Haddad (2008) went beyond determining the factors that affect knowledge sharing to understand how they can lead to successful implementation of it among company presidents, human resource managers, project managers, and business development managers in construction organizations of the United States. Saini et al. (2018) determined the critical success factors associated with the effectiveness of transferring and sharing tacit knowledge in lean and agile construction processes among project managers, executives, and consultants in the UK. However, all these studies focused on the factors impacting the knowledge sharing process among white-collar employees in the construction and engineering industries. These studies did not pay attention to the knowledge sharing process among blue-collar workers, who are on the frontline of construction projects. Additionally, the studies cover various parts of the world (e.g., North America, Western Europe, and Asia), but not the MENA region, which has a unique environment.

The MENA region features a high rate of development owing to the increase in population and in living standards. Saudi Arabia, Qatar, and United Arab Emirates have been spending over $100 billion on construction projects on a yearly basis for the past decade. The vast majority of these projects are built by a generally undertrained, underpaid, young, and migrant workforce.

Despite low labor wages in the MENA region, labor costs account for a large percentage of total project costs (El-Gohary and Aziz 2014; Kiomjian et al. 2016). Although the average monthly wage for a construction worker in United Arab Emirates is $1,156 (Indeed 2020), a study by Deloitte showed that labor wages remain the largest portion of construction costs in Dubai's construction industry (Deloitte 2016). Such cost inefficiencies impact project performance, where construction organizations deliver projects late and over budget, giving rise to very costly claims and disputes (Emam et al. 2014). Zooming in on the causes of these pitfalls reveals that they are highly correlated with rework, lack of formal training, and poor labor productivity (Emam et al. 2014). Accordingly, it is appealing to investigate the knowledge sharing process while taking a country in the MENA region as a testbed. The country chosen for the investigation is Lebanon because the authors have access to a large number of its construction sites and because of the cooperative nature of construction managers and their teams. Although Lebanon may have a unique environment, the state of the industry, and particularly labor conditions, in Lebanon resemble those in other countries. For example, the local construction industry is not attractive for the brightest and educated strata of society and does not pay as well as other sectors and, in addition, has a challenging environment. This is the case in other countries in the Middle East and in other parts of the world.

Theoretical Background

Job performance is highly dependent on three basic factors: motivation, ability, and environment (Porter and Lawler 1968). Ability has to do with one's skills and knowledge, environment with resources and support, and motivation with the desire to perform, usually through goal-directed behavior. Accordingly, motivation is fundamental to driving worker behavior with respect to certain actions, such as knowledge sharing, which, if properly done, would also enhance workers' skills and expand their environment. Several motivation theories discuss factors that act as motivators for job performance. Maslow's (1958) hierarchy of needs starts by satisfying physiological needs, which are usually met by salary; then individuals look to have their social needs, such as bonding with others, met, and then esteem needs, which are satisfied by peer recognition. Other than the basic need for money that which is a universal motivator, employees seek recognition and desire amicable relationships at work. Recognition is among the motivators identified by the two-factor theory of Herzberg (2017); motivators are factors that are considered to be intrinsic to a job, such as enjoying the work and achieving high performance.

The literature recognizes many drivers acting as motivators for individuals to share their knowledge where such a process is assessed by behavioral intention (Ryu et al. 2003). Intention to share knowledge is how much workers aim to share their implicit knowledge at a later time (Dennis 1996). According to Ajzen (1985), intention is governed by external and internal factors. Intention determines behavior or is expected to predict an individual's attempt to perform an action, and previous studies have shown that there is a strong link between behavioral intention and actual behavior (Choi et al. 2008; Tohidinia and Mosakhani 2010). Thus, the proposed model will examine the knowledge sharing behavior of construction workers using behavioral intention as the dependent variable. To develop a theoretical model of the possible factors driving workers' intentions to share knowledge, the theory of reasoned action (TRA) is followed by considering the impact attitude and subjective norms have on influencing individuals' willingness to engage in knowledge sharing behavior (Fishbein and Ajzen 1975). TRA assumes that individuals take into consideration available information and implicitly or explicitly assess the consequences of their actions; thus, the theory suggests that a person's intention to engage in or not engage in a particular behavior is the determinant of the action. Without the interference of unexpected events, individuals are expected to act in accordance with their intentions (Ajzen 1985). To understand human behavior, the determinants of intentions must be identified. According to TRA, an individual's intention is a function of a personal determinant, which is the individual's positive or negative evaluation of performing the behavior, termed *attitude*, and the individual's perception of social pressure placed on him/her to engage in or not engage in a certain behavior, also known as *subjective norm* (Ajzen 1985). The relative importance of these two basic determinants is identified depending on the investigated intention. Naturally, these two determinants are influenced by a number of factors.

Researchers have identified several factors that influence white-collar workers' intention to share knowledge. Some treat knowledge sharing as a social exchange exercise that can be motivated by benefits such as anticipated or enhanced reciprocal relationships (Bock et al. 2005; Zhang and Ng 2013), sense of self-worth (Bock et al. 2005), personal benefits (Zhang and He 2015), and economic rewards (Zhang and Ng 2013). Other factors are contextual and so related to the organizational environment such as top management support (Connelly and Kelloway 2003; Zhang and Ng 2013), team support and interaction (Ni et al. 2018; Zhang and Ng 2013), knowledge feedback (Zhang and Ng 2013), trust (Ni et al. 2018; Zhang and He 2015), and organizational climate (Bock et al. 2005). Also, Chow and Chan (2008) found that among managers, social network and shared goals affect intention to share knowledge while social trust does not have a significant impact. However, other aspects of professional trust must be considered that arise from an organization's environment and that might impact individuals' self-esteem (Chen et al. 2011); these can be largely determined by influential factors of management support and culture (An and Ahmad 2010).

Accordingly, in this paper, the authors study a set of personal and social motivational drivers that are expected to influence construction workers' knowledge sharing intentions. To test this hypothesis, organizational climate factors focusing on trust within the team (supervisor and colleagues), personal factors focusing on how the workers perceive the worthiness of their knowledge sharing to project performance, and social factors focusing on the relationships that have developed between the workers due to knowledge sharing will be studied. These factors represent the general hypotheses tested in this paper. Upon reviewing the literature, the authors chose fairness and affiliation, sense of self-worth, and anticipated reciprocal relationships, respectively, as the indicators of the aforementioned drivers to undergo quantitative assessment. Since TRA is adopted, items measuring attitude, subjective norms, and intention are considered. As indicated earlier, and using the findings of the literature review, a set of factors that are expected to influence attitude and subjective norms are chosen for the investigation.

It is important to clarify that the items used to measure attitude do not reflect innate attitude. Some people are extroverts by nature and like to talk about their experiences and so help others without expecting anything in return. This describes their innate attitude toward knowledge sharing, meaning they already have a positive attitude toward sharing knowledge regardless of the job setting, the cause, and the environment. This aligns with the discussion by Calder and Staw (1975) on how altruistic intrinsic motivation originates in certain individuals who like to engage in knowledge sharing exercises for the sake of personal enjoyment and challenge. However, in this study and model, the authors do not target innate attitude but rather focus on how workers' attitudes are altered after being affected by a certain set of factors corresponding to job setting and environment. The authors wish to study how the working environment in which construction workers find themselves at construction sites shapes their attitudes toward knowledge sharing.

