Unveiling heterogenous knowledge-oriented leadership and knowledge acquisition based hybrid work agility of knowledge workers

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Abstract

Purpose – *With new hybrid working models in place post COVID-19, it is requisite that knowledge workers (KWs) stay agile. Knowledge-oriented leadership (KOL) can help employees with essential knowledge acquisition (KA) facilitating the journey toward hybrid work agility (HWA). This study, thus, aims to explore the impact of KOL and KA on HWA and reveal whether this effect stems uniformly from a single homogenous population or if there is unobserved heterogeneity leading to identifiable segments of agile KWs.*

Design/methodology/approach – *Data was collected through stratified sampling from 416 employees from 20 information technology enabled services companies involved in knowledge-intensive tasks. Partial least squares (PLS) structural equation modeling approach, using SMART PLS 4.0, has been applied to examine the effect of KOL and KA on HWA. Finite mixture PLS, PLS prediction-oriented segmentation and multigroup analysis have been used to identify segments, test segment-specific path models and analyze the significance of the differences in the path coefficients for unobserved heterogeneity. Predictive relevance of the model has been determined using PLS Predict.*

Findings – *Results indicate that KOL contributes to employees' KA and HWA. A significant positive relationship is also reported between KA and HWA. The model has medium predictive relevance. A two-segment solution has been delineated, wherein independent agile KWs (who value autonomy and personal agency over leadership for KA) and dependent agile KWs (who depend on leaders for relational and structural support for KA) have been identified. Thus, KOL and KA play a differential role in determining HWA.*

Research limitations/implications – *The authors' major contribution to the knowledge body constitutes the determination of antecedents of HWA and a typology of agile KWs. Future researchers may conduct segment-wise qualitative analysis to delineate other variables that contribute to HWA.*

Practical implications – *Technological advances necessitate that knowledge-intensive industries foster agility in employees for strategic agility of the organization. For effecting agile adaption of an organization to the knowledge economy conditions, it is pertinent that the full potential of this human resource be used. By profiling HWA of KWs on the basis of dimensions of KOL and the level of their KA, organizations will be able to help employees adapt better to rapidly changing work conditions.*

Originality/value – *HWA is a novel concept and very germane in a hybrid working environment. To the best of the authors' knowledge, this is the first study to examine the effects of the dimensions of KOL and KA in relation to HWA, along with an empirical examination of unobserved heterogeneity in the aforementioned relationship.*

Keywords *Hybrid work agility, Agility, Knowledge-oriented leadership, Knowledge acquisition, PLS-POS, FIMIX-PLS, PLS Predict, Unobserved heterogeneity*

Paper type *Research paper*

1. Introduction

It is not the strongest of the species that survives, nor the most intelligent. It is the one that is most adaptable.

– Charles Darwin.

(Information about the authors can be found at the end of this article.)

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The transformative effect of multidimensional advancements, like technological changes and rapid globalization, results in inevitable volatility in the business environment. This demands a level of agility from the workforce to be able to anticipate change and adapt to it speedily (Baran and Woznyj, 2021). As global businesses move toward hybrid working models, knowledge workers (KWs) have been compelled to adapt to digital work structures (Coetzee *et al.*, 2021; Fayard *et al.*, 2021). Hybrid environments are here to stay (Gratton, 2021), in turn highlighting the need for KWs' hybrid work agility (HWA). Furthermore, the acquisition of new knowledge has been deemed particularly important for KWs to survive in these turbulent times (Chen *et al.*, 2018). In this regard, knowledge-oriented leaders provide their followers with direction, vision and motivation, helping them acquire essential knowledge (Politis, 2002) and facilitating their journey toward HWA. In this paper, we seek to study the unexplored and sought-after interrelationships between these three constructs – HWA, knowledge-oriented leadership (KOL) and knowledge acquisition (KA).

Our study is novel in its ability to address the existing gaps in the literature in the following four ways. First, it has been found that the number of empirical studies that focused on studying organizational drivers of employees' work agility are scarce (Ajgaonkar *et al.*, 2022; Harsch and Festing, 2020). In this regard, we have tried to extend the literature on the work agility of employees by studying its relationship with KOL and KA. Second, the majority of studies on individual-level work agility are limited to manufacturing, operations and service industry, with a dearth of empirical research in the information technology (IT) sector (Ajgaonkar *et al.*, 2022). Our research addresses this gap by using a sample of KWs from this sector. Further to the best of our knowledge, our study is novel in its attempt to examine the effects of the dimensions of KOL and KA in relation to HWA. Finally, no other study has attempted to study unobserved heterogeneity in the aforementioned relationship. According to a structured review on latent class analysis by Sarstedt *et al.* (2022), it has been observed that only 45 studies have been published in this area. Of these, very few have been published in the area of human resource management. Ours is the first research to obtain a heterogenous profile of agile KWs using advanced techniques for latent class analysis, like finite mixture partial least squares (FIMIX-PLS) and PLS prediction-oriented segmentation (PLS-POS).

Based on this, we identify the following research objectives (RO):

RO1. To explore the impact of KOL and KA on the HWA of knowledge workers in the Indian information technology enabled services (ITeS) industry.

RO2. To identify data heterogeneity in the KWs in the Indian ITeS industry.

RO3. To examine group-specific analysis built on data heterogeneity.

RO4. To compare differences between the group-specific model and aggregate-based model.

Our major contribution to literature lies in delineating some novel antecedents of HWA while providing strong evidence of unobserved heterogeneity in agile KWs. The two-segment solution obtained indicates that KOL and KA play a differential role in determining employees' HWA. We identify two types of agile KWs – *independent agile KWs*, who value autonomy and personal agency over leadership for KA, and *dependent agile KWs*, who depend on leaders for relational and structural support for KA. Our research also provides signposts for organizational leaders regarding the development of agile workers suited for the hybrid work environment.

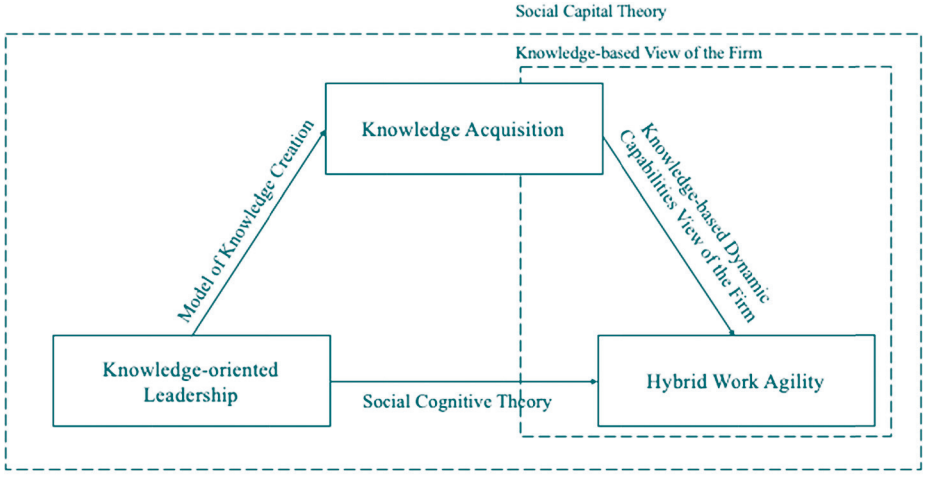
The remainder of this paper is structured as follows. Section 2 is dedicated to a discussion of theoretical underpinnings. Relevant literature and hypotheses are detailed in Section 3. In Section 4, we outline the methodology. Section 5 summarizes our findings. These findings, along with the implications of the study, are discussed in Section 6. The conclusion of our study is presented in Section 7.

