The Impact of Knowledge Management on Knowledge Worker Productivity

Journal:	*Baltic Journal of Management*
Manuscript ID	BJM-12-2017-0404.R3
Manuscript Type:	Original Article
Keywords:	Knowledge management, productivity, knowledge worker, knowledge work, Knowledge worker productivity, Knowledge work productivity

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Abstract

Purpose – The productivity of knowledge workers is crucial not only for organizational innovation and competitiveness but also for sustainable development. In the context of knowledge-intensive firms, implementation of knowledge management is likely to increase knowledge worker productivity. Therefore, this study aims to examine the influence of knowledge management on knowledge worker productivity.

Methodology – A research framework on the effects of knowledge management processes on knowledge worker productivity is established and empirically tested with data from 336 knowledge workers at five mobile network operator companies in Pakistan.

Findings – The results indicate that knowledge creation and knowledge utilization impact knowledge worker productivity positively and statistically significantly. However, knowledge sharing does not have statistically significant impact on knowledge worker productivity. Demographic factors (gender, managerial position, and formal education level) do not moderate the relationship between knowledge management and knowledge worker productivity statistically significantly.

Research limitations – The key limitations are the cross-sectional nature of the data and the geographic limitation to telecom companies in Pakistan.

Practical implications – Irrespective of gender, education, and managerial position, implementation of knowledge management can increase knowledge worker productivity.

Therefore, knowledge management practices should be implemented to enhance the knowledge-worker productivity via fostering the knowledge-worker's engagement in and propensity to knowledge management processes.

Originality –

This study is among the first to examine the likely influence of knowledge management on the productivity of knowledge workers conclusively while controlling for three individual demographic factors. This study also addresses the effectiveness of knowledge management in the little-explored cultural context of Pakistan.

Keywords – Knowledge management, knowledge worker productivity, knowledge worker, knowledge work, knowledge work productivity, productivity

Paper Type Research Paper

Introduction

In contemporary knowledge-based economies, the productivity of knowledge workers functions as a vital source of organizational innovation, performance, and sustainability (Domenech *et al.*, 2016). Peter Drucker (1999) has claimed that fostering the productivity of knowledge workers (workers whose input is knowledge resources to yield knowledge-based intellectual output, such as new solutions and products) is the most extraordinary challenge for management in the 21st century. Knowledge worker productivity refers to knowledge worker efficiency to optimize *knowledge work* for knowledge-based intellectual output (Drucker, 1999). Knowledge work here refers to the intellectual and cognitive tasks that involve creating and applying knowledge for improvisations (Bosch-Sijtsema *et al*., 2009).

According to Drucker's (1999) theory of knowledge worker productivity, five individual-level factors affect knowledge worker productivity, which, in turn, translates into innovation performance: knowledge-based tasks and self-management skills for managing unstructured knowledge work, job autonomy, continuous teaching and learning, knowledge worker treatment as an asset, and a focus on the quantity and the quality of the output. A critical look at these five factors implies that they are available to workers only in a knowledge-based collaborative and supportive environment so that their productivity increases. How then can such a work environment be produced?

In this paper, we claim that the solution can be found in applying knowledge management in the organization. Knowledge management deals with and covers the practices and processes that enable the efficient and effective management of knowledge resources (Alavi and Leidner, 2001; Gold *et al.*, 2001). Several studies demonstrated that executing knowledge management provides a work environment that is conducive for knowledge work (Haas and Hansen, 2007; Kianto *et al*., 2016; Shujahat *et al.*, 2017). However, there is a shortage of empirical evidence for the likely influence of various knowledge processes on knowledge worker productivity conclusively.