Research Objectives and Methodology

The review of the relevant literature targeted several studies on knowledge sharing among white-collar workers in the engineering and construction industries. However, none targeted the factors that drive the intentions of construction workers to share their tacit knowledge. Accordingly, the objective of this study is twofold. First, it aims to identify the factors that affect construction workers' behavioral intentions toward knowledge sharing. Second, it aims to assess the relationships between these factors to propose on-site construction-specific techniques to improve the behavior of construction workers with respect to knowledge sharing.

This paper follows a positivist paradigm that requires the use of quantitative methods to test hypothetical deductive generalizations (Grix 2018). It covers a subject with enough knowledge to pose hypotheses and formulate a theoretical framework, so quantitative research suits it (Amaratunga et al. 2002). Thus, the authors decided to use a questionnaire to collect data and perform statistical

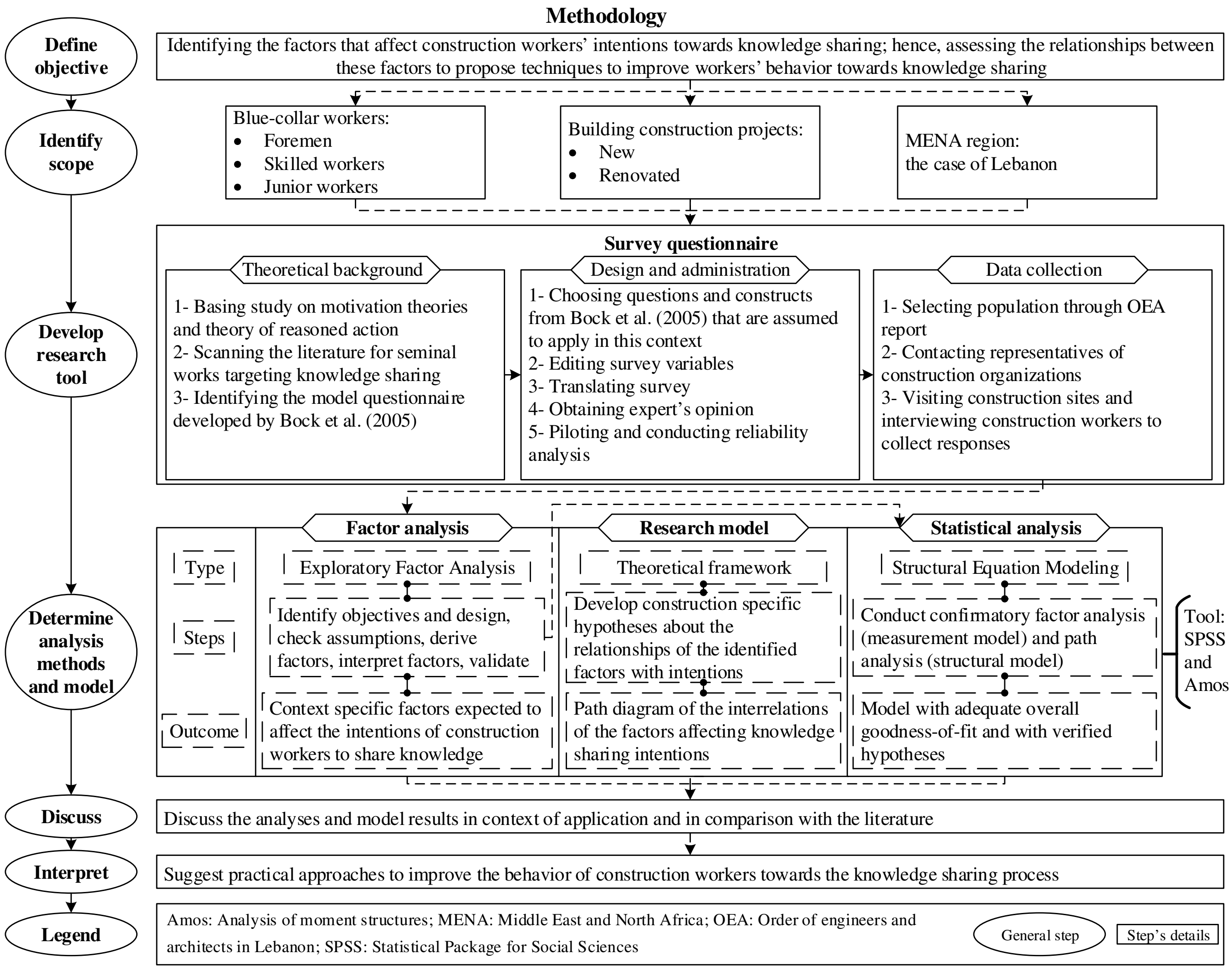

Fig. 1. Research methodology.

analysis, as shown in Fig. 1. The questions targeted foremen, skilled workers, and junior workers at a random set of new and renovated building construction projects in Lebanon, the testbed for the study. Because of the expected limitations of the respondents' understanding of the survey questions, piloting was done as well. The results were first analyzed through EFA to determine the factors. The research model and hypotheses were developed in the context of the study and were tested by conducting confirmatory factor analysis (CFA) to validate the EFA results and path analysis to confirm the suggested theoretical model. The primary methodology was a questionnaire, coupled with interviews while collecting the questionnaire data, which allowed the authors to explore another set of observations that further explained the numerical results qualitatively and evaluate them in the context of application.

Survey Design and Administration

The authors scanned the literature to prepare a questionnaire that would reflect the ideas discussed in the theoretical background. Since the study focuses on workers' willingness to transfer knowledge to colleagues, the authors found the questions by Bock et al. (2005) to be most relevant. Bock et al. (2005) studied the role of nine constructs in determining white-collar employees' intention to share explicit and implicit knowledge. Given this paper's context of application, some constructs were considered relevant, such as fairness and affiliation, some were irrelevant, such as innovativeness and extrinsic rewards, while some were modified in how they were phrased, the questions included, and the terms used, such as *anticipated reciprocal relationships* and *sense of self-worth*. Hence, the survey was designed by choosing factors judged to be applicable among construction workers, removing irrelevant measures within the chosen factors, modifying professional terms to match the construction industry context, and translating them to the native language (Arabic) of the participants. As hinted in the literature review section, certain factors lean more toward the work environment's effect on attitude and, thus, intention to share knowledge. The questions in the survey that were chosen to study the given hypothesis focus more on the role of the supervisor and interactions among colleagues where both reflect the work culture at the project site. These include factors related to fairness and affiliation. In this way, the authors believe they have contextualized the instrument to construction blue-collar workers.

The final version of the survey was established after considering experts' opinions and piloting the survey, and the results were tested for reliability to assess its applicability. The final version included three sections with an introductory paragraph explaining the purpose of the study. The first section collected personal characteristics of the participants. The middle section required the

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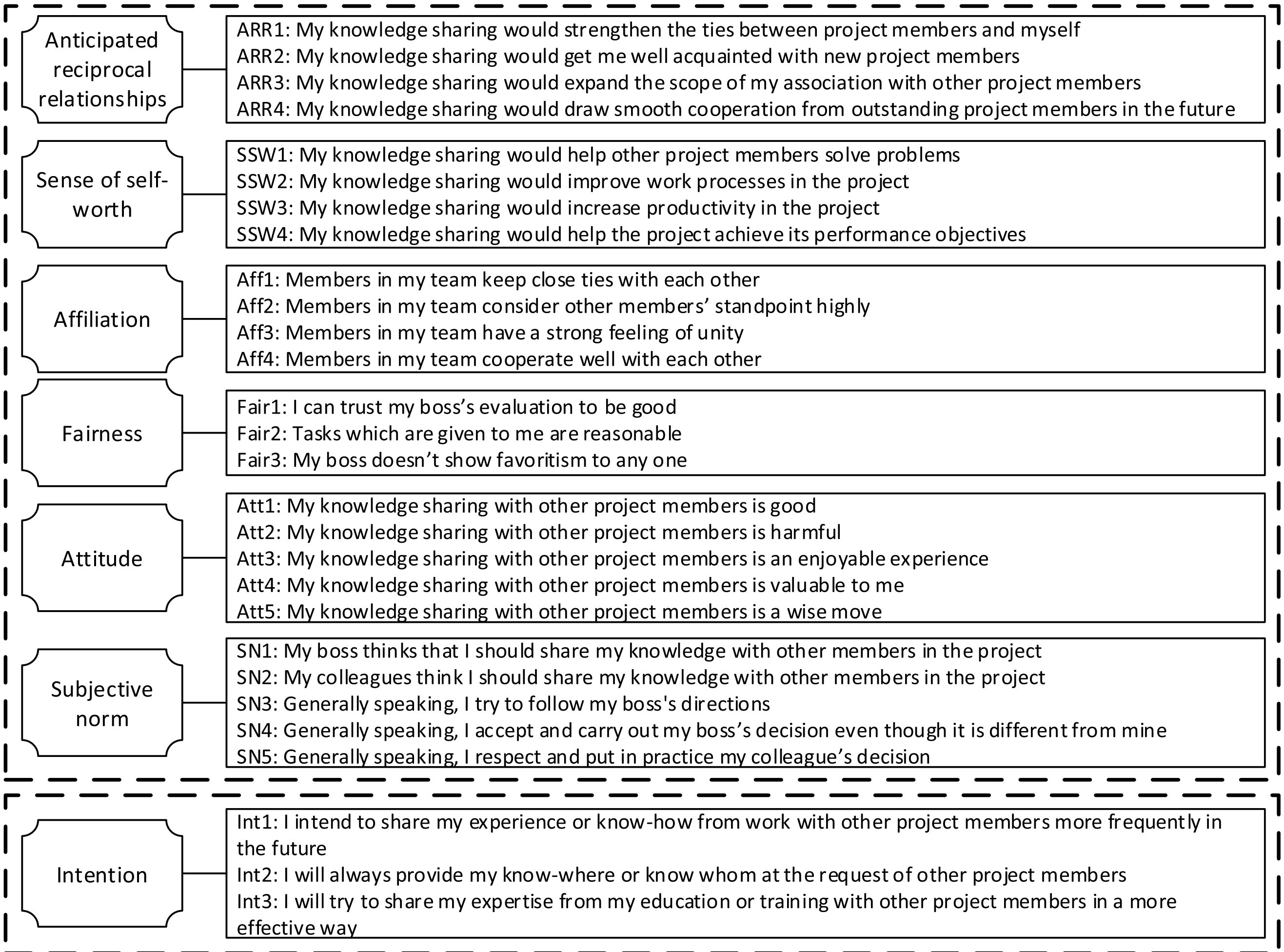

Fig. 2. Factors affecting knowledge sharing and their indicators and codes.

participants' assessment of the current situation of knowledge sharing using a five-point Likert scale ranging from 1 (totally disagree) to 5 (totally agree). The last section investigated the intentions of the workers to share their knowledge. Fig. 2 shows the final questions with the division of the items under the factors.

Data Collection and Characteristics of the Sample

A report by the Order of Engineers and Architects in Lebanon for 2018 showed that approximately 90% of the construction permits issued were for residential, commercial, and educational buildings (OEA 2018). Accordingly, the authors contacted representatives of construction organizations and visited a total of 16 building sites. Subsequently, 171 responses were distributed and personally collected by the authors on sites, of which 137 were identified as usable/complete, yielding an effective response rate of approximately 80%. After checking relevant data cleaning techniques, 34 responses were disregarded either because they were incomplete or because they contained inconsistent answers, such as age range versus experience range.

Table 1 shows the demographics information of the respondents, which indicates that many respondents (38%) occupy the youngest age range, so most of them have the least experience (31%), unlike in North America, where the average age for construction workers

Table 1. Demographic information of respondents

Variable	Category	Number of cases	Frequency (%)
Age	16–25	52	38.0
	26–35	49	35.8
	36–45	27	19.7
	46–55	8	5.8
	56+	1	0.7
Experience	0–4	43	31.4
	5–9	41	29.9
	10–14	26	19.0
	15–19	7	5.1
	20–24	8	5.8
	25–29	5	3.7
	30+	7	5.1
Education	Not educated	11	8.0
	Elementary	45	32.9
	Middle	14	10.2
	Secondary	40	29.2
	Technical	14	10.2
	Bachelor	13	9.5
Position	Junior worker	69	50.4
	Skilled worker	50	36.5
	Foreman	18	13.1

is 41 (Davis 2017), in the UK it is 45, and in China it is 40 (Coates 2018; Zhao 2018). More than 50% of the respondents did not finish their education, unlike in the US, where only 20% of the construction workforce is not educated (CPWR 2010). The junior position is highly occupied since most of the construction workers in the region do not receive formal training and join the industry once they reach the legal working age (Kiomjian et al. 2016). The collected data span across different work trades, such as gypsum finishing, painting, tiling, plastering, concrete, electrical fixing, mechanical fixing, and plumbing, for example.

Data Analysis Methods

Factor analysis is a multivariate technique to identify the separate dimensions (factors) of a model structure and determine the degree to which each variable is explained by each dimension. Usually, CFA is approached first based on theory; however, owing to the context of the survey's application, which matched neither the professional level nor the region of previous studies, construct reliability was checked using Cronbach's alpha. Although a Cronbach's alpha value of 0.6–0.7 is adopted in light of exploratory research (Hair et al. 1998), the results yielded unreliable values. Even though the constructs are based on an existing model, the numerical tests indicate that the model is not applicable because it is in the current context of application. Thus, EFA is used to identify the factorial structure of the measured variables (Child 2006) to either check the applicability of the original proposed factorial structure (Fig. 2) when applied to blue-collar construction workers or extract new factors applicable to this context from the measured items. To validate the EFA results and meet the objective of this study, which is determining the factors affecting workers' intentions to share knowledge and their underlying relationships, a structural equation model is created using SPSS 25 and Amos 26.

According to Hair et al. (1998), to factor analyze, a sample size of 100 or more is preferable, with a minimum of observations of five times the number of variables to be analyzed. In this study, 25 variables from the middle section of the survey (Fig. 2) are analyzed, so a minimum of 125 responses are needed. As for structural equation modeling (SEM), the sample size (137 respondents) might be smaller than that of similar studies in the literature; however, as indicated by Hair et al. (1998), a sample size ranging between 100 and 200 would be enough for any multivariate regression type of analysis such as SEM. This is echoed by the work of Boomsma (1984) and Sideridis et al. (2014), who argue for a similar sample size for a power of 80% and a ratio of number of measured variables to number of latent factors.

Analysis and Model

This section presents the factor analysis done to extract the factors, provides theoretical justification for the results, and defines the research hypotheses and theoretically based model. A table of summary statistics on the responses to each question is provided in the Appendix. The results show that the mean ranged between 3.46 and 4.64 while the standard deviation ranged between 0.64 and 1.58. Even though a large amount of the collected data came from junior or less experienced personnel (Table 1), there is not enough evidence to show that results would have been different if more experienced workers had participated. A series of t-tests were conducted on the survey questions to check for differences between skilled and unskilled workers. Of the 28 tests on each of the variables, 27 were statistically insignificant, which suggests that there is no significant difference across the two groups.

Factor Analysis

Assumptions were checked to determine the suitability of performing EFA by conducting Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) test. Bartlett's test determines the multivariate normality of variables where the p-value was found to be 0, indicating that the variables are related ($p < 0.05$), and KMO value tests for the adequacy of the variables to conduct EFA, which is 0.831 (closest to 1) (George and Mallery 2016). Thus, EFA can be performed.

Principal component analysis was used for factor extraction to summarize the original information (variance) in a minimum number of factors (Hair et al. 1998). Then an adequate rotation method (oblique-OBLIMIN) of the components (factors) was used to redistribute variances and obtain theoretically more meaningful factor patterns (Hair et al. 1998). After which, the practical and statistical significance of the item factor loadings was ensured using a cutoff value of 0.5 considering a power level of 80%, 0.05 significance level, and the sample size (Hair et al. 1998).

Eigenvalues were used as a selection method for the number of components to be extracted. Considering the number and meaningfulness of variables in the study, five components of eigenvalues larger than 1, which were expected to have an effect on the knowledge sharing intentions of construction workers, emerged from this analysis, accounting for 63.5% of the total variance explained. Table 2 shows the factor loadings and component results of the 25 variables reduced to 21 variables and categorized into 5 components. The results show that most of the items from the adopted factors still load together, but there are some exceptions where other items are now part of new components. Accordingly, these results were assessed by face validity, and Att1 and Aff1 were removed since in the context of construction workers, they do not seem to be supported where they loaded. Also, Att2 was removed since it is a negatively worded question that creates confusion upon translation. EFA was carried out again, and 18 items are now categorized under 5 components (Table 2) accounting for 68.287% of the total variance explained. The new factorial structure is theoretically justified considering the context of application and is later confirmed through CFA. Although most of the items loaded on previously defined factors, considering the blue-collar construction worker context, the authors labeled the five extracted components as follows:

- Component 1 (professional contributions), including SSW1, SSW2, SSW3, and SSW4. According to Cox et al. (2003), key performance indicators help assess the performance of a construction operation by measuring effectiveness, efficiency, and quality for both workmanship and product. This factor evaluates how knowledge sharing improves the efficiency of the workmanship, such as through helping others solve problems, and how it ensures the effectiveness of the product, such as by achieving performance objectives. This factor reflects the valuableness of worker knowledge sharing for project performance.
- Component 2 (supervisor support), including Fair1, Fair2, Fair3, and SN1. This factor reflects the role of supervisors in establishing a knowledge sharing environment by treating workers fairly and encouraging them to share their knowledge. The supervisor's role is echoed by the organizational climate he creates, which is conditioned by gaining the workers' trust on his decisions and performance on site. Mach et al. (2010) demonstrated that trust is a predictor of individual behavior and team performance. Thus, it is expected that when workers at the lower levels of the hierarchy trust those at upper levels, the former will be encouraged to perform better since they will be satisfied with the professional fairness approach of their supervisors.
- Component 3 (attitude), including Att3, Att4, and Att5. This factor relates to the workers' feelings toward their in-context

Table 2. Results of EFA for factors affecting knowledge sharing intentions

Item	Component 1	Component 2	Component 3	Component 4	Component 5
	Factor loading—first EFA				
ARR1	**0.882**	−0.061	0.015	0.080	0.133
ARR2	**0.704**	−0.042	−0.127	−0.085	0.023
ARR3	**0.705**	−0.120	−0.104	−0.064	−0.240
ARR4	**0.803**	0.054	0.128	0.056	−0.081
SSW1	**0.533**	0.089	−0.182	0.055	−0.160
Fair1	0.114	**0.752**	0.016	0.148	0.021
Fair2	−0.200	**0.579**	−0.257	0.022	−0.215
Fair3	−0.009	**0.605**	0.068	0.343	−0.226
Att1	0.016	**0.586**	−0.211	−0.225	0.093
SN1	−0.041	**0.694**	0.170	−0.268	−0.027
SSW2	0.481	0.156	**−0.522**	−0.033	0.043
SSW3	0.386	−0.015	**−0.510**	−0.172	−0.229
SSW4	0.285	0.072	**−0.650**	−0.205	−0.066
Aff1	0.028	0.128	**−0.570**	0.060	−0.392
Att2	−0.116	−0.206	−0.158	**−0.620**	−0.147
Att3	0.350	0.181	0.341	**−0.461**	−0.326
Att4	0.359	0.210	0.313	**−0.492**	−0.254
Att5	0.061	0.239	0.023	**−0.793**	0.151
Aff2	0.027	−0.007	−0.371	0.101	**−0.677**
Aff3	−0.012	0.067	0.063	0.000	**−0.870**
Aff4	0.152	0.029	0.035	−0.143	**−0.730**
	Factor loading—second EFA				
SSW1	**0.427**	0.083	0.063	0.313	−0.087
SSW2	**0.698**	0.096	−0.006	0.252	0.075
SSW3	**0.709**	−0.083	0.027	0.152	−0.213
SSW4	**0.845**	−0.050	0.039	0.016	−0.047
Fair1	0.059	**0.799**	0.021	0.120	0.071
Fair2	0.400	**0.516**	0.110	−0.346	−0.080
Fair3	−0.137	**0.730**	−0.214	0.108	−0.227
SN1	−0.029	**0.594**	0.507	−0.092	0.060
Att3	−0.080	0.023	**0.712**	0.193	−0.294
Att4	−0.039	0.033	**0.736**	0.187	−0.227
Att5	0.099	−0.085	**0.835**	−0.063	0.122
ARR1	0.087	0.048	−0.010	**0.845**	0.125
ARR2	0.258	−0.064	0.141	**0.581**	0.015
ARR3	0.241	−0.110	0.088	**0.589**	−0.259
ARR4	−0.016	0.149	0.054	**0.782**	−0.105
Aff2	0.456	0.032	−0.152	−0.099	**−0.598**
Aff3	−0.036	0.087	0.044	−0.017	**−0.878**
Aff4	0.068	−0.013	0.196	0.070	**−0.745**

Note: Factor loading absolute value greater than 0.4.

knowledge sharing. The decision to share knowledge depends on the worker's feelings about it (Ajzen and Fishbein 1977).

- Component 4 (social contributions), including ARR1, ARR2, ARR3, and ARR4. This factor reflects how knowledge sharing affects the relationships of project members. According to Javernick-Will (2012), social team integration based on reciprocity is a very critical motivator for sharing knowledge under the umbrella of social motivators. Working in a dynamic and interactive environment like a construction site relies on having smooth social ties among workers and overcoming behavioral barriers (Baiden et al. 2006). Thus, the role played by knowledge sharing in enhancing team integration can make it a key motivator for workers to share their knowledge.
- Component 5 (team affiliation), including Aff2, Aff3, and Aff4. This factor asks about the professional atmosphere among team members, reflecting the importance of organizational climate in ensuring a unified crew. Workers' sense of belongingness with the crew drives their behavior as team players and contributors to work (Mitropoulos and Memarian 2012).

Although the earlier test of reliability of the original constructs as extracted from Bock et al. (2005) yielded unreliable results, the new indicators' distribution across constructs resembles the model of Bock et al. (2005) but with certain modifications applicable to the context of application and justified with theoretical and practical reasoning in the discussion section. The reliability of the scales, which assesses the degree of consistency between multiple measurements of a variable, must be checked (Hair et al. 1998). Cronbach's alpha is a widely used reliability coefficient. As previously mentioned, a Cronbach's alpha value ranging between 0.6 and 0.7 is desirable (Hair et al. 1998). As shown in Table 3, all the extracted constructs have adequate reliability, and the dependent variable intention has a Cronbach's alpha value of 0.834.