2. Theoretical background

Our conceptual model is underpinned by the social capital theory (Nahapiet and Ghoshal, 1998) and the knowledge-based view (KBV) of the firm (Grant, 1996) (see Figure 1). We have drawn on the social capital theory to understand individual behavior in an organizational context. According to this theory, an individual's social network, comprising the whole set of embedded resources within, influences knowledge processes in an organization (Chiu *et al.*, 2006; Thomas and Paul, 2019). The theory stipulates that individual behavior stems from cognitive, relational and structural dimensions (identified as social capital). The cognitive dimension encapsulates shared representations and systems of meaning among actors. The relational dimension comprises personal relations (like respect and friendship) developed within the organization through interactions. The structural dimension constitutes the patterns of connection (like network ties and hierarchy) between actors (Nahapiet and Ghoshal, 1998). Social capital has been identified as essential for explaining the mechanisms involved in creating and exploiting collaborative advantage as well as intellectual capital, both critical to innovation and agility in this knowledge economy (Nahapiet, 2008). Considering the nature of ITeS firms, especially project-based work, and the stronger influence of leaders (Zia, 2020), it has been suggested that knowledge-oriented leaders can encourage employees to practice knowledge management activities (e.g. KA). Furthermore, HWA, an individual employee behavior, can be predicted using KOL (contributing relational and structural resources) and KA (cognitive resource).

To understand how individual-level KA can contribute to HWA, we draw upon the KBV of the firm (Grant, 1996) and knowledge-based dynamic capabilities (KBDC) approach (Zheng *et al.*, 2011), which integrates KBV with dynamic capabilities approach. KBV establishes KA as one of the vital characteristics of knowledge, with significant implications for organizational learning, response to volatile environments and agility (Yang, 2021). The KBDC approach further suggests that achieving sustainable competitive advantage depends on the ability of organizations to create and configure their dynamic capabilities in changing business environment (Zia, 2020). For this, firms need appropriate knowledge management practices (like KA) to enhance dynamic capabilities (like HWA). Thus, immediate managers can create a supportive environment that enables KA and work agility

Figure 1 Conceptual framework



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(Arsawan *et al.*, 2022; Muhammed and Zaim, 2020). On this theoretical footing, we propose that KOL and KA contributed to the HWA of KWs.

3. Literature review and hypotheses development

The social context for work has undergone significant change owing to rapid technological advances, ever-mounting globalization and changing work structures (Abuanzeh *et al.*, 2022; Wallin *et al.*, 2020). The emerging global workplace has altered employment relationships and spurred an intense competition among human resources (Burke and Ng, 2006). Technological advances like automation, Industry 4.0, artificial intelligence and machine learning have transformed the way we work, giving rise to a new world order where machines are capable of replacing human resources (Chuang and Graham, 2018). These advances are accompanied with a pressure to adapt and transfer one's skill sets and knowledge base to changing contexts (Jackson and Tomlinson, 2020). The COVID-19 crisis has further reshaped the labor market. A hybrid model of work has come to dominate the workplace, where a mix of home and office arrangements are used (Gratton, 2021). This has considerably boosted the use of technology, making workflows more complex. The workforce, in turn, needs to be prepared for a future that does not guarantee stability (Lent, 2018). In light of the dynamic and competitive global market, contemporary career scholars have started to stress on the notion of agility – identifying it as "capability *du jour*" (Gee, 2022; Ulrich and Yeung, 2019).

3.1 Hybrid work agility

The term "agility" comes from its Latin root "agilitas," which is translated as the capability to think and reach conclusions swiftly. Centered around the ideas of speed and flexibility (Su, 2011), the concept originated in manufacturing studies and has since been extended to organizations, supply chains, business relationships and the workforce (Breu *et al.*, 2002). Researchers postulate that an organization's journey toward an "agile organization" can be attained through an "agile workforce." The agility of the workforce comprises two facets, namely, the ability to respond to change and then use it to one's advantage as an opportunity (Petermann and Zacher, 2022). An agile workforce, capable of proactively identifying viable solutions, is crucial for the growth of organizations when faced with rapid and unanticipated changes (Alavi *et al.*, 2014; Muduli, 2016). Especially, technology or research and development companies rely on human resources to lead them through changing economic and social dynamics, profit from market opportunities and increase their return on investment (Caputo *et al.*, 2020). They provide a sustainable competitive advantage for an organization by improving performance and innovation (Munteanu *et al.*, 2020). Organizations that depend on their employees to deliver products with cutting-edge technologies to customers are especially concerned with the agility of the workforce. This construct has gained even more prominence post the COVID-19 pandemic, demanding a reappraisal of flexible working arrangements. Workers' ability to adapt to digital technologies and hybrid working structures determined the survival of KWs during and after the pandemic (Coetzee *et al.*, 2021).

Thus, work agility in the hybrid environment or HWA depends on an individual's ability to adapt quickly to the technological environment, seeing technology is a major driver of the knowledge era. Agile workers are characterized by their responsiveness to market developments and resilience in acclimatizing to changes in the business landscape (Coetzee, 2021; Paul *et al.*, 2020; Petermann and Zacher, 2022; Sherehiy and Karwowski, 2014). The hybrid work model also exemplifies the need for professional flexibility, with which one can accomplish various tasks (Breu *et al.*, 2002; Qin and Nembhard, 2015; Sherehiy and Karwowski, 2014). Demonstrating such versatility ensures a better fit while improving individual and organizational outcomes (Muduli, 2016). Innovative work behaviors are a key feature of agile talents (Salmen and Festing, 2021). The postpandemic,

hybrid work organization has also necessitated a degree of learning agility on the part of its workers. Agile learning is driven by an intrinsic desire to continuously learn from experiences and apply these lessons to improve work performance (Alavi *et al.*, 2014; Coetzee, 2021; Huang *et al.*, 2021). This pro-learning attitude of agile workers is evident from their constant need to upgrade their knowledge and skill sets to stay relevant in the business context (Coetzee *et al.*, 2022; Sherehiy and Karwowski, 2014). In complex working environments with a high degree of cognitive demands on an individual, agile learning becomes essential for converting knowledge into valuable insights (Salmen and Festing, 2021).

3.2 Knowledge-oriented leadership and hybrid work agility

Organizational literature is giving increasing precedence to knowledge and structural conditions that can influence its flow (Alinasab *et al.*, 2022; Caputo, 2021). Jamali *et al.* (2006) identify knowledge as a cornerstone for agility. The ability to adapt, adjust and respond is derived from how successfully knowledge is used in an organization system. Knowledge management has developed as an indispensable organizational function, facilitating strategic thinking and agility (Tooranloo and Saghafi, 2019). The role of a leader has been identified as paramount in effective knowledge management (Sadeghi and Mostafavi Rad, 2018; Singh, 2008), with a lack of leader support being the underlying cause behind many failed knowledge management projects (Yang *et al.*, 2014). In a knowledge organization, a leader must lead through a knowledge lens (Ribière and Sitar, 2003). It is pertinent that KWs see leaders as supportive and committed to the knowledge culture.

Donate and de Pablo (2015) integrated leadership theory with knowledge literature and pioneered the concept of KOL to this effect. Knowledge-oriented leaders embody a mix of transformational and transactional leadership styles with a singular focus on motivation and communication (Donate and de Pablo, 2015; Naqshbandi and Jasimuddin, 2018). They are responsible for giving direction to KWs and influencing the process of change adoption (Bertoldi *et al.*, 2018). They develop a strategic vision and then communicate the set organizational knowledge goals to employees. They motivate KWs by providing knowledge-specific support (Zia, 2020) and implementing a system of training, rewards and incentives (Shariq *et al.*, 2019).