Previous studies have addressed the influence of knowledge management on knowledge worker productivity (Constantinescu, 2009; Datta et al., 2005; Feng *et al*., 2005; Haas and Hansen, 2007; Iranzadeh and Pakdelebonab, 2014), but these studies were not conclusive, for the following reasons. First, these studies arrived at contradictory findings in which some knowledge management processes were not found to be significant predictors of knowledge worker productivity (Haas and Hansen, 2007; Iranzadeh and Pakdelebonab, 2014). Second, these studies tended to examine the study variables from a limited perspective, either addressing knowledge management as a unitary concept or measuring productivity with the task efficiency dimension only (Haas and Hansen, 2007). Finally, these studies did not examine data from knowledge workers and knowledge-intensive service sectors explicitly.

Recent literature focused on contextual factors as they are important for understanding managerial challenges in different contexts (Domenech *et al*., 2016; Sergeeva and Andreeva, 2016). Thus far, knowledge management and knowledge worker productivity issues have mostly been studied in the context of developed economies, and the Pakistani, or more generally, the South Asian, context has been ignored. However, it is essential to understand the foundation of knowledge worker productivity in the context of developing economies. Moreover, knowledge management and knowledge worker productivity issues have been studied without consideration of individual demographic differences (Haas and Hansen, 2007). Thus, data collection in Pakistan for a study on knowledge management and knowledge worker productivity while controlling for demographic differences would produce new knowledge. Moreover, such a study would extend the knowledge management debate to unexplored geographic and cultural contexts.

To bridge these gaps in the literature, this study examines whether and how knowledge management processes impact knowledge worker productivity. A survey research strategy was employed. Data were collected through questionnaires from 336 knowledge workers in all five mobile network operator companies in the Pakistani telecom sector. Subsequently, the data were examined with partial least squares modeling.

The research objectives of this study are as follows:

1. To investigate whether and how knowledge management impacts knowledge worker productivity.
2. To investigate whether there are significant intragroup differences among knowledge workers with different formal education levels, managerial positions, and gender, in the influence of knowledge management on knowledge worker productivity.

The rest of the article is composed of the following sections. Section 2 reviews the literature on knowledge management and productivity of knowledge workers. Section 3 explains the methodology, including the sample, data gathering, and data analysis. Section 4 discusses the data analysis and results. Finally, Section 5 and Section 6 discuss and conclude the findings.

Theoretical background

Knowledge worker productivity

Knowledge work is the generation and application of knowledge by highly skilled and autonomous workforce to produce tangible and intangible outcomes (Bosch-Sijtsema *et al.*, 2009). A many-sided concept, knowledge work can be viewed as a profession, an individual's activity, or a characteristic (Dahooie *et al.*, 2011). A knowledge worker is an employee who is identified by knowledge-based tasks improvisations (knowledge generation and knowledge use as input) that result in knowledge-based intellectual output (Thomas and Baron, 1994). By this definition, managers, analyst programmers, and concept designers, for example, can be considered knowledge workers (Curado and Bontis, 2006). Similarly, some studies define knowledge worker as employee who is competent enough to grasp knowledge about the job more than anyone else in the organization. This type of employee can gather, synthesize, and apply knowledge (Turriago-Hoyos *et al*., 2016). Moreover, a knowledge worker is the employee who has a non-routine, complex, and situation-specific job (Bosch-Sijtsema *et al*., 2009).

The traditional definition of a manual worker's productivity driven by the intersection of scientific management theory, predominance of production firms, and manual work in the 20th century was the ratio of the output to the inputs used (Drucker, 1999). However, this simple definition of productivity is no longer feasible for knowledge worker productivity in this century because of the intersection of the present predominance of the knowledge economy, knowledge-intensive service sectors, and knowledge work that is unstructured and intellectual compared to manual work. Consequently, knowledge worker productivity is dominant and refers to a knowledge worker's efficiency in optimizing knowledge work for maximum knowledge-based intellectual output (Drucker, 1999).

Unlike manual worker productivity, there are no universally or generally accepted methods or dimensions or factors that measure knowledge worker productivity which makes it difficult to choose factors or dimensions for measurement purposes (Drucker, 1999; Ramírez and Nembhard, 2004). Unlike manual worker productivity, knowledge worker productivity is a matter of the quality and quantity of the output because of the unstructured and intellectual nature of knowledge work (Drucker, 1999; Palvalin et *al*., 2015). Thus, the construct of knowledge worker productivity should be composed of dimensions that measure the quality and quantity of output, i.e., efficiency and effectiveness. In this vein, Ramírez and Nembhard (2004) carried out an extensive systematic review of more than 60 years of literature to find the taxonomy of generally accepted categories or dimensions for measuring knowledge worker productivity. Their findings indicated that overall knowledge worker productivity measurement dimensions arranged by frequency of use are quantity, cost and profitability, timeliness or meeting time demands, autonomy, efficiency, quality, effectiveness, customer satisfaction, creativity/innovative behavior, project success, responsibility of and importance to knowledge work, knowledge worker's perception of productivity, and absenteeism. Previous studies, on average, used two to three dimensions depending on the study context (Ramírez and Nembhard, 2004).

Therefore, knowledge worker productivity can be measured in three dimensions: timeliness or meeting time demands, work or task (knowledge) efficiency, and job autonomy. Timeliness refers to the degree to which a worker meets deadlines and captures overtime and other time-related issues. Similarly, work or task (knowledge) efficiency measures doing things right so that knowledge-based tasks are completed, meeting all the standards of time and quality (Ramírez and Nembhard, 2004; Tangen, 2005). The work efficiency and timeliness dimensions measure the quantity of the output (efficiency) while meeting quality of output (effectiveness) standards (Lerner *et al*., 2001; Ramírez and Nembhard, 2004; Tangen, 2005). Finally, job autonomy is the extent to which a worker has independence on the job and the number of tasks he or she can do at once (Morgeson and Humphey, 2006; Ramírez and Nembhard, 2004). In knowledge-based jobs or knowledge work, autonomy can be used as a substitute to estimate the range of the dimensions of the other qualities of output (effectiveness), such as innovative behavior and customer satisfaction (Ramírez and Nembhard, 2004). Job autonomy has been a dimension of productivity of knowledge workers in the literature (Butt *et al.*, 2018; Imran and Usman, 2011).

The reported determinants or factors of knowledge worker productivity can be categorized into two types: organizational factors and individual factors (Bosch-Sijtsema *et al.*, 2009; Butt *et al.*, 2018; Drucker, 1999; Maciariello, 2009). Organizational factors include the company strategy, structure, quality of human resources, and organization function and ability to put worker knowledge into action using tools, processes, and products, and consequently yielding innovation performance output. Working on these organizational factors promotes the three practices that are crucial for new knowledge creation and innovation: continuous improvement, continuous exploitation of knowledge, and genuine innovation (Bosch-Sijtsema *et al*., 2009). Individual factors are related to a knowledge worker and include intrinsic motivation, belief in the organization's mission, worker's knowledge management engagement and task monitoring, work-based learning orientation, theoretical knowledge, analytical knowledge, formal education, expertise in the subject, communication skills, promotion of peace and stability, and "creative destruction."

However, this study argues that knowledge management can also impact knowledge worker productivity, but these issues have relatively been ignored in the factors. In addition, knowledge management correlates with individual and organizational factors of knowledge worker productivity to impact knowledge worker productivity positively.

Knowledge management processes

Knowledge management is a management function and discipline that is meant to formulate, implement, and evaluate the strategies that ensure the right flow of knowledge to the right person at the right time and in the right place (Constantinescu, 2009; Feng *et al.*, 2005; Shujahat *et al*., 2017). Knowledge management can be split into two components: critical success factors for knowledge management (also referred to as knowledge management practices and knowledge management infrastructure) and its processes (Gold *et al.*, 2001; Inkinen *et al.*, 2015). This paper focuses on knowledge management processes, i.e., the flows of knowledge and process of applying expertise in an organization (Alavi and Leidner, 2001; Gold *et al.*, 2001).

Knowledge management processes have been defined differently by different studies. After conducting a systematic literature review of knowledge management and innovation performance, Costa and Monteiro (2016) concluded that knowledge management processes include the generation, acquisition, storage, and leveraging of knowledge. Inkinen (2016) defined this process as one that includes other knowledge subprocesses encompassing acquisition, generation, codification, transfer, and leveraging of knowledge. In contrast, in the present study, knowledge management process refers to the process that is composed of sub-processes, including creation, sharing, and utilization of knowledge (Andreeva *et al.*, 2017; De Winne and Sels, 2010; Kang *et al.*, 2007; Nonaka and Takeuchi, 1995; Shujahat *et al.*, 2017). This operational definition might seem different from other definitions of knowledge management processes. However, this is not the case for two reasons. First, previous investigations carried out in Pakistan suggest that knowledge management processes can be simplified to these three fundamental knowledge processes that exist in knowledge-intensive service sectors (Ahmad *et al.*, 2017; Shujahat *et al.*, 2018). Second, Andreeva and Kianto (2011) stated that knowledge management processes are cyclically correlated, and their difference lies in their level of aggregation. The three knowledge management processes encompass other processes. For example, knowledge creation encompasses knowledge assimilation and knowledge acquisition as antecedents (Costa and Monteiro, 2016; Nonaka and Takeuchi, 1995).

Knowledge management processes are complex, intertwined, and qualitative at large. However, these processes can be and have been measured quantitatively and reliably in a plethora of previously validated measurement scales (Darroch, 2003; Gold *et al.*, 2001; Zack *et al.*, 2009). Thus, studies on knowledge management processes can be carried out with a case study research design, and quantitative measurement scales can also be adopted. The three knowledge management processes are explained below.

Knowledge creation is a process and an organizational capability to create new knowledge in terms of new ideas and solutions (Andreeva and Kianto, 2011; Kianto *et al*., 2016). Knowledge creation is a dynamic and interactive process that aims to target the relationships that involve the generation of new knowledge. Knowledge can be created and converted from explicit knowledge to tacit knowledge, and from tacit knowledge to explicit knowledge by four processes (socialization, externalization, combination, and internalization (SECI)). These four processes are called the organizational knowledge creation theory or SECI model (Nonaka and Takeuchi, 1995). There are four antecedents of knowledge creation processes (Andreeva and Kianto, 2011). First, there must be an opportunity to create new knowledge. Knowledge management provides this opportunity through the enabling learning environment. Second, intrinsic motivation of the knowledge worker is imperative for knowledge creation. Third, there must be a capability to create knowledge. Finally, newly created knowledge must be perceived as important. When new knowledge is perceived as important, it is then systematically utilized to innovate in the organization.

Knowledge sharing is the knowledge movement among the different units and actors within an organization (Andreeva and Kianto, 2011; Hooff and De Ridder, 2004; Nonaka, 1994). Different authors define different elements of knowledge sharing. For example, Olander *et al*. (2016) stated that knowledge sharing can be categorized into formal and informal knowledge-sharing types. Moreover, Hooff and De Ridder (2004) state that knowledge sharing is composed of knowledge collection and knowledge donation. Knowledge collection is related to consulting employees in a firm to gain knowledge while knowledge donation is related to communicating one's knowledge to others. Knowledge sharing can happen only when the owner actor of the knowledge gives it to another willingly, and the demander receives and adopts it (Hooff and De Ridder, 2004). Knowledge sharing determinants include trust, intrinsic and extrinsic motivation, job satisfaction, norms and values of an organization, and leadership support (Andreeva and Kianto, 2011; Hooff and De Ridder, 2004; Olander *et al*., 2016).

Knowledge utilization relates to implementing the knowledge an individual actor and unit have (Lee *et al*., 2013). Knowledge utilization is the mechanism of an organization to store, retrieve, access, and use knowledge effectively for strategic purposes (Gold et *al*., 2001). The antecedents of knowledge utilization are reward, trust, and open-mindedness, long-term orientation, R&D fund allocation and facilities, information technology, less information redundancy or optimal level of knowledge, knowledge sharing, knowledge assimilation, knowledge creation, willingness and motivation, and knowledge bases (Lee *et al.*, 2013; Song *et al*., 2005).

Knowledge management and knowledge worker productivity

This study uses the three methods to investigate the relationship between knowledge management and knowledge worker productivity: Drucker's theory, previous findings, and assimilated arguments. The use of these three methods ways of reasoning reinforces following two stances in this subsection. First, knowledge management could enhance knowledge worker productivity. Second, Knowledge management and knowledge worker productivity association is the little-investigated area that demands further exploration. The three methods are applied as follows.

According to Drucker's (1999) theory, there are six individual determinants for enhancing knowledge worker productivity. First, it requires determining what the knowledge worker's actual task or job is. A nurse's task is to take care of patients and not to answer phone calls from patients' relatives and filing paperwork. Similarly, a knowledge worker's task is and should be knowledge work that is unstructured and adds value. A knowledge worker must be able to recognize, manage, and perform unstructured and intellectual *knowledge work* which, in turn, requires self-management skills. Second, a knowledge worker must have job autonomy. Third, a knowledge worker must innovate continuously. This continuous innovation must be part of the worker's job. Fourth, there should be continuous learning and teaching. Fifth, unlike manual worker productivity, the quality and quantity of the output are imperative for knowledge worker productivity. Sixth, the knowledge worker should be managed as an asset instead of a cost.

The six points of Drucker's (1999) theory can be simplified to knowledge-based job and self-management, continuous innovation push to the worker, knowledge worker treatment as an asset, focus on the quality of the output, continuous learning and teaching, and autonomy to act as determinants of knowledge worker productivity. The literature review showed that knowledge management correlates with the determinants of Drucker's theory. For example, different studies reported that knowledge management provides employee empowerment and learning-by-doing opportunities, enhances the total quality management, treats the knowledge (created by the knowledge worker) as a strategic asset under the emerging lens of the knowledge-based view of HRM (human resource management), and is meant to foster the organizational innovation performance (Ahmad *et al.*, 2015; Andreeva *et al.*, 2017; De Winne and Sels, 2010; Hasani and Sheikhesmaeili, 2016; Nisula and Kianto, 2016. Thus, knowledge management correlates with the determinant of productivity postulated by Drucker's theory to enhance knowledge worker productivity.

Many studies have empirically addressed the association of knowledge management and knowledge worker productivity: Constantinescu (2009), Datta *et al.* (2005), Feng *et al.* (2005), Haas and Hansen (2007), and Iranzadeh and Pakdelebonab (2014). Iranzadeh and Pakdelebonab

(2014) tested the effect of knowledge management processes on the task efficiency of university teachers. The overall results suggest that knowledge management nurtures task efficiency positively and significantly. Haas and Hansen (2007) collected data from 182 sales teams. The authors concluded that codified knowledge sharing decreases task-on-time while advice sharing enhances the quality of the task performance and competencies. However, in contrast, personal advice knowledge sharing does not decrease time-on-task. Constantinescu (2009) tested the knowledge management effect on labor productivity. The objective data were drawn from European companies. Labor productivity was measured using the formula the logarithm of the sales divided by the number of employees. The findings indicate that knowledge management implementation and practices generally enhance labor productivity. Feng *et al.* (2005) showed using the objective data that U.S. organizations that adopt knowledge management systems had higher labor productivity than those that did not.

However, these studies were not conclusive for the following reasons. First, these studies did not uncover the causality mechanisms from literature. Second, these studies had contradictory findings in which some knowledge processes are not significant predictors of task efficiency and timeliness (Haas and Hansen, 2007; Iranzadeh and Pakdelebonab, 2014). Third, most of these studies measured knowledge management processes as unitary variables and productivity from the efficiency or quantity of the output dimension (see Constantinescu, 2009) while ignoring the separate dimensions of knowledge management processes. However, Drucker's (1999) theory suggests that knowledge worker productivity dimensions or factors should be used to measure the quality and quantity of the output. Thus, there is a gap in the literature that could be filled. Fourth, some of the studies measured productivity using objective data from companies reports (Constantinescu, 2009). However, Drucker (1999) postulated that nurturing productivity is the job and responsibility of the knowledge worker. Thus, the use of subjective data from knowledge workers themselves makes more sense. Moreover, the use of objective data indicates that knowledge worker productivity was measured only from the quantity of the output (efficiency) while the quality of the output dimension (effectiveness) was ignored. Finally, these research papers did not collect data explicitly from knowledge workers- who are characterized by knowledge work and formal higher education- and knowledge-intensive service sectors. Considering these gaps, it seems imperative to investigate the relationship of knowledge management processes and knowledge worker productivity in depth.

Finally, assimilated arguments from literature also suggest that knowledge management could enhance knowledge worker productivity. Knowledge management ensures the optimal level of knowledge provision at the right time and the right place to the right workers (Constantinescu, 2009; Datta *et al.*, 2005; Feng *et al.*, 2005; Shujahat *et al.*, 2017). The optimal knowledge provision, in turn, facilitates knowledge work and efficient decision-making and processes while avoiding three conditions that impede productivity: “information overload” (the condition where a worker has too much information that impedes decision-making), “no information” (the condition where a worker has no information so that the worker is not likely to decide which alternative to choose for decision-making), and “information cost” (the time and resources that a knowledge worker allocates because of the tendency to search for information and knowledge regarding the job internally (Bhatija *et al.*, 2017; Constantinescu, 2009; Feng *et al.*, 2005). Thus, knowledge management enhances productivity. Hypotheses regarding knowledge processes and knowledge worker productivity are formulated in detail.

The service sector is the most dynamic and knowledge-intensive sector because of the high customer customization demands and involvement with the service process. Therefore, business processes are complicated to codify in knowledge form in the service sector unlike the production sector (Miles, 2005). Thus, the knowledge creation process seems more important for knowledge-intensive service sectors than for production sectors. Knowledge can be generated and converted from explicit knowledge to tacit knowledge and vice versa through the SECI cycle of knowledge creation in a shared and collective context known as “ba” (Nonaka and Takeuchi, 1995). Knowledge creation through this cycle provides knowledge to each worker that can be used for performance on the job in terms of customers’ solutions to their dynamic problems and continuous process improvement (Constantinescu, 2009; Feng *et al.*, 2005; Haas and Hansen, 2007; Iranzadeh and Pakdelebonab, 2014; Martinkenaite, 2011).

H1: Knowledge creation affects knowledge worker productivity positively and statistically significantly.

Codification and personalization are the two key knowledge management strategies (Hansen *et al.*, 1999). Personalization strategy facilitates direct human interactions through job engagement and job enlargement that, in turn, promote knowledge sharing or the optimal flow of knowledge among the actors in an organization (Hansen *et al.*, 1999; Shujahat *et al.*, 2017). Knowledge sharing can be manifested in various ways, such as lessons learned sharing, best practices, and failure stories (Constantinescu, 2009; Datta *et al.*, 2005; Feng *et al.*, 2005; Kim *et al.*, 2014; Shujahat *et al.*, 2017). An increase in knowledge sharing promotes an increase in knowledge bases, knowledge assimilation, and knowledge creation for potential knowledge use (Feng *et al.*, 2005; Nonaka and Takeuchi, 1995). In other words, knowledge sharing enhances knowledge worker ambidexterity by facilitating use of knowledge exploration (knowledge creation) and knowledge exploitation (knowledge utilization) (Caniëls *et al.*, 2017). Knowledge sharing facilitates exploration activities by idea sharing among knowledge workers. Similarly, knowledge sharing facilitates knowledge exploitation by decