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HOW SUCCESSFUL IS KNOWLEDGE SHARING IN A VIRTUAL ENGINEERING OFFICE?

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ABSTRACT
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According to a report by S&P Global (2020), more than 2/3 of companies worldwide shifted to a work-from-home strategy due to the COVID-19 pandemic and many companies started adopting this new way of work. The imposed remote form of communication renders knowledge sharing among colleagues challenging. Previous studies tackled the process of knowledge sharing but failed to assess the effect of a sudden emergency leading to remote work. To fill this gap, this paper proposes an integrated methodology to understand how the transition to a virtual work setting affects the knowledge sharing process and drivers. A survey targeting engineering companies is used to capture the work from-home-experience. The survey focuses on personal and external drivers affecting knowledge sharing intention, behavior, and outcomes. Personal drivers include motivation, enhanced personal relationships, and knowledge feedback. External drivers focus on the effectiveness of information and communication technology (ICT) in facilitating knowledge transfer. The nature of collected data was identified and analysis was conducted using Exploratory Factor Analysis (EFA) and Structural Equation Modelling (SEM). The results show that traditional factors such as enhanced personal relationships become less influential in remote work environments while ICT becomes more appealing. Incorporating these preliminary results with advanced statistical studies will enable companies to plan and implement strategies to foster knowledge sharing in different environments.

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CHAPTER I

INTRODUCTION

Construction projects are unique endeavors requiring intense coordination and collaboration among engineers. Knowledge is shared among project participants at various stages of the project, in particular during the design phase. Engineering organizations need to capitalize on the knowledge of their human capital to survive in today's competitive market (Javernick-Will 2012). Thus, it is important to understand the dynamics of knowledge sharing. Specifically, the contributions of individual employees to knowledge transfer should be fully understood. Due to their multi-disciplinary backgrounds, employees in engineering organizations interact continuously and share knowledge to improve project performance (Zhang and Fai Ng 2012). A typical team is composed from various expertise that get shuffled on different projects. This shuffling process allows the acquired knowledge to be transferred and applied on subsequent projects, thus avoiding the repetition of mistakes (Bresnen et al. 2003).

The work setting in engineering companies fosters an encouraging environment to share knowledge. Engineers' typical workday includes numerous informal and formal instances for them to share knowledge. The day frequently begins with colleagues drinking their morning coffee and chatting before diving into work. This constitutes the first instance where engineers could informally share knowledge and develop relationships between each other. Another informal get-together is during their lunch break. On the other hand, engineers are used to regularly communicating through formal scheduled meetings and sharing information across different departments (i.e., electrical, civil, mechanical, etc.). All the above-mentioned occasions as well as regular breaks throughout the day, constitute a major contribution to the knowledge sharing process by creating relationships and constant communication between engineers.

In response to the COVID-19 pandemic, engineering companies around the world were subject to several prolonged lockdowns. Consequently, these firms had to manage their resources, and handle all work virtually. Platforms like Zoom, Webex, and Microsoft Teams are used to conduct meetings and exchange information. A major concern for practitioners is whether the knowledge sharing between colleagues has been compromised. The work-from-home environment created a virtual community consisting of employees, a shared purpose, policies, and computer systems (Preece 2000). Fostering a virtual community necessitates extra supply of knowledge and the readiness to exchange this knowledge (Chui et al. 2006). Readiness touches upon internal and external factors. Internal factors are relevant to the individual's personality, whereas external factors have to do with factors such as technology. (Zhang and Fai Ng 2012).

This study examines the process of knowledge sharing in engineering companies operating in a virtual environment. Engineers in various companies are emphasizing the importance of external resources on the knowledge transfer remotely. Thus, this study could assist companies in providing the necessary organizational support and technologies needed to enhance the knowledge sharing process. As a result, employees are more likely to share knowledge and to do it effectively. Ma et al. (2008), Kivrak et al. (2008), and many other researchers discussed the factors enhancing knowledge sharing and the positive influence of organizational support on knowledge sharing. However, these studies are limited to hands-on and face-to-face knowledge sharing in engineering companies; and not extending to consider the changes due to remote and virtual communication.

For example, a typical workday for a civil engineer at the office includes discussing design steps of a building with his/her work colleagues and conducting meetings to relay any updates Moreover, the engineer spends time training an intern through explaining design principles, giving out hand-books, discussing daily tasks, etc. All these necessitate the transfer of knowledge and most importantly tacit knowledge.

The aim of this study is to identify the major factors and barriers affecting knowledge sharing in a work-from-home environment using virtual means to facilitate the transition on engineers. Even though the pandemic might soon cease from becoming a threat, some companies may still rely on remote and virtual work. Moreover, this study will also evaluate the outcomes resulting from an effective knowledge sharing process. The study includes background information on the topic, which is followed by research objectives and methodology. Then, analysis conceptual model, research hypotheses, and descriptive analysis are presented. This is followed by a statistical analysis, discussion of the results, conclusions, and openings for future research.

CHAPTER II

LITERATURE REVIEW

This section discusses the knowledge sharing process in engineering organizations emphasizing the need to study the process in the context of virtual and remote means of work and highlighting main findings and gaps of previous studies.

A. Definition & Types of Knowledge

Knowledge is the combination of information, experiences, and values originating and residing in the minds of the bearer (Davenport and Prusak 1998). This knowledge is considered as a personal asset that individuals value. Individuals weigh the potential advantages versus disadvantages of knowledge sharing, such as: loss of knowledge power when they are no longer the sole owners of this knowledge (Gray 2001), the time and effort to transfer the knowledge (Kankanhalli et al. 2005), and the mechanisms to trade knowledge (Wasko and Faraj 2000). Individuals are more likely to engage in knowledge sharing when the benefits override the expenses (Zhang and Fai Ng 2012).

The two main types of knowledge are tacit (implicit) and explicit knowledge. Both are important for engineers. Explicit knowledge is the one acquired theoretically in school or university. It denotes the knowledge that can be conveyed through words or figures (Zhang 2015). Tacit knowledge, on the other hand, is embedded in the minds of individuals based on their experience (Koskinen 2003). Polayni (1996) explained tacit knowledge by stating: "We know more than we can tell". Tacit knowledge is barely transferred directly to individuals since it is rooted in the human brain due to continuous experience (Woo et al. 2004; Chinowsky and Carrillo 2007; An and Ahmad 2010). Thus, the transfer of tacit knowledge between individuals is intricate yet valuable. This study focuses mainly on the transfer on tacit knowledge emphasizing its importance and complexity.

Javernick-Will (2011) stated that social interactions help manage and facilitate tacit knowledge sharing. Social interaction such as language and mutual trust are enhanced through face-to-face collaborations (Koskinen et al. 2003). Tacit-knowledge sharing is critical in the construction sector and improves team collaboration (An and Ahmad 2010; Rezgui et al. 2010; Chinowsky et al. 2011). Following the start of the COVID-19 pandemic, this face-to-face interaction was highly decreased rendering the sharing of knowledge, whether tacit or explicit, more complex.

B. Factors Affecting Knowledge Sharing

Many researchers studied the motivators and barriers to knowledge sharing. Some of these factors are internal, like motivation, tackling the characteristics of the individual. Others are external, for example technologies, dealing with the organization and resources that aid in the knowledge sharing process.

Knowledge sharing among engineers depends on the willingness and readiness of employees to distribute their acquired knowledge with their colleagues (Davenport and Prusak 1998). Firms try to capitalize on the knowledge of employees and enhance the sharing process to benefit the organization as a whole. For an individual to share knowledge, some personal and internal factors encouraging the knowledge sharing process need to be considered. The main link is the intention of employees to actually share knowledge. Bock (2005) specified that subjective norms influence the intention to share knowledge through the attitude of the individual as shown in Figure 1.

Figure 1 Subjective Norms relation to Intention (Bock, 2005)

Many factors could affect the attitude towards knowledge sharing. Ryu et al. (2003) claims that individuals tend to share knowledge only if they think it is important and valuable. Constant et al. (1994) state that attitude towards knowledge sharing is highly determined by the social exchange relationship of two individuals. Social exchange deals with the relationship itself between two individuals regardless of any extrinsic benefit (Blau 1967; Organ and Konovsky 1989). If a person provides a favor or benefits the other, they expect the same behavior in return. This reciprocity of favors initiates numerous rounds of favors between both individuals (Zhang 2015). Other studies, such as Bock and Kim (2002), claim that knowledge sharing is used to strengthen the relationship ties between individuals. Thus, enhanced personal relationships may be an incentive to developing a positive attitude towards knowledge sharing.

Some researchers advise organizations to increase their economic rewards inciting employees to share knowledge (Bartol and Srivastava 2002; Cabrera and Cabrera 2005; Hall 2001). It is important for organizations to seek methods to encourage and motivate employees to share knowledge. These methods could vary from continuous moral support to financial rewards or promotions. Motivation could be through monetary (e.g., higher salary) or non-monetary (e.g., job security, promotion) economic rewards.

Motivation enhanced by extrinsic rewards positively affect employees' attitude towards knowledge sharing (Huang et al. 2008). Another form of motivation is knowledge feedback. Wasko and Faraj's (2000) study conveys that feedback aided respondents to improve their thinking and acquire new insights. In an engineering team, engineers obtain continuous feedback when sharing their knowledge. Feedback, such as suggestions and mistakes pointed out, may develop a constructive attitude towards knowledge sharing.

Apart from personal motivators and social relationships, external resources and technologies may augment the knowledge sharing among employees. An important aspect to study is the behavior of the individual when sharing knowledge. As mentioned earlier, the individual's intention to share knowledge is dependent on his/her attitude towards knowledge sharing. Consequently, the intention to share knowledge predicts the behavior of knowledge sharing. This sequence is suggested by the theory of reasoned action (TRA) assuming that individuals have volitional control on their behavior (Ajzen and Fishbein 1980). However, Armitage and Conner (2001) argue the presence of external constraints on behavior regardless of the individual's intention to share knowledge. Accordingly, another predictor to intention and behavior was added which is perceived behavior control (PBC). This is known as the theory of planned behavior (TPB), which is an extension of TRA. Ajzen (1991) proceeds by stating that behavioral control beliefs affect PBC and deal with the presence or absence of resources to share knowledge. These resources are known as Information and communication technologies (ICT). ICT help in speeding up and facilitating the knowledge sharing process depending on their quality (Cabrera et al. 2006) and usability (Lin 2007). ICT aid in removing the constraints due to physical distance and provide richness in remote communication. Online databases, intranet, and virtual communities are some of the forms and new methods provided by ICT. These applications increase the opportunities and prospects of knowledge sharing. For them to be effective, ICT should entail minimum levels of quality, accessibility, speed, and ease of use (Choi et al. 2008; Connelly and Kelloway

2003; Hall 2001). Working from home or communication through virtual means is highly dependent on the quality of the ICT provided by the organization. ICT allow individuals to share knowledge with numerous receivers simultaneously (Zhang and Fai Ng 2013). Investing in these technologies will expedite the process of knowledge sharing.

In summary, attitude and perceived behavioral control both affect intention and behavior towards knowledge sharing as mentioned by many studies. Individuals are more prone to engage in the process of knowledge sharing if they have the intention to do so. Organizations are struggling to increase the knowledge sharing behavior of employees (Bock 2005). The sharing process will benefit the group as a whole and may be an incentive for all team members to engage in the sharing process. Studies dealing with knowledge sharing outcomes are very limited. Thus, this study will also highlight the outcomes generating from this process and how it will affect employees in an engineering organization.

C. Knowledge Sharing in Engineering Organizations

Knowledge is one of the essential assets in the engineering industry due to its significant role in driving innovation and creating value (Zhang 2015). Table 1 portrays a summary of some of the studies addressing the process of knowledge sharing in engineering organizations. Table 1 highlights the description and level of participants used in each study. Most of the studies used surveys and statistical analysis. Most studies highlight the barriers and motivators of knowledge sharing in a face-to-face environment failing to study the outcomes. Our study focuses on the factors affecting knowledge sharing as well as the outcomes of this process in a virtual environment, which is described in the following section. Our aim is to tailor these factors to a remote and virtual environment and identify new factors that may play a role in enhancing the knowledge sharing process.

Study	Description	Level
Javernick-Will (2012)	Understanding the motivators driving knowledge sharing participation in construction and engineering organizations	Executive managers, knowledge managers, project managers, and project engineers
Kivrak et al. (2008)	Understanding the drivers and barriers for knowledge management and the methods used for capturing and sharing explicit and implicit knowledge in construction contracting companies (KPfc)	General managers, business development managers, and bid proposal managers
Poleacovschi et al. (2018)	Understanding the impact of organizational control on tacit and codified knowledge accessibility in engineering organizations	Engineers, architects, and scientists
Othman et al. (2018)	Studying the critical success factors in implementing knowledge management in consultant firms for construction industry	Engineering consultants at construction firms
Jarkas (2011)	Factors affecting construction labor productivity, constructability affects labor productivity	Engineers, designers, contractors
Kasas (2008)	Factors influencing construction labor productivity, organizational behavior (motivation)	Managing staff
Zhang (2015)	Critical factors affecting tacit knowledge sharing and the importance of trust	Project managers, team members, building engineers
Kiomjian, Srour (2016)	The relationship between quality, learning, and productivity is not always a positive one.	Owner, architect, contractor
Koskiken (2003)	What kind of social engagements enhance tacit knowledge sharing in a project. (Face to face communication and trust and language)	Temporary project
Al-Emad (2018)	Issues facing construction workers from safety to poor living conditions and many more (20 recommendations)	Leaders/Experts with foreign workers
Bock (2005)	What inhibits and facilitates knowledge sharing (trust/relationships, rewards, organizational climate)	Managers
Al-Alawi (2007)	Organizational knowledge sharing between staff and the factors that affect and enhance this sharing (trust, communication)	Staff/Employees in an organization

Amayah (2017)	Knowledge sharing barriers in public sector. Social interaction, rewards, and organizational support enhance knowledge sharing.	Public sector/ Lower-level employees
Zhang and Fai Ng (2012)	Studying the factors affecting knowledge sharing attitudes in the construction industry	Project managers, site agent engineers, quantity surveyors, and safety managers

Table 1 Studies addressing the process of knowledge sharing in context of engineering

D. Virtual Communities & Knowledge Sharing

The ongoing pandemic led to the prevalence of a new reality, i.e., work-from-home. The pandemic is causing virtual communities to increase at an unparalleled rate. A survey by PWC (2020) showed that traditional work environments are slowly fading away. This transition to a virtual work environment has, in turn, caused disruptions to the process of knowledge sharing. Knowledge sharing in a virtual or online community, i.e., one with no face-to-face interaction, requires individuals to devote effort.

It is very crucial for the online communities to assist participants in developing interpersonal relationships (Zhang and Hiltz 2003). Social ties and trust encourage knowledge sharing in a virtual community. The most significant factor in increasing knowledge sharing in virtual communities is trust (Andrews and Preece 2002). Korzenny (1978) justified that virtual communication generates a sense of belonging, regardless of their physical distance. However, Kiesler (1986) argues by saying: “Without nonverbal tools, a sender cannot easily alter the mood of a message, communicate a sense of individuality, or exercise dominance or charisma”. Also, a virtual community could mean less privacy promoting the feeling of responsibility and accountability of doing things right. However, this shared platform could help team members exchange knowledge and learn from other’s mistake.

Most studies regarding knowledge sharing in virtual communities deal with how employees from different backgrounds and cultures mesh and exchange knowledge. This study will focus on knowledge sharing in a virtual community of employees working in an engineering organization. The emphasis on engineering organization stems from the fact that the type of work conducted by engineers used to necessitate physical presence. In other words, sharing large-size documents, reviewing drawings, working on local servers that support engineering software, etc. are daily tasks that impede the feasibility of constantly working remotely. Moreover, the daily interaction and communication between engineers is critical for junior resources who rely on the on-site nature of the engineering work to learn.

CHAPTER III

RESEARCH OBJECTIVES AND METHODOLOGY

None of the mentioned studies assessed the impact of a sudden emergency leading to remote work on the process of knowledge sharing. Following the onset of the COVID-19 pandemic, millions of companies shifted to a work from home environment and employees had to rapidly adjust. Consequently, the objective of this study is to understand how the transition from a face-to-face work environment to a virtual setting affects the knowledge sharing process and drivers. The imposed remote form of communication introduced difficulties to the knowledge sharing process.

To achieve this objective, a theoretical framework with a set of hypotheses is developed; thus, employing quantitative research (Amaratunga et al. 2002). Hence, a survey is distributed to a number of employees in different engineering companies in diverse countries. Questions were drafted to understand the factors affecting knowledge sharing, associated with a remote work environment. The collected data was first tested using Exploratory Factor Analysis (EFA) to determine a new set of constructs. Using this technique allows for identifying the separate dimensions of the structure, and then determining the degree to which each variable (e.g., I intend to inform colleagues where to find knowledge and who to ask for this knowledge) is explained by each dimension (e.g., Intention). Then, the theoretical-based model along with the corresponding hypotheses is tested via Structural Equation Modelling (SEM) to analyze and validate the EFA results. SEM can test the hypothesized multiple causal relationships since it is able to show the relationships between each factor identified as construct/ latent variable and its corresponding indicator as well as being efficient for a series of multiple-regression equations to be estimated simultaneously (Fang et al. (2015); Hair et al. (1998)). It is a two-step modeling method that integrates factor analysis and path analysis (Hair et al. 1998), to show hypothesized relationships between latent variables and their indicators and the links between the independent and dependent latent variables respectively (Hair et al. 1998). Figure 2 shows the steps constituting the methodology.

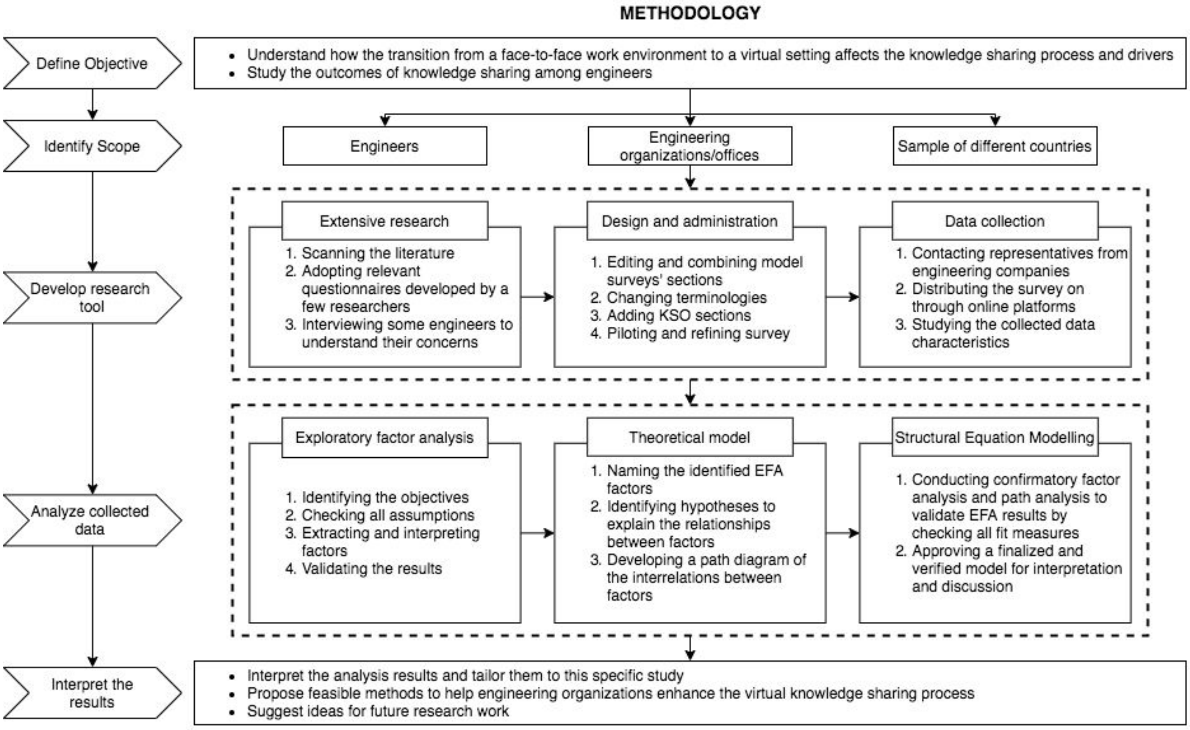


Figure 2 Methodology

CHAPTER IV

RESEARCH MODEL AND TOOL

This section portrays the research model adopted along with the corresponding hypotheses that need to be tested. Moreover, the survey design and administration steps are also explained.

