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The Role of Transactive Memory System on Knowledge Creation in IT Projects to Accelerate Digital Innovation

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Abstract. In 21st century globalization features a high degree of competition, which compels Information Technology (IT) project managers to evolve in order to maintain their position in workplace. Transactive Memory System (TMS) is an antecedent of Knowledge Creation (KC) that has been proposed in previous articles of Tung et al. (2022) as having relationship to the process of knowledge creation to accelerate digital innovation (DI). This paper discusses an empirical investigation into relationship between TMS, KC and DI. Structural equation modelling was applied to a data set consisting of 403 IT project managers who were employed by MSC IT companies. We found that TMS has a positive impact on KC, resulting KC to foster DI. This article lends support to the research framework proposed by past literature, which indicates that it is necessary to generate new knowledge in order to be able to develop DI in IT initiatives and connect KC and DI through the lens of Theory of Organisational KC theory. The practical implication is when project managers are required to work in an environment characterised by volatility, uncertainty, complexity, and ambiguity, TMS can promote KC to achieve competitive advantages, which in turn help facilitate the DI. This study provides empirical evidence on how KC has a direct impact on DI and add to the current body of knowledge.

Keywords: Knowledge Creation, Digital Innovation, Information Technology, Transactive Memory System

1. Introduction

Malaysian government has set target to achieve developed nation status by 2025 through the implementation of Industry 4.0 (I4.0). I4.0 is built on the utilisation of various technological advancements, such as Big Data Analytics, Autonomous Robots, Internet of Things, Cyber-Security, Cloud Computing, Additive Manufacturing, and Augmented Reality (Rüßmann et al., 2015). As a result, National Industry 4.0 Strategy and Share Prosperity Vision 2030 have been introduced by the Malaysian government with the aim of expediting the adoption of high-technology to enhance efficiency and competitiveness in the Information Technology (IT) sectors.

The implementation of advanced technology within the context of I4.0 is anticipated to expedite the process of knowledge creation (KC) and facilitate the development of digital innovation (DI). KC is a dynamic amalgamation of structured experience, personal values, situational context, and unstructured experience that serves as a foundation for assessing and developing novel experiences and information (Davenport and Prusak, 2000).

Nevertheless, past studies found the emergence of I4.0 has brought transformation in the field of IT projects. The decrease in social contact resulting from globalisation and remote work poses a significant challenge for IT project managers. Specifically, past literatures reported IT project managers lack of transactive memory system (TMS) to effectively identify team knowledge when confronted with crises, constantly changing situations and the need to determine solutions to problems (Ren, 2020, Krasnokutska and Podoprykhina, 2020).

In meantime, IT project managers play a crucial role in comprehending, amalgamating, and implementing technical expertise to facilitate the creation of novel solutions (Nagaraj et al., 2020). IT project managers' expertise can provide various benefits such as enhancing the clarity of purpose, generating a sense of urgency, accelerating execution speed, refining marketing messages, boosting employee motivation, and contributing to market success through KC to accelerate DI (Mahmoud-Jouini et al., 2016). Past studies have examined the correlation between TMS and KC within the IT sector (Cao and Ali, 2018), as well as in the manufacturing and petrochemical industries (Choi et al., 2010) and higher education institutions (Lewis et al., 2005). Nevertheless, the relationship between KC and DI has not been addressed.

This study aims to fill a gap in the existing literature by employing a proposed theoretical model developed by Tung et al. (2022). The model establishes a connection between TMS and KC, and KC linked to DI. The present study employs a dataset consisting of surveys obtained from 403 IT project managers. This study makes a contribution to the existing literature by utilising the Theory of Organisational Knowledge Creation (TOKC) and Transactive Memory (TM) theory to assess the correlation between KC and DI.

The proposed research model suggests that there exists a positive correlation between TMS and KC, and that KC has a positive association with DI. The subsequent sections of this paper are structured in the following manner. Section 2 provides a comprehensive review of the theoretical framework and hypotheses. Section 3 outlines the methodology and data used in the study. Finally, Section 4 presents the empirical analysis and results. Section 5 presents a comprehensive analysis of the results obtained from the research, while Section 6 offers a summary of the study's key findings and draws conclusions based on the evidence presented.