The fundamental idea behind this style of leadership is to promote a positive culture of KA and sharing (Yang *et al.*, 2014). They act as catalysts for implementing knowledge processes, ensuring knowledge is diffused efficiently in the organization. KOL promotes an institutional culture where values of continuous learning and innovation are supreme (Yang *et al.*, 2014). Lakshman and Rai (2021) characterize knowledge leaders as those who have a pro-learning attitude and propagate that throughout the organization. They instill a learning orientation in employees by stimulating them intellectually, putting them in challenging situations and tolerating mistakes (Shamim *et al.*, 2019; Shariq *et al.*, 2019).

In this vein, Ghoshal *et al.* (1997) have also proposed that inculcating or changing individual behavior requires changing the behavioral context first. A prominent influence over employee behaviors is leadership style (Zia, 2020). Thus, its role must be considered when studying the agile behavior of the workforce. It is up to the leader to create a learning environment within the organization such that employees feel encouraged to be proactive, innovative and act with agility (Alavi *et al.*, 2014).

KOL allows for knowledge diffusion in the organization by demonstrating supportive behavior that is instrumental in fulfilling followers' needs and creation of a friendly environment (Bertoldi *et al.*, 2018). They mentor their followers, invest time and money in them and then recognize them for their efforts. Consequently, they foster a relational context that emphasizes trust, cooperation and respect (Zhang and Guo, 2019). Knowledge-oriented leaders, thus, develop personal relations with their followers, contributing to relational capital. They also communicate objectives and responsibilities of people across departments and hierarchies, providing strategic vision and direction in a company

(Bertoldi *et al.*, 2018). By facilitating the provision of requisite resources to followers, KOL promotes structural capital in an organization. Thus, from a social capital perspective (Nahapiet and Ghoshal, 1998), KOL contributes relational and structural resources elemental in predicting individual employee behavior, HWA. Furthermore, the social cognitive theory of human agency establishes individuals as self-developing, self-regulating and proactive beings (Bandura, 2001). However, the theory acknowledges the inability of humans to exercise direct control over institutional practices and social conditions governing their everyday lives. Under such circumstances, individuals seek valued outcomes by exercising a socially mediated mode of agency – proxy agency. Situating this in the context of our study, KOL can serve as a proxy agent (Zia, 2020) influencing employee behavior leading to HWA.

These two theories, along with extant literature serve as basis for our first hypothesis:

H1. There exists a positive relationship between KOL and HWA of knowledge workers in ITeS industry.

3.3 Knowledge-oriented leadership and knowledge acquisition

To deepen our understanding of the relationship between KOL and HWA, our study also sought to distinguish the underlying mechanisms through which KOL relates to HWA. KA, focused on identification and pursuit of new knowledge to embed it within one's existing knowledge (O'Leary, 2002), is a concept closely related to both these constructs. It involves the development of an individual knowledge base from varied sources and then building on that knowledge base (Al-emran and Teo, 2020; Ashrafi *et al.*, 2005). Human resource play an important role in generation of knowledge in an organization (Thomas and Gupta, 2022a). KA is an indispensable part of individual as well as organizational learning. However, acquisition of knowledge cannot occur in a vacuum (Carley, 1986). The social context is important in this regard, as individual knowledge is consistently being constructed through interactions with the world (Carley, 1986; Yli-renko *et al.*, 2001). The more the comprehensiveness of the source, type and channel of KA, the greater would be the extent of KA (Chen *et al.*, 2022). Liu and Liu (2008) identified formal education, training, self-directed learning, experimentation and imitation as important sources of individual KA.

Nonaka *et al.*'s (1996) model of knowledge creation also proposes that the keystone of knowledge creation in an organization is the leadership that positions it as vital. Knowledge-based leaders can provide a psychological environment which allows employees to gain from organizational resources (Shamim *et al.*, 2019). According to contingent and situational theories of leadership as well, leaders are capable of influencing employee behaviors by adjusting their behavior as per the situation and expected outcomes. Research has shown that leadership styles that are characterized by mutual trust and respect for subordinates' ideas and feelings and encourage participative behavior are correlated stronger with KA than autocratic leadership styles (Politis, 2001). Politis (2002) also found that some dimensions of transformational leadership enable KA of followers. Jayasingam *et al.* (2010) found leaders with expert power to positively impact KA of followers. Zia (2020) in her study on the relationship between KOL and individual knowledge management behavior found a positive association between KOL and KA, an element of KM. Based on this, we propose the following hypothesis:

H2. There exists a positive relationship between KOL and KA of knowledge workers in ITeS industry.

3.4 Knowledge acquisition and hybrid work agility

In today's hypercompetitive environment, knowledge is one of the most critical factors determining success (Boateng *et al.*, 2014; Caputo *et al.*, 2021; Chen *et al.*, 2022). It forms the basis for other capabilities that KWs can leverage to outperform their competition

(Bloodgood, 2019). An important point to note regarding acquisition of knowledge is that it depends on the social context, as much as it does on an individual's research and inquiry activities. Thus, while individuals in close knit social groups may develop similar cognitive structures, they can still evaluate those structures differently (Carley, 1986). This can be connected to the concept of "lifeworld" as postulated by Habermas' theory (Fairtlough, 1991; Habermas, 1985) wherein one's cognitive horizon is represented in terms of the "background environment of competencies, practices and leader attitudes." Consequently KA, as a cognitive resource, depends not just on an individual's ability to imbibe the knowledge but also on who is imparting the knowledge in terms of shared beliefs, goals and vision (KOL). Drawing on the conceptualization of the social capital theory that shared systems of meanings and interpretation (cognitive capital) influence behavior, it can be hypothesized that KA impacts HWA.

Furthermore, the KBDC view of the firm (Zheng *et al.*, 2011) serves as an important interpretative lens to study the relationship between KA and HWA (Ashrafi *et al.*, 2005). The theory suggests that achieving sustainable competitive advantage depends on the ability of organizations to create and configure their dynamic capabilities with changing business environment. For this, firms need appropriate knowledge management (like KA) to enhance dynamic capabilities (like HWA). KA elevates employees' participation in adaptive, proactive and resilient behavioral activities (Almahamid, 2018). Yang (2021) in their study on manufacturing supply chains found a link between KA and agility. However, an empirical investigation of this relationship as applicable to workforce has not yet been conducted. Citing this gap, we propose the following hypothesis:

H3. There exists a positive relationship between KA and HWA of knowledge workers in ITeS industry.

3.5 Unobserved heterogeneity

Moreover, prior research on agility does not furnish any information concerning the heterogeneity of KWs in the ITeS sector. This assumption of homogeneity is seldom applicable in social sciences as individuals differ greatly in their behavioral dispositions. KWs may be heterogeneous in how they perceive and evaluate unobserved constructs, indicating the need to account for different group-specific structural model path coefficients (Fiedler and Sarstedt, 2014; Sarstedt, 2008). Thus, we find literature to be lacking directions on how KWs differ and how these differences aid in the understanding of their behavioral intentions.

Furthermore, more than identifying distinct segments of hybrid KWs, our study also explores variables that explain differences in HWA patterns. Given that existing research has not identified agile employee segments based on KOL and KA and that the variables that could explain the distinctions amongst the ascertained segments are also unknown, this study aims to help theoretical understanding of HWA phenomenon. Thus, in this study, we also test a proposition built on constructs, rather than just hypotheses that test relationships between specific variables (Bacharach, 1989; Dessart *et al.*, 2019). In addition, the study is supplemented with hypotheses that test relationships between KOL, KA and HWA specifically, thereby further clarifying the model under consideration. In this context, we present the following proposition:

P1. Different segments can be identified among knowledge workers of ITeS sector, for whom the relationships between the KOL and KA dimensions and HWA can be significantly different.