Research Model and Hypotheses

The authors were inspired by motivation theories and seminal works while considering the contextual application of the study and the developed constructs, relevant to the construction industry

Table 3. Validity and reliability analysis results

Construct	Item	Cronbach's alpha	Factor loading	CR	AVE
Professional contributions	SSW1	0.815	0.545	0.832	0.560
	SSW2		0.714		
	SSW3		0.869		
	SSW4		0.823		
Supervisor support	Fair1	0.656	0.692	0.670	0.340
	Fair2		0.539		
	Fair3		0.522		
	SN1		0.557		
Attitude	Att3	0.796	0.827	0.805	0.590
	Att4		0.897		
	Att5		0.529		
Social contributions	ARR1	0.832	0.744	0.817	0.527
	ARR2		0.685		
	ARR3		0.720		
	ARR4		0.754		
Team affiliation	Aff2	0.784	0.681	0.780	0.542
	Aff3		0.750		
	Aff4		0.775		
Intention	Int1	0.828	0.780	0.834	0.627
	Int2		0.820		
	Int3		0.774		

Note: CR = composite reliability; AVE = average variance extracted; SSW= sense of self-worth; Fair = fairness; SN = subjective norm; Att = attitude; ARR = anticipated reciprocal relationships; Aff = affiliation; and Int = intention.

in Lebanon, to hypothesize the causal relationships between them and build the model studying their effects on the intentions of construction workers to share their knowledge. Based on TRA, where attitudinal considerations are considered more influential than subjective norms, and the context of application results from EFA, the research model is shown in Fig. 3 and the hypotheses are explained as follows:

- An established open organizational climate by supervisors reinforces trust among individuals themselves and with their supervisors (Janz and Prasarnphanich 2003). Such trust improves the individual's perception of the working environment, leading to a better sense of belonging to a team.

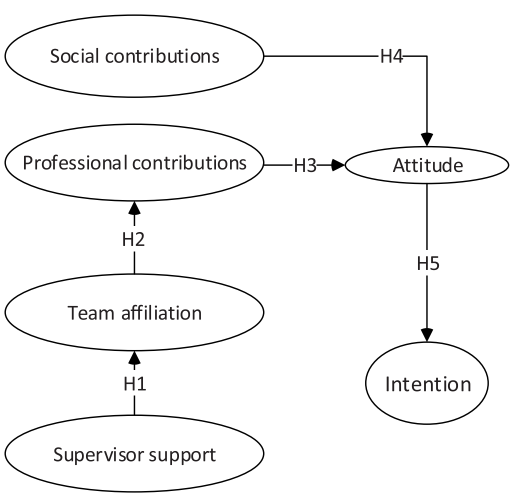

Fig. 3. Path diagram of interrelations of factors affecting knowledge sharing intentions.

H1: Supervisor support has a positive effect on worker's sense of team affiliation.

- Individuals who feel they belong to an organization strive to execute their tasks while looking for the organization's best interests (Javernick-Will 2012). Owing to the known positive correlation between knowledge sharing and organizational performance (Allameh et al. 2014), affiliated team members tend to be more interested in sharing their knowledge if they think it will improve performance.

H2: Team affiliation positively impacts the professional contributions associated with workers' knowledge sharing.

H3: The more confident workers are that their knowledge sharing is professionally valuable to project performance, the more favorable will be their attitude toward knowledge sharing.

- When individuals feel the effect their knowledge sharing has on improving their relationships with other project members, and thus the social environment at work, they will be more encouraged to share their knowledge with team members (Titi Amayah 2013).

H4: The more positive workers are that their knowledge sharing will enhance their relationships with other project members, the more favorable will be their attitude toward knowledge sharing.

- Considering the job setting, a positive attitude toward knowledge sharing is developed if individuals have a satisfied feeling for the organizational climate and thus believe that their knowledge sharing is beneficial at the social and professional levels. According to TRA, an individual with a positive attitude toward an action will most probably intend to do it (Ajzen and Fishbein 1977).

H5: The more favorable workers' attitude are to knowledge sharing, the more inclined they will be to share their knowledge.

Statistical Analysis

This section provides the methods and results for the statistical analysis performed on the data. SEM is a popular mode of analysis used in analyzing survey results that are based on hypothesized models. It is a hybrid model of two components: a measurement model that is tested by CFA and a structural model that is measured by path analysis (Kline 2015). The measurement model shows the hypothesized relationships between latent variables and their indicators, as shown in Table 2, while the structural model links the independent and dependent latent variables, as shown in Fig. 3. This integration of analysis is only done by SEM, making it preferable over multiple regression analysis.

Upon interpreting the model, the authors found that the model had a poor fit compared to the desired values of the overall model fit, so model respecification was performed to improve the fit of the model, which is a natural step in SEM to improve the fit of the model at hand such that major assumptions are already satisfied. This does not mean that a new model is developed; rather it means that certain modifications are performed on the available model to satisfy numerical thresholds. According to Garson (2015), a better model fit can be achieved by correlating pairs of errors of indicators and of constructs by considering high values of modification indexes while maintaining theoretical sense. The errors are denoted by *e* and the residuals of constructs by *res*. Fig. 4 and the results shown in the following sections are those of the model after respecification.

Confirmatory Factor Analysis

CFA is performed to confirm the convergent and discriminant validity of the measurement model where the measurement model fit is

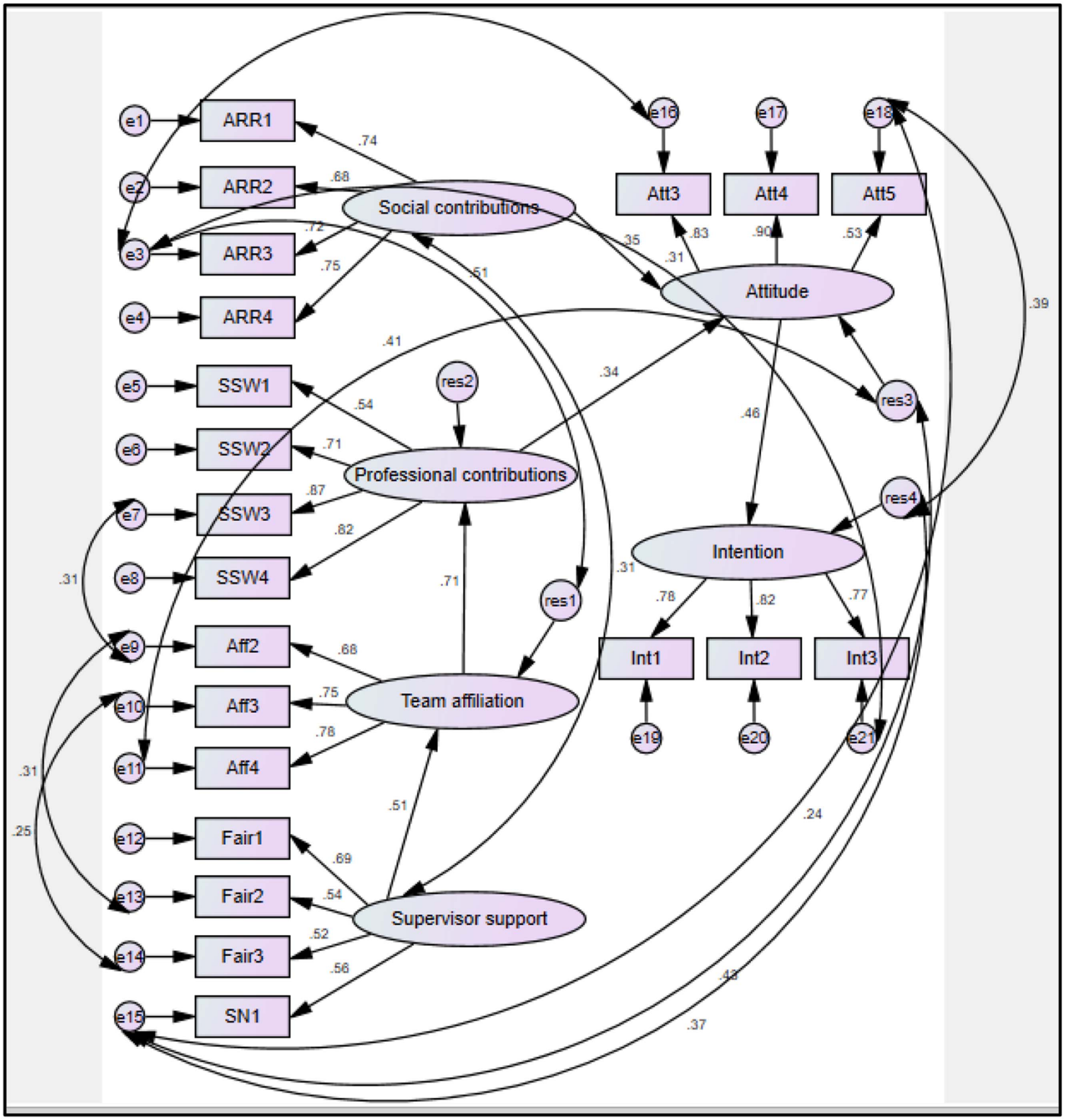

Fig. 4. Structural model with standardized path coefficients.

checked by performing reliability and validity analysis. As shown in Table 3, all constructs have adequate construct reliability. As for convergent validity, it is assessed through three measures. The first is by examining that the estimated factor loadings are greater than 0.5 and assessing their statistical significance at the 0.05 level (Hair et al. 1998). The results indicate that all items are significant at the 0.01 level and exceed the acceptable loading value (Table 3). The second is by assessing composite reliability (CR) that shows what level the indicators can "indicate" the common latent unobserved construct is on, and it must be greater than 0.7 (Hair et al. 1998). The more reliable the measures are, the higher the authors' confidence is that the individual indicators are consistent in their measurements. The third is by checking that the average variance extracted (AVE) "reflects the overall amount of variance in the indicators accounted for by the latent construct," and it must be greater than 0.5 (Hair et al. 1998). Higher AVE values reflect that the indicators truly represent the latent construct. As indicated in Table 3, CR values and AVE values are satisfactory except for the construct *supervisor support*, where the CR is marginal, but the AVE is below the cutoff. This can be explained by the factor loading values that are at the threshold; however, this construct has a critical practical denotation among the workers. As for discriminant validity, it is ensured when the square root of the AVE for each construct is greater than the levels of correlations involving the construct (Chin et al. 1997). Table 4 shows that all the values satisfy the condition. Therefore, the model sufficiently meets the convergent validity and reliability criteria and has favorable discriminant validity.

Table 4. Discriminant validity results

Construct	Social contributions	Supervisor support	Professional contributions	Attitude	Team affiliation	Intention
Social contributions	0.73	—	—	—	—	—
Supervisor support	0.123	0.58	—	—	—	—
Professional contributions	0.627[a]	0.248[a]	0.75	—	—	—
Attitude	0.453[a]	0.283[a]	0.398[a]	0.77	—	—
Team affiliation	0.413[a]	0.398[a]	0.560[a]	0.363[a]	0.74	—
Intention	0.287[a]	0.199[b]	0.232[a]	0.468[a]	0.270[a]	0.79

Note: The values are those of correlations, while the diagonal bold values are the square roots of AVE.
[a]Correlation is significant at 0.01 level (two-tailed).
[b]Correlation is significant at 0.05 level (two-tailed).

Table 5. Overall goodness-of-fit indexes

Goodness-of-fit measure	Level of acceptable fit	Calculation of measure
Absolute fit measures		
Goodness-of-fit index (GFI)	Higher values are better	0.870
Root-mean-square error of approximation (RMSEA)	≤0.08	0.055
Incremental fit measures		
Comparative fit index (CFI)	Higher values are better (≥0.9)	0.943
Incremental fit index (IFI)	Higher values are better (≥0.9)	0.944
Nonnormed fit index (NNFI)	≥0.9	0.930
Parsimonious fit measures		
Normed chi-square (χ^2/df)	Between 1 and 3	1.414
Parsimonious goodness-of-fit index (PGFI)	Higher values are better (>0.5 and <1)	0.648
Parsimonious normed fit index (PNFI)	Higher values are better (>0.5)	0.682
Akaike information criterion (AIC)	Smaller values are better (compared to the 2 models done by Amos)	361 < 462; 462 < 1,494

Table 6. Results for hypothesis testing

Hypothesis	Path	Path coefficient	CR	p-value	Result
H1	Supervisor support→Team affiliation	0.515	4.091	***	Supported
H2	Team affiliation→Professional contributions	0.706	5.015	***	Supported
H3	Professional contributions→Attitude	0.336	3.965	***	Supported
H4	Social contributions→Attitude	0.351	3.514	***	Supported
H5	Attitude→Intention	0.465	4.632	***	Supported

Note: ***Significant at 0.001 level (two-tailed).

The overall model fit indicates the degree to which the specified indicators represent the hypothesized constructs, which is assessed by absolute fit measures, incremental fit measures, and parsimonious fit measures. As shown in Table 5, all fit indexes meet satisfactory levels (Diamantopoulos et al. 2000; Fang et al. 2015; Hair et al. 1998; Tabachnick et al. 2007). Therefore, it can be deduced that the measurement model fits the survey data well and is suitable for testing the research hypotheses.

Path Analysis

Fig. 4 shows the structural model with standardized factor loadings or path coefficients. To assess the significance for each hypothesis, the critical ratio (CR) value must exceed 1.96 and the p-value must be significant at the 0.05 level (Hair et al. 1998). This determines whether or not the hypothesis is statistically supported. The p-value results presented in Table 6 show that all the hypotheses are significant even at the 0.001 level, which indicates that all the hypotheses are verified. Based on the significant statistical results, each of the supported hypotheses verifies the link between two of the constructs, and the interrelationships between the hypotheses in the path model determine the drivers affecting the workers' behavioral intention. All the hypotheses are significant at the same level; however, the path coefficients are higher for H1 and H2 than for H3, H4, and H5; where H1 describes the link between supervisor support and team affiliation, H2 describes the influence of team affiliation on professional contributions, H3 justifies the effect of professional contributions on attitude, H4 justifies the impact of social contributions on attitude, and H5 completes the relationships by linking attitude to intention. As shown in Table 6, attitude has a very significant impact on intention. Both antecedents of attitude, social and professional contributions, positively affect it. Similarly, the links between supervisor support and team affiliation, as well as team affiliation with professional contributions, are very strong.

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Theoretical Implications and Discussion of Results Using Interviews

This study identified the factors that play a role in shaping the behavior of construction workers with respect to knowledge sharing while relying on the participants' cultural framework to label these factors. Individualistic cultures, such as in North America and Europe, emphasize the private self, whereas the collectivist self receives greater emphasis in collectivistic cultures, such as in East Asia and Middle Eastern or Arabian countries (Darwish and Huber 2003). Thus, individualistic societies focus more on self-realization and individual initiatives while collectivistic societies focus more on group interests and needs (Triandis et al. 1988). Since this study is based in Lebanon, a Middle Eastern country, it is more reasonable to label the questions inquiring about the impact knowledge sharing has on project performance as professional contributions and not as sense of self-worth. Nevertheless, construction workers function in teams; thus, their teamwork performance defines their success. Whatever they can accomplish as a team is considered by them to be a contribution to project performance and not the fulfilment of self-realization. Also, collectivistic societies concern themselves with developing social links (Hui and Triandis 1986); thus, improving relationships with others is considered a social contribution to work group loyalty. The EFA results disregarded the so-called subjective norms factor that aimed to measure how much workers are willing to comply with their colleagues and supervisors' decisions. During data collection, the authors realized that the workers were confused while answering such questions since they strongly respect the hierarchal system and already obey their supervisors' decisions, illustrating the acceptance of authority by the collectivistic culture (Kagitcibasi and Berry 1989).

This paper adopts a multistep research methodology by developing a theoretically based model, using a survey questionnaire, conducting interviews, and building a structural equation model to interpret the relationships between multiple factors influencing the behavioral intention of construction workers with respect to knowledge sharing. This section discusses the hypothesis results in reference to the context of application upon interviewing workers while collecting responses and in reference to the existing literature.

The authors classify supervisor support as an organizational climate driver that, if properly implemented, enhances mutual trust in the organization (Issa and Haddad 2008). If the receiver of the knowledge is persuaded by its sender, this indicates that the receiver trusts the sender. Similarly, when workers acknowledge that their supervisors treat them fairly and reasonably allocate tasks, they will trust them and thus accept to move by their recommendations. As discussed by Issa and Haddad (2008), trust helps create positive behavior while reducing conflicts and promoting a better work environment. When a supervisor encourages team members to share their knowledge, he is promoting a collaborative atmosphere among them. This reflects better team affiliation behavior as indicated in the significant relationship between supervisor support and team affiliation (H1 in Table 6). However, the method supervisors use to show their support among white-collar works somehow differs. For instance, among Hong Kong construction professionals, top management encourages employees to share their knowledge, but they also need to provide them with the resources they need to innovate (Zhang and Ng 2013).

Another organizational climate driver is team affiliation, which significantly influences professional contributions (H2 from Table 6). Highly affiliated crew members who listen to each other's advice tend to make good progress at work. Thus, nurturing ties helps shape team behavior and direct efforts toward common goals of achieving project performance objectives. According to one foreman: "If workers know each other, good behavior is sustained among them; thus, better productivity is achieved." Many foremen explained to the authors that since workers are relatives in many cases, a higher sense of unity is achieved and they tend to be more willing to teach each other; so a strongly affiliated team creates an encouraging and competitive learning environment (Xue et al. 2011). Thus, project performance improves from having a coherent team and continuous learning opportunities driven by a trusting organizational climate.

Professional contributions are identified as a personal driver for workers' intentions to share knowledge. According to Ni et al. (2018), since tacit knowledge is highly personal, its sharing is certainly influenced by how much its sharers can see its contributions to the organization's performance. Similarly, workers need to realize how much their knowledge sharing can increase labor productivity. Accordingly, they ought to be more willing to be part of the knowledge transfer cycle. The results of the study show a significant relationship between professional contributions and attitude (H3 from Table 6), confirming that when workers feel the impact of their shared knowledge on project performance, they will have a favorable attitude toward sharing it. Workers clarified to the authors that they are concerned with achieving task objectives so as to get paid faster, which makes the knowledge sharing exercise valuable to them. This also aligns with Maslow's (1958) motivation theory, which prioritizes fulfilling physiological needs to perform one's job well. Since most of the workers in this study were young and uneducated (Table 1), they did not value the long-term benefits with respect to work projects of combining each worker's own personal knowledge. If they did value this, then professional contributions would have a more significant effect on attitude. This would be more in line with the findings of Gillani et al. (2018), who suggested that a result of using the knowledge sharing initiative as a key performance indicator would be greater sharing of knowledge among employees.

Social contributions are classified as a social driver proven to have a significant relationship with attitude (H4 in Table 6). Such a result aligns with the findings of Fulk (2017) and Xue et al. (2011), who emphasized the importance of social influence in directing employees toward identifying closely with their colleagues, encouraging them to share their knowledge. It is important to have strong social relationships among workers since they work together for months on the same project; hence, feeling acquainted with project participants makes them happier and motivated to work better. Thus, they need to be socially comfortable with their colleagues to have a favorable attitude toward knowledge sharing. Becoming socially motivated pushes workers to share knowledge, which aligns with the findings of Javernick-Will (2012) on the popularity of social motivations as a knowledge sharing driver. This result contradicts the findings by Zhang and Ng (2013), where the effect of personal relationships on white-collar employees' attitude toward knowledge sharing is not significant. This can be attributed to the cultural differences where Hong Kong was previously led by Western colonies contributing to the behavior of construction professionals by separating between personal relationships and work while being in the work environment, unlike in Lebanon, where most workers are migrant workers who come from the same social network and join the same projects to preserve their social ties. This difference is further explained by the features of an individualistic culture versus a collectivistic one.

Confirming the theory of reasoned action by Ajzen and Fishbein (1977) and in alignment with several studies covering different industries and regions, such as those by Bock et al. (2005), Tohidinia and Mosakhani (2010), Xue et al. (2011), and Zhang and Ng (2012, 2013), the results in this study confirm that attitude significantly impacts behavioral intentions (H5 in Table 6). When workers feel that their knowledge sharing is wise, enjoyable, and valuable, they endorse a positive attitude toward it; thus, they are inclined to exercise it more. In Eastern cultures, valuing reciprocity renders the knowledge sharing exercise a "wise move" for workers because of the concept of giving back to others, just like exchanging services. This was proven by Javernick-Will (2012) to be one of the most important social motivators to share knowledge. Attitude plays a mediating role between personal and social drivers on the one hand and intention on the other, where these drivers are the benefits that are expected to motivate workers to share their knowledge more.

Practical Implications

Several researchers have studied the factors affecting labor productivity and suggested labor incentives or team-building exercises to improve such productivity (Jarkas and Bitar 2012; Shan et al. 2011). However, none looked closely at the knowledge sharing exercise that takes place between workers and how critical it is to improve this exercise as a means of improving productivity. Accordingly, this section suggests several approaches to improving the behavior of workers toward knowledge sharing using the model results of the proven significant links between the identified factors. This study shows how some of the previously defined practices, among others, can function with respect to construction workers. It also shows how nontraditional training techniques and engaging methods affect the identified constructs individually and collectively based on the links between them. This will provide a sequential framework for the contractor to follow to improve the well-being of work environment to establish an efficient knowledge sharing process. To do that, one needs to understand how workers think by studying their behavioral intentions and the links between the factors that affect them.

The first step is to understand what affects the construct supervisor support. The contractor needs to emphasize empowering the leadership role of the supervisor (Arnold et al. 2000). This can be achieved in several ways, such as by coaching supervisors to give pep talks to workers, which can reinforce trust. Supervisors must raise awareness to treat all workers equally and avoid discrimination based on nationality, years of conducting business together, relatedness, or position. Migrant workers discussed with the authors the effect of ethnic discrimination on team integration and how they are not welcomed among their local counterparts. As one worker explicitly put it, "Local workers do not perceive me as worthy enough to share their knowledge with me since I'm a migrant." Following the notion of leading by example (Arnold et al. 2000), supervisors need to demonstrate positive behavior since workers will tend to imitate their supervisors' behavior. The mentioned approaches ensure fairness in the work environment. An act of encouragement by supervisors with respect to knowledge sharing can be to preserve intellectual property for the knowledge holder by identifying the best knowledge sharer of the week. In this way workers will feel recognized before their peers, especially those at the top levels of the organizational hierarchy; one foreman mentioned that he was not willing to share all his knowledge with other workers because he does not want to make his coworkers eligible to take his place. Thus, having trustworthy, fair, and encouraging supervisors would reduce jealousy that frequently occurs among workers and incentivize them to work collaboratively, thereby improving team cohesion as well.

Competition can help boost the cooperative spirit among workers and teach them teamwork so that those on the same crew are assigned to the same team competing against another crew from another trade. In this way, workers on the same team will learn how to cooperate to achieve a common goal. On the one hand, this enhances team affiliation, and on the other hand it creates a competitive learning environment, forcing them to focus on achieving a common goal, which is to meet project objectives and deliver the expected product. Thus, this untraditional approach also positively impacts professional contributions.

Workers need to perceive that their knowledge sharing is key in improving project performance. This can be achieved when they receive performance appraisal, which will cause them to enjoy knowledge sharing. Also, workers need to be given knowledge feedback and constructive criticism when they share knowledge. This will make them feel recognition, fine-tune their information, and increase their basket of skills. Thus, they will feel that the knowledge sharing exercise is valuable. These two examples illustrate how refining workers' perceptions of professional contributions strongly impact their attitudes as well.

Since a construction site is dynamic in nature and is a place where workers work together for months, develop social trust, and make new friends. Accordingly, they need reasons to improve their social ties. Sharing knowledge is one method to strengthen such ties, but the motive to exercise knowledge sharing more frequently is that these knowledge sharers will be noticed by their supervisors, and their employer may recommend them to other employers, indicating their level of experience, or keep them on their team for other projects. For instance, one foreman explained to the authors that his crew had been working with him for 7 consecutive years owing to the strong ties between them based on mutual trust and smooth cooperation. The professional results of social ties developed through knowledge sharing can make workers feel that sharing knowledge is wise.

The industry relies on hiring migrant workers that require reduced investment in wages and services to save money, so supervisors do not use economic rewards (promotions, salary raises, or bonuses) as incentives to share knowledge. Instead, they can use market coupons, phone charging cards, and festival tickets for workers' families. Basically, these workers care about receiving their salaries to provide for their families. Although such rewards were not considered in the model, an extra motivation would definitely encourage their behavior toward knowledge sharing.

All the identified social and personal factors illustrate the benefits workers can gain from sharing their knowledge, which when felt will enhance their intentions and encourage certain behavior toward knowledge sharing. Once they start sharing knowledge more, the abilities that underlie their information and skills will develop, and their resource base and support will expand. This would be the first step toward maintaining knowledge capital as part of knowledge management initiatives. In fact, this process turns out to constitute a cycle: the more workers see the benefits of knowledge sharing, the more they are motivated to share their knowledge. The more they share their knowledge, the greater the chances that they will receive feedback to improve it and, thus, the more they are able to sustain it. The more they feel the impact of these improvements, the more they realize the benefits, and the cycle repeats.

It is advised to use the necessary applicable tactics presented in this framework on site since not all construction sites face the same problems and not all crews engage in the same behavior. Accordingly, the contractor can make use of the survey questionnaire and the verified model using the indicators to question workers on site, and upon assessment of the results the contractor will target constructs with weaknesses and accordingly apply the recommended approaches. In this way, the contractor will be efficient and not waste resources on factors that are properly established.

Conclusions

Labor behavior is a key factor in defining construction project performance; yet not enough actions are taken to target the weaknesses of workers' influencing behaviors, such as that of knowledge sharing. This paper represents one of the first attempts to study the factors affecting knowledge sharing behavioral intentions among construction workers, where such factors were identified through EFA and their relationships were proven significant through SEM. Hence, the authors were able to identify the personal and social factors driving workers' intentions to share knowledge considering the influence organizational climate (supervisor support and team affiliation) has on determining the status of professional contributions that, along with social contributions, strongly determine workers' attitude toward knowledge sharing, which affects their behavioral intentions.

The authors built a framework for construction professionals who appreciate knowledge management and seek the interest of their organization. Although Lebanon was the case study used for data collection, the framework is not restricted to construction workers in the MENA region but can be applied elsewhere. The overarching methodology—literature review leading to a conceptual framework, conducting a survey and interviews, EFA, and CFA, and performing analysis—is generalizable and can be applied in different contexts. Although the other aspects of the study cannot be taken as is to another study, they provide interesting insight from the data collected in Lebanon and the thought process could be applied to another context, particularly among construction workers in other areas of the world where certain cultural factors will play a role in shaping the differences in the results. The main objective of this study is to maximize positive intentions of construction workers toward sharing their tacit knowledge. The measures of the constructs were used to highlight the areas that require focus considering the chain of links between the constructs leading to behavioral intention. The greater goal in connection with positive behavior toward knowledge sharing is to increase productivity, decrease conflicts among workers, and establish an effective learning environment, which would preserve tacit knowledge, decrease rework, lower costs, shorten project duration, and improve quality. Quantitative analysis allowed the authors to identify the factors affecting knowledge sharing and to examine their interrelationships. To complete the picture, the observations and discussions held with workers during data collection validated the results of the model, which gives it a stronger foundation to build on in future endeavors.

The natural research extension to this work would be to study ways to preserve the tacit knowledge shared between workers. Since the first step in doing that is to get workers to transfer their tacit knowledge, the authors identified the factors affecting their knowledge sharing intentions and suggested methods to make the knowledge sharing exercise more appealing and efficient. The next step is to preserve this knowledge. Thus, it would be interesting to investigate options for doing so considering new technological means of virtual reality and drones that can be used to codify and document tacit knowledge such that recording discussions of crew members and making novice workers watch them will become part of their training. Hence, one would want to study the factors impacting the success of this method of preserving tacit knowledge considering the efforts, resources, and time spent on it.

We recommend collecting data from more sites while making necessary observations to be able to compare the initial survey responses across different projects. The idea here is to draw insights and identify patterns across different environmental and project-specific conditions. Also, a limitation on the work is utilizing the same data set in EFA and CFA; thus, collecting more data from other sites will help in further testing the model using validation data sets. The scope of the study, which targeted construction workers of diverse trades yet pertained to construction buildings only, is one limitation of this work that could be addressed by studying workers from other types of construction projects, such as transportation and infrastructure, or considering various trades, such as the behavioral differences between electromechanical technicians and steel workers.

Appendix. Descriptive Analysis

Item	Mean	Standard deviation
ARR1	4.36	0.98
ARR2	4.33	0.98
ARR3	4.34	0.93
ARR4	4.30	0.99
SSW1	4.42	0.90
SSW2	4.55	0.70
SSW3	4.61	0.66
SSW4	4.51	0.79
Aff1	4.03	1.14
Aff2	3.97	1.18
Aff3	4.15	1.18
Aff4	4.28	0.91
Fair1	4.23	1.00
Fair2	4.17	0.98
Fair3	3.46	1.58
Att1	4.41	0.72
Att2	4.66	0.72
Att3	4.35	0.94
Att4	4.47	0.85
Att5	4.47	0.79
SN1	4.20	0.96
SN2	4.29	0.84
SN3	4.54	0.82
SN4	3.51	1.32
SN5	3.85	1.01
Int1	4.50	0.78
Int2	4.56	0.71
Int3	4.64	0.64

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request. These include the survey responses, EFA results, and SEM results.

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