2. Literature Review

2.1. Transactive Memory System

The theory of transactive memory posits that it is a collective attribute of a team and is not exclusively attributed to any one individual within the team. Over time, it has been constructed through the contributions of its individual constituents (Wegner, 1987). In addition, TMS pertains to a cognitive framework in which personalised information is encoded, retained, and retrieved through a shared cognitive structure that emphasises comprehension of one another's distinct knowledge domains. (Wegner, 1987). The concept comprises of three sub-elements including specialization, credibility, and co-ordination (Lewis et al., 2005).

The perception of a team member's ability to effectively handle a task would determine their level of credibility (Akgün et al., 2006). The establishment of high credibility among team members has been shown to serve as motivating factor for increased collaboration, as individuals are more likely to rely on the competence of their peers (Akgün et al., 2006). This collaborative environment facilitates the creation of new knowledge and enables the transfer of tacit knowledge among multiple team members (Martin and Bachrach, 2018). The process of knowledge transfer is an integral component of the KC process (Nonaka and Nishihara, 2018).

Previous research has indicated that the utilisation of TMS has resulted in enhanced innovation performance, as evidenced by studies conducted by Steinberg et al. (2017) and Da Costa et al. (2018). This improvement has been attributed to the Internalization and Socialization modes of KC process, as identified by Whitehead et al. (2016) and Khachlouf and Quélin (2018).

2.2. Knowledge Creation

Knowledge Creation refers to continuous endeavour of obtaining fresh perspectives, insights, and information, which enables one to surpass the constraints of their prior self and evolve into a new self (Nonaka and Takeuchi, 1995). Nonaka and Takeuchi (1995) proposed the TOKC, which suggests that the process of KC is facilitated through four stages: socialization, externalization, combination, and internalisation. These stages are collectively referred to as the SECI process.

Socialization refers to the process of individuals engaging in direct interpersonal interactions that facilitate the sharing of implicit knowledge as a result of their physical and cognitive proximity (Nonaka and Takeuchi, 1995). The process of externalisation requires individuals to surpass their personal boundaries in order to disseminate tacit knowledge acquired through socialisation to other members of the group. This is achieved by articulating the knowledge in explicit form, thereby enhancing its accessibility and comprehensibility to other members of the group (Nonaka and Takeuchi, 1995).

Combination process necessitates the transcendence of groups, wherein newly acquired knowledge is integrated with pre-existing organisational knowledge to facilitate the distribution of it in explicit knowledge (Nonaka and Takeuchi, 1995). Lastly, internalization pertains to the process by which individuals assimilate explicit knowledge and transform it into implicit tacit knowledge (Nonaka and Takeuchi, 1995).

KC's research pertains to multidimensional studies that encompass various aspects of human interactions, organisational behaviour, organisational learning, and leadership (Kao and Wu, 2016, Goswami and Agrawal, 2022). Previous research has acknowledged that KC constitutes a sub-process within the broader framework of knowledge management (KM) (Abbas and Sağsan, 2019). The differentiation between KM and KC is predicated upon their distinct areas of research emphasis, with KM being primarily concerned with the socio-technological dimension. Conversely, the research conducted by KC is investigating the socio-cognitive perspective in the field of knowledge management (Autio et al, 2021).

2.3. Digital Innovation

Digital Innovation (DI) pertains to the utilisation of nascent technologies in diverse creative endeavours. (Nambisan et al., 2017). Previous research conducted over the years demonstrates the extensive scope and profound insights offered by the literature on DI. Concurrently, while organisations are seeking novel insights on digital transformation, DI literature remains ambiguous and lacks a cohesive viewpoint (Kohli and Melville, 2019).

Past literature explicates the fundamental attributes of DI which is digital information that underlie the development of digital products, services, and processes (Yoo et al., 2010). Specifically, digital information can be stored, modified, transmitted, and monitored, as well as its programmable nature and self-referentiality. Fichman et al. (2014) delineated the four discrete stages of the DI procedures, namely discovery, development, diffusion, and impact, based on the pre-existing DI definitions.