A. Research Model and Hypotheses

Remote communication and work from home environments may alter the factors affecting the knowledge sharing intention, behavior, and outcomes. This study examines these drivers and their underlying relationships. The personal drivers include motivation, enhanced personal relationships, and knowledge feedback. On the other hand, the external drivers focus on the effectiveness of Information and Communication Technologies (ICT) in facilitating or hindering knowledge transfer. Thus, a theoretical based model is established based on several hypotheses linking various constructs. Figure 4 portrays the interrelations between constructs based on the previously listed hypotheses.

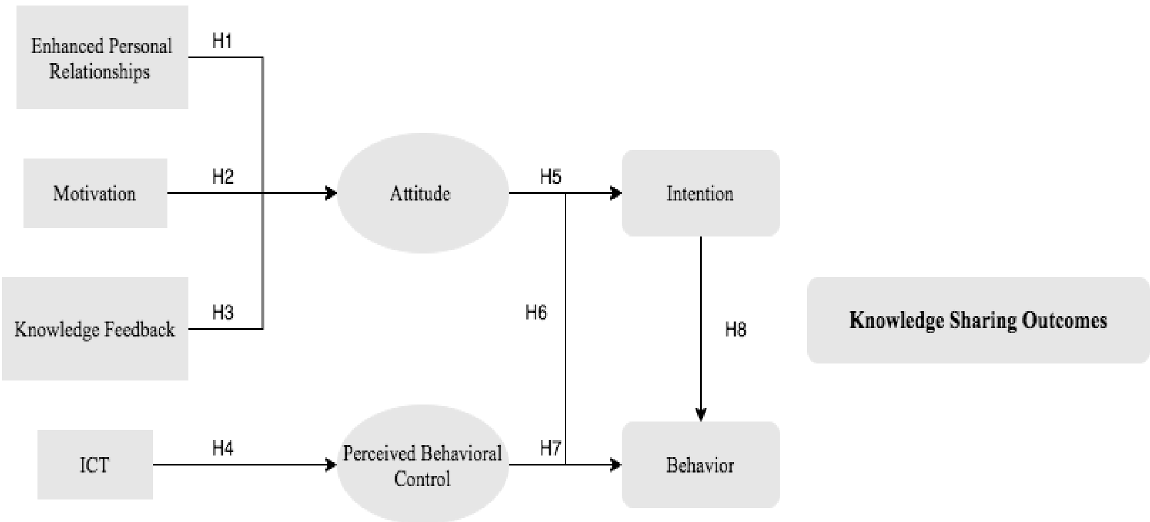


Figure 3 Interrelations between constructs

A paper titled “Using Structural Equation Modelling to Study the Factors Affecting Knowledge Sharing Intention among Construction Workers” (Sanboskani et al., 2020) focuses on how attitude is altered after being affected by a certain set of factors corresponding to the setting of the job. Sanboskani (2020)’s work is driven by personal factors that shape the attitude of construction workers in Lebanon. The above framework (Figure 4) adopts some of the personal factors tested by Sanboskani (2020) but focuses on the effect of external factors such as ICT that influence knowledge sharing through remote means. This study applies the theory of planned behavioral control which is derived from the theory of reasoned action. Moreover, in contrast to Sanboskani’s (2020) work, this framework incorporates a construct to study and quantify the knowledge sharing outcome in a virtual setting which is called “Knowledge Sharing Outcomes”.

Table 2 lists the developed set of hypotheses followed by separate supporting paragraphs to each.

Hypothesis ID	**Hypothesis**
H1	The more enhanced personal relationships are among employees, the more favorable the attitude is towards knowledge sharing
H2	Employee’s encouraging attitude towards knowledge sharing is heightened by constant motivation.
H3	The more frequent constructive knowledge feedback is, the more positive the attitude of employees is towards knowledge sharing
H4	Effective ICT have a positive effect on individuals’ behavioral control over knowledge sharing with other employees
H5	Employee’s intention to share knowledge is strengthened by a positive attitude towards knowledge sharing
H6	Individuals’ perceived behavioral control over knowledge sharing has a positive

		effect on their intention to share knowledge with other employees
H7		The greater the perceived behavioral control over knowledge sharing is, the greater the effectiveness of employee behavior is
H8		A greater intention to share knowledge leads to better knowledge sharing behavior of employees within the engineering organization

Table 2 List of Hypothesis

Similarly, to a face-to-face environment, virtual knowledge sharing depends heavily on personal relationships among colleagues as shown by Bock (2005). The pandemic caused work relationships to fade away due to the physical distance between colleagues. Thus, this hypothesis aims on studying the effect (if any) of the relationships between colleagues at work on the knowledge sharing process. As such, we propose the following:

H1: The more enhanced personal relationships are among employees, the more favorable the attitude is towards knowledge sharing.

Economic rewards failed to positively affect the attitude of colleagues towards knowledge sharing (Bock 2005; Zhang 2012). The pandemic may have played a role in affecting the mentality of engineers due to the long working hours and unbalanced work-life hours. As a result, combining economic rewards with reduced workload into a construct titled motivation may enhance virtual knowledge sharing.

H2: Employee's encouraging attitude towards knowledge sharing is heightened by constant motivation.

As shown by Bock (2005), constructive feedback has a positive effect on the attitude of an individual towards face-to-face knowledge sharing. Similarly, virtual knowledge sharing may be dependent on this feedback. The lack of regular informal feedback that happens in engineering offices and the de-motivation of working remotely away from colleagues can lead to decrease knowledge sharing. Thus, constructive feedback can encourage the knowledge sharing process.

H3: The more frequent constructive knowledge feedback is, the more positive the attitude of employees is towards knowledge sharing.

The knowledge sharing behavior of employees is highly dependent on accessible and effective communication systems (Zhang 2013). Also, Lin & Lee (2005), argued that enhanced IT support, increases the chances of virtual knowledge sharing. Engineers working from home may not all have access to efficient communication systems which may affect the ease of sharing knowledge.

H4: Effective ICT have a positive effect on individuals' behavioral control over knowledge sharing with other employees.

The individuals' attitude towards an action is driven by their intention to do this action (Ajzen and Fishbein 1980). The intention to share knowledge is directly related to the attitude towards knowledge sharing as shown by Bock (2005). The quarantine that was imposed by the pandemic affected the perceptions and attitude of individuals towards work in general. Specifically, in order for colleagues to have the intention to share knowledge with each other, they need to have a positive attitude towards the knowledge sharing process. The priorities of individuals changed during the pandemic diverting focus from additional activities previously done.

H5: Employee's intention to share knowledge is strengthened by a positive attitude towards knowledge sharing.

During the work-from-home setting, if engineers found the means to easily share knowledge, this would increase their intention to do so. Perceived behavioral control is the perceived ease or difficulties one has over performing a behavior (Zhang, 2013). The intention to virtually share knowledge is greatly associated with the ease (improved technologies) to share this knowledge.

H6: Individuals' perceived behavioral control over knowledge sharing has a positive effect on their intention to share knowledge with other employees.

Most engineering offices are equipped with the necessary technologies to perform the needed tasks. On the other hand, individual houses may not contain the needed furniture to facilitate the work of engineers during the pandemic. If the employees find it simple and accessible to virtually share their knowledge, their behavior will be shifted towards greater knowledge sharing (Zhang 2012). Behavior is the action itself and facilitating the achievement of this action will logically increase its occurrence.

H7: The greater the perceived behavioral control over knowledge sharing is, the greater the effectiveness of employee behavior is.

Employees with higher intention towards knowledge sharing tend to have a positive behavior towards the process (Zhang 2012).

H8: A greater intention to share knowledge leads to better knowledge sharing behavior of employees within the engineering organization

Although not widely available in the literature, knowledge sharing outcomes portray the differences between face-to-face and virtual interaction. This final construct will be used to analyze and discuss the implications of such situations and link it to the results of the interrelated constructs.

B. Research Tool

The type of information needed helps us choose between qualitative and quantitative research. This study relies on quantitative research which aims to quantify the participant's responses and either proving or disapproving the hypotheses. Given that surveys offer a well-established approach in similar organizational psychology contexts, we use it as the main instrument in this study. This approach is in-line with the social distancing requirements associated with the context of this study. Accordingly, a questionnaire survey was distributed to engineering companies. The survey design and data collection are highlighted in this sub-section.

1. Survey Design

To develop the survey, we started with an exhaustive scan of the literature. Surveys developed by Bock (2005), Zhang & Fai Ng (2012), and Lin & Lee (2013) were adapted as model questionnaires since they encompass most of the information available in the literature. The questions mainly tackled the drivers of knowledge sharing and the effect of external/internal factors on behavior, intention, and outcomes. Subsequently, selected surveys were modified to suit this specific study. For example, words such as "individuals" and "colleagues" were replaced by "employees" to highlight people working in the engineering company. Numerous sections were combined. Then, a section titled "Knowledge Sharing Outcomes" was added to show the changes observed due to remote working. This section is not widely available in the literature and lacks substantial research. These questions help understand if virtual knowledge sharing demands more effort in training new employees. Also, the results of this section show if working alone from home would increase the chance of making errors.

These sections were chosen after conducting interviews with 7 engineers to understand their challenges and concerns regarding knowledge sharing during a pandemic. We asked general questions related to their everyday work routines at home. The results of these interviews showed that knowledge sharing virtually is highly dependent on external factors such as technologies and is also affected by the motivation of employees to maintain job security in this unaccounted-for situation. Also, it was clear from their responses that there is little work-life balance, and they are spending more time working than they did before at the office.

The survey did not require translation to other languages since most participants understand English. Background and organization questions are of multiple-choice nature, except for one open-ended question about the main head office location of the firm the participant is working in. The rest of the questions were answered using a 5-point Likert scale ranging from 1 (totally disagree) to 5 (totally agree). Each of these questions was asked twice to incorporate the situations before and during the lockdown. Thus, the participant answers the same question while picturing him/herself before the pandemic and while working in the office and the other while working from home during the pandemic.

The final survey integrated 5 main sections with an introductory paragraph explaining the purpose of the study. The first section tackled background questions such as gender, education, and experience to acquire information on the demographics of the participants. Demographics would allow for further dissection of the results after finalizing the survey. The second section collects information on the general strategies followed by the organization. The third section includes a set of questions to understand the barriers and motivators of knowledge sharing. Questions are related to attitude, enhanced personal relationships, perceived behavioral control, motivation, knowledge feedback, information and communication technologies, intention, and behavior. All questions in this section must be answered by remembering the situation before the pandemic while working from the office. The fourth section is a duplicate of the previous requiring the employees to answer the same questions taking into consideration the pandemic and lockdown. The fifth and last section is drafted to highlight the effects of these drivers. These capture the knowledge sharing outcomes of employees.

The variables of each construct were based on previous studies and tailored to the current pandemic situation. The common rule adopted for all constructs is a minimum of three variables per construct. Some the constructs and variables are listed as is in previous studies. Other constructs were drafted to include new questions applicable to the shift from traditional work settings to a work-from-home situation. Figure 4 lists the constructs with their respective set of questions. Each construct is assigned a name: enhanced personal relationships (items EPR1 to EPR3), motivation (items MOT1 to MOT4), knowledge feedback (items KF1 to KF3), information and communication technologies (items ICT1 to ICT4), attitude (items ATT1 to ATT5), perceived behavioral control (items PBC1 to PBC3), intention (items INT1 to INT3), behavior (items B1 to B4), and knowledge sharing outcomes (items KSO1 to KSO5).

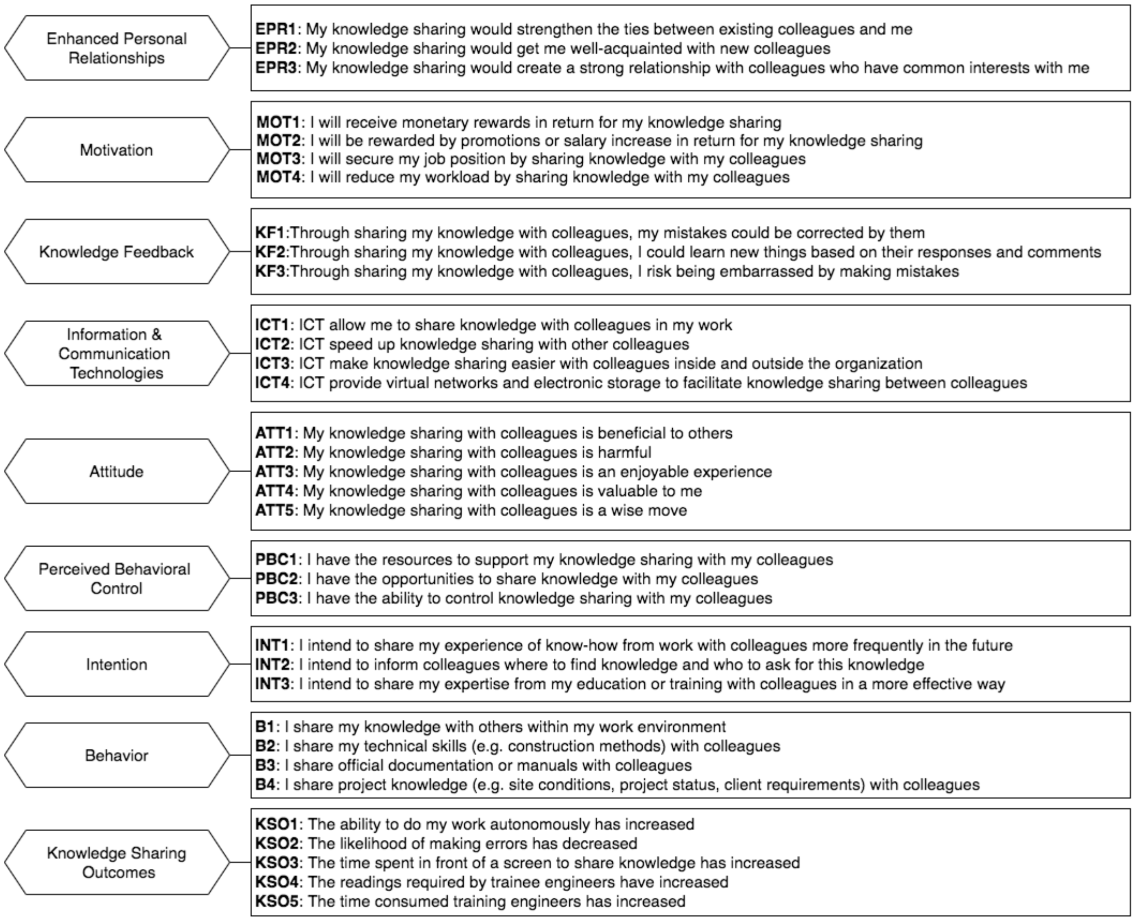


Figure 4 Constructs and Questions

2. <u>Piloting of the Survey</u>

After finalizing the survey, piloting was done to test the suitability of questions. The questions were answered by 10 engineers from various organizations. The participants were aided while answering to closely monitor and observe their reactions and understanding of each question. Thus, any unaccounted impediment could be later fixed. The time needed to fill the survey is around 10 minutes.

To check for reliability, we checked the Cronbach alfa, and adopted 0.7 as the cut off value (Wang et al., 2014). Each construct was tested twice yielding an alpha prior to the lockdown and another one during the lockdown. The values varied between 0.60 and 0.97, which is acceptable. The second question pertaining to attitude: “My knowledge sharing with colleagues is harmful" necessitated reverse coding both prior and during lockdown situations. Reverse coding was used for questions with negative connotation since people may answer the opposite of what they mean. Moreover, question three in the knowledge feedback construct: "Through sharing my knowledge with colleagues, I risk being embarrassed by making mistakes" also needed reverse coding. The strategy of reverse coding was used to increase the alpha values. Also, a question needed rephrasing in the ICT construct after thoroughly going through the comments of the participants of the survey. The final version of the survey is shown in Appendix A.

3. Survey Administration

The organizations selected to answer the survey are located in numerous countries around the world. These countries were chosen based on the contacts of the research group and their availability to support in gathering data. Engineers working in these companies were the target participants. However, due the pandemic and the increasingly alarming numbers of people infected, the survey was distributed online through e-mail, LinkedIn, WhatsApp, or any other mean to reach the highest number of respondents possible. The aim of the study and objectives were explained in the survey to avoid any ambiguities.

The companies that answered the survey remained anonymous. The nature and culture of the company could affect the survey results and discussions. The way companies operate and deal with employees is different. Moreover, the way companies reacted during the pandemic is also different. Hence, the location, culture, size, type, etc. of a company play a major role in analyzing the results. This limitation will be discussed later.

CHAPTER V

DATA COLLECTION AND CHARACTERISTICS OF THE SAMPLE

This section presents the process of data collection and describes the demographics of the sample.

A. Data Collection

The research team obtained the approval of the institutional review board (IRB) at AUB to conduct the study. This approval is required when dealing with human subjects which is the case in this study. The research team was also granted approval from the engineering organizations to distribute surveys among its employees. Representatives of these companies were contacted to facilitate the distribution and collection process. These representatives were referred to by members from the research team or any close acquaintance to be able to reach a high response rate. At first, around 20 companies were targeted and then each contact was asked to send the survey to any relevant individual or entity that might be interested in participating. The survey was distributed using Google forms by sending the link through e-mails or by messages. Due to the pandemic and lockdown, the distribution process was more complex and required extensive communication to be able to reach the wanted number of responses. The collection process took around 5 months. All data and graphs were clearly saved using google forms, which facilitated data cleaning and storing. Then, these responses were extracted to an excel file for data cleaning.

Several representatives of these companies were contacted to facilitate the distribution and collection process. 168 responses were collected, out of which 149 were identified as usable/complete yielding an effective response rate of about 89%.

B. Data Cleaning

Once exported to Microsoft Excel, the collected responses were subject to a thorough cleaning process before generating data for statistical analysis. The survey included a clear paragraph stating the objective of this research and clear instructions on how to answer the questions along with the scale. The scale includes what each value stands for. Also, definitions are given at the beginning of each one of the five sections. All these explanations decrease the probability of error occurrence. However, the survey is not guaranteed to be lacking any errors. After all data was collected and the desired sample size was reached, the results were directly transferred electronically from the form into Excel sheets. Keying errors (Jones and Hidiroglou 2013) are avoided during this process since there is no manual inputting of the data.

When a question is expected to be filled and is empty, this is considered as a **missing value** question specifically a true missing field. As Jones and Hidiroglou (2013) specified, respondents could make writing errors like skipping questions or sections. Responses with missing fields were removed from the data used in analysis.

There may be questions with **negative denotation** where reverse coding could be required to include the true meaning of the responses (two questions in this study). For example, “My knowledge sharing with other project members is harmful” is one of these questions. The answers to such questions should be in opposite sense from the other questions.

Also, illogical and **inconsistent responses** are considered as errors. In this survey, errors were detected by checking the question related to age and to years of experience. For example, a respondent cannot choose 21-30 years' age and choose 21+ years of experience at the same time.

After a thorough data cleaning process, 19 responses were disregarded either because they are incomplete (16 responses) or because they contain inconsistent answers such as age range vs experience range (3 responses).

C. Demographics

Table 3 portrays the demographics of the respondents showing a based on gender where 62% are males and 38% are females. In terms of education, 38% of the respondents have a bachelor's degree, 58% have a master's degree, and 4% hold a PhD. Also, more than 50% of the respondents are in the youngest age range (21-30 years) justifying the high percentage of people with little or no experience. More than half of the respondents have joined their organizations recently meaning they were subject to training which requires extensive knowledge sharing.

Variable	Category	Number of cases	Frequency (%)
Age	21-30	81	54.4
	31-40	42	28.2
	41-50	19	12.8
	51-60	5	3.3
	61+	2	1.3
Experience	0-5	67	45.0
	6-10	37	25.0
	11-15	11	7.3
	16-20	16	10.7
	21+	18	12.0
Education	Bachelor	56	37.6
	Master's	87	58.4

	PhD	6	4.0
Years with Organization	0-5	89	59.8
	6-10	27	18.0
	11-15	17	11.5
	16-20	9	6
	21+	7	4.7

Table 3 Demographic Information of Respondents

Table 4 presents information related to the organizations' strategies. As expected around 80% of the organizations did not have the option of remote work prior to the pandemic which makes the sudden shift more challenging. Nonetheless, some organizations are considering the option of maintaining such remote form of work for some of their employees; thus, requiring an efficient virtual knowledge sharing system which necessitates understanding its drivers. Finally, around 2/3 of the respondents think that they and their colleagues are emotionally affected by the pandemic which is expected to influence their tendency to share knowledge.

VARIABLE	**CATEGORY**	**FREQUENCY (%)**
Did employees work remotely before the covid-19 pandemic?	Yes	19.5
	No	80.5
Will employees pursue work remotely after the covid-19 pandemic ends?	Yes	30.2
	No	35.6
	I do not know	34.2
To what degree do you think your organization's employees are emotionally affected by the covid-19 pandemic?	1	0.7
	2	6.0
	3	28.2
	4	45.6
	5	19.5

Table 4 Information related to Organization

CHAPTER VI

STATISTICAL ANALYSIS

The following section presents the steps followed to analyze the collected data. It starts with a detailed description of the adopted Exploratory Factor Analysis (EFA). Then, Confirmatory Factor Analysis (CFA) and Path Analysis, which are embedded in Structural Equation Modelling (SEM) analysis, are also portrayed. This methodology is widely adopted and supported by the literature. Hair et al. (1998) defines SEM as a two-step modelling method that helps in testing multiple causal relationships between the constructs and variables studied. It also studies the links between dependent and independent latent variables. Statistical Package for Social Sciences (SPSS) and Analysis of moment structures (Amos) are the software commonly used for such analysis (Arbuckle 2006). Thus, EFA and CFA suit the quantitative nature of the collected data and ensure the identification of hidden dimensions between variables that cannot be detected using direct statistical methods. The results of EFA and CFA are used to test the variables that drive knowledge sharing in a virtual environment.

A. Exploratory Factor Analysis (EFA)

Factor analysis is a multivariate technique that identifies the degree to which each variable is explained by each construct. Thus, it helps with the structuring of a set of variables into different constructs/factors. The two main objectives of factor analysis are data reduction and summarization.

Factor analysis can be done through Confirmatory Factor Analysis (CFA) and Exploratory Factor Analysis (EFA). CFA is used to when the structure of the variables and constructs is available in theory. Thus, CFA helps evaluate how close the collected data is to the theoretical results. Due to the sudden impact of the pandemic, the addition of variables and constructs, and the unavailability of such structure in the literature, we started with EFA. EFA is used to identify a structure between a set of variables satisfying data reduction. The structure is identified by placing variables on the construct with the highest loading. The following parts discuss the detailed steps followed to conduct the analysis. This analysis was conducted twice on the collected data pre-covid and during covid. Thus, the following steps portray the detailed procedure followed using the data "pre-covid". Similarly, the results were identified for the data "during covid".

1. Identify the objectives of factory analysis

The main objectives of factor analysis are summarization and data reduction. Summarization is analyzing a set of variables to identify the latent variables using R factor analysis. Summarization is deriving underlying dimensions that describe the data in a smaller number of concepts than the individual variables once understood. Data reduction is creating a new set of variables or identifying some variables from a larger set. When extracting variables, we look at the loadings of the variables on each construct. In this case, the objective is to group variables into meaningful constructs using both summarization and data reduction.

2. Design for factor analysis

Since R factor analysis is used, the first step is calculating the input data which is the correlation matrix between variables. Next, the number, type and measurement properties of variables should be identified. Thus, the variables are chosen ordinal since they follow the Likert scale. Also, the minimum number of variables per construct is 3 satisfying the general requirements. Finally, we should check that the sample size satisfies the minimum requirements to satisfy the analysis. 168 responses were collected, out of which 149 were identified as usable/complete. Hair et al. (1998) a sample size ranging between 100 and 200 would be enough. All the constructs will be used in the following steps except Behavior, Intention, and Knowledge Sharing Outcomes.

3. Check assumptions for EFA

The following tests and assumptions are all checked using SPSS. First, the majority of the correlations between variables (in the correlation matrix) must be higher than 0.3. The next step is doing the Bartlett test of sphericity to further test the presence of correlations between variables. The p-value for Bartlett's test of sphericity should be less than 0.05 and the KMO value is recommended to be the closest to 1. The results showed a p-value of 0 and a KMO value of 0.769, thus suggesting the presence of correlations.

4. Factor extraction and rotation

Factor extraction can be done through two ways: common factor analysis or component analysis. After identifying the objective of factor analysis and going through the literature, component analysis was used. Principal Component Analysis (PCA) is the method of summarizing the original information into smaller components/ minimum number of factors. The original variables and components are primarily assembled based on the literature and then, using PCA, a new set of components is extracted. The most widely used method to determine the number of components extracted is the latent root criterion which is based on the Eigenvalues. Thus, after performing all necessary steps on SPSS, the research extracts the factors with Eigenvalues greater than 1 (Significant). Another way is resorting to the Scree test criterion which is based on the shape of the resulting curve and the cutoff value. The point where the slope starts changing determines the number of components to be extracted.

Before finalizing the extraction of factors, a rotation of factors is needed to deliver a more meaningful interpretation of the variables. Un-rotated factor solutions tend to extract factors in the order of importance, thus almost every variable will load on the first factor. There are two types of rotations: orthogonal and oblique. Orthogonal rotations are widely used and accessible in most software, however oblique rotations are more realistic and aim on obtaining more theoretical significant factors. In this study, OBLIMIN (SPSS) is the oblique rotation approach used. The final model shows 5 extracted factors.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	5.855	29.277	29.277	5.855	29.277	29.277	4.764
2	2.285	11.423	40.700	2.285	11.423	40.700	2.332
3	2.205	11.027	51.727	2.205	11.027	51.727	3.343
4	1.456	7.281	59.008	1.456	7.281	59.008	2.621
5	1.197	5.986	64.994	1.197	5.986	64.994	3.477
6	.935	4.676	69.670				
7	.881	4.403	74.073				
8	.700	3.499	77.571				
9	.663	3.317	80.888				
10	.560	2.799	83.686				
11	.504	2.518	86.205				
12	.461	2.307	88.512				
13	.427	2.134	90.646				
14	.381	1.907	92.553				
15	.319	1.594	94.147				
16	.285	1.424	95.571				
17	.260	1.302	96.873				
18	.257	1.285	98.158				
19	.202	1.008	99.166				
20	.167	.834	100.000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Figure 5 Extracted factors based on Eigenvalues

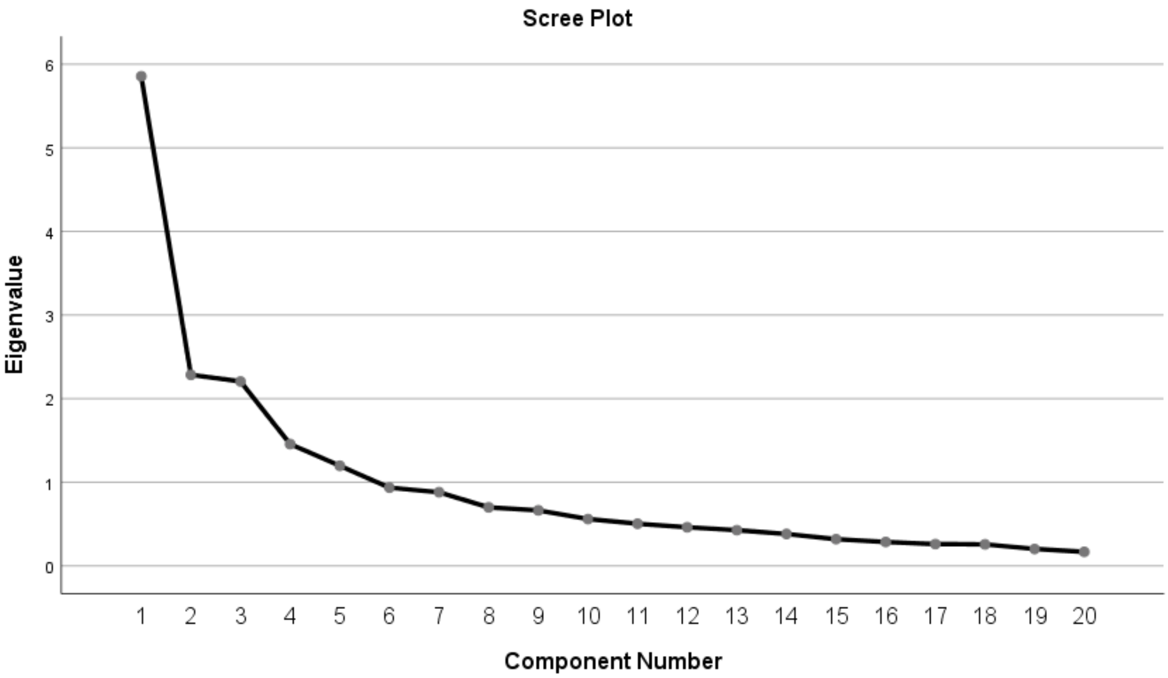


Figure 6 Scree Plot

5. <u>Ensure significance of factor loadings</u>

Both practical and statistical significance must be assessed to identify the significance of factor loadings in the factor matrix. According to Hair et al. (1998), for 80% power and significance of 0.05, and according to the sample size at hand (123), a factor loading of 0.5 is adopted. Loadings greater than +- 0.3 are considered acceptable, loadings greater than +- 0.4 are more important, and loadings greater than +- 0.5 are practically significant. Moreover, with a sample size of 149, a cutoff value of factor loadings above 0.5 is statistically significant. As shown in Figure 7, all factor loadings are significant.

Pattern Matrix[a]

	Component				
	1	2	3	4	5
ATT1	.640	-.085	.021	.191	-.069
ATT3	.762	.115	-.030	.023	-.044
ATT4	.810	-.045	.053	-.012	.042
ATT5	.753	.041	-.083	.071	.031
PBC1	-.010	-.115	.064	.809	.151
PBC2	.235	-.013	-.082	.775	-.068
PBC3	.085	-.051	.007	.563	.175
EPR1	.780	-.020	-.054	-.044	.019
EPR2	.639	.007	-.026	-.104	.233
ICT1	.089	-.009	-.832	.078	-.058
ICT2	.000	-.084	-.900	-.069	-.021
ICT3	-.038	.041	-.636	-.002	.133
ICT4	.041	-.030	-.887	-.048	.010
MOT1	-.059	.816	-.039	-.080	.121
MOT2	.086	.845	.162	-.085	.080
MOT3	.049	.799	.025	-.068	-.073
INT1	-.011	.040	-.045	.086	.840
INT2	.086	-.003	-.057	.010	.784
INT3	.046	.026	-.020	.092	.844
MOT4	-.107	.465	-.132	.366	-.142

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.[a]

a. Rotation converged in 7 iterations.

Figure 7 Pattern matrix

6. <u>Identify the new factors</u>

The output on SPSS consists of two matrices: the factor pattern matrix and the factor structure matrix. Typically, the results of the pattern matrix (Figure 8) are used, where the factors are represented by columns with numbers as headings and the variables are those on the rows. Each variable is scanned to determine the highest loading and its corresponding component. If a component has less than three variables or the variables cannot be logically combined, we should repeat the model by reasonably deleting variables. These components are considered undefined. Deletion of any variable varies according to the objective of the study and the variable itself. Then, model re-specification is applied, and the variables are loaded again on different factors. Then, we should check the communality of variables and decide on an acceptable level (0.5).

After determining the highest loading of each variable, we group the variables into their corresponding components and name them accordingly. The total number of variables was reduced to 20 after 5 variables were deleted after several trials. The second question pertaining to Attitude “My knowledge sharing with colleagues is harmful” and the third question belonging to Knowledge Feedback “Through sharing my knowledge with colleagues, I risk being embarrassed by making mistakes”, were deleted since they contained negative connotation. Thus, the respondents answered these questions as opposed to what they meant. EPR3, KF1, KF2 were considered troublesome questions since they were being shuffled between different constructs and they were not aligned with the other questions listed. After deleting these 5 variables, there were no more undefined constructs, and the model was used in all subsequent steps.

According to Figure 8, we label the 5 constructs based on some research and personal judgement. Constructs 2,3,4, and 5 were named solely according to the literature since their questions remained the same as the original set before the extraction. Construct 1 contains variables pertaining to attitude and enhanced personal relationships. The first construct was labeled Perspective since it incorporates how knowledge sharing would affect the relationship between colleagues. Table 5 shows the final constructs with their corresponding names and questions.

CONSTRUCT #	CONSTRUCT NAME	ID	QUESTION	NEW ID
1	Perspective	ATT1	My knowledge sharing with colleagues is beneficial to others	P1
		ATT3	My knowledge sharing with colleagues is an enjoyable experience	P2
		ATT4	My knowledge sharing with colleagues is valuable to me	P3
		ATT5	My knowledge sharing with colleagues is a wise move	P4
		EPR1	My knowledge sharing would strengthen the ties between existing colleagues and me	P5
		EPR2	My knowledge sharing would get me well-acquainted with new colleagues	P6
2	Motivation	MOT1	I will receive monetary rewards in return for my knowledge sharing	MOT1
		MOT2	I will be rewarded by promotions or salary increase in return for my knowledge sharing	MOT2
		MOT3	I will secure my job position by sharing knowledge with my colleagues	MOT3
		MOT4	I will reduce my workload by sharing knowledge with my colleagues	MOT4
3	Information & Communication Technologies	ICT1	ICT allow me to share knowledge with colleagues in my work	ICT1

		ICT2	ICT speed up knowledge sharing with other colleagues	ICT2
		ICT3	ICT make knowledge sharing easier with colleagues inside and outside the organization	ICT3
		ICT4	ICT provide virtual networks and electronic storage to facilitate knowledge sharing between colleagues	ICT4
4	Perceived Behavioral Control	PBC1	I have the resources to support my knowledge sharing with my colleagues	PBC1
		PBC2	I have the opportunities to share knowledge with my colleagues	PBC2
		PBC3	I have the ability to control knowledge sharing with my colleagues	PBC3
5	*Intention*	*INT1*	*I intend to share my experience or know-how from work with colleagues more frequently in the future*	*INT1*
		INT2	*I intend to inform colleagues where to find knowledge and who to ask for this knowledge*	*INT2*
		INT3	*I intend to share my expertise from my education or training with colleagues in a more effective way*	*INT3*

Table 5 Final constructs- Pre

These new constructs were the result of the EFA analysis performed on the collected data constituting the pre-pandemic situation. Similarly, Table 6 shows the results of the EFA analysis conducted on the collected data pertaining to the situation during the pandemic (i.e., currently).

CONSTRUCT #	CONSTRUCT NAME	ID	QUESTION	NEW ID
1	Attitude	ATT1	My knowledge sharing with colleagues is beneficial to others	ATT1
		ATT3	My knowledge sharing with colleagues is an enjoyable experience	ATT2
		ATT4	My knowledge sharing with colleagues is valuable to me	ATT3
		ATT5	My knowledge sharing with colleagues is a wise move	ATT4
2	Motivation	MOT1	I will receive monetary rewards in return for my knowledge sharing	MOT1
		MOT2	I will be rewarded by promotions or salary increase in return for my knowledge sharing	MOT2
		MOT3	I will secure my job position by sharing knowledge with my colleagues	MOT3
		MOT4	I will reduce my workload by sharing knowledge with my colleagues	MOT4
3	Information & Communication Technologies	ICT1	ICT allow me to share knowledge with colleagues in my work	ICT1
		ICT2	ICT speed up knowledge sharing with other colleagues	ICT2
		ICT3	ICT make knowledge sharing easier with colleagues inside and outside the organization	ICT3
		ICT4	ICT provide virtual networks and electronic storage to facilitate knowledge sharing between colleagues	ICT4
4	Enhanced Personal Relationships	EPR1	My knowledge sharing would strengthen the ties between existing colleagues and me	EPR1
		EPR2	My knowledge sharing would get me well-acquainted with new colleagues	EPR2
		EPR3	My knowledge sharing would create a strong relationship with colleagues who have common interests with me	EPR3

5	Knowledge Sharing Resources	PBC1	I have the resources to support my knowledge sharing with my colleagues	R1
		PBC2	I have the opportunities to share knowledge with my colleagues	R2
		KF1	Through sharing my knowledge with colleagues, my mistakes could be corrected by them	R3
6	Intention	INT1	I intend to share my experience or know-how from work with colleagues more frequently in the future	INT1
		INT2	I intend to inform colleagues where to find knowledge and who to ask for this knowledge	INT2
		INT3	I intend to share my expertise from my education or training with colleagues in a more effective way	INT3

Table 6 Final constructs- During

After going through the previously listed steps, the second question pertaining to Attitude "My knowledge sharing with colleagues is harmful" and the third question belonging to Knowledge Feedback "Through sharing my knowledge with colleagues, I risk being embarrassed by making mistakes", were deleted since they contained negative connotation. Also, KF2 and PBC3 were deleted since they were causing problems to the model rendering it illogical and undefined. Constructs 1, 2, 3, 4, and 6 are extracted from the literature and original model. However, Construct 5 was labeled Knowledge Sharing Resources since it explains that resources, opportunities, and colleagues are both considered as a source/resource to aid the improvement of the process of knowledge sharing.

7. Develop a Theoretical Based Model and Draw a Path Diagram of Causal Relationships

Before moving on with the validation, we established a new model. According to the new set of constructs established during EFA, a new path diagram is drawn based on different hypotheses. Figures 8 and 9 show the newly established diagrams, pre and during COVID respectively; based on the results of the previous sections. Also, Tables 7 and 8 list the newly written hypotheses based on research and judgment. The previously listed 9 hypotheses were tested using EFA based on 2 sets of data: Pre-pandemic and during pandemic. EFA for pre-pandemic data yielded a new set of 6 constructs and 6 hypotheses that will need to be validated using SEM. Similarly, EFA for during pandemic data yielded a new set of 7 constructs and 7 hypotheses.

The path diagrams are drawn based on literature, common sense and hypothetical relationships. After collecting the constructs and their variables from the EFA model, the constructs are joined based on previous models found in the literature. However, some of the relationships differ due to the impact of the pandemic. Both Figures 8 and 9 are developed based on hypothesizing the link between the newly established constructs post-pandemic.

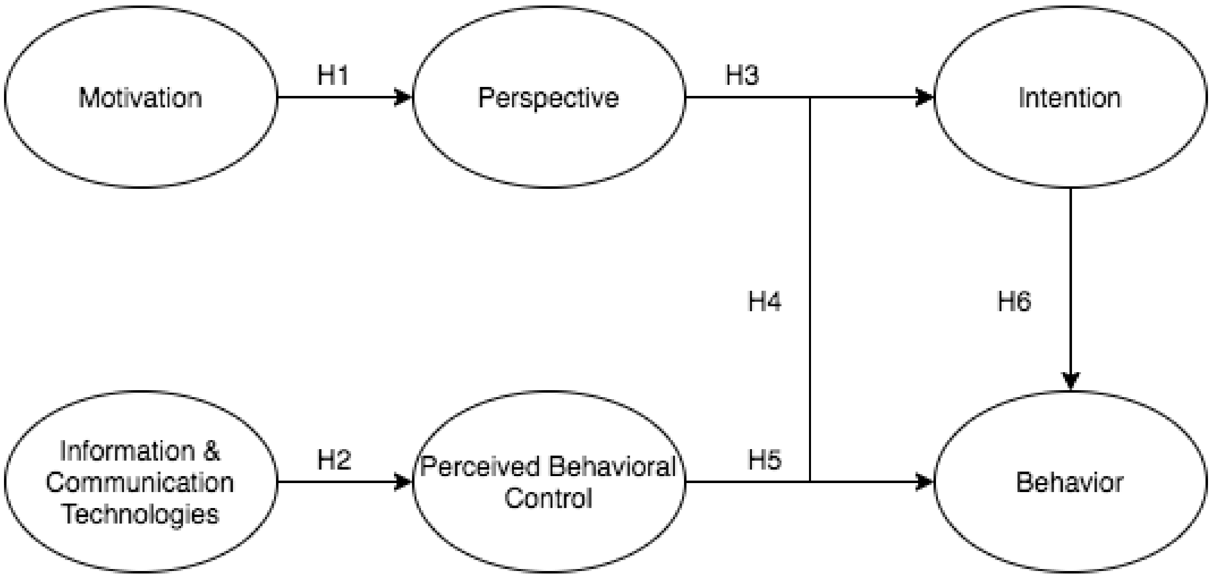


Figure 8 Path diagram of the newly establish constructs- PRE

Hypothesis ID	**Hypothesis**
H1	Employee’s positive perspective towards knowledge sharing is enhanced by constant motivation

H2	Effective ICT have a positive effect on individuals' behavioral control over knowledge sharing with other employees
H3	Employee's intention to share knowledge is strengthened by a positive perspective towards knowledge sharing
H4	Individuals' perceived behavioral control over knowledge sharing has a positive effect on their intention to share knowledge with other employees
H5	The greater the perceived behavioral control over knowledge sharing is, the greater the effectiveness of employee behavior is
H6	A greater the intention to share knowledge leads to better knowledge sharing behavior of employees within the engineering organization

Table 7 List of Hypothesis- PRE

- H1: Employee's positive perspective towards knowledge sharing is enhanced by constant motivation

Economic rewards failed to encourage colleagues towards knowledge sharing (Bock 2005; Zhang 2012). However, combining economic rewards with reduced workload into a construct titled motivation may enhance knowledge sharing and positively affect the perspective of employees towards the transfer knowledge.

- H2: Effective ICT have a positive effect on individuals' behavioral control over knowledge sharing with other employees

The knowledge sharing behavior of employees is highly dependent on accessible and effective communication systems (Zhang 2013). Also, Lin & Lee (2005), argued that enhanced IT support, increases the chances of knowledge sharing.

- H3: Employee's intention to share knowledge is strengthened by a positive perspective towards knowledge sharing

The individuals' perspective towards an action is driven by their intention to do this action (Ajzen and Fishbein 1980). The intention to share knowledge is directly related to the attitude towards knowledge sharing as shown by Bock (2005). This construct titled perspective is dominated by variables belonging to the previous attitude construct.

- H4: Individuals' perceived behavioral control over knowledge sharing has a positive effect on their intention to share knowledge with other employees

Perceived behavioral control is the perceived ease or difficulties one has over performing a behavior (Zhang, 2013). The intention to share knowledge is greatly associated with the ease (improved technologies) to share this knowledge.

- H5: The greater the perceived behavioral control over knowledge sharing is, the greater the effectiveness of employee behavior is

If the employees find it simple and accessible to share their knowledge, their behavior will be shifted towards greater knowledge sharing (Zhang 2012). Behavior is the action itself and facilitating the achievement of this action will logically increase its occurrence.

- H6: A greater the intention to share knowledge leads to better knowledge sharing behavior of employees within the engineering organization

Employees with higher intention towards knowledge sharing tend to have a positive behavior towards the process (Zhang 2012).

Based on the above list of hypotheses, we identified the exogenous and endogenous constructs shown in Table 8. Exogenous constructs are the independent or source variables while endogenous constructs are the dependent or response variables that are predicted by other constructs.

Exogenous Constructs	Endogenous Constructs
Motivation	Perceived Behavioral Control
Perspective	Intention
Information & Communication Technologies	Behavior

Table 8 Exogenous and endogenous constructs- PRE

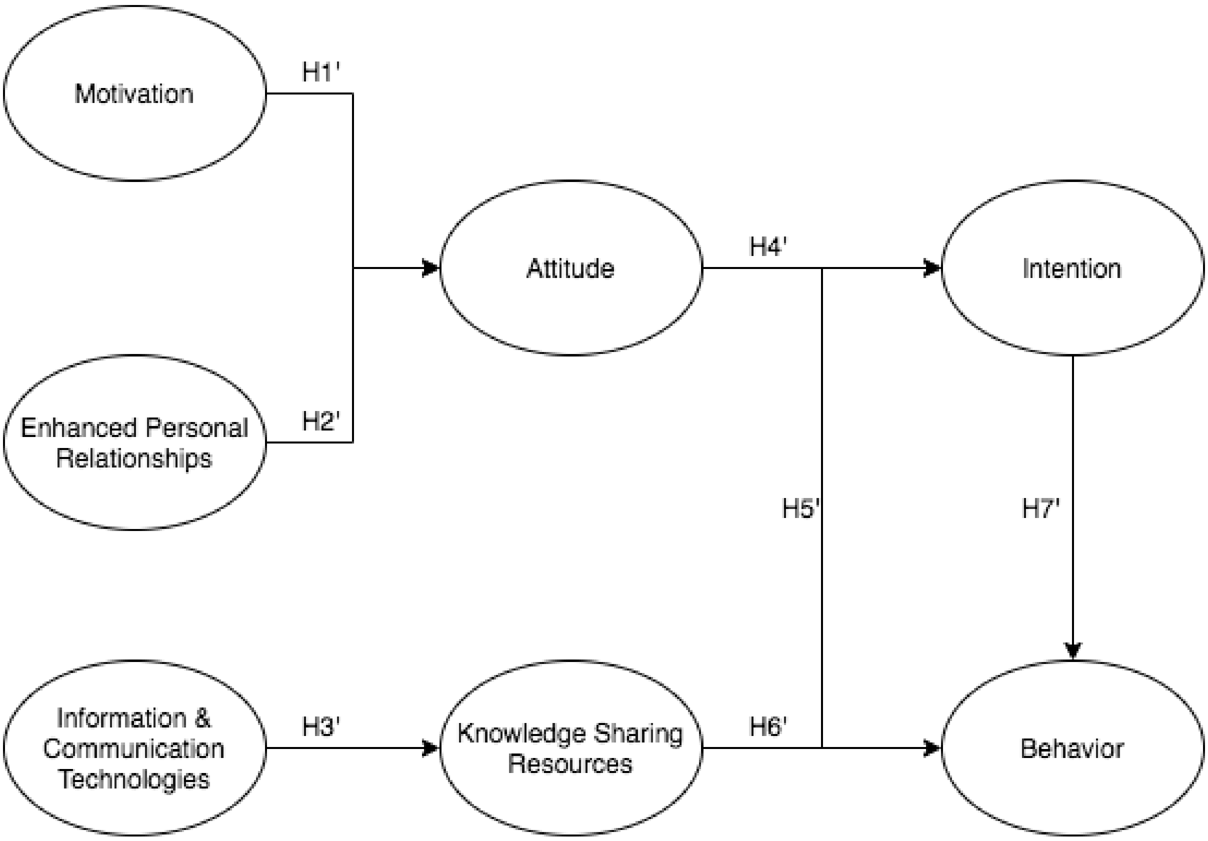


Figure 9 Path diagram of the newly establish constructs- During

Hypothesis ID	Hypothesis
H1'	Employee's encouraging attitude towards virtual knowledge sharing is heightened by constant motivation
H2'	The more enhanced personal relationships are among employees, the more favorable the attitude is towards virtual knowledge sharing
H3'	Effective ICT lead to improved virtual knowledge sharing resources used between employees

H4’	Employee’s intention to virtually share knowledge is strengthened by a positive attitude towards knowledge sharing
H5’	The availability of stable knowledge sharing resources positively affects the intention of employees to share knowledge virtually
H6’	The more improved the knowledge sharing resources are, the greater the effectiveness of employee behavior is
H7’	A greater the intention to share knowledge leads to better virtual knowledge sharing behavior of employees within the engineering organization

Table 9 List of Hypotheses- During

- H1’: Employee’s encouraging attitude towards virtual knowledge sharing is heightened by constant motivation

Economic rewards failed to positively affect the attitude of colleagues towards knowledge sharing (Bock 2005; Zhang 2012). However, combining economic rewards with reduced workload into a construct titled motivation may enhance virtual knowledge sharing.

- H2’: The more enhanced personal relationships are among employees, the more favorable the attitude is towards virtual knowledge sharing

Similarly, to a face-to-face environment, virtual knowledge sharing depends heavily on personal relationships between colleagues as shown by Bock (2005).

- H3’: Effective ICT lead to improved virtual knowledge sharing resources used between employees

The effectiveness of the ICT positively affects the knowledge sharing resources used by colleagues to virtually transfer this knowledge.

- H4’: Employee’s intention to virtually share knowledge is strengthened by a positive attitude towards knowledge sharing

The individuals’ attitude towards an action is driven by their intention to do this action

(Ajzen and Fishbein 1980). The intention to share knowledge is directly related to the attitude towards knowledge sharing as shown by Bock (2005).

- H5': The availability of stable knowledge sharing resources positively affects the intention of employees to share knowledge virtually

Stable, constant, and enhanced knowledge sharing resources facilitate the process of virtually sharing knowledge. This ease of transfer has a positive effect on the intention of colleagues to share knowledge.

- H6': The more improved the knowledge sharing resources are, the greater the effectiveness of employee behavior is

If the employees find it simple and accessible to share their knowledge, their behavior will be shifted towards greater knowledge sharing (Zhang 2012). Behavior is the action itself and facilitating the achievement of this action will logically increase its occurrence. This was applicable for knowledge sharing in the office; however, its importance is emphasized for virtual knowledge sharing. The more resources available, the greater the occurrence of knowledge sharing.

- H7': A greater the intention to share knowledge leads to better virtual knowledge sharing behavior of employees within the engineering organization

Employees with higher intention towards virtual knowledge sharing tend to have a positive behavior towards the process (Zhang 2012).

In the same manner, we identified the exogenous and endogenous constructs as shown in Table 10.

Exogenous Constructs	Endogenous Constructs
Motivation	Attitude
Enhanced Personal Relationships	Knowledge Sharing Resources
Information & Communication Technologies	Intention
	Behavior

Table 10 Exogenous and endogenous constructs- During

In order to validate the above models, confirmatory factor analysis is used which is part of structural equation modelling (SEM). SEM differs from other modeling approaches since it tests the direct and indirect effects on pre-assumed causal relationships. SEM will test the above hypothesis and identify if each variable fits under the corresponding constructs.

B. Structural Equation Modeling (SEM): CFA & Path Analysis

SEM is a hybrid model made of two components: measurement model and structural model. The measurement model is tested by confirmatory factor analysis and the structural model is tested by path analysis (Kline 2015). The measurement model shows the relationship between the constructs and their indicators as shown in Tables 5 and 6. On the other hand, the structural model shows that the constructs are linked together based on the hypothesized relationships as shown in Figures 8 and 9. Sanboskani (2020) summarizes the expected outcomes and results in Figure 10 shown below.

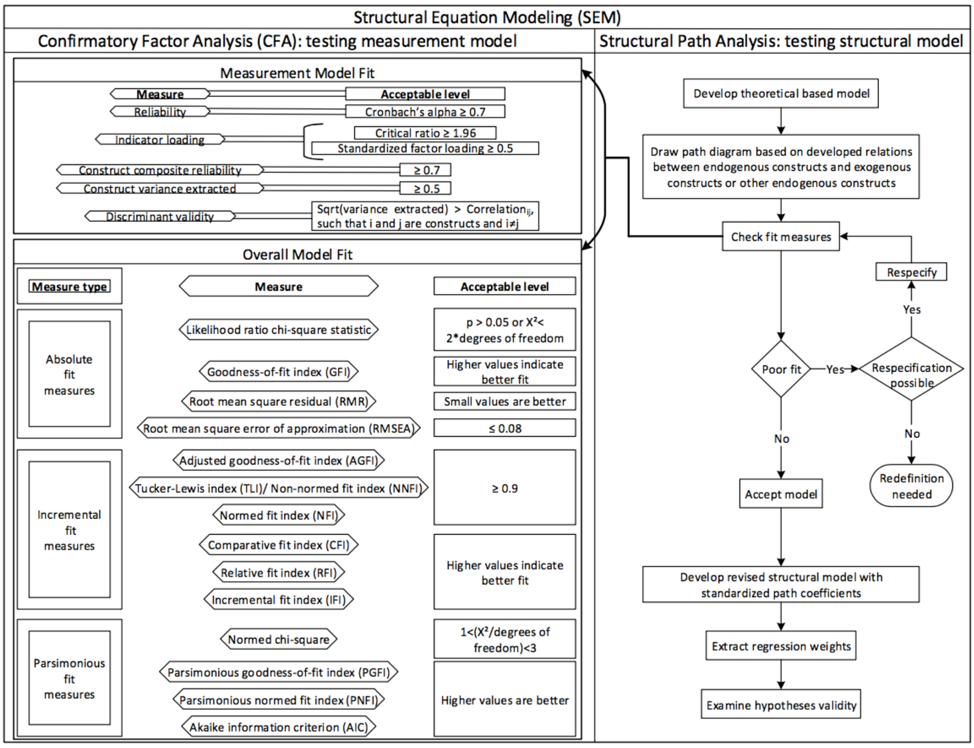


Figure 10 Structural Equation Modelling Steps and Iterations

The following detailed steps are based on the set of data pertinent to employees' situation PRE-COVID19 pandemic.

1. <u>Convert the path diagram into structural and measurement models</u>

Structural Model:

A set of structural equations is developed in order to examine the relationship between the endogenous and exogenous constructs. For each link, a structural coefficient is estimated. Table 11 shows the first and last structural model developed in this study.

The tables show 13 runs in order to portray the changes in the steps conducted in order to achieve a better model fit. The method of conducting these runs and the impact are explained in the subsequent sections.

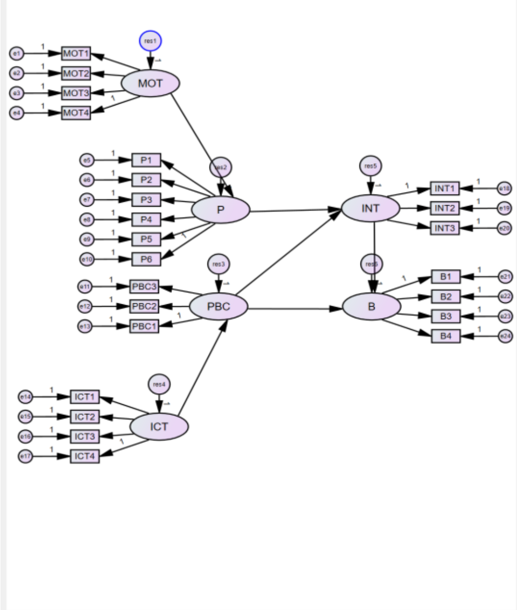
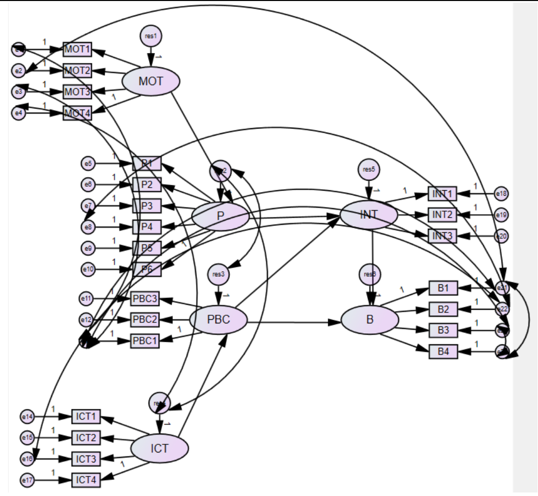
Run 1	Run 13
	

Table 11 First and last structural model on AMOS

Measurement Model:

Several things need to be checked to specify the measurement model. The measurement model shows the hypothesized relationships between latent variables and their indicators. The measurement model is developed by checking the number of indicators per construct and specifying the reliability of the construct.

Specifying the measurement model:

Specifying the measurement model consists of assigning variables to each construct, i.e., defining the construct. This can be employed for both endogenous and exogenous constructs. The construct which is the latent variable is measured by the "indicators". Thus, this known as confirmatory factor analysis.

Determining the number of indicators:

The minimum number of indicators per construct is three as also shown in this study. There is no maximum number of indicators.

Accounting for construct reliability:

There are several ways to establish reliability. In this study, empirical estimation can be used since each construct has 3 or more variables. Reliability will be checked using loading coefficients and the detailed steps are shown later.

Correlations among constructs:

Besides the structural and measurement models, there may be some relationships that need to be specified manually based on the literature. Exogenous constructs can be related and affect the endogenous constructs.

2. <u>Choose the input data and estimate the proposed model</u>

Input Data:

The data was already cleaned and free of any missing records or inconsistent responses. Also, all the records were already transferred to SPSS to perform the previously described EFA analysis. Thus, the correlation matrix is extracted from SPSS to Amos to conduct CFA. The measurement model is used to test to what degree the variables belong to their corresponding constructs and the structural model shows the latent construct scores.

Hair et al. (1998) stated that a sample size ranging between 100 and 200 is enough to perform SEM. In this study, 149 responses were identified as usable responses to conduct SEM.

Independent observations, random sampling of respondents, and linearity of all relationships are the assumptions needed to pursue SEM (Hair et al. 1998). These assumptions are satisfied in this study, but we should also check the multivariate normality and kurtosis of the data. After checking these measures, we can choose the estimation method as shown in the following step.

Model Estimation:

As mentioned before, we should perform normality tests in order to choose the estimation method. Maximum likelihood estimation (MLE) is used when normality is satisfied. In order to satisfy normality for each construct, the kurtosis value must be less than 8 and the absolute value for skewness must be less than 3 (Kline 2011). Also, Bentler (2007) states that in order to satisfy multivariate normality, the multivariate value should be less than 5. In case the previous measures are not met, and non-normality is identified, we can resort to bootstrapping as an estimation process (Pek et al. 2018).

Table 12 shows the changes to normality from the first to the last run. Results of univariate normality indicate that there is no problem in skewness and kurtosis.

Run 1

Assessment of normality (Group number 1)

Variable	min	max	skew	c.r.	kurtosis	c.r.
B4	1.000	5.000	-1.274	-6.349	1.352	3.369
B3	1.000	5.000	-1.108	-5.522	.556	1.385
B2	2.000	5.000	-1.195	-5.956	.916	2.282
B1	1.000	5.000	-1.871	-9.324	5.143	12.814
INT3	2.000	5.000	-.744	-3.709	-.039	-.097
INT2	2.000	5.000	-.631	-3.146	-.100	-.250
INT1	2.000	5.000	-.280	-1.394	-.797	-1.987
PBC3	2.000	5.000	-.533	-2.657	-.250	-.624
PBC2	2.000	5.000	-.567	-2.827	-.321	-.801
PBC1	1.000	5.000	-1.167	-5.814	2.241	5.583
ICT1	2.000	5.000	-.775	-3.861	-.137	-.342
ICT2	1.000	5.000	-.817	-4.071	.260	.649
ICT3	1.000	5.000	-1.302	-6.488	1.122	2.796
ICT4	1.000	5.000	-1.151	-5.737	1.746	4.351
MOT1	1.000	5.000	.990	4.936	-.005	-.012
MOT2	1.000	5.000	.676	3.367	-.458	-1.142
MOT3	1.000	5.000	.168	.836	-.842	-2.098
MOT4	1.000	5.000	-.184	-.917	-1.042	-2.597
P1	2.000	5.000	-.906	-4.515	.156	.388
P2	2.000	5.000	-.537	-2.677	-.641	-1.597
P3	2.000	5.000	-.870	-4.336	.257	.641
P4	2.000	5.000	-.901	-4.491	.002	.005
P5	2.000	5.000	-1.019	-5.078	.552	1.376
P6	2.000	5.000	-.911	-4.539	.350	.871
Multivariate					106.720	18.438

Run 13

Variable	min	max	skew	c.r.	kurtosis	c.r.
B4	1.000	5.000	-1.274	-6.349	1.352	3.369
B3	1.000	5.000	-1.108	-5.522	.556	1.385
B2	2.000	5.000	-1.195	-5.956	.916	2.282
B1	1.000	5.000	-1.871	-9.324	5.143	12.814
INT3	2.000	5.000	-.744	-3.709	-.039	-.097
INT2	2.000	5.000	-.631	-3.146	-.100	-.250
INT1	2.000	5.000	-.280	-1.394	-.797	-1.987
PBC3	2.000	5.000	-.533	-2.657	-.250	-.624
PBC2	2.000	5.000	-.567	-2.827	-.321	-.801
PBC1	1.000	5.000	-1.167	-5.814	2.241	5.583
ICT1	2.000	5.000	-.775	-3.861	-.137	-.342
ICT2	1.000	5.000	-.817	-4.071	.260	.649
ICT3	1.000	5.000	-1.302	-6.488	1.122	2.796
ICT4	1.000	5.000	-1.151	-5.737	1.746	4.351
MOT1	1.000	5.000	.990	4.936	-.005	-.012
MOT2	1.000	5.000	.676	3.367	-.458	-1.142
MOT3	1.000	5.000	.168	.836	-.842	-2.098
MOT4	1.000	5.000	-.184	-.917	-1.042	-2.597
P1	2.000	5.000	-.906	-4.515	.156	.388
P2	2.000	5.000	-.537	-2.677	-.641	-1.597
P3	2.000	5.000	-.870	-4.336	.257	.641
P4	2.000	5.000	-.901	-4.491	.002	.005
P5	2.000	5.000	-1.019	-5.078	.552	1.376
P6	2.000	5.000	-.911	-4.539	.350	.871
Multivariate					106.720	18.438

Table 12 Normality Assessment

The issue of non-normality can be solved by bootstrapping which is a popular estimation process option (Pek et al. 2018). However, it is not always enough to perform only bootstrapping but might also need to perform Bollen-Stine bootstrap to improve the chi-squared value to be within the chi-squared distribution. The distribution of chi-square values associated with each of the bootstrap samples with a total of 500 samples was examined. Table 13 shows that the chi-square value from the model was 493.057

primarily. Then, the chi-square value became 330.359 which falls in the heart of the distribution indicating a good model fit. Another indication is the p-value <0.05, thus the first run indicated the need to re-specify the model. Then the p-value became 0.194 which is greater than 0.005 indicating the model fit is improving.

<table>
<tr><th>Run 1</th><th>Run 13</th></tr>
<tr>
<td>Bootstrap Distributions (Default model)

ML discrepancy (implied vs sample) (Default model)

|--------------------
162.877 |*
187.461 |*
212.045 |****
236.629 |***********
261.213 |***************
285.797 |****************
310.381 |*****************
N = 500 334.966 |***************
Mean = 308.257 359.550 |*********
S. e. = 2.621 384.134 |******
408.718 |****
433.302 |**
457.886 |**
482.470 |*
507.054 |*
|--------------------

Bollen-Stine Bootstrap (Default model)

The model fit better in 499 bootstrap samples.
It fit about equally well in 0 bootstrap samples.
It fit worse or failed to fit in 1 bootstrap samples.
Testing the null hypothesis that the model is correct, Bollen-Stine bootstrap p = .004</td>
<td>ML discrepancy (implied vs sample) (Default model)

|--------------------
148.305 |*
170.213 |*
192.120 |***
214.028 |*******
235.936 |*************
257.843 |***************
279.751 |*****************
N = 500 301.658 |****************
Mean = 289.247 323.566 |*************
S. e. = 2.427 345.474 |******
367.381 |*****
389.289 |***
411.197 |***
433.104 |**
455.012 |*
|--------------------

Bollen-Stine Bootstrap (Default model)

The model fit better in 404 bootstrap samples.
It fit about equally well in 0 bootstrap samples.
It fit worse or failed to fit in 96 bootstrap samples.
Testing the null hypothesis that the model is correct, Bollen-Stine bootstrap p = .194</td>
</tr>
</table>

Table 13 Bootstrap Distribution

3. <u>Assess the identification of the structural model</u>

Order Condition:

SEM requires an over-identified model with degrees of freedom (df) >0. Both runs indicate an over identified model with degrees of freedom>0.

<table>
<tr><th>Run 1</th><th>Run 13</th></tr>
<tr>
<td>Notes for Model (Default model)

Computation of degrees of freedom (Default model)

Number of distinct sample moments: 300
Number of distinct parameters to be estimated: 54
Degrees of freedom (300 - 54): 246</td>
<td>Computation of degrees of freedom (Default model)

Number of distinct sample moments: 300
Number of distinct parameters to be estimated: 66
Degrees of freedom (300 - 66): 234</td>
</tr>
</table>

Table 14 Degrees of Freedom

Rank Condition:

In order to satisfy the rank condition, two rules need to be checked. The first is the three-measure rule which states that each construct with three or more indicators is always identified. The second is the recursive model (paths only go one way) rule which states that a recursive model with identified constructs is always identified. All rules are satisfied.

4. <u>Evaluating goodness-of-fit criteria</u>

The goodness of fit is checked on the level of overall model and measurement and structural models. The offending estimates need to be checked and ensure acceptable estimates first.

Offending Estimates:

Offending estimates come in 3 forms: negative error variance, standardized coefficients exceeding or close to 1, and very large standard errors.

Run 1

Negative Error Variance

Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
res1	.144	.086	1.676	.094	par_25
res4	.445	.074	5.973	***	par_26
res2	.234	.052	4.494	***	par_27
res3	.245	.065	3.750	***	par_28
res5	.190	.041	4.589	***	par_29
res6	.149	.047	3.159	.002	par_30
e10	.266	.036	7.500	***	par_31
e9	.235	.033	7.204	***	par_32
e8	.236	.036	6.625	***	par_33
e7	.175	.026	6.753	***	par_34
e6	.342	.045	7.655	***	par_35
e5	.292	.037	7.892	***	par_36
e4	1.452	.173	8.395	***	par_37
e3	.745	.109	6.814	***	par_38
e2	.490	.115	4.247	***	par_39
e1	.542	.103	5.264	***	par_40
e17	.188	.033	5.690	***	par_41
e16	.864	.106	8.133	***	par_42
e15	.218	.040	5.472	***	par_43
e14	.225	.037	5.996	***	par_44
e13	.427	.062	6.908	***	par_45
e12	.024	.091	.263	.792	par_46
e11	.462	.059	7.899	***	par_47
e18	.256	.038	6.768	***	par_48
e19	.168	.027	6.218	***	par_49
e20	.163	.034	4.778	***	par_50
e21	.439	.061	7.226	***	par_51
e22	.424	.059	7.242	***	par_52
e23	.455	.092	4.954	***	par_53
e24	.465	.066	7.067	***	par_54

Run 13

Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
res1	.170	.088	1.931	.053	par_37
res4	.450	.075	6.028	***	par_38
res2	.233	.052	4.473	***	par_39
res3	.287	.063	4.566	***	par_40
res5	.191	.042	4.585	***	par_41
res6	.166	.046	3.629	***	par_42
e10	.271	.036	7.611	***	par_43
e9	.229	.032	7.239	***	par_44
e8	.232	.034	6.750	***	par_45
e7	.184	.026	7.032	***	par_46
e6	.340	.044	7.707	***	par_47
e5	.291	.037	7.934	***	par_48
e4	1.436	.170	8.457	***	par_49
e3	.769	.105	7.304	***	par_50
e2	.454	.113	4.005	***	par_51
e1	.511	.094	5.427	***	par_52
e17	.186	.033	5.711	***	par_53
e16	.866	.106	8.149	***	par_54
e15	.234	.040	5.839	***	par_55
e14	.212	.036	5.820	***	par_56
e13	.369	.053	6.921	***	par_57
e12	.148	.049	3.020	.003	par_58
e11	.426	.054	7.887	***	par_59
e18	.259	.038	6.835	***	par_60
e19	.167	.027	6.230	***	par_61
e20	.156	.034	4.605	***	par_62
e21	.331	.057	5.856	***	par_63
e22	.410	.055	7.438	***	par_64
e23	.650	.097	6.679	***	par_65
e24	.541	.081	6.700	***	par_66

Standardized Coefficients

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
P	<---	MOT	-.109
PBC	<---	ICT	.319
INT	<---	P	.663
INT	<---	PBC	-.006
B	<---	PBC	.245
B	<---	INT	.503
P6	<---	P	.686
P5	<---	P	.727
P4	<---	P	.783
P3	<---	P	.772
P2	<---	P	.658
P1	<---	P	.604
MOT4	<---	MOT	.300
MOT3	<---	MOT	.665
MOT2	<---	MOT	.807
MOT1	<---	MOT	.760
ICT4	<---	ICT	.838
ICT3	<---	ICT	.538
ICT2	<---	ICT	.847
ICT1	<---	ICT	.825
PBC1	<---	PBC	.624
PBC2	<---	PBC	.983
PBC3	<---	PBC	.518
INT1	<---	INT	.755
INT2	<---	INT	.792
INT3	<---	INT	.857
B1	<---	B	.575
B2	<---	B	.572
B3	<---	B	.753
B4	<---	B	.594

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
P	<---	MOT	-.048
PBC	<---	ICT	.374
INT	<---	P	.666
INT	<---	PBC	-.021
B	<---	PBC	.399
B	<---	INT	.445
P6	<---	P	.680
P5	<---	P	.735
P4	<---	P	.782
P3	<---	P	.758
P2	<---	P	.662
P1	<---	P	.607
MOT4	<---	MOT	.325
MOT3	<---	MOT	.657
MOT2	<---	MOT	.838
MOT1	<---	MOT	.781
ICT4	<---	ICT	.841
ICT3	<---	ICT	.535
ICT2	<---	ICT	.835
ICT1	<---	ICT	.836
PBC1	<---	PBC	.689
PBC2	<---	PBC	.889
PBC3	<---	PBC	.572
INT1	<---	INT	.751
INT2	<---	INT	.792
INT3	<---	INT	.864
B1	<---	B	.702
B2	<---	B	.596
B3	<---	B	.645
B4	<---	B	.522

Standard Errors

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
P	<---	MOT	-.140	.132	-1.058	.290	par_19
PBC	<---	ICT	.250	.079	3.146	.002	par_20
INT	<---	P	.793	.131	6.047	***	par_21
INT	<---	PBC	-.006	.083	-.075	.940	par_24
B	<---	PBC	.218	.086	2.545	.011	par_22
B	<---	INT	.401	.095	4.225	***	par_23
P6	<---	P	1.000				
P5	<---	P	1.055	.135	7.823	***	par_1
P4	<---	P	1.257	.151	8.325	***	par_2
P3	<---	P	1.045	.127	8.235	***	par_3
P2	<---	P	1.051	.147	7.159	***	par_4
P1	<---	P	.842	.127	6.621	***	par_5
MOT4	<---	MOT	1.000				
MOT3	<---	MOT	2.027	.633	3.202	.001	par_6
MOT2	<---	MOT	2.527	.772	3.272	.001	par_7
MOT1	<---	MOT	2.269	.696	3.263	.001	par_8
ICT4	<---	ICT	1.000				
ICT3	<---	ICT	.889	.134	6.616	***	par_9
ICT2	<---	ICT	1.117	.097	11.478	***	par_10
ICT1	<---	ICT	1.037	.093	11.183	***	par_11
PBC1	<---	PBC	1.000				
PBC2	<---	PBC	1.577	.266	5.917	***	par_12
PBC3	<---	PBC	.788	.137	5.772	***	par_13
INT1	<---	INT	1.000				
INT2	<---	INT	.913	.098	9.282	***	par_14
INT3	<---	INT	1.157	.118	9.814	***	par_15
B1	<---	B	1.000				
B2	<---	B	.978	.195	5.006	***	par_16
B3	<---	B	1.663	.293	5.668	***	par_17
B4	<---	B	1.084	.211	5.128	***	par_18

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
P	<---	MOT	-.057	.095	-.599	.549	par_19
PBC	<---	ICT	.322	.084	3.837	***	par_20
INT	<---	P	.799	.155	5.166	***	par_21
INT	<---	PBC	-.021	.104	-.202	.840	par_24
B	<---	PBC	.393	.108	3.634	***	par_22
B	<---	INT	.436	.102	4.300	***	par_23
P6	<---	P	1.000				
P5	<---	P	1.076	.136	7.898	***	par_1
P4	<---	P	1.253	.150	8.370	***	par_2
P3	<---	P	1.035	.128	8.109	***	par_3
P2	<---	P	1.066	.148	7.193	***	par_4
P1	<---	P	.853	.128	6.651	***	par_5
MOT4	<---	MOT	1.000				
MOT3	<---	MOT	1.854	.506	3.666	***	par_6
MOT2	<---	MOT	2.511	.657	3.823	***	par_7
MOT1	<---	MOT	2.166	.571	3.792	***	par_8
ICT4	<---	ICT	1.000				
ICT3	<---	ICT	.880	.131	6.718	***	par_9
ICT2	<---	ICT	1.098	.096	11.442	***	par_10
ICT1	<---	ICT	1.048	.092	11.454	***	par_11
PBC1	<---	PBC	1.000				
PBC2	<---	PBC	1.292	.154	8.362	***	par_12
PBC3	<---	PBC	.788	.123	6.402	***	par_13
INT1	<---	INT	1.000				
INT2	<---	INT	.918	.099	9.248	***	par_14
INT3	<---	INT	1.172	.120	9.807	***	par_15
B1	<---	B	1.000				
B2	<---	B	.837	.136	6.131	***	par_16
B3	<---	B	1.200	.192	6.265	***	par_17
B4	<---	B	.793	.180	4.402	***	par_18

Table 15 Offending Estimates

Overall Model Fit:

The overall model fit indicates the degree to which the indicators represent their corresponding constructs. One requirement is achieving parsimony by having a large number of degrees of freedom indicating a better model fit. The overall model fit is assessed based on goodness-of-fit measures that are divided into 3 categories: absolute fit measures, incremental fit measures, and parsimonious fit measures. One or two goodness-of-fit measures are enough to assess the overall model fit. Acceptable fit measures for both Runs 1 and 13 are shown in Table 16.

Goodness-of-Fit Measure	Levels of Acceptable Fit	Run 1	Run 13	Acceptability
Absolute fit measures				
Likelihood ratio chi-square statistic (x2)	Not statistically significant or statistically significant x2 must be less than 2 times model's degrees of freedom	493.057 (2x246=492)	330.359 (2x234=468)	Model may fit the data
Goodness-of-fit index (GFI)	Higher values indicate better fit	0.803	0.863	Acceptable
Root mean square residual (RMR)	Small values are better	0.099	0.057	Acceptable
Root mean square error of approximation (RMSEA)	≤ 0.08	0.082	0.053	Acceptable
Incremental fit measures				
Adjusted goodness-of-fit index (AGFI)	≥ 0.9	0.760	0.825	Marginal
Tucker-Lewis index (TLI)/ Non-normed fit index (NNFI)	≥ 0.9	0.814	0.924	Acceptable
Normed fit index (NFI)	≥ 0.9 (0.8)	0.721	0.813	Marginal
Comparative fit index (CFI)	Higher values are better (≥ 0.9)	0.834	0.935	Acceptable
Relative fit index (RFI)	Higher values are better	0.687	0.780	Acceptable
Incremental fit index (IFI)	Higher values are better	0.838	0.937	Acceptable
Parsimonious fit measures				
Normed chi-square: x2/df	Between 1 and 3	1.002	1.41	Acceptable
Parsimonious goodness-of-fit index (PGFI)	Higher values are better, greater than 0.5 and closer to 1	0.659	0.673	Acceptable
Parsimonious normed fit index (PNFI)	Higher values are better, greater than 0.5	0.643	0.689	Acceptable
Akaike information criterion (AIC)	Smaller values are better (compared to the 2 models done my Amos)	601.057	462.359	Acceptable

Table 16 Goodness-of-Fit Measures

Measurement Model Fit:

The first step in assessing the measurement model fit is checking the reliability of each construct. Cronbach’s alpha is used to check reliability. Then, we check the significance of the indicator loadings, composite reliability, and variance extracted.

Indicator loadings:

According to Hair et al. (1998), for 80% power and significance of 0.05, and according to the sample size at hand, a factor loading of 0.5 is adopted. Also, all loadings must have a CR value greater than 1.96. The runs show that all factor loadings are greater than 0.5 except MOT-MOT4. All loadings have a critical ratio (CR) greater than 1.96 as shown in Table 17.

Run 1	Run 13

Run 1

Factor Loading

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
P	<---	MOT	-.109
PBC	<---	ICT	.319
INT	<---	P	.663
INT	<---	PBC	-.006
B	<---	PBC	.245
B	<---	INT	.503
P6	<---	P	.686
P5	<---	P	.727
P4	<---	P	.783
P3	<---	P	.772
P2	<---	P	.658
P1	<---	P	.604
MOT4	<---	MOT	.300
MOT3	<---	MOT	.665
MOT2	<---	MOT	.807
MOT1	<---	MOT	.760
ICT4	<---	ICT	.838
ICT3	<---	ICT	.538
ICT2	<---	ICT	.847
ICT1	<---	ICT	.825
PBC1	<---	PBC	.624
PBC2	<---	PBC	.983
PBC3	<---	PBC	.518
INT1	<---	INT	.755
INT2	<---	INT	.792
INT3	<---	INT	.857
B1	<---	B	.575
B2	<---	B	.572
B3	<---	B	.753
B4	<---	B	.594

Run 13

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
P	<---	MOT	-.048
PBC	<---	ICT	.374
INT	<---	P	.666
INT	<---	PBC	-.021
B	<---	PBC	.399
B	<---	INT	.445
P6	<---	P	.680
P5	<---	P	.735
P4	<---	P	.782
P3	<---	P	.758
P2	<---	P	.662
P1	<---	P	.607
MOT4	<---	MOT	.325
MOT3	<---	MOT	.657
MOT2	<---	MOT	.838
MOT1	<---	MOT	.781
ICT4	<---	ICT	.841
ICT3	<---	ICT	.535
ICT2	<---	ICT	.835
ICT1	<---	ICT	.836
PBC1	<---	PBC	.689
PBC2	<---	PBC	.889
PBC3	<---	PBC	.572
INT1	<---	INT	.751
INT2	<---	INT	.792
INT3	<---	INT	.864
B1	<---	B	.702
B2	<---	B	.596
B3	<---	B	.645
B4	<---	B	.522

Run 1

Critical Ratio

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
P	<---	MOT	-.140	.132	-1.058	.290	par_19
PBC	<---	ICT	.250	.079	3.146	.002	par_20
INT	<---	P	.793	.131	6.047	***	par_21
INT	<---	PBC	-.006	.083	-.075	.940	par_24
B	<---	PBC	.218	.086	2.545	.011	par_22
B	<---	INT	.401	.095	4.225	***	par_23
P6	<---	P	1.000				
P5	<---	P	1.055	.135	7.823	***	par_1
P4	<---	P	1.257	.151	8.325	***	par_2
P3	<---	P	1.045	.127	8.235	***	par_3
P2	<---	P	1.051	.147	7.159	***	par_4
P1	<---	P	.842	.127	6.621	***	par_5
MOT4	<---	MOT	1.000				
MOT3	<---	MOT	2.027	.633	3.202	.001	par_6
MOT2	<---	MOT	2.527	.772	3.272	.001	par_7
MOT1	<---	MOT	2.269	.696	3.263	.001	par_8
ICT4	<---	ICT	1.000				
ICT3	<---	ICT	.889	.134	6.616	***	par_9
ICT2	<---	ICT	1.117	.097	11.478	***	par_10
ICT1	<---	ICT	1.037	.093	11.183	***	par_11
PBC1	<---	PBC	1.000				
PBC2	<---	PBC	1.577	.266	5.917	***	par_12
PBC3	<---	PBC	.788	.137	5.772	***	par_13
INT1	<---	INT	1.000				
INT2	<---	INT	.913	.098	9.282	***	par_14
INT3	<---	INT	1.157	.118	9.814	***	par_15
B1	<---	B	1.000				
B2	<---	B	.978	.195	5.006	***	par_16
B3	<---	B	1.663	.293	5.668	***	par_17
B4	<---	B	1.084	.211	5.128	***	par_18

MOT2	<---	MOT	[illegible]	[illegible]	[illegible]	[illegible]
MOT1	<---	MOT	2.166	.571	3.792	***	par_8
ICT4	<---	ICT	1.000				
ICT3	<---	ICT	.880	.131	6.718	***	par_9
ICT2	<---	ICT	1.098	.096	11.442	***	par_10
ICT1	<---	ICT	1.048	.092	11.454	***	par_11
PBC1	<---	PBC	1.000				
PBC2	<---	PBC	1.292	.154	8.362	***	par_12
PBC3	<---	PBC	.788	.123	6.402	***	par_13
INT1	<---	INT	1.000				
INT2	<---	INT	.918	.099	9.248	***	par_14
INT3	<---	INT	1.172	.120	9.807	***	par_15
B1	<---	B	1.000				
B2	<---	B	.837	.136	6.131	***	par_16
B3	<---	B	1.200	.192	6.265	***	par_17
B4	<---	B	.793	.180	4.402	***	par_18

Table 17 Indicator Loadings

Composite Reliability and Variance Extracted:

The composite reliability of each construct is calculated to ensure a value of 0.7 and above. Equation 1 is used to calculate the composite relatability of each construct. The standardized loadings are the factor loadings obtained from Amos output and ε_j is the measurement error for each indicator. It is calculated as shown in equation 2.

Equation 1

$$Construct\ reliability = \frac{(\sum standardized\ loading)^2}{(\sum standardized\ loading)^2 + \sum \varepsilon_j}$$

Equation 2

$$\varepsilon_j = 1 - reliability_j = 1 - (standardized\ loading_j)^2$$

Item	Construct	λ		λ^2		ε (ERROR VARIANCE)		Composite Reliability		Variance Extracted	
		Run 1	Run 13	Run 1	Run 13	Run 1	Run 13	Run 1	Run 13	Run 1	Run 13
P1	Perspective	0.604	0.607	0.365	0.368	0.635	0.632	0.86	0.86	0.50	0.5
P2		0.658	0.662	0.433	0.438	0.567	0.562				
P3		0.772	0.758	0.596	0.575	0.404	0.425				
P4		0.783	0.782	0.613	0.612	0.387	0.388				
P5		0.727	0.735	0.529	0.540	0.471	0.460				
P6		0.686	0.680	0.471	0.462	0.529	0.538				
	SUM	4.230	4.224	3.006	2.995	2.994	3.005				
MOT 1	Motivation	0.760	0.781	0.578	0.610	0.422	0.390	0.74	0.76	0.44	0.46
MOT 2		0.807	0.838	0.651	0.702	0.349	0.298				
MOT 3		0.665	0.657	0.442	0.432	0.558	0.568				
MOT 4		0.300	0.325	0.090	0.106	0.910	0.894				
	SUM	2.532	2.601	1.761	1.849	2.239	2.151				

Table 18 Measurement Model Fit

ICT1	Information & Comm. Technologies	0.825	0.836	0.681	0.699	0.319	0.301	0.85	0.85	0.60	0.60
ICT2		0.847	0.835	0.717	0.697	0.283	0.303				
ICT3		0.538	0.535	0.289	0.286	0.711	0.714				
ICT4		0.838	0.841	0.702	0.707	0.298	0.293				
	SUM	3.048	3.047	2.390	2.390	1.610	1.610				
PBC1	Perceived Behav. Control	0.624	0.689	0.389	0.475	0.611	0.525	0.77	0.77	0.54	0.53
PBC2		0.983	0.889	0.966	0.790	0.034	0.210				
PBC3		0.518	0.572	0.268	0.327	0.732	0.673				
	SUM	2.125	2.150	1.624	1.592	1.376	1.408				
B1	Behavior	0.575	0.702	0.331	0.493	0.669	0.507	0.72	0.71	0.39	0.38
B2		0.572	0.596	0.327	0.355	0.673	0.645				
B3		0.753	0.645	0.567	0.416	0.433	0.584				
B4		0.594	0.522	0.353	0.272	0.647	0.728				
	SUM	2.494	2.465	1.578	1.537	2.422	2.463				
Int1	Intention	0.755	0.751	0.570	0.564	0.430	0.436	0.84	0.85	0.64	0.65
Int2		0.792	0.792	0.627	0.627	0.373	0.373				
Int3		0.857	0.864	0.734	0.746	0.266	0.254				
	SUM	2.404	2.407	1.932	1.938	1.068	1.062				

The variance extracted reflects on convergent validity (Alumran et al. 2014). Higher variance extracted values reflect that the indicators represent the respective constructs. Equation 3 is used to calculate the variance and a value of 0.5 and above is considered acceptable.

$$Variance\ extracted = \frac{\sum(standardized\ loading)^2}{\sum(standardized\ loading)^2 + \sum \varepsilon_j}$$

Equation 3

Table 18 shows the different calculated values for runs 1 and 13 and how they changed.

Structural Model Fit:

The structural model fit is tested based on the significance of the estimated coefficients. Each hypothesis will be either rejected or supported based on 0.05 significance level. All values were significant, however model re-specification is needed to enhance the model.

Run 1

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
P	<---	MOT	-.140	.132	-1.058	.290	par_19
PBC	<---	ICT	.250	.079	3.146	.002	par_20
INT	<---	P	.793	.131	6.047	***	par_21
INT	<---	PBC	-.006	.083	-.075	.940	par_24
B	<---	PBC	.218	.086	2.545	.011	par_22
B	<---	INT	.401	.095	4.225	***	par_23
P6	<---	P	1.000				
P5	<---	P	1.055	.135	7.823	***	par_1
P4	<---	P	1.257	.151	8.325	***	par_2
P3	<---	P	1.045	.127	8.235	***	par_3
P2	<---	P	1.051	.147	7.159	***	par_4
P1	<---	P	.842	.127	6.621	***	par_5
MOT4	<---	MOT	1.000				
MOT3	<---	MOT	2.027	.633	3.202	.001	par_6
MOT2	<---	MOT	2.527	.772	3.272	.001	par_7
MOT1	<---	MOT	2.269	.696	3.263	.001	par_8
ICT4	<---	ICT	1.000				
ICT3	<---	ICT	.889	.134	6.616	***	par_9
ICT2	<---	ICT	1.117	.097	11.478	***	par_10
ICT1	<---	ICT	1.037	.093	11.183	***	par_11
PBC1	<---	PBC	1.000				
PBC2	<---	PBC	1.577	.266	5.917	***	par_12
PBC3	<---	PBC	.788	.137	5.772	***	par_13
INT1	<---	INT	1.000				
INT2	<---	INT	.913	.098	9.282	***	par_14
INT3	<---	INT	1.157	.118	9.814	***	par_15
B1	<---	B	1.000				
B2	<---	B	.978	.195	5.006	***	par_16
B3	<---	B	1.663	.293	5.668	***	par_17
B4	<---	B	1.084	.211	5.128	***	par_18

Run 13

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
P	<---	MOT	-.057	.095	-.599	.549	par_19
PBC	<---	ICT	.322	.084	3.837	***	par_20
INT	<---	P	.799	.155	5.166	***	par_21
INT	<---	PBC	-.021	.104	-.202	.840	par_24
B	<---	PBC	.393	.108	3.634	***	par_22
B	<---	INT	.436	.102	4.300	***	par_23
P6	<---	P	1.000				
P5	<---	P	1.076	.136	7.898	***	par_1
P4	<---	P	1.253	.150	8.370	***	par_2
P3	<---	P	1.035	.128	8.109	***	par_3
P2	<---	P	1.066	.148	7.193	***	par_4
P1	<---	P	.853	.128	6.651	***	par_5
MOT4	<---	MOT	1.000				
MOT3	<---	MOT	1.854	.506	3.666	***	par_6
MOT2	<---	MOT	2.511	.657	3.823	***	par_7
MOT1	<---	MOT	2.166	.571	3.792	***	par_8
ICT4	<---	ICT	1.000				
ICT3	<---	ICT	.880	.131	6.718	***	par_9
ICT2	<---	ICT	1.098	.096	11.442	***	par_10
ICT1	<---	ICT	1.048	.092	11.454	***	par_11
PBC1	<---	PBC	1.000				
PBC2	<---	PBC	1.292	.154	8.362	***	par_12
PBC3	<---	PBC	.788	.123	6.402	***	par_13
INT1	<---	INT	1.000				
INT2	<---	INT	.918	.099	9.248	***	par_14
INT3	<---	INT	1.172	.120	9.807	***	par_15
B1	<---	B	1.000				
B2	<---	B	.837	.136	6.131	***	par_16
B3	<---	B	1.200	.192	6.265	***	par_17
B4	<---	B	.793	.180	4.402	***	par_18

Table 19 Structural Model Fit

5. <u>Interpreting and Modifying the Model</u>

After performing CFA, it was shown that the model has a relatively poor fit. In order to improve its fit, we performed re-specification by correlating the errors and residuals of the variables and constructs. Modification indices will be examined to check which errors and residuals will be correlated. Modification indices suggest a change in the model based on how much the chi-square value would change had the coefficient been estimated. A theoretical justification must be available for any change based on modification indices (Hair et al. 1998).

Relationships in the model are either theoretically inferred (between variables and constructs) or empirically inferred (between errors). Model re-specification can occur through modifying the empirical relationships only.

As shown in Tables 11 to 19, 13 runs were made to reach an improved model fit. Each run will be described and justified below, however the results of the final run are shown in each of the previously listed tables.

Run 1: It was made by correlating e2 and e21. When employees are rewarded by promotions or salary increases for sharing knowledge, they will be encouraged to share more knowledge within the work environment.

Run 2: It was made by correlating e16 and e22. When knowledge sharing is facilitated by ICT inside and outside the organization, employees will be able to share more their technical skills with colleagues.

Run 3: It was made by correlating e23 and e24. When official documentation or manuals is shared with colleagues, this encourages the sharing of project knowledge also.

Run 4: It was made by correlating e1 and e13. If monetary rewards are received for sharing knowledge, employees will have the ability to acquire resources to support their knowledge sharing.

Run 5: It was made by correlating e13 and e23. If resources are available to share knowledge, then the probability of sharing official documentation and manuals will increase.

Run 6: It was made by correlating res2 and res4. The availability of technologies to facilitate and speed up the knowledge sharing process will support colleagues in sharing knowledge and developing relationships.

Run 7: It was made by correlating res2 and res3. If control over resources and opportunities to share knowledge is available, this would make knowledge sharing with colleagues valuable and beneficial and strengthen the ties with colleagues.

Run 8: It was made by correlating e4 and res4. The availability of effective ICT that will facilitate and speed the knowledge sharing process will motivate employees to share knowledge thus reducing individual workload.

Similarly, the following correlations were made in order to reach logical results and based on the outcomes of the runs.

Run 9: It was made by correlating e3 and e13.

Run 10: It was made by correlating e21 and e13.

Run 11: It was made by correlating e21 and e24.

Run 12: It was made by correlating e14 and e22.

Run 13: It was made by correlating e8 and e22.

Similarly, CFA analysis was conducted on data during COVID-19 to check the factors that affect knowledge sharing in the virtual environment. The steps of the analysis are shown in the Appendix C. After running the model, it was shown that the model has a relatively poor fit. In order to improve its fit, we will perform re-specification by correlating the errors and residuals of the variables and constructs. As shown in Appendix C, 18 runs were made to reach an improved model fit.

CHAPTER VII

DISCUSSION

This section focuses on discussing the obtained results and interpreting the importance of each in reference to the context of the study.

This study aims at determining a set of factors that affects knowledge sharing among engineers working in a virtual setting. Previous literature studies supported the formation of a survey that was used to collect the needed data to conduct the analysis. The collected data does not explicitly match the factors identified in the literature to affect knowledge sharing due to the difference in the nature of virtual work and the different scope presented. This work focuses on using the extracted factors to develop an integrative understanding of the behavior of engineers working in a virtual environment towards knowledge sharing and what affected this change in behavior. Also, intention to share knowledge will be assessed upon studying the causal relationships between them.

Based on EFA results, factors were derived that affect the knowledge sharing process pre-pandemic and during the pandemic. The factors that were extracted and attributed to the situation pre-pandemic are: perspective, motivation, information and communication technologies, perceived behavioral control, and intention. On the other hand, the factors attributed to the situation during the pandemic and virtual knowledge sharing are attitude, motivation, information and communication technologies, enhanced personal relationships, knowledge sharing resources, and intention.

A. Discussion of Hypotheses Results

The situation pre and during pandemic will be analyzed by taking a closer look into the significance of each hypothesis and the meaning of each factor with regards to the knowledge sharing process.

1. Pre-Pandemic

Javernick-Will (2012) discussed the popularity of motivation as a driver for sharing knowledge. Motivation is considered as a personal driver that affects the engineer's motive to share knowledge. Huang et al. (2008) states that motivation enhanced by extrinsic rewards positively affect employees' attitude towards knowledge sharing. However, in this study, it was shown that motivation is not a direct indicator of perspective towards knowledge sharing. Perspective towards knowledge sharing which is mainly based on attitude and personal relationships between engineers is not driven by economic rewards and reduced workload (H1, Table 7). This result was aligned with the findings of Bock (2005) and Zhang (2012) which state that economic rewards failed to encourage colleagues towards knowledge sharing.

External drivers focus on the effectiveness of information and communication technology (ICT) in facilitating knowledge transfer. The knowledge sharing behavior of employees is highly dependent on accessible and effective communication systems (Zhang 2013). Also, Lin & Lee (2005), argued that enhanced IT support, increases the chances of virtual knowledge sharing. This study shows that ICT has a positive effect on the perceived behavioral control of engineers towards knowledge sharing (H2, Table 7). Engineers agree that technologies play an important role towards knowledge sharing even when working from the office and in the presence of the whole team. The nature of work of engineers is dependent on the transfer of large documents, drawings, and files which is facilitated through accessible technologies. Thus, having accessible ICT will lead to the availability of resources and opportunities that support the knowledge sharing process of engineers. These resources and opportunities grant engineers control over the knowledge sharing process, thus justifying the perceived behavioral control factor.

The individuals' perspective towards an action is driven by their intention to do this action (Ajzen and Fishbein 1980). The results of this study show that engineers' intention to share knowledge is strengthened by a positive perspective towards knowledge sharing which validates H3 in Table 7. The intention to share knowledge is directly related to the attitude towards knowledge sharing as shown by Bock (2005). Perspective is dominated by variables belonging to the attitude construct described by Bock (2005).

Perceived behavioral control is the perceived ease or difficulties one has over performing a behavior (Zhang, 2013). It was identified that the intention to share knowledge is not associated with the ease (improved technologies) to share this knowledge (H4, Table 7). This shows that intention which is considered an internal driver linked to the personal attributes of an engineer is not directly affected by perceived behavioral control which is an external factor. Facilitating the process of knowledge sharing will benefit engineers whose attitude and intention are already directed towards encouraging knowledge sharing.

Perceived behavioral control is the perceived ease or difficulties one has over performing a behavior (Zhang, 2013). Behavior is the action itself and this study identified that facilitating the achievement of this action will logically increase its occurrence (H5, Table 7). If the employees find it simple and accessible to share their knowledge, their behavior will be shifted towards greater knowledge sharing (Zhang 2012).

In this study, behavior is considered the external and physical outcome which constitute the knowledge sharing itself. The constructs analyzed were leading to the final construct of behavior. Each construct would directly or indirectly affect the behavior of knowledge sharing between engineers. The intention to share knowledge led to increasing the occurrence of the knowledge sharing process, as it was identified by this study (H6, Table 7). Employees with higher intention towards knowledge sharing tend to have a positive behavior towards the process (Zhang 2012).

2. <u>During the Pandemic</u>

In this study, motivation was the result of a combination of economic rewards and reduced workload in order to test its effect on knowledge sharing. Bock (2005) and Zhang (2012) identified that economic rewards failed to positively affect the attitude of colleagues towards knowledge sharing. Similarly, combining economic rewards with reduced workload into a construct titled motivation did not enhance the attitude towards virtual knowledge sharing between engineers (H1', Table 9). The attitude of engineers working remotely was not incentivized through motivation in terms of economic rewards. The pandemic has affected the mentality of individuals, thus negatively affecting their attitude towards work and the environment as a whole.

Enhanced personal relationships are common across engineers working together. Working remotely decreased the frequency of engineers meeting informally and building relationships outside work. This study shows that these relationships affect the attitude of engineers when it comes to sharing knowledge and supporting each other with work (H2',

Table 9). Similarly, to a face-to-face environment, virtual knowledge sharing depends heavily on personal relationships between colleagues as shown by Bock (2005).

One of the most important factors for knowledge sharing when working remotely is ICT. ICT help in speeding up and facilitating the knowledge sharing process depending on their quality (Cabrera et al. 2006) and usability (Lin 2007). ICT aid in removing the constraints due to physical distance and provide richness in remote communication. On the other hand, the construct of knowledge sharing resources incorporates variables related to the availability of resources and opportunities to share knowledge with colleagues. The results of these studies show that the availability of accessible and effective ICT does not increase the opportunities of knowledge sharing (H3', Table 9). These opportunities or resources can be linked to the presence of engineers in the office and the face-to-face meetings they conduct. The frustration from employees towards technology could have altered the results of the survey leading to a biased conclusion. Answering the questions during the peak of a pandemic caused participants to be emotionally affected.

As previously discussed, the intention of engineers to share knowledge virtually is linked to their attitude. The previously shown results prove that a constructive attitude towards knowledge sharing leads to a higher intention to complete this action (H4', Table 9). The individuals' attitude towards an action is driven by their intention to do this action (Ajzen and Fishbein 1980). The intention to share knowledge is directly related to the attitude towards knowledge sharing as shown by Bock (2005). Both these constructs are considered personal factors attributed to the engineers themselves.

Knowledge sharing resources related to the opportunities given to engineers is considered an external factor. Stable, constant, and enhanced knowledge sharing resources facilitate the process of virtually sharing knowledge. However, this ease of transfer has no direct effect on the intention of colleagues to share knowledge (H5', Table 9).

If the employees find it simple and accessible to share their knowledge, their behavior will be shifted towards greater knowledge sharing (Zhang 2012). Behavior is the action itself and facilitating the achievement of this action will logically increase its occurrence. However, the availability of resources and opportunities may facilitate knowledge sharing but did not increase the occurrence of sharing knowledge (H6', Table 9).

Employees with higher intention towards virtual knowledge sharing tend to have a positive behavior towards the process (Zhang 2012). A positive intention towards knowledge sharing showed an enhanced approach to the behavior of knowledge sharing itself in a virtual setting (H7', Table 9). Thus, the personal factor which is intention played a major role in increasing the occurrence of knowledge sharing.

As per the discussed results, most of the factors that affect knowledge sharing are linked to the personal attributes of the individuals. Moreover, these personal factors became heightened when work shifted to a remote setting during the pandemic. This is linked to the fact that the sudden shift to isolation during the pandemic mentally affected individuals and their attitude towards work and knowledge sharing.

B. Practical Implications

Globally, 16% of companies are fully remote (Simovic, 2022). This same study found that about 62% of workers aged 22 to 65 claim to work remotely at least occasionally.

This emphasizes the importance of this study and of finding ways to increase the probability of knowledge sharing in a virtual work-from-home setting.

As previously proven, the resources or opportunities did not play a major role in increasing the probability of sharing knowledge in a virtual setting. Moreover, economic rewards did not motivate employees to increase knowledge sharing. Internal/personal factors such as personal relationships, intention and attitude were the major contributors to incentivizing employees to share knowledge remotely. On the other hand, the external factor ICT supported employees in facilitating the knowledge sharing process remotely.

Based on these results, engineering companies need to focus on the personal drivers and mental wellbeing of employees to guarantee knowledge sharing. All around the world, working-from-home a one or two days a week has become the “new normal”, thus the strategy and approach of companies should be shifted to accommodating this hybrid model and adapting to the new ways of work. Suggestions to ensure constant transfer of knowledge could include company-wide knowledge sharing sessions to expose employees to new initiatives and project ideas developed by their colleagues. These knowledge sharing sessions would portray the achievements of various teams and what they are working on. Moreover, it would encourage employees to share knowledge with each other on a daily basis. Another example is periodic mental health sessions to follow-up with employees’ personal issues. These sessions will support in hitting productivity goals and presenting time for employees to focus on sharing knowledge. Due to the pandemic, anxiety and depression have increased causing people to shift their priorities. This mental condition affects employees performance at work, thus affecting their interest in sharing knowledge and proposing additional initiatives. The Center for Disease Control and Prevention (CDC) statistics show that depression interferes with an employee’s ability to complete “physical job tasks about 20% of the time.” It also can cause a 35% reduction in cognitive performance. Also, the company should focus on organizing informal events to enhance personal relationships between employees and develop friendly acquaintances outside work settings. Employees attending events and communicating with their colleagues will incentivize them to share knowledge when needed.

CHAPTER VIII

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

Knowledge sharing is an asset in a company's portfolio and companies with enhanced knowledge sharing tend to succeed in making revenues and retaining employees. The objective of this study is to assess the factors affecting knowledge sharing among engineers in a physical work setting and in a remote virtual setting. Also, the study focuses on the changes affecting the knowledge sharing drivers due to the shift to a work-from-home environment.

As a first step, a survey was written and distributed to engineers to be able to collect enough data to support the analysis. After the data was collected, SEM was used to test the validity of the identified hypotheses and to check the relationship between the factors and their respective variables. After the analysis was conducted, a list of factors was identified for the situation pre pandemic as well as during pandemic.

In order to emphasize and understand the importance and outcomes of knowledge sharing, a section titled knowledge sharing outcomes was added. The first question was used to assess the ability of individuals to complete work and tasks independently. Most of the respondents (more than 70%) agree that this ability increased when they were obliged to work remotely and from home. When the pandemic started, individuals were forced to work independently and rely on themselves. However, this required extensive knowledge sharing between co-workers to ensure a smooth transition. Another question tackled the frequency of making errors while working remotely. Around 50% of respondents agree that the remote form of work has no direct relationship with likelihood of making errors, thus companies should consider the option of maintaining this hybrid mode of work. On the other side, inevitably the time spent in front of a screen has increased to accommodate virtual meetings and calls. More than 80% of respondents believe that the time spent in front of a screen to share knowledge has increased.

Another topic that was discussed in the survey was the issue of training new joiners and integrating them in the work environment remotely. Based on survey results, it was a bit challenging to train new joiners and to transfer knowledge easily. More than 60% of respondents admit that more readings were given to trainees to accommodate the lack of face-to-face training and support provided as soon as they join the company. Moreover, around 70% of the respondents agree that the time and effort consumed training new joiners has increased to ensure proper integration and transfer of needed skills and knowledge to complete the needed work.

Finally, the sudden shift to virtual work has been challenging to most of the engineers especially considering the nature of their work. The working environment is shifting to a hybrid model and companies must adapt. The most important factor in overcoming the challenges associated with a hybrid model is the constant sharing of knowledge. Knowledge sharing would ensure a smooth transition focusing on the assets of the individuals and their previous experiences. This study lists some of the factors that enhance the knowledge sharing process for both face-to-face and remote forms of work. This work contributes by adding new constructs to the construction knowledge management literature from the performed EFA to understand the drivers behind behavior of engineers in a virtual setting. Practically speaking, suggestions were given to improve individual and team behavior of engineers based on challenges discussed in the analysis. Accordingly, this study is one among the first endeavors for studying the knowledge sharing process among engineers in a virtual remote setting.

Nevertheless, this research work has some limitations or challenges opening the horizons for future works. One of the limitations is the scope of the study that focused on targeting employees of engineering companies only. Another study could assess how results might differ for other types of workers and companies. Considering the model itself, a larger dataset could support in validating the model and the discussed results. The study was conducted during the pandemic and access to employees was rather limited. Another study could consider interviewing engineers and visiting the office to understand how this pandemic practically affected the working environment. Also, this study was based on the availability of a variable factor which is the pandemic. The pandemic is not a constant factor, hence other studies should consider focusing on virtual knowledge sharing without the effects associated with the pandemic. Also, other studies can use data analytics and programming to simulate the behavior of individuals while changing different parameters. Most importantly, participants answering the survey were biased towards the emotional effect of the pandemic at that time. If the same survey is to be distributed again, the results might differ. Thus, studies should consider the analysis away from the direct effect of the pandemic during this specific timeframe. Another limitation is the lack of information regarding the nature and culture of the companies participating in the study. Moreover, the lack of information regarding the disciplines of each of the engineers answering the survey. Different companies and different engineering disciplines react differently to knowledge sharing and reacted differently to the shift to a work-from-home environment during the pandemic. Future studies should consider factoring in the culture at the company itself and how it affects the knowledge sharing process.

APPENDICES

Appendix A: Survey

Knowledge Sharing in a Virtual Environment
Dr. Issam Srour
Marilyn Karam

Hello. My name is Marilyn Karam. I am a graduate student at the Maroun Semaan Faculty of Engineering and Architecture at AUB. I would like to invite you to participate in a research study about the changes employees are facing due to shift to a work from home environment and how they are sharing knowledge.

Before we begin, I would like to take a few minutes to explain why I am inviting you to participate and what will be done with the information you provide. You will be asked to participate in a short survey and answer some background questions followed by other questions to understand the knowledge sharing process. Please stop me at any time if you have questions about the study.

I am doing this study as part of my Master's degree at AUB. I will be sending the survey to several employees from various engineering companies and will use the information as the basis for my thesis. I may also use this information in articles that might be published, as well as in academic presentations. Your individual privacy and confidentiality of the information you provide will be maintained in all published and written data analysis resulting from the study.

Your participation should take approximately 5 minutes. Please understand your participation is entirely on a voluntary basis and you have the right to withdraw your consent or discontinue participation at any time without penalty. The benefits which may reasonably be expected to result from this study are the improvement of the knowledge sharing process in your company. You will receive no payment or compensation for your participation.

If at any time and for any reason, you would prefer not to answer any questions, please feel free to skip those questions. If at any time, you would like to stop participating, please tell me. We can take a break, stop and continue at a later date, or stop altogether. You will not be penalized for deciding to stop participation at any time.

If you have any questions, you are free to ask them now. If you have questions later, you may contact me at mak130@mail.aub.edu. If you have questions about your rights as a participant in this research, you can contact the following office at AUB: irb@aub.edu.lb or +961-01350000 ext:5445

Are you interested in participating in this study?

- ○ Yes
- ○ No

Objective of Survey:

-Assess the changes and effects on the knowledge sharing process after the transition from a face-to-face to a remote work environment
-Analyze the new methods of knowledge sharing and the behavior of employees through virtual platforms
-Identify if employees are more prone to share knowledge remotely rather than face to face

Knowledge Sharing Intention:

Knowledge is defined as the theoretical or practical understanding of information. This knowledge could be acquired through experience and/or from classroom education. Knowledge sharing refers to a process between two or more individuals which consists of transferring and capturing the information. Knowledge flow could occur through meetings, everyday discussions, e-mails, or any other form of communication.

In some of the questions you need to select an answer:
1: Strongly Disagree
2: Disagree
3: Neutral
4: Agree
5: Strongly Agree

The survey will be divided into 5 brief parts:

Part 1 includes a few background and demographic questions.
Part 2 includes general questions concerning the organization you are currently working in.
Part 3 tackles the main survey questions. In this section, the questions need to be answered with respect to your situation prior to the pandemic, i.e. while working in the office.
Part 4 incorporates the same questions as Section 3. However, the questions need to be answered with respect to your situation during the pandemic, i.e. while working from home.
Part 5 includes very few questions portraying the outcomes resulting from the transition of working in the office to working from home.

Please answer this survey if you are engaged in any formal or informal training. The training process could consist of training junior colleagues or being trained by senior colleagues.

Background

1. **Gender**

- Male
- Female
- Prefer not to say
- Other:

2. **Age**

- 21-30
- 31-40
- 41-50
- 51-60
- 61+

3. **Years of Experience**

- 0-5
- 6-10
- 11-15
- 16-20
- 21+

4. **Education**

- Bachelor
- Master's
- PhD
- Other:

Organization

1. **Main Head Office Location**

____

2. **Years working with current organization**

- 0-5
- 6-10
- 11-15
- 16-20
- +21

3. **Did employees work remotely before the COVID-19 pandemic?**

- Yes
- No

4. Will employees pursue work remotely after the COVID-19 pandemic ends?

- Yes
- No

5. To what degree do you think your organization's employees are emotionally affected by the COVID-19 pandemic?

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Attitude

- My knowledge sharing with colleagues is beneficial to others

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- My knowledge sharing with colleagues is harmful

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- My knowledge sharing with colleagues is an enjoyable experience

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- My knowledge sharing with colleagues is valuable to me

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- My knowledge sharing with colleagues is a wise move

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Perceived Behavioral Control

"Perceived behavioral control is the perceived ease or difficulties one has over performing a behavior" (Zhang, 2013)

- I have the resources to support my knowledge sharing with my colleagues

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- I have the opportunities to share knowledge with my colleagues

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- I have the ability to control knowledge sharing with my colleagues

Pre-Lockdown

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Enhanced Personal Relationship

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- My knowledge sharing would strengthen the ties between existing colleagues and me

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- My knowledge sharing would get me well-acquainted with new colleagues

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- My knowledge sharing would create a strong relationship with colleagues who have common interests with me

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

ICT (Information & Communication Technologies)

ICT consist of the methods and technologies used for communication or in this case knowledge sharing. It could vary between online databases, intranet, virtual communities, etc.… High quality technologies facilitate the knowledge sharing transfer by removing temporal and physical distance between colleagues. These means provide access to stored knowledge and increase communication between individuals. (Zhang, 2013)

- ICT allow me to share knowledge with colleagues in my work

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

- ICT speed up knowledge sharing with other colleagues

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- ICT make knowledge sharing easier with colleagues outside the organization

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- ICT provide virtual networks and electronic storage to facilitate knowledge sharing between colleagues

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Knowledge Feedback

- Through sharing my knowledge with colleagues, my mistakes could be corrected by them

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- Through sharing my knowledge with colleagues, I could learn new things based on their responses and comments

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- Through sharing my knowledge with colleagues, I risk being embarrassed by making mistakes

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Motivation

- I will receive monetary rewards in return for my knowledge sharing

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- I will be rewarded by promotions or salary increase in return for my knowledge sharing

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- I will secure my job position by sharing knowledge with my colleagues

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- I will reduce my workload by sharing knowledge with my colleagues

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

Intention

- I intend to share my experience or know-how from work with colleagues more frequently in the future

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

- I intend to inform colleagues where to find knowledge and who to ask for this knowledge

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	⬭	⬭	⬭	⬭	⬭	Strongly Agree

Mark only one oval.

During Lockdown

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- I intend to share my expertise from my education or training with colleagues in a more effective way

Mark only one oval.

Pre-Lockdown

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Mark only one oval.

During Lockdown

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Behavior

- I share my knowledge with others within my work environment

Mark only one oval.

Pre-Lockdown

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Mark only one oval.

During Lockdown

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- I share my technical skills (e.g. construction methods) with colleagues

Mark only one oval.

Pre-Lockdown

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Mark only one oval.

During Lockdown

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- I share official documentation or manuals with colleagues

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- I share project knowledge (e.g. site conditions, project status, client requirements) with colleagues

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

During Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Knowledge Sharing Outcomes

- The ability to do my work autonomously has increased

Pre-Lockdown

Mark only one oval.

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Mark only one oval.

During Lockdown

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- The likelihood of making errors has decreased

Mark only one oval.

Pre-Lockdown

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Mark only one oval.

During Lockdown

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- The time spent in front of a screen to share knowledge has increased

Mark only one oval.

Pre-Lockdown

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Mark only one oval.

During Lockdown

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- The readings required by trainee engineers have increased

Mark only one oval.

Pre-Lockdown

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Mark only one oval.

During Lockdown

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

- The time consumed training engineers has increased

Mark only one oval.

Pre-Lockdown

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Mark only one oval.

During Lockdown

	1	2	3	4	5	
Strongly Disagree	◯	◯	◯	◯	◯	Strongly Agree

Appendix B: Goodness-of-Fit Measures

Goodness-of-Fit Measure	Levels of Acceptable Fit	Acceptability
	Absolute fit measures	
Likelihood ratio chi-square statistic (x2)	Not statistically significant or statistically significant x2 must be less than 2 times model's degrees of freedom	Model may fit the data
Goodness-of-fit index (GFI)	Higher values indicate better fit (0.85)	(Marginal)
Root mean square residual (RMR)	Small values are better (0.076)	(Marginal)
Root mean square error of approximation (RMSEA)	≤ 0.08 (0.09)	Acceptable (marginal)
	Incremental fit measures	
Adjusted goodness-of-fit index (AGFI)	≥ 0.9 (0.8)	(Marginal)
Tucker-Lewis index (TLI)/ Non-normed fit index (NNFI)	≥ 0.9 (0.8)	(Marginal)
Normed fit index (NFI)	≥ 0.9 (0.8)	(Marginal)
Comparative fit index (CFI)	Higher values are better (≥ 0.9)	(Adequate)
Relative fit index (RFI)	Higher values are better	
Incremental fit index (IFI)	Higher values are better	
	Parsimonious fit measures	
Normed chi-square: x2/df	Between 1 and 3	Good
Parsimonious goodness-of-fit index (PGFI)	Higher values are better, greater than 0.5 and closer to 1	Good
Parsimonious normed fit index (PNFI)	Higher values are better, greater than 0.5	Good
Akaike information criterion (AIC)	Smaller values are better (compared to the 2 models done my Amos)	Good

Appendix C: CFA Results – During Pandemic

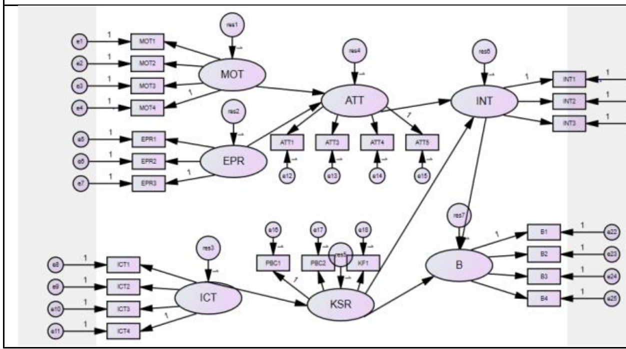
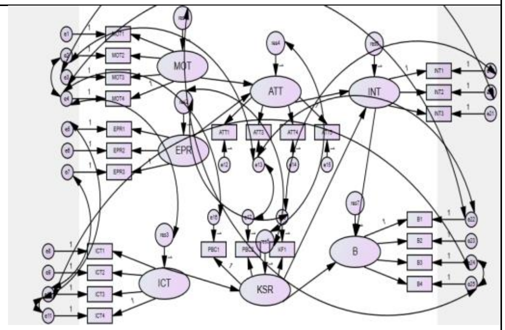
Run 1	Run 18
	

Table 20 First and last structural model on AMOS - During

Run 1

Assessment of normality (Group number 1)

Variable	min	max	skew	c.r.	kurtosis	c.r.
B4	1.000	5.000	-1.525	-7.602	2.936	7.315
B3	1.000	5.000	-1.251	-6.232	1.432	3.569
B2	1.000	5.000	-1.099	-5.478	.940	2.343
B1	1.000	5.000	-1.100	-5.481	1.701	4.238
KF1	1.000	5.000	-.721	-3.594	.101	.251
PBC2	1.000	5.000	-.586	-2.922	-.500	-1.245
PBC1	1.000	5.000	-.760	-3.785	.068	.169
ICT1	1.000	5.000	-1.363	-6.793	2.561	6.382
ICT2	1.000	5.000	-1.373	-6.843	2.412	6.011
ICT3	1.000	5.000	-1.479	-7.370	2.220	5.531
ICT4	1.000	5.000	-1.199	-5.973	1.850	4.609
INT3	2.000	5.000	-.629	-3.135	.102	.255
INT2	2.000	5.000	-.733	-3.654	.364	.907
INT1	2.000	5.000	-.480	-2.393	-.551	-1.372
ATT1	2.000	5.000	-1.043	-5.198	.716	1.785
ATT3	1.000	5.000	-.569	-2.837	-.315	-.784
ATT4	1.000	5.000	-.823	-4.100	.584	1.456
ATT5	1.000	5.000	-1.006	-5.014	.859	2.141
EPR1	1.000	5.000	-.872	-4.347	.837	2.086
EPR2	1.000	5.000	-.657	-3.272	.148	.369
EPR3	1.000	5.000	-.685	-3.416	-.237	-.591
MOT1	1.000	5.000	.934	4.655	.041	.102
MOT2	1.000	5.000	.761	3.793	-.463	-1.154
MOT3	1.000	5.000	.285	1.418	-.909	-2.265
MOT4	1.000	5.000	-.001	-.004	-1.310	-3.264
Multivariate					193.155	32.085

Run 18

Assessment of normality (Group number 1)

Variable	min	max	skew	c.r.	kurtosis	c.r.
B4	1.000	5.000	-1.525	-7.602	2.936	7.315
B3	1.000	5.000	-1.251	-6.232	1.432	3.569
B2	1.000	5.000	-1.099	-5.478	.940	2.343
B1	1.000	5.000	-1.100	-5.481	1.701	4.238
KF1	1.000	5.000	-.721	-3.594	.101	.251
PBC2	1.000	5.000	-.586	-2.922	-.500	-1.245
PBC1	1.000	5.000	-.760	-3.785	.068	.169
ICT1	1.000	5.000	-1.363	-6.793	2.561	6.382
ICT2	1.000	5.000	-1.373	-6.843	2.412	6.011
ICT3	1.000	5.000	-1.479	-7.370	2.220	5.531
ICT4	1.000	5.000	-1.199	-5.973	1.850	4.609
INT3	2.000	5.000	-.629	-3.135	.102	.255
INT2	2.000	5.000	-.733	-3.654	.364	.907
INT1	2.000	5.000	-.480	-2.393	-.551	-1.372
ATT1	2.000	5.000	-1.043	-5.198	.716	1.785
ATT3	1.000	5.000	-.569	-2.837	-.315	-.784
ATT4	1.000	5.000	-.823	-4.100	.584	1.456
ATT5	1.000	5.000	-1.006	-5.014	.859	2.141
EPR1	1.000	5.000	-.872	-4.347	.837	2.086
EPR2	1.000	5.000	-.657	-3.272	.148	.369
EPR3	1.000	5.000	-.685	-3.416	-.237	-.591
MOT1	1.000	5.000	.934	4.655	.041	.102
MOT2	1.000	5.000	.761	3.793	-.463	-1.154
MOT3	1.000	5.000	.285	1.418	-.909	-2.265
MOT4	1.000	5.000	-.001	-.004	-1.310	-3.264
Multivariate					193.155	32.085

Table 21 Normality Assessment – During

Run 1

Bootstrap Distributions (Default model)

ML discrepancy (implied vs sample) (Default model)

```
                               |--------------------
                     199.007   |*
                     229.608   |*
                     260.209   |*****
                     290.810   |************
                     321.411   |*************
                     352.011   |********************
                     382.612   |*****************
N = 500              413.213   |*************
Mean = 372.834       443.814   |*********
S. e. = 3.195        474.415   |******
                     505.016   |****
                     535.616   |**
                     566.217   |*
                     596.818   |*
                     627.419   |*
                               |--------------------
```

Run 18

Bootstrap Distributions (Default model)

ML discrepancy (implied vs sample) (Default model)

```
                               |--------------------
                     184.852   |*
                     212.130   |*
                     239.408   |******
                     266.686   |**********
                     293.964   |**************
                     321.241   |****************
                     348.519   |*****************
N = 500              375.797   |************
Mean = 346.678       403.075   |***********
S. e. = 3.037        430.353   |*******
                     457.631   |****
                     484.909   |**
                     512.187   |*
                     539.465   |*
                     566.743   |*
                               |--------------------
```

Bollen-Stine Bootstrap (Default model)

The model fit better in 500 bootstrap samples.
It fit about equally well in 0 bootstrap samples.
It fit worse or failed to fit in 0 bootstrap samples.
Testing the null hypothesis that the model is correct, Bollen-Stine bootstrap p = .002

Bollen-Stine Bootstrap (Default model)

The model fit better in 413 bootstrap samples.
It fit about equally well in 0 bootstrap samples.
It fit worse or failed to fit in 87 bootstrap samples.
Testing the null hypothesis that the model is correct, Bollen-Stine bootstrap p = .176

Table 22 Bootstrap Distribution - During

Run 1

Notes for Model (Default model)

Computation of degrees of freedom (Default model)

Number of distinct sample moments:	325
Number of distinct parameters to be estimated:	57
Degrees of freedom (325 - 57):	268

Run 18

Notes for Model (Default model)

Computation of degrees of freedom (Default model)

Number of distinct sample moments:	325
Number of distinct parameters to be estimated:	75
Degrees of freedom (325 - 75):	250

Table 23 Degrees of Freedom – During

Run 1

Negative Error Variance

Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
res1	.327	.132	2.476	.013	par_26
res2	.585	.105	5.582	***	par_27
res3	.369	.067	5.491	***	par_28
res4	.381	.067	5.719	***	par_29
res5	.502	.133	3.777	***	par_30
res6	.224	.049	4.598	***	par_31
res7	.176	.041	4.267	***	par_32
e4	1.621	.193	8.409	***	par_33
e3	.641	.085	7.520	***	par_34
e2	.259	.068	3.807	***	par_35
e1	.288	.067	4.297	***	par_36
e7	.332	.051	6.515	***	par_37
e6	.168	.042	4.010	***	par_38
e5	.268	.044	6.061	***	par_39
e15	.193	.038	5.073	***	par_40
e14	.222	.038	5.787	***	par_41
e13	.652	.083	7.872	***	par_42
e12	.293	.039	7.594	***	par_43
e19	.339	.045	7.594	***	par_44
e20	.069	.020	3.393	***	par_45
e21	.158	.026	6.096	***	par_46
e11	.234	.033	7.131	***	par_47
e10	.718	.087	8.297	***	par_48
e9	.113	.030	3.741	***	par_49
e8	.161	.030	5.377	***	par_50
e16	.533	.105	5.077	***	par_51
e17	.300	.120	2.494	.013	par_52
e18	.652	.086	7.568	***	par_53
e22	.272	.041	6.566	***	par_54
e23	.278	.048	5.742	***	par_55
e24	.481	.069	7.006	***	par_56
e25	.417	.057	7.303	***	par_57

Run 18

Variances: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
res1	.475	.159	2.992	.003	par_44
res2	.615	.104	5.886	***	par_45
res3	.347	.066	5.266	***	par_46
res4	.385	.066	5.809	***	par_47
res5	.443	.111	3.996	***	par_48
res6	.234	.048	4.842	***	par_49
res7	.201	.043	4.736	***	par_50
e4	1.519	.190	8.005	***	par_51
e3	.651	.084	7.780	***	par_52
e2	.202	.065	3.134	.002	par_53
e1	.344	.063	5.425	***	par_54
e7	.317	.049	6.429	***	par_55
e6	.158	.040	3.970	***	par_56
e5	.292	.044	6.597	***	par_57
e15	.189	.037	5.175	***	par_58
e14	.228	.038	6.060	***	par_59
e13	.671	.083	8.040	***	par_60
e12	.295	.039	7.660	***	par_61
e19	.329	.043	7.590	***	par_62
e20	.070	.019	3.670	***	par_63
e21	.160	.025	6.380	***	par_64
e11	.255	.035	7.353	***	par_65
e10	.733	.085	8.585	***	par_66
e9	.106	.032	3.284	.001	par_67
e8	.150	.031	4.857	***	par_68
e16	.610	.089	6.876	***	par_69
e17	.245	.091	2.677	.007	par_70
e18	.652	.084	7.745	***	par_71
e22	.203	.041	4.992	***	par_72
e23	.281	.050	5.646	***	par_73
e24	.623	.079	7.845	***	par_74
e25	.516	.064	8.071	***	par_75

Standardized Coefficients

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
ATT	<---	MOT	-.036
ATT	<---	EPR	.535
KSR	<---	ICT	.090
INT	<---	ATT	.606
INT	<---	KSR	.075
B	<---	KSR	.128
B	<---	INT	.631
MOT4	<---	MOT	.410
MOT3	<---	MOT	.720
MOT2	<---	MOT	.898
MOT1	<---	MOT	.884
EPR3	<---	EPR	.799
EPR2	<---	EPR	.895
EPR1	<---	EPR	.822
ATT5	<---	ATT	.857
ATT4	<---	ATT	.827
ATT3	<---	ATT	.611
ATT1	<---	ATT	.670
INT1	<---	INT	.716
INT2	<---	INT	.921
INT3	<---	INT	.834
ICT4	<---	ICT	.782
ICT3	<---	ICT	.510
ICT2	<---	ICT	.915
ICT1	<---	ICT	.868
PBC1	<---	KSR	.698
PBC2	<---	KSR	.835
KF1	<---	KSR	.517
B1	<---	B	.728
B2	<---	B	.783
B3	<---	B	.687
B4	<---	B	.650

Standardized Regression Weights: (Group number 1 - Default model

			Estimate
ATT	<---	MOT	-.141
ATT	<---	EPR	.538
KSR	<---	ICT	-.077
INT	<---	ATT	.608
INT	<---	KSR	.057
B	<---	KSR	.136
B	<---	INT	.647
MOT4	<---	MOT	.488
MOT3	<---	MOT	.714
MOT2	<---	MOT	.919
MOT1	<---	MOT	.860
EPR3	<---	EPR	.812
EPR2	<---	EPR	.902
EPR1	<---	EPR	.803
ATT5	<---	ATT	.864
ATT4	<---	ATT	.826
ATT3	<---	ATT	.611
ATT1	<---	ATT	.674
INT1	<---	INT	.741
INT2	<---	INT	.922
INT3	<---	INT	.839
ICT4	<---	ICT	.759
ICT3	<---	ICT	.489
ICT2	<---	ICT	.921
ICT1	<---	ICT	.878
PBC1	<---	KSR	.650
PBC2	<---	KSR	.867
KF1	<---	KSR	.537
B1	<---	B	.819
B2	<---	B	.791
B3	<---	B	.581
B4	<---	B	.518

Standard Errors

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
ATT	<---	MOT	-.046	.105	-.441	.659	par_9
ATT	<---	EPR	.511	.088	5.799	***	par_10
KSR	<---	ICT	.105	.115	.917	.359	par_22
INT	<---	ATT	.496	.080	6.201	***	par_13
INT	<---	KSR	.063	.070	.899	.369	par_25
B	<---	KSR	.100	.068	1.464	.143	par_23
B	<---	INT	.585	.099	5.904	***	par_24
MOT4	<---	MOT	1.000				
MOT3	<---	MOT	1.454	.307	4.736	***	par_1
MOT2	<---	MOT	1.821	.364	4.997	***	par_2
MOT1	<---	MOT	1.773	.355	4.989	***	par_3
EPR3	<---	EPR	1.000				
EPR2	<---	EPR	1.075	.095	11.362	***	par_4
EPR1	<---	EPR	.976	.091	10.720	***	par_5
ATT5	<---	ATT	1.000				
ATT4	<---	ATT	.947	.085	11.147	***	par_6
ATT3	<---	ATT	.853	.111	7.708	***	par_7
ATT1	<---	ATT	.669	.077	8.642	***	par_8
INT1	<---	INT	1.000				
INT2	<---	INT	1.038	.101	10.231	***	par_11
INT3	<---	INT	1.005	.104	9.651	***	par_12
ICT4	<---	ICT	1.000				
ICT3	<---	ICT	.828	.134	6.182	***	par_14
ICT2	<---	ICT	1.254	.106	11.797	***	par_15
ICT1	<---	ICT	1.156	.101	11.413	***	par_16
PBC1	<---	KSR	1.000				
PBC2	<---	KSR	1.168	.218	5.349	***	par_17
KF1	<---	KSR	.686	.131	5.233	***	par_18
B1	<---	B	1.000				
B2	<---	B	1.199	.146	8.238	***	par_19
B3	<---	B	1.183	.159	7.427	***	par_20
B4	<---	B	.997	.141	7.061	***	par_21

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
ATT	<---	MOT	-.152	.083	-1.840	.066	par_9
ATT	<---	EPR	.513	.085	6.021	***	par_10
KSR	<---	ICT	-.087	.085	-1.027	.304	par_22
INT	<---	ATT	.515	.097	5.307	***	par_13
INT	<---	KSR	.054	.097	.553	.580	par_25
B	<---	KSR	.131	.086	1.524	.127	par_23
B	<---	INT	.658	.104	6.320	***	par_24
MOT4	<---	MOT	1.000				
MOT3	<---	MOT	1.195	.212	5.643	***	par_1
MOT2	<---	MOT	1.518	.262	5.790	***	par_2
MOT1	<---	MOT	1.431	.242	5.912	***	par_3
EPR3	<---	EPR	1.000				
EPR2	<---	EPR	1.061	.087	12.225	***	par_4
EPR1	<---	EPR	.927	.079	11.704	***	par_5
ATT5	<---	ATT	1.000				
ATT4	<---	ATT	.938	.081	11.608	***	par_6
ATT3	<---	ATT	.847	.103	8.186	***	par_7
ATT1	<---	ATT	.664	.075	8.885	***	par_8
INT1	<---	INT	1.000				
INT2	<---	INT	.999	.088	11.293	***	par_11
INT3	<---	INT	.974	.094	10.411	***	par_12
ICT4	<---	ICT	1.000				
ICT3	<---	ICT	.814	.106	7.698	***	par_14
ICT2	<---	ICT	1.300	.116	11.225	***	par_15
ICT1	<---	ICT	1.204	.109	11.040	***	par_16
PBC1	<---	KSR	1.000				
PBC2	<---	KSR	1.287	.193	6.670	***	par_17
KF1	<---	KSR	.770	.135	5.679	***	par_18
B1	<---	B	1.000				
B2	<---	B	1.066	.115	9.235	***	par_19
B3	<---	B	.876	.127	6.905	***	par_20
B4	<---	B	.682	.111	6.161	***	par_21

Table 24 Offending Estimates - During

Goodness-of-Fit Measure	**Levels of Acceptable Fit**	**Run 1**	**Run 18**	**Acceptability**
Absolute fit measures				
Likelihood ratio chi-square statistic (x2)	Not statistically significant or statistically significant x2 must be	657.395 (2x268=536)	407.358 (2x250=500)	Acceptable

	less than 2 times model's degrees of freedom			
Goodness-of-fit index (GFI)	Higher values indicate better fit	0.743	0.826	Acceptable
Root mean square residual (RMR)	Small values are better	0.130	0.095	Acceptable
Root mean square error of approximation (RMSEA)	≤ 0.08	0.099	0.065	Acceptable
Incremental fit measures				
Adjusted goodness-of-fit index (AGFI)	≥ 0.9	0.688	0.774	Marginal
Tucker-Lewis index (TLI)/ Non-normed fit index (NNFI)	≥ 0.9	0.788	0.908	Acceptable
Normed fit index (NFI)	≥ 0.9 (0.8)	0.721	0.827	Acceptable
Comparative fit index (CFI)	Higher values are better (≥ 0.9)	0.810	0.923	Acceptable
Relative fit index (RFI)	Higher values are better	.687	0.792	Acceptable
Incremental fit index (IFI)	Higher values are better	0.813	0.925	Acceptable
Parsimonious fit measures				
Normed chi-square: x2/df	Between 1 and 3	2.45	1.63	Acceptable
Parsimonious goodness-of-fit index (PGFI)	Higher values are better, greater than 0.5 and closer to 1	0.613	0.636	Acceptable
Parsimonious normed fit index (PNFI)	Higher values are better, greater than 0.5	0.644	0.689	Acceptable
Akaike information criterion (AIC)	Smaller values are better (compared to the 2 models done my Amos)	771.395	557.358	Acceptable

Table 25 Goodness-of-Fit measures - During

Run 1	Run 18

Factor Loading

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
ATT	<---	MOT	-.036
ATT	<---	EPR	.535
KSR	<---	ICT	.090
INT	<---	ATT	.606
INT	<---	KSR	.075
B	<---	KSR	.128
B	<---	INT	.631
MOT4	<---	MOT	.410
MOT3	<---	MOT	.720
MOT2	<---	MOT	.898
MOT1	<---	MOT	.884
EPR3	<---	EPR	.799
EPR2	<---	EPR	.895
EPR1	<---	EPR	.822
ATT5	<---	ATT	.857
ATT4	<---	ATT	.827
ATT3	<---	ATT	.611
ATT1	<---	ATT	.670
INT1	<---	INT	.716
INT2	<---	INT	.921
INT3	<---	INT	.834
ICT4	<---	ICT	.782
ICT3	<---	ICT	.510
ICT2	<---	ICT	.915
ICT1	<---	ICT	.868
PBC1	<---	KSR	.698
PBC2	<---	KSR	.835
KF1	<---	KSR	.517
B1	<---	B	.728
B2	<---	B	.783
B3	<---	B	.687
B4	<---	B	.650

Standardized Regression Weights: (Group number 1 - Default model

			Estimate
ATT	<---	MOT	-.141
ATT	<---	EPR	.538
KSR	<---	ICT	-.077
INT	<---	ATT	.608
INT	<---	KSR	.057
B	<---	KSR	.136
B	<---	INT	.647
MOT4	<---	MOT	.488
MOT3	<---	MOT	.714
MOT2	<---	MOT	.919
MOT1	<---	MOT	.860
EPR3	<---	EPR	.812
EPR2	<---	EPR	.902
EPR1	<---	EPR	.803
ATT5	<---	ATT	.864
ATT4	<---	ATT	.826
ATT3	<---	ATT	.611
ATT1	<---	ATT	.674
INT1	<---	INT	.741
INT2	<---	INT	.922
INT3	<---	INT	.839
ICT4	<---	ICT	.759
ICT3	<---	ICT	.489
ICT2	<---	ICT	.921
ICT1	<---	ICT	.878
PBC1	<---	KSR	.650
PBC2	<---	KSR	.867
KF1	<---	KSR	.537
B1	<---	B	.819
B2	<---	B	.791
B3	<---	B	.581
B4	<---	B	.518

Critical Ratio

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
ATT	<---	MOT	-.046	.105	-.441	.659	par_9
ATT	<---	EPR	.511	.088	5.799	***	par_10
KSR	<---	ICT	.105	.115	.917	.359	par_22
INT	<---	ATT	.496	.080	6.201	***	par_13
INT	<---	KSR	.063	.070	.899	.369	par_25
B	<---	KSR	.100	.068	1.464	.143	par_23
B	<---	INT	.585	.099	5.904	***	par_24
MOT4	<---	MOT	1.000				
MOT3	<---	MOT	1.454	.307	4.736	***	par_1
MOT2	<---	MOT	1.821	.364	4.997	***	par_2
MOT1	<---	MOT	1.773	.355	4.989	***	par_3
EPR3	<---	EPR	1.000				
EPR2	<---	EPR	1.075	.095	11.362	***	par_4
EPR1	<---	EPR	.976	.091	10.720	***	par_5
ATT5	<---	ATT	1.000				
ATT4	<---	ATT	.947	.085	11.147	***	par_6
ATT3	<---	ATT	.853	.111	7.708	***	par_7
ATT1	<---	ATT	.669	.077	8.642	***	par_8
INT1	<---	INT	1.000				
INT2	<---	INT	1.038	.101	10.231	***	par_11
INT3	<---	INT	1.005	.104	9.651	***	par_12
ICT4	<---	ICT	1.000				
ICT3	<---	ICT	.828	.134	6.182	***	par_14
ICT2	<---	ICT	1.254	.106	11.797	***	par_15
ICT1	<---	ICT	1.156	.101	11.413	***	par_16
PBC1	<---	KSR	1.000				
PBC2	<---	KSR	1.168	.218	5.349	***	par_17
KF1	<---	KSR	.686	.131	5.233	***	par_18
B1	<---	B	1.000				
B2	<---	B	1.199	.146	8.238	***	par_19
B3	<---	B	1.183	.159	7.427	***	par_20
B4	<---	B	.997	.141	7.061	***	par_21

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
ATT	<---	MOT	-.152	.083	-1.840	.066	par_9
ATT	<---	EPR	.513	.085	6.021	***	par_10
KSR	<---	ICT	-.087	.085	-1.027	.304	par_22
INT	<---	ATT	.515	.097	5.307	***	par_13
INT	<---	KSR	.054	.097	.553	.580	par_25
B	<---	KSR	.131	.086	1.524	.127	par_23
B	<---	INT	.658	.104	6.320	***	par_24
MOT4	<---	MOT	1.000				
MOT3	<---	MOT	1.195	.212	5.643	***	par_1
MOT2	<---	MOT	1.518	.262	5.790	***	par_2
MOT1	<---	MOT	1.431	.242	5.912	***	par_3
EPR3	<---	EPR	1.000				
EPR2	<---	EPR	1.061	.087	12.225	***	par_4
EPR1	<---	EPR	.927	.079	11.704	***	par_5
ATT5	<---	ATT	1.000				
ATT4	<---	ATT	.938	.081	11.608	***	par_6
ATT3	<---	ATT	.847	.103	8.186	***	par_7
ATT1	<---	ATT	.664	.075	8.885	***	par_8
INT1	<---	INT	1.000				
INT2	<---	INT	.999	.088	11.293	***	par_11
INT3	<---	INT	.974	.094	10.411	***	par_12
ICT4	<---	ICT	1.000				
ICT3	<---	ICT	.814	.106	7.698	***	par_14
ICT2	<---	ICT	1.300	.116	11.225	***	par_15
ICT1	<---	ICT	1.204	.109	11.040	***	par_16
PBC1	<---	KSR	1.000				
PBC2	<---	KSR	1.287	.193	6.670	***	par_17
KF1	<---	KSR	.770	.135	5.679	***	par_18
B1	<---	B	1.000				
B2	<---	B	1.066	.115	9.235	***	par_19
B3	<---	B	.876	.127	6.905	***	par_20
B4	<---	B	.682	.111	6.161	***	par_21

Table 26 Indicator Loadings – During

Item	Construct	Cronbach's alpha		λ		λ^2		ε (ERROR VARIANCE)		Composite Reliability		Variance Extracted	
		Run 1	Run 18	Run 1	Run 18	Run 1	Run 18	Run 1	Run 18	Run 1	Run 18	Run 1	Run 18
ATT1	Attitude			0.670	0.674	0.449	0.454	0.551	0.546	0.83	0.84	0.56	0.56
ATT3				0.611	0.611	0.373	0.373	0.627	0.627				
ATT4				0.827	0.826	0.684	0.682	0.316	0.318				
ATT5				0.857	0.864	0.734	0.746	0.266	0.254				
	SUM			2.965	2.975	2.241	2.256	1.759	1.744				
EPR1	Enhanced Personal Relationship			0.822	0.803	0.676	0.645	0.324	0.355	0.88	0.88	0.71	0.71
EPR2				0.895	0.902	0.801	0.814	0.199	0.186				
EPR3				0.799	0.812	0.638	0.659	0.362	0.341				
	SUM			2.516	2.517	2.115	2.118	0.885	0.882				
MOT 1	Motivation			0.884	0.860	0.781	0.740	0.219	0.260	0.83	0.84	0.57	0.58
MOT 2				0.898	0.919	0.806	0.845	0.194	0.155				
MOT 3				0.720	0.714	0.518	0.510	0.482	0.490				
MOT 4				0.410	0.488	0.168	0.238	0.832	0.762				
	SUM			2.912	2.981	2.274	2.332	1.726	1.668				
ICT1	Information & Comm. Technologie s			0.868	0.878	0.753	0.771	0.247	0.229	0.86	0.86	0.62	0.61
ICT2				0.915	0.921	0.837	0.848	0.163	0.152				
ICT3				0.510	0.489	0.260	0.239	0.740	0.761				
ICT4				0.782	0.759	0.612	0.576	0.388	0.424				
	SUM			3.075	3.047	2.462	2.434	1.538	1.566				
KSR1	Knowledge Sharing Resources			0.517	0.537	0.267	0.288	0.733	0.712	0.73	0.73	0.48	0.49
KSR2				0.835	0.867	0.697	0.752	0.303	0.248				
KSR3				0.698	0.650	0.487	0.423	0.513	0.578				
	SUM			2.050	2.054	1.452	1.463	1.548	1.537				
B1	Behavior			0.728	0.819	0.530	0.671	0.470	0.329	0.81	0.78	0.51	0.48
B2				0.783	0.719	0.613	0.626	0.387	0.374				
B3				0.687	0.581	0.472	0.338	0.528	0.662				
B4				0.650	0.518	0.423	0.268	0.578	0.732				
	SUM			2.848	2.709	2.038	1.902	1.962	2.908				
INT1	Intention			0.716	0.741	0.513	0.549	0.487	0.451	0.87	0.87	0.69	0.70
INT2				0.921	0.922	0.848	0.850	0.152	0.150				
INT3				0.834	0.839	0.696	0.704	0.304	0.296				
	SUM			2.471	2.502	2.056	2.103	0.944	0.897				

Table 27 Measurement Model Fit - During

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