4. Methodology

4.1 Procedure and participants

The IT industry is at the forefront of technological innovation and new technology adoption (Thomas, 2022). In the past decade, India has emerged as a global IT hub. It has become

the world's largest sourcing destination for IT-related services, with Indian ITeS companies accounting for approximately 55% of the global service sourcing market (IBEF, 2022). Moreover, this industry employs a large pool of skilled talent, housing 75% of the global digital talent in India. Owing to these developments, India has emerged as a knowledge powerhouse of the world (Jayswal, 2021). The recent COVID-19 pandemic, however, has presented a host of challenges and new prospects for the Indian ITeS companies (ECLAC and CII, 2021; Jain *et al.*, 2022). In a post-COVID world, the survival and success of this industry depends on how workplaces are restructured and work practices are redefined (Dutta *et al.*, 2021; Thomas, 2021). Against this setting, it is imperative that the workforce be agile enough to adapt to changing hybrid working structures. Thus, the research scope for this study included employees working in knowledge-intensive tasks ITeS sector. The study was conducted between July 2022 and August 2022. Data was collected from a representative sample using multistage sampling. At the first stage, we adopted stratified sampling technique wherein a list of companies belonging to ITeS sector was drawn from CMIE Prowess database. From this list, we selected those ITeS companies with registered offices in National Capital Territory (NCT) of Delhi, returning a total of 94 companies. We further shortlisted high-growth companies with annual financial turnover of at least 400 crores, because large, high-growth companies are more likely to be focused on agility and accept the hybrid working culture. OECD (2016) defines a high-growth company as "enterprises with average annualized growth greater than 20% per annum, over a three year period" wherein growth can be measured either by turnover or by the number of employees. We have chosen the former as our selection criteria. This left us with 20 ITeS companies with registered offices in NCT of Delhi. Next, we used purposive sampling to reach the sample of the study. Human resource managers of these 20 companies from ITeS sector were contacted using LinkedIn or personal connections. Lists of employees' email addresses were obtained, on the condition of confidentiality and that all data would be used for academic research only. The population of our study comprises KWs working in ITeS sector in the middle management level. This is because agility and KA of the workforce at the middle level depends on leadership at the top level (Das *et al.*, 2022; Singh, 2008). The final sample of our study, thus, comprised 416 respondents working at the middle level in knowledge-intensive tasks in the ITeS sector.

4.2 Measures

For the purpose of this study, we have used all self-constructed measures, detailed in Table 1. The responses were measured with a seven-point Likert scale with values ranging from 1 (strongly disagree) to 7 (strongly agree). Convergent and discriminant validity of the measures has been assessed and the instruments have been confirmed using procedures detailed by Hair *et al.* (2017b) (refer Subsection 5.1 for details).

4.3 Methods

We have used PLS structural equation modeling (PLS-SEM) method for creating, estimating and assessing our conceptual model (Hair *et al.*, 2017b; Hair *et al.*, 2019a). This approach has been used keeping in mind the causal predictive nature of this research (Sarstedt *et al.*, 2020). We have also used PLS Predict to determine the predictive relevance of our model. With PLS-SEM, variance in latent constructs is explained through maximization of the R^2 value and minimization of the error terms (Hair *et al.*, 2011). However, recent literature has established that the validity of the structural model results can be threatened under the assumption of a single homogenous population (Hair *et al.*, 2016).

To overcome this limitation, we have also examined unobserved data heterogeneity using a combination of latent class techniques, FIMIX-PLS (Hahn *et al.*, 2002; Rigdon *et al.*, 2010) and PLS-POS (Becker *et al.*, 2013). This combination is preferred for obtaining superior results (Kamath *et al.*, 2019; Sarstedt *et al.*, 2017). The supposition underlying these

Table 1 Measures

Construct	Dimensions	No. of items	Sample item	Cronbach's alpha
Knowledge-oriented leadership		21		0.94
	Institutionalized learning orientation	11	My leader promotes a learning culture in the organization	
	Selfless knowledge disposition	6	My leader can go out of the way to help me acquire knowledge	
	Social responsiveness	4	My leader motivates me to keep learning	
Knowledge acquisition		18		0.93
	Proactive information seeking	7	I attend several training programs to keep my knowledge updated	
	Institution based learning	6	My organization is well-equipped to provide me with requisite knowledge	
	Divergent learning	5	I prefer to obtain useful knowledge from various sources	
Hybrid work agility		22		0.93
	Hybrid learning orientation	10	I am always trying to learn something to adjust in the hybrid environment	
	Task versatility	8	I am always on the lookout for something new to do	
	Contemporary technology ability	4	I keep updating my skill-sets in order to capitalize on new technologies	

Source: Created by authors

techniques is that the overall population is a mix of group-specific density functions (Hair *et al.*, 2016), that is, data arises from several segments or subpopulations. FIMIX-PLS has been used to estimate probability of the respondent's segment membership and, subsequently, identify the number of segments (Hair *et al.*, 2017b). PLS-POS has been used to estimate segment specific models (Henseler *et al.*, 2015). Multigroup analysis (MGA) was used to analyze the significance of the differences in the path coefficients. The segment solution can be profiled by turning unobserved heterogeneity into observed heterogeneity in the data set using this process (Haverila *et al.*, 2021). All the hypothesized relationships have been examined using SmartPLS 4.0 (Ringle *et al.*, 2022).

5. Results

In line with requisite thumb rules (Hair *et al.*, 2019b), we have evaluated the results of PLS-SEM by first assessing the measurement model. Once these were adjudged as satisfactory, the results of structural model were examined. Unobserved heterogeneity has been assessed using processes of FIMIX-PLS, PLS-POS and MGA.

5.1 Measurement model assessment

Measurement model, or the outer model, delineates the relationship between a construct and its indicators (Hair *et al.*, 2017a, 2017b, 2017c). Assessment of the measurement model includes an examination of individual indicator reliability and internal consistency reliability (reliability of each construct's composite of measures) (Hair *et al.*, 2017b; Ringle *et al.*, 2020). We have used indicator loadings to establish individual indicator reliability. Loadings above 0.70 indicate that more than 50% of the indicator's variance is explained by the construct, thereby demonstrating satisfactory indicator reliability (Sarstedt *et al.*, 2020). Results indicate that all factor loadings are greater than the specified cutoff value of 0.7. For establishing internal consistency reliability, we have used Cronbach's alpha (α) and composite reliability (CR) measures. Because, α and CR are greater than the specified

threshold of 0.7 (Hair *et al.*, 2017b; Nunnally and Bernstein, 1994), internal consistency reliability has been confirmed. The results in Table 2 summarize these findings.

Model fit was evaluated with normed fit index (NFI) and standardized root mean-square residual (SRMR) values. Our model demonstrates an NFI value of 0.98 (which is greater than the threshold of 0.9) and SRMR value of 0.065 (lower than the threshold of 0.08) indicating a good model fit (Hair *et al.*, 2017a, 2017b, 2017c).

Furthermore, nomological validity was established through experts in the focus group interview. Convergent and discriminant validity of the measures were also examined (Hair *et al.*, 2017b; Hair *et al.*, 2019b). For assessing convergent validity, we have used average variance extracted (AVE) (Hair *et al.*, 2017a, 2017b, 2017c). It was found that all measures yield satisfactory levels of convergent validity in terms of AVE, with reported values greater than the threshold of 0.5 (Bagozzi and Yi, 1988; Henseler *et al.*, 2009). We also found support for discriminant validity of our model in terms of heterotrait–monotrait ratio (HTMT) of correlations because all HTMT values fall below the cutoff value of 0.9 (Henseler *et al.*, 2015; Kline, 2011; Liu *et al.*, 2021) (see Table 3). This indicates that all the constructs in our model are empirically distinct from other constructs in the structural model. Because all the requisite values are satisfactory, the measurement model stands confirmed.

5.2 Structural model assessment

Once the measurement model's reliability and validity were established, we assessed the structural model. The structural model, or the inner model, describes the relationship between the latent constructs (Hair *et al.*, 2017a). The structural model (Figure 2) assessment comprised an analysis of aggregate based data and assessment of predictive relevance using PLS Predict.

5.2.1 Analysis of aggregate based data. For testing the structural model, we assessed the statistical significance and relevance of path coefficients, coefficient of determination (R^2) and effect size (f^2). But first, we checked our structural model for multicollinearity by examining variance inflation factor (VIF) values. VIF returns the amount of variance of a coefficient estimate that is inflated because of its presence in the model. In our model, all

Table 2 Measurement model assessment

Constructs	*Subconstructs*	*Factor loadings*	*Cronbach's alpha*	*CR*	*AVE*
KOL	ILO	0.950	0.961	0.961	0.719
	SKD	0.807	0.916	0.918	0.704
	SR	0.802	0.847	0.849	0.766
KA	PIS	0.889	0.917	0.922	0.669
	IBL	0.862	0.894	0.894	0.653
	DL	0.860	0.921	0.922	0.759
HWA	HLO	0.928	0.948	0.95	0.684
	TV	0.897	0.94	0.941	0.705
	CTA	0.765	0.869	0.876	0.719

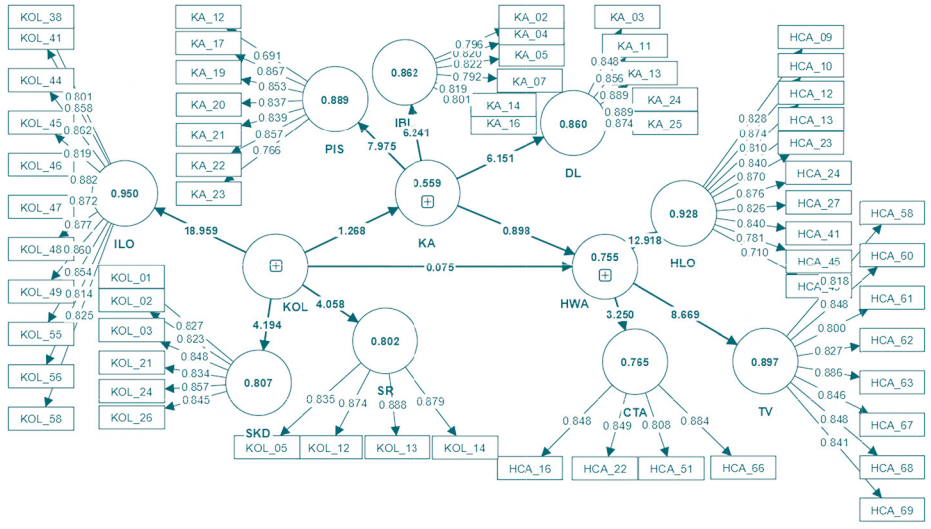
Source: Created by authors

Table 3 Assessment of discriminant validity using HTMT criterion

Constructs	*KOL*	*KA*	*HWA*
KOL		0.774	0.753
KA			0.888
HWA			

Source: Created by authors

Figure 2 PLS-SEM aggregate model



Source: Created by authors

VIF values lie below the upper limit of 5 (Hair *et al.*, 2019a), indicating an absence of multicollinearity. Next, path coefficients were analyzed to study the strength of the relationships between the constructs. In line with the suggestions of Hair *et al.* (2017b), bootstrapping was performed (with 10,000 subsamples) to test statistical significance of every path coefficient. We have chosen 5% ($p < 0.05$) as the level of significance for analyzing our results. The relationship between KOL and HWA was found to be significant ($\beta = 0.204$, $t = 4.227$, $p < 0.05$). These results are consistent with existing research which identifies leadership as an important influence over employee behaviors, like agility (Alavi *et al.*, 2014). Furthermore, a positive and significant relationship between KOL and KA was observed ($\beta = 0.748$, $t = 21.682$, $p < 0.05$). This situates KOL as a determinant of KA, in accordance with prior research which has established KOL as an important source of direction and vision in an organization, responsible for promoting KWs' KA (Yang *et al.*, 2014). The relationship between KA and HWA was also found to be significant ($\beta = 0.706$, $t = 14.255$, $p < 0.05$). This result is in line with the study conducted by Yang (2021) in context of manufacturers in the field of supply chain operations. Thus, *H1–H3* are supported.

Following this, the explanatory power of the model was estimated with R^2 (Hair *et al.*, 2011). Our model has an R^2 value of 75.4, representing substantial explanatory power (Chin, 1998). Finally, f^2, which indicates variation in R^2 owing to exclusion of independent variables one by one from the model, was estimated. From Table 4 we observe that KOL has a substantial effect on KA. In comparison, the effect of KOL on HWA is small. However, KA has a very large effect on HWA (Chin, 2010).

Table 4 Assessing effect size: f^2

Constructs	*HWA*	*KA*	*KOL*
HWA			
KA	0.898		
KOL	0.075	1.268	

Source: Created by authors

5.2.2 Assessing the predictive relevance using PLS Predict. The R^2 statistics discussed above only describe the in-sample explanatory power of the model. To estimate the out-of-sample predictive relevance of our model for HWA, we have applied PLS Predict as well (Danks *et al.*, 2017; Shmueli *et al.*, 2016). It is grounded on the concepts of training sample (part of the overall data set used for model estimation) and holdout samples (remaining part of the data set not used for estimating model parameters) (Danks *et al.*, 2017; Hair *et al.*, 2019b). PLS Predict is a holdout sample-based procedure that generates case-level predictions on a construct or item-level predictions. This signifies that PLS Predict can assess the accuracy of a model even while predicting the outcome value of new cases (Shmueli *et al.*, 2019). Following the suggestions given by Shmueli *et al.* (2019) and Hair *et al.* (2019a, 2019b) for evaluating predictive relevance of our model, we initialized the PLS Predict process using 10 folds (k = 10). It was ensured that the training sample in a single fold still met the minimum sample size requirements (Kock and Hadaya, 2018), computed with G*Power software. To begin with, we examined the Q^2_{Predict} values of the PLS-SEM model. A positive Q^2_{Predict} value, as observed for HWA, indicates that the PLS-SEM analysis for indicators of our key target construct outperforms the most naive benchmark – linear regression model (LM) (i.e. the indicator means from the training sample). Next, we examined the distribution of prediction errors in our model, which we found to be asymmetrically distributed. We have thus used mean absolute error (MAE) values obtained for PLS-SEM with LM benchmark. It is evident from Table 5 that MAE values of majority of the indicators in the PLS-SEM analysis yield smaller prediction errors compared to the LM, indicating medium predictive power of our model (Shmueli *et al.*, 2019).