Kohli and Melville (2019) proposed a theoretical framework that incorporates various DI activities, namely initiate, develop, implement, and exploit, to generate outcomes that encompass products, services, or processes. Firk et al. (2021) introduced a novel construct of digital knowledge, characterised by competencies and proficiencies in IT domains that are positively linked with DI.

Lyytinen's (2022) proposed three distinct categories of embedding that serve to define DI. These categories include operational embedding, virtual embedding, and contextual embedding. Each of these elements represents a leverage point for the potential expansion of DI, and they interact in a dynamic manner.

2.4. Linking Transactive Memory System to Knowledge Creation

TMS has been found to have a positive impact on the ability to create new knowledge (Cao and Ali, 2018) by leveraging the expertise of fellow members for the purpose of generating innovative knowledge (Smith et al., 2005). Moreover, the employment of TMS enabled the transmission of implicit knowledge (Martin and Bachrach, 2018) and making the transfer of knowledge which is a crucial element of KC (Nonaka and Nishihara, 2018).

Both Steinberg et al. (2017) and Da Costa et al. (2018) found that TMS was responsible for an increase in innovative performance. Internalization, as stated by Whitehead et al. (2016), and the socialisation process of KC, as described by Khachlouf and Quélin (2018), have both contributed to the improvement in innovation performance that has been achieved as a result of their contributions. (2018). Thus, the following hypothesis is proposed:

H1. TMS is positively related with KC.

2.5. Linking Knowledge Creation to Digital Innovation

KC is an essential component for fostering innovative ideas and improving overall organisational effectiveness. (Konno and Schillaci, 2021). Previous studies have demonstrated that there is a significant positive association between the production of new information and the introduction of novel ideas. (Alshanty and Emeagwali, 2019, Konno and Schillaci, 2021). According to the findings of a number of research, DI has been discovered to have a substantial influence on the persons' personalities as well as their occupational choices and their professional growth (Del Giudice et al., 2021).

In organisations, individuals are able to learn specialised information through KC, and they may then combine that knowledge to produce a new body of knowledge, which ultimately leads to the development of new DI (Nambisan, 2017; Pershina et al., 2019). Thus, the following hypothesis is proposed:

H2. KC is positively related with DI.

The proposed theoretical model is shown in Figure 1, which is adapted from Tung et al.'s (2022) work. It posits that there exists a positive relationship between TMS and KC. Furthermore, it suggests that KC plays a crucial role in expediting the formation of DI.

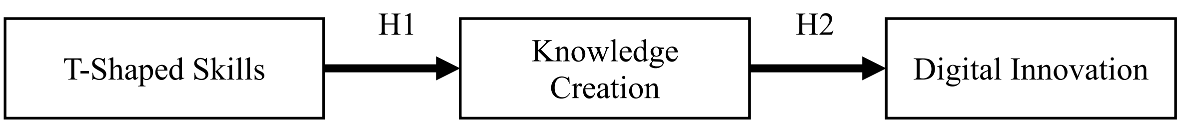

Fig. 1: Theoretical Model

3. Method

3.1. Population

The population for this study is IT project managers, who possess comprehensive knowledge of project operations and are responsible for guiding the project and supporting team members and stakeholders to the fullest extent possible. Hence, the project manager can offer significant insights. The present study seeks to identify eligible participants who are project managers employed in IT companies certified by the Multimedia Super Corridor (MSC) in Malaysia's Klang Valley. The inclusion criteria require respondents to possess a minimum of five years of experience in managing IT projects. The exploration of project managers' feedback regarding the antecedents of knowledge creation is believed to facilitate the growth of the sector and innovation, particularly in Malaysia.

The selection of the IT sector in Malaysia as the subject of study was based on specific reasons. Initially, it is noteworthy that in 2021, the information technology industry constituted 22.6% of Malaysia's gross domestic product (ITA, 2022). The IT software and service sector has experienced a growth rate twice in IT industry in the past, primarily due to the substantial support provided by the Malaysian government. Moreover, the escalating accessibility and prevalence of the Internet within Malaysia are stimulating consumer demand.

3.2. Sample and Data Collection

The study utilised non-probability sampling techniques in selecting participants. The author elaborated extensively on the rationales for utilising non-probability purposive sampling as per Rowley's (2014) recommendation. The predominant use of non-probability samples in social science research is due to the indistinct boundaries surrounding who may or may not be excluded from the population. Secondly, the task of compiling a complete sampling frame is often a daunting challenge in practical situations. In addition, it is noteworthy that attaining a response rate of 100% is improbable even when a researcher is successful in obtaining a suitable sampling frame and executing probabilistic sampling, as non-response may introduce a potential source of bias.

Notion to Hair et al. (2014), a minimum sample size of 200 is required for conducting Structural Equation Modeling (SEM) analysis. G Power software version 3.1 was utilised to determine the minimum sample size required for the study. The calculation from G Power software indicate that a sample size of 146 respondents is necessary, with a medium impact size of 0.15. The study adopts recognised level of significance (α) of 0.05 and a predicted power ($1-\beta$) of 0.95, which will serve as the accepted power level for the test.

Four hundred online questionnaires were disseminated to project managers employed at IT firms in Malaysia's Klang Valley that have been operate in Multimedia Super Corridor (MSC) area. The data were gathered between the months of February and August in the year 2022. The utilisation of online questionnaires is selected because it rejects responses that exhibit missing values, thus reducing the possibility of data loss that may arise from such missing values. In the event that any of the criteria for non-standard responses are satisfied, the online survey submissions shall be promptly declined.

3.3. Measures

The constructs of the research were adopted from Tung et al. (2022) pertaining to the subjects under examination. The primary constructs under investigation in this study are assessed using seven-point Likert-scales from strongly disagree to strongly agree. The measures of constructs were derived from prior research. TMS measures were derived from Lee and Choi's (2003) while the KC measures were adapted from Choi, Lee, and Yoo's (2010). Additionally, DI measurement was adapted from Nylén and Holmström (2015) and Su et al. (2013).

Henseler et al. (2018) posited that structural equations can be measured using three distinct models, namely common factor models, causal indicator models, and composite models. The present study models the measurements for the variables as composites, which are design constructs that stem from theoretical thinking (Henseler, 2018). As a result, Mode A composites have been utilised for the purpose of operationalization.

3.4. Data analysis

To investigate the given hypotheses, this study used Partial Least Squares (PLS) path modeling, which is a variance-based Structural Equation Modeling (SEM) approach recommended by Henseler et al. (2018). The use of PLS-SEM allows the creation of a research model that correctly depicts a specified hypothesis. This is accomplished by converting theoretical notions into unobservable variables known as latent variables and empirical conceptions into indicators.

Notion to Henseler (2018), Partial Least Squares (PLS) is used in variety of study genres including confirmatory, explanatory, exploratory, descriptive, and predictive research. The objective of this study is to use confirmatory research to examine the relationship between independent variables and dependent variables. To evaluate the measurement model, the study used SmartPLS 3 analytic software as suggested by Sarstedt et al. (2016).

4. Results

A total of 310 questionnaires were filled out by participants out of a total of 400 that were distributed. As a result of the survey's administration, a total response rate of 77.5% was obtained. After the straight linings were removed, the total number of completed questionnaires was 304, with a net response rate of 76%. Jorg et al. (2016) suggested three-stage approach for evaluating the PLS-SEM model. First, begin with the identification of the model assessment. Secondly, it is imperative to assess the reliability and validity of the measurement model. Thirdly, the path modelling within the structural model must be evaluated.

The respondents' demographic indicates that 62.5% (190 participants) of the respondents were male, while 37.5% (114 participants) were female. With regards to ethnicity, the majority of respondents, specifically 58.6%, identified as Chinese. Meanwhile, 19.7% of the participants identified as Malay, 17.1% as Indian, and the remaining 4.6% identified as belonging to other ethnic groups. The results indicate that significant proportion of participants (53.6%) possess work experience ranging from 5 to 10 years in the field of IT. Additionally, 22.7% of the respondents reported having an experience of 11 to 15 years, whereas 23.7% of the participants had 16 or more years of experience.

4.1. Measurement model

The assessment of the model fit was conducted by calculating the Standardised Root Mean Square Residual (SRMR), following the recommendations outlined by Henseler et al. (2015). The SRMR values of saturated model (0.15) and estimated model (0.16) are insignificant as they exceed the threshold of 0.08 (Hu and Bentler, 1999). The results indicate that the level of adequacy of the research model's fit is insufficient.

However, according to Hair et al. (2017), The utilisation of SRMR as the sole metric is employed to determine the potential for a misleading model fit. The influence of SRMR cannot be exclusively attributed to the degree of model misrepresentation. Additional variables, such as the magnitude of factor loading and the dimensions of the model, could potentially impact the SRMR.

Table 1: Indicator loadings, Cronbach's Alpha, CR and AVE output

Construct	Indicator	Outer Loading	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Transactive Memory System	TMS1	0.91	0.85	0.93	0.61
	TMS2	0.86			
	TMS4	0.67			
	TMS5	0.59			
	TMS6	0.62			
Knowledge Creation	SOC1	0.77	0.87	0.89	0.62
	SOC2	0.81			
	SOC3	0.83			
	SOC4	0.73			
	EXT1	0.91			
	EXT2	0.72			
	EXT3	0.67			
	EXT4	0.84			
	EXT5	0.71			
	COM1	0.78			
	COM2	0.75			
	COM3	0.87			
	COM4	0.81			
	COM5	0.56			
	INT1	0.73			
	INT2	0.85			
	INT3	0.83			
	INT4	0.71			
Digital Innovation	DIN1	0.72	0.81	0.83	0.57
	DIN3	0.84			
	DIN4	0.83			
	DIN5	0.69			
	DIN6	0.64			

Table 1 summarises the measurement model findings from the PLS-SEM analysis, which include indicator loadings, Cronbach's Alpha (CA), Composite Reliability (CR) and Average Variance Extracted (AVE). The loading of the indicators met the minimum threshold value of 0.71, as recommended by Hair et al. (2017), indicating that the indicators' reliability was achieved. The removal of indicators DIN2 and TMS3 with loadings of 0.41 and 0.39 respectively improve the values of CR and AVE for the constructs.

All constructs' CA were reported more than the minimum required criterion of 0.70 (Roldán and Sánchez-Franco, 2012). All constructs' CR values are above recommended threshold of 0.70 (Bagozzi and Yi, 1998), AVE values above than the specified minimal level of 0.50 (Bagozzi and Yi, 1998) indicating that the convergent validity was achieved.

4.2. Structural model

Table 2 summarises the structural model findings from the PLS-SEM analysis, which include standardised path coefficients (ß), p-value, t value, R square adjusted and the confidence interval bias corrected. A one-tailed test will be utilised if the coefficient has a positive sign based on the hypothesis that predicts the relationship (Kock, 2015). The estimates' stability was investigated using percentile confidence generated from a bootstrap test with 5,000 resamples (Hair et al., 2014). Furthermore, Variance Inflation Factor (VIF) created for the exogenous latent variable in the model is less than 5.0 (Hair et al., 2017), indicating that there was no collinearity between the predictor variable.

Table 2: Standardised path coefficients (ß), p-values, and confidence intervals.

Hypotheses	**Beta Value (ß)**	**p value**	**t value**	**R square adjusted**	**Confidence interval bias corrected**	
					lower bias corrected bootstrap 95%	**upper bias corrected bootstrap 95%**
H1: Transactive Memory System →Knowledge Creation	0.41	0.000**	8.93	0.17	0.31	0.49
H2: Knowledge Creation → Digital Innovation	0.60	0.000**	17.97	0.36	0.53	0.66

Note: ** p < 0.001

The findings indicate that H1 was supported, as evidenced by the statistically significant positive correlation between TMS and KC ($ß = 0.41$, $p < 0.001$). This implies that TMS enhances KC among IT project managers and team members. Hypothesis H2 was supported as the study demonstrate a statistically significant positive correlation ($ß = 0.60$, $p < 0.001$) between KC and DI. This means that KC helps IT project managers and team members improve their DI. The upper and lower bounds of the bootstrap confidence interval do not contain zero numbers. As a result, both hypotheses H1 & H2 were accepted.

In the case with any data that is self-reported, there exists a possibility for the occurrence of Common Method Bias (CMB). This issue has been addressed in accordance with prior scholarly works (Podsakoff et al., 2003; Chin et al., 2013). Podsakoff et al. (2003) proposed the incorporation of marker variable in the research model. By introducing a marker variable adopted from Oreg (2003) to the endogenous construct, the discrepancy between R square value prior to and post the inclusion of the marker variable is evaluated. The R square discrepancy prior to and post the inclusion of the marker variable observed in DI (0.002), KC (0.003), and TMS (0.019) does not meet the criteria for statistical significance. The analysis results suggest that the potential impact of CMB on this study is not a significant concern. Figure 2 shown the results from structural equation analysis.

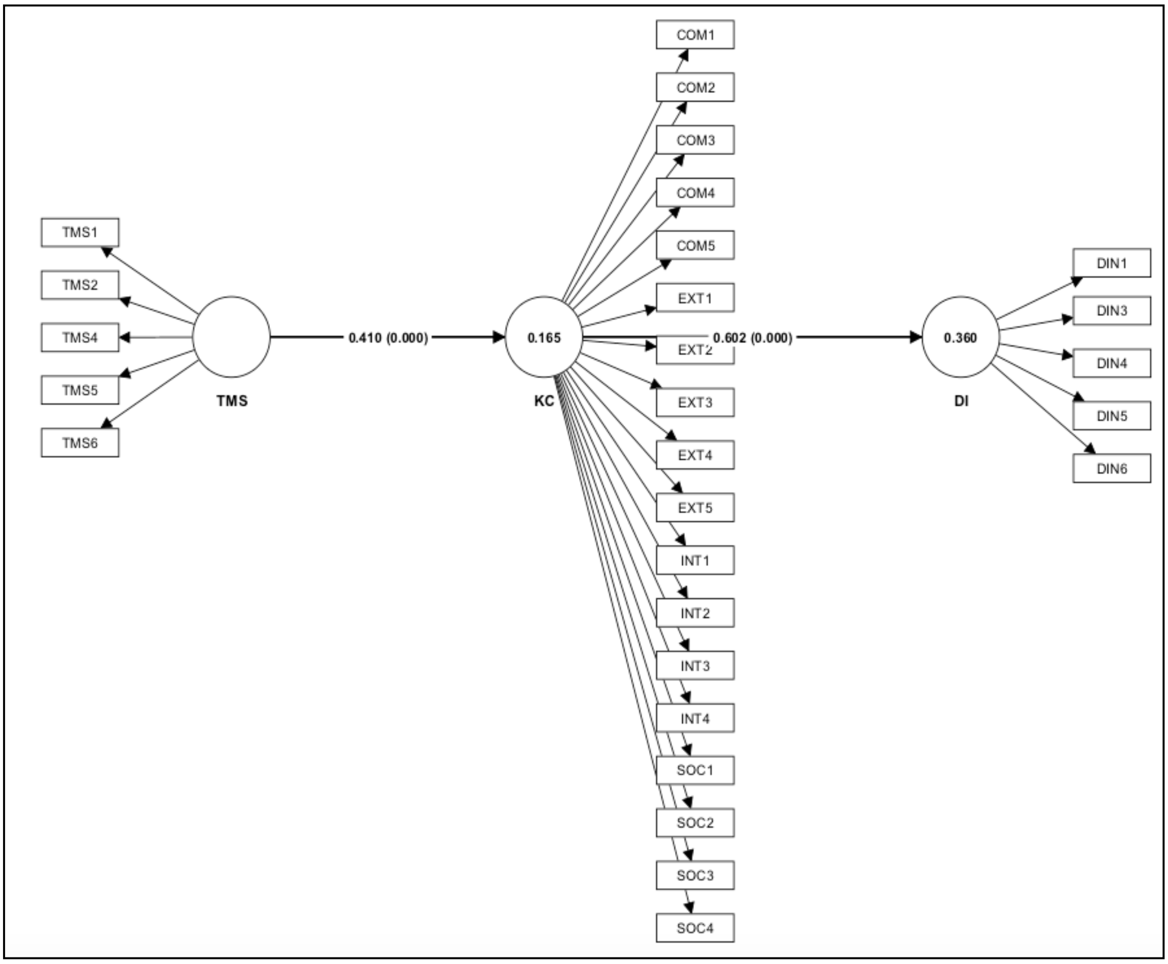

Fig.2: Results from structural equation analysis

5. Discussion

This study endeavours to examine the effects of TMS on KC, and the relationship between KC and DI among project managers operating in IT sector. The findings of the study indicate a positive correlation between TMS and KC. Thus, it shows that Hypothesis 1 was accepted. The research conducted by Lyu et al. (2022) posits that the establishment of affirmative cognitive associations via TMS can supports employees in identifying suitable collaborators for a specific undertaking, generating recollections influenced by the proficiency of fellow team members, and simplifying the procedure of assimilating and utilising collective knowledge. Consequently, TMS facilitates enhanced team productivity by enabling team members to leverage the expertise and insights of their colleagues to enhance KC.

The findings of the study indicate a positive correlation between KC and DI. Thus, it shows that Hypothesis 2 was accepted. IT project managers have had the chance to acquire a comprehensive understanding of technical knowledge through the examination of technical specification documents or through socialisation process with peers. This scenario has the potential to generate novel insights, such as acquiring a fresh design methodology that can enhance the system or gathering user feedback to aid the technical team in making improvements.

5.1. Theoretical implications

This research examines theoretical model proposed by Tung et al. (2022) and contributed to the existing transactive memory theory that clarifies how TMS plays a significant role in shaping KC, and understand the relationship of KC with DI. Historically, TMS has been used to describe the idea of knowledge-sharing networks and the cultivation of awareness of each other's areas of expertise within the context of group-level management research (Hollingshead, 1998). Since each team member can now specialise in their own knowledge domain while still being able to recognise and incorporate the information of other team members, TMS has increased coordination and efficiency among teams (Lewis et al., 2005). Cao et al. (2021) research confirmed that TMS facilitated the SECI mode of KC.

5.2. Practical implications

TMS has been the subject of much conjecture and research, but until recently, it was unclear whether or not it had a significant role in KC (Cao and Ali, 2018). This research provides project managers' knowledge of TMS and support them in developing specialise knowledge of other team members, all of which contribute to the need among IT projects to address the challenges in their daily work.

This study relates KC with DI in the context of I4.0. I4.0 was created to improve business intelligence, allowing the IT sector to adapt new technologies and procedures, as well as use data and information during project implementation. This study assists project managers in developing strategies with the use of TMS, which is a facilitator for new KC. Following that, the use of cutting-edge technologies was expected to boost the IT industry. KC has the potential to facilitate DI while also delivering a variety of fresh ideas and creativity.

5.3. Limitation and future recommendations

The utilisation of a cross-sectional sample constrains the explication of the postulated associations. Subsequent investigations may benefit from employing a longitudinal sample, thereby enabling the examination of causal relationships and providing a more all-encompassing perspective on the impact of KC on DI over an extended period.

Despite the project manager serving as the primary informant in the investigation and being considered a highly dependable source of information regarding the constructs being studied, there remains a potential for data bias resulting from the use of a sole informant. It is recommended that in the future, efforts should be made to integrate data from additional external sources, including project team members and suppliers.

Subsequent studies ought to endeavour to incorporate the gathering of extrinsic quantitative data in order to enhance the credibility of the results. Moreover, the research model could be augmented with various novel variables. The examination of various IT tools (Nambisan, 2017) may aid in comprehending the actual impact of KC on DI.

6. Conclusion

Drawing upon the insights from the TOKC, this study analysed theoretical framework from past literature that elucidates the relationship between TMS and KC, as well as the influence of KC on DI. Upon conducting a survey on IT MSC firms located in Klang Valley, Malaysia, the research model was tested and yielded results indicating a positive correlation between TMS and KC, as well as a positive correlation between KC and DI. The findings indicate that respondents were able to construct a shared understanding of 'who knows what' within their project teams, resulting in the generation of new knowledge for everyone. As a consequence, TMS boosts team productivity by enhancing team members' ability to learn and contribute to their colleagues' KC. The KC result serves as a critical component in accelerating DI. Respondents were given the option to learn new field technology by reading technical specification documents or communicating with colleagues. Even a modest step forward may result in the creation of novel insights, which could lead to new DI.

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