5.3 Partition of aggregate-based data using finite mixture partial least squares and partial least squares prediction-oriented segmentation

From the analysis of aggregate-based data, we have obtained valuable insights into the complex relationships between HWA, KOL and KA. However, this analysis is based on the

Table 5 Assessment of predictive relevance for hybrid work agility

Items of the dependent variable	*PLS-SEM* *MAE*	*PLS-SEM* *Q^2Predict*	*LM* *MAE*	*PLS-SEM – LM* *MAE*
HCA_16	0.859	0.28	0.921	–0.062
HCA_22	0.958	0.224	0.958	0
HCA_51	0.925	0.191	0.957	–0.032
HCA_66	0.756	0.329	0.792	–0.036
HCA_09	0.865	0.283	0.915	–0.05
HCA_10	0.788	0.305	0.807	–0.019
HCA_12	0.801	0.284	0.807	–0.006
HCA_13	0.785	0.314	0.79	–0.005
HCA_23	0.75	0.385	0.741	0.009
HCA_24	0.765	0.335	0.783	–0.018
HCA_27	0.774	0.335	0.784	–0.01
HCA_41	0.758	0.415	0.75	0.008
HCA_45	0.837	0.327	0.836	0.001
HCA_49	0.793	0.28	0.767	0.026
HCA_58	0.815	0.353	0.778	0.037
HCA_60	0.779	0.393	0.797	–0.018
HCA_61	0.84	0.308	0.834	0.006
HCA_62	0.794	0.307	0.814	–0.02
HCA_63	0.636	0.468	0.645	–0.009
HCA_67	0.692	0.355	0.704	–0.012
HCA_68	0.788	0.354	0.764	0.024
HCA_69	0.768	0.289	0.787	–0.019

Source: Created by authors

over-simplistic assumption of a homogenous population, discounting the effect of individual differences. Individuals often vary in their perceptions of unobserved constructs, and in such cases, model estimates based on aggregate data can produce misleading results (Sarstedt *et al.*, 2019). Subgroups may exist in our data, necessitating an assessment of group-specific structural model path coefficients (Sarstedt, 2008). Thus, for identifying and treating this unobserved heterogeneity, aggregate-based data has to be partitioned into segments. For partitioning the observations, researchers have recommended using a combination of two latent class techniques – FIMIX-PLS and PLS-POS (Hair *et al.*, 2017a, 2017b; Sarstedt *et al.*, 2017). The main advantage of FIMIX-PLS is that it allows for computation of likelihood-based information criteria indicating the number of segments that can be retained from the aggregate data (Hair *et al.*, 2016). PLS-POS, in comparison, is valuable for obtaining superior estimates for segment specific models (Dessart *et al.*, 2019; Hair *et al.*, 2017a, 2017b, 2017c; Sarstedt and Cheah, 2019). It is aimed at maximizing the explained variance in the resultant segment solution (Hair *et al.*, 2017a, 2017b, 2017c; Haverila *et al.*, 2021). In this study, we used the two together, such that the obtained FIMIX-PLS partition is used as the preliminary partition for PLS-POS for estimating segment specific models (Dessart *et al.*, 2019). We followed a three-step process: First, we ascertained the minimum sample size to establish maximum number of segments possible. Next, we ran FIMIX-PLS to determine the appropriate segment size. Finally, we used PLS-POS to estimate the model-specific segmentation solutions.

5.3.1 Minimum sample size. Observations were partitioned into segments according to the suggestions of Hair *et al.* (2016). First, we determined the upper-bound range of possible segment solutions. This was determined using interplay of our sample size and the minimum sample size requirements for estimating the model reliably. We used G*Power software to determine minimum sample size (K). For an appropriate effect size and alpha level with power established at 0.95, it was found that a minimum sample size of 89 participants would be required. Dividing the sample size ($N = 416$) by minimum sample size ($K = 89$), the greatest integer obtained returns a theoretical upper bound of 5. Thus, the maximum possible number of segment solutions was established to be 5 (i.e. $416 \div 89$).

5.3.2 Finite mixture partial least squares. Now, to determine the number of segments, we examined Akaike's information criterion (AIC), Bayesian information criterion (BIC), consistent AIC (CAIC), modified AIC with factor 3 (AIC3), AIC4 and minimum description length with factor 5 (MDL5) fit indices.

The detailed information criteria and normed entropy statistics (EN) are given in Table 6. The smaller the value of an information criterion, the better the segmentation solution. As per the guidelines by Hair *et al.* (2016), we can select more segments than indicated by

Table 6 Fit indices for one-to-five segment solution

Criteria	*No. of segments* 1	2	3	4	5
AIC (Akaike's information criterion)	4,296.917	3,307.487	2,833.91	2,601.019	2,474.286
AIC3 (modified AIC with factor 3)	4,319.917	3,354.487	2,904.91	2,696.019	2,593.286
AIC4 (modified AIC with factor 4)	4,342.917	3,401.487	2,975.91	2,791.019	2,712.286
BIC (Bayesian information criteria)	4,389.623	3,496.929	3,120.089	2,983.934	2,953.938
CAIC (consistent AIC)	4,412.623	3,543.929	3,191.089	3,078.934	3,072.938
HQ (Hannan–Quinn criterion)	4,333.573	3,382.392	2,947.064	2,752.422	2,663.939
MDL5 (minimum description length with factor 5)	4,944.446	4,630.698	4,832.803	5,275.594	5,824.544
LnL (log-likelihood)	–2,125.46	–1,606.74	–1,345.96	–1,205.51	–1,118.14
EN (normed entropy statistics)	0	0.81	0.894	0.84	0.812
NFI (nonfuzzy index)	0	0.843	0.899	0.824	0.788
NEC (normalized entropy criterion)	0	78.964	44.164	66.386	

Source: Created by authors

MDL5 and less than indicated by AIC. Based on this, we observe that we need to choose between a two- and five-segment solution. Furthermore, it has been suggested that if AIC3 and CAIC or AIC4 and BIC indicate the same number of segments, this particular segmentation solution should be chosen. In our case, these criteria point toward a five-segment solution, and thus, retaining a smaller number of segments is justified (Hair *et al.*, 2017a, 2017b, 2017c). Consequently, we have complemented this with the use of normed entropy statistic (EN > 0.5). Higher values of this statistic indicate a better quality partition solution (Hair *et al.*, 2016; Ringle *et al.*, 2010). We observe that the highest value (EN = 0.894) corresponds to a three-segment solution. In addition, Hair *et al.* (2017c) suggest that researchers should note the size of the segment produced by FIMIX-PLS. If an extraneous segment is found, such that it is too small to undergo a valid analysis, it should be dropped. We found our third segment to be extremely small in size (8% of the total sample) and hence dropped it to focus on the analysis of the other two larger segments. The other two segments of KWs constitute 68.2% and 23.4% of the aggregate data set, respectively. Thus, further analysis was run on 387 observations instead of the initial 416.

5.3.3 Partial least squares prediction-oriented segmentation. Because the results of FIMIX-PLS indicate a significant degree of heterogeneity, we proceed with PLS-POS for estimating segment-specific models (Sarstedt *et al.*, 2019). The two-segment solution obtained from FIMIX-PLS was taken as the input for PLS-POS. A FIMIX segmentation using the two-segment solution was chosen to ensure that each observation was ascribed to one of the two segments and sum of all construct weighted R^2 was chosen as the optimization criterion in PLS-POS. A search depth of 387 was used, that is, equal to the number of observations. The results (see Table 7) indicate that R^2 of HWA for both the segments (0.812 and 0.827) and the weighted average (0.819) are a significant improvement over HWA R^2 for the aggregate data set (0.755). For KA, the R^2 values of segment 1 were found to be higher than the R^2 values of the original data set, whereas R^2 values of segment 2 were found to be lower than the values of the original data set. Furthermore, the weighted average R^2 values of HWA of the PLS-POS solution (0.819) was much higher than the R^2 (0.755) values of the full data set. Thus, as per the average sample-weighted R^2 criteria, the two-segment solution fits the data better than an assumption of homogeneity.

5.3.4 Finite mixture and multigroup analysis. The results obtained for aggregate based analysis are different from the group-specific analysis (see Table 8). For testing the statistical significance of every path coefficient in the FIMIX segments, we conducted bootstrapping with 10,000 subsamples, following the procedure given by Hair *et al.* (2017a, 2017b, 2017c). We compare the two segments to understand the differential effect of KOL and KA on HWA.

5.3.5 Model comparisons. The results of the FIMIX-PLS are detailed in Table 8. Segment 1, labeled as independent agile KWs (68.2% of the sample), base their HWA majorly on the perception of KA (β = 0.882, $p < 0.01$). Such people are very independent in their own spirits, so much that KOL seems to have a negligible impact on this segment of KWs (β = 0.069, $p < 0.01$). These workers fully depend on themselves and their ability to acquire knowledge to be agile in this dynamic environment, rather than dependence on the leader. Hence, they give importance to their own KA, which explains the major variation in HWA contributed by KA.

Table 7 PLS-POS results

Constructs	*Original sample* R^2	*Average weighted* R^2	*POS segment 1*	*POS segment 2*
HWA	0.755	0.819	0.812	0.827
KA	0.559	0.536	0.69	0.343

Source: Created by authors

Table 8 Results of FIMIX-PLS

	Original sample	t-*statistics*	*FIMIX-PLS segment 1*	t-*statistics*	*FIMIX-PLS segment 2*	t-*statistics*
N	387		230		157	
Relative segment size (100%)	100		58.8		41.2	
Path						
KOL → HWA	0.204	4.227	0.069*	2.103	0.267**	3.947
KOL → KA	0.748	21.682	0.872**	28.382	0.64**	8.106
KA → HWA	0.706	14.255	0.882**	20.931	0.585**	7.44
Measurement model assessment						
AVE	+		+		+	
CR	+		+		+	
Discriminant validity	+		+		+	
R^2						
Knowledge acquisition	0.559		0.76		0.409	
Hybrid work agility	0.755		0.89		0.613	

Notes: $^{**}p < 0.05$; $^{*}p < 0.10$; "+" = measurement model evaluation criterion fulfilled
Source: Created by authors

Segment 2, identified as dependent agile KWs (23.4%), base their HWA on perceptions of KOL (β = 0.64, $p < 0.01$) and KA (β = 0.585, $p < 0.01$). KOL seems to have a more significant impact on HWA for KWs in this segment, compared to segment 1. Surprisingly, the impact of KA is much less comparatively, indicating that this category of KWs depends greatly on the leader for direction and vision. Both the segments demonstrate an increase in R^2 compared to the aggregate model, reflecting that the two-segment solution fits the data better than an assumption of homogeneity.

In the final step, descriptions of the two segments are drawn. This is based on assigning each of the observations, based on the maximum membership probability, to one of the two groups (Schirmer *et al.*, 2018). Of all the demographic and psychographic characteristics, only *locus* of control shows a suitable and good fit with the FIMIX-PLS segmentation results. Subsequently, the data set has been split into two groups. Group 1 represents individuals with an internal locus of control (ILOC) and Group 2 represents individuals with an external locus of control (ELOC). The results of the group-specific PLS-SEM and their differences have been given in Table 9. The significance of the differences has been determined using a double bootstrap routine by running a PLS MGA (Sarstedt *et al.*, 2011).

The results show that the two groups are distinct. KA determines HWA for ILOC group (β = 0.777, $p < 0.01$) and for ELOC group (β = 0.547, $p < 0.01$). There exists a significant difference between ILOC employees and ELOC employees in terms of the impact of KA on HWA ($|\Delta 12|$ = 0.234, $p < 0.01$). This may be attributable to the fact that employees with

Table 9 PLS results of multigroup analysis based on locus of control

	Paths	*Group 1* Internal locus of control	*Group 2* External locus of control	$\|\Delta 12\|$ (Group 1 – Group 2)
N		268	119	
Path relationship	KOL → HWA	0.156**	0.302**	–0.153
	KOL → KA	0.747**	0.724**	0.024
	KA → HWA	0.777**	0.547**	0.234*
R^2	KA	0.76	0.409	
	HWA	0.89	0.613	

Notes: $^{**}p < 0.05$; $^{*}p < 0.10$
Source: Created by authors

ILOC give more impetus to KA as an intrinsic, thereby impacting their workforce agility. Contrarily, the employees with ELOC are more dependent on others for the aforementioned constructs and their relationships. There exists no significant difference between ILOC group ($\beta = 0.156$, $p < 0.01$) and ELOC group ($\beta = 0.302$, $p < 0.01$) in terms of the impact of KOL on HWA. This is because both the groups give importance to the role of knowledge-oriented leader in terms of determining HWA; former because of their instinct to sustain their workforce agility, and the latter because of their intrinsic nature of dependence on the leader. For both ILOC ($\beta = 0.747$, $p < 0.01$) and ELOC ($\beta = 0.724$, $p < 0.01$) groups, KOL has a significant impact on KA, thereby explaining the role of knowledge leader in the ITeS industry.

6. Discussion and implications

The results of our study provide empirical evidence for the effect of KOL and KA on HWA. It has been found that KOL significantly impacts KA and HWA of KWs in the Indian ITeS sector. KA has also been found to positively influence HWA in the aggregate sample. Furthermore, through a segmented analysis of this population, we have also been able to establish the existence of unobserved heterogeneity in the aforementioned relationship. We have identified two segments which have been discussed in detail under. Implications of our study for research and practice are also discussed in the following subsections.

6.1 Segment discussion

Concentrating on studying the differential impact of KOL and KA on HWA, we found two segments on the basis of employees' dependence on their leader: independent and dependent agile KWs. Our first FIMIX-PLS segment, *independent agile KWs*, comprises employees who exemplify the characteristics of achievement-orientation and self-motivation. These employees depict ILOC wherein they attribute their ability to manage HWA on the basis of their own effort toward KA (Chen *et al.*, 2016). They demonstrate a very strong dependence on their own KA, in comparison to external influences like KOL. These individuals fully hinge on their own abilities to acquire knowledge and become agile in the volatile labor market, placing a high premium on autonomy and career development. This can be the reason why many Indian employers have been reporting an increase in employee productivity since the shift to hybrid (Poly, 2022). Our second FIMIX-PLS segment, *dependent agile KWs*, is composed of individuals who depend on their leaders for adapting to the hybrid work environment. Such individuals derive structural and relational support from the leader for nurturing agile behavior. They exhibit ELOC wherein KA by self has to be supplemented with external sources like KOL for impacting HWA. Accommodating the needs of such employees can be the reason why reports iterate the need to for Indian employers to build a healthy work culture and workplace relationships to avoid burnout (Poly, 2022). This is a compelling contribution, as it uncovers the differential role of the constructs when studying HWA of different segments of KWs.

6.2 Research implications

Our paper contributes to scholarship on employees' work agility, and specifically work agility in the hybrid environment in multiple ways, presenting substantial implications for body of knowledge. Our first contribution lies in presenting a conceptual framework that offers significant insight into the role of organizational as well as individual drivers of HWA. This model facilitates a better understanding of KOL, KA and HWA within the context of social capital theory and KBV of the firm. Work agility in general and HWA in particular, in itself is a very novel and underexplored construct (Ajgaonkar *et al.*, 2022; Harsch and Festing, 2020). For a country like India, which is a major exporter of IT services across the globe, research in the area is even more prudent. As India prepares for its next phase of

growth in this sector, only firms with a workforce equipped to deal with the ever-changing technological environment and respond with agility will be able to survive (Ahammad *et al.*, 2021). Thus, by the means of this research we have been able to study nature and predictors of HWA in depth, extending the literature on work agility. KOL and KA have been established as antecedents of HWA in the Indian context. These results emphasize the importance of leadership in affecting employee behavior (Nahapiet, 2008), in addition to accenting the vital role played by management policies in fostering employee agility (Sherehiy and Karwowski, 2014). Our findings endorse the postulations of social capital theory (Nahapiet and Ghoshal, 1998) that leadership is a crucial factor in an organizational setting impacting employee behavior, in an Indian context. KOL, particularly, combines the best of transformational and transactional leadership styles, adding in a mix of motivational and communication elements (Donate and de Pablo, 2015). Knowledge-oriented leaders, responsible for inculcating a culture of learning and innovation, can help prepare the workforce for a future that does not guarantee stability (Lent, 2018). Such leaders endorse an innovation-oriented culture in the organization. They guide their followers on matters of acquisition and integration of knowledge which can be fruitful for successful knowledge exploration and utilization (Naqshbandi and Jasimuddin, 2018), further paving the way for HWA. Future researchers can direct efforts toward identifying other such organizational and individual drivers of HWA in an Indian context. The research may also be extended to other countries. Comparative studies that highlight differences amongst different country contexts may also help further the body of literature in this field.

Furthermore, our study provides strong evidence of heterogeneity in agile KWs through the use of latent class analysis and segmentation profiling. The stark difference observed across the two segments suggests that different strategies are required on the part of leaders to deal with these two segments. To this end, we draw on the foundations of path-goal theory of leadership (House, 1971). The theory is predicated on a meta-proposition that effective leaders engage in behaviors complementary to their followers' abilities and context, to compensate for any deficiencies. This is requisite for followers' satisfaction and work performance (House, 1996), especially in the hybrid work environment. This leadership theory identifies four leadership behaviors that can be used in varying solutions: achievement oriented (focused on enhancing performance standards), supportive (attentive to followers' needs), directive (explains expectations and provides guidance) and participative (encourages participation in decision-making) (Alanazi *et al.*, 2013). Our first obtained segment of KWs – *independent agile KWs* – demonstrates responsibility and control over their KA. In such a situation, the dyadic relationship between leader and follower may benefit from an achievement-oriented behavior on part of the leader (House, 1996). Our second segment – *dependent KWs* – is characterized by a dependence on leader for direction and motivation for fostering agility in the hybrid environment. Because the nature of tasks is unstructured coupled with immense pressure in this hybrid environment, these KWs may benefit from direction and support from the leader. Thus, participative, directive and supportive leadership styles are more suited for such workers (Alanazi *et al.*, 2013). Thus, our research expands the path-goal theory of leadership via its application to HWA. Future researchers can align their efforts to study these differences in more detail. In addition, it may be prudent to conduct segment-wise qualitative analysis to delineate other variables that contribute to work agility in the hybrid environment in India. A segmented analysis of HWA can also be conducted in context of different countries and industries.

6.3 Practical implications

Majority of Indian employers believe hybrid work models are here to stay (NASSCOM, 2022; Poly, 2022), necessitating resilient workforce strategies that balance speed and adaptability (PwC, 2022). The hybrid work environment is more complicated as compared to a

completely remote or in-office environment. This necessitates that knowledge-intensive industries foster agility in employees for strategic agility of the organization (Sherehiy and Karwowski, 2014). For effecting agile adaption of an organization to the knowledge economy conditions, it is pertinent that the full potential of the human resource be used. Prior research has established that in times of rapid change, human resources play a consequential role in capitalizing on market opportunities and ensuring organization survival (Caputo *et al.*, 2021). Providing a flexible environment, where employees are equipped with tools and support required to be productive, increases chances of organizational success (Chatterjee *et al.*, 2022). But enabling flexibility and anytime working is also accompanied by the risk of burnout (Poly, 2022). Many Indian employers feel an unhealthy culture is being propagated and employees need to be protected from burnout. Microsoft's (2022) Work Trend Index Pulse Report also suggests the need for better logistics, efficiency and communication to sustain hybrid models. Prior research demonstrates that investments in information and communication technologies hold potential to improve returns for a business (Caputo *et al.*, 2022). In addition, India suffers from some additional bottlenecks, like resistance to shift from work from home (WFH) models, that make sustaining hybrid work a challenge. In this regard, it is important to study what impacts agility of the workforce and direct efforts accordingly. The way companies implement an approach is of immense consequence. To succeed in today's highly competitive world, consonance-oriented relational strategies are necessary (Saviano *et al.*, 2018). Incidentally, knowledge-oriented leaders build relational capital by investing time, money, respect and trust with their followers (Zhang and Guo, 2019). Thus, organizations can invest in the development of knowledge leaders, who play an instrumental role in influencing HWA amongst employees in the Indian ITeS sector. Owing to a hybrid work context, there has been a proliferation in the sources of knowledge. How employees acquire knowledge and from whom can play an important role in determining their HWA, reiterating the importance of KOL. Knowledge leaders can support employees' capabilities and build associations that help keep KWs intrinsically motivated (Thomas and Gupta, 2022b).

Furthermore, our study also provides a segmented profile of KWs. This implies that the aggregate model is not sufficient, and the two distinct sets of KWs have to be dealt differently in terms of their characteristics and requirements as employees of the organization. It is pertinent that KWs are first typified based on which segment they belong to and then leader's behavioral strategies be adapted accordingly. By profiling HWA of KWs on the basis of dimensions of KOL and the level of their KA, organizations will be able to help employees adapt better to rapidly changing work conditions.

7. Conclusion

As the nature of work and careers has evolved in the post-COVID era, it has become apparent that hybrid working models are here to stay. Maintaining agility in the hybrid working models reduces job uncertainty and increases competitive advantage in changing employment contexts. In this study, we aimed to study the impact of KOL and KA on HWA of human capital. Our findings indicate that KOL positively influences employees' KA and HWA. A significant positive relationship has also been evidenced between KA and HWA of human capital. Our model demonstrates medium predictive relevance. Furthermore, we have accounted for unobserved heterogeneity in our model, by delineating a two-segment solution typified as independent agile KWs and dependent agile KWs. We characterize *independent agile KWs* as those workers who value autonomy and personal agency over leadership for KA. *Dependent agile KWs* are those who depend on leaders for relational and structural support for KA. This result signifies that there is a difference between aggregate-based data analysis and group-specific data analysis. Thus, KOL and KA play a differential role in determining HWA of independent agile KWs and dependent KWs. Our results provide initial explanations for profiling KWs in terms of their HWA on the basis of

their dependence (or lack thereof) on knowledge leaders in the organization. We have attempted to situate these results in the context of path-goal leadership theory to identify the different strategies leaders can use to manage the two categories of agile workers. This opens avenues for empirical examination in this direction in the future. Future researchers can also conduct in-depth qualitative analysis to identify other determinants of HWA, keeping in mind the segmented profile of KWs. Finally, considering how hybrid work has become the dominant working model for KWs across the globe (Future Forum Pulse, 2022), it will be reasonable to say that the findings of our study are generalizable to KWs across geographical boundaries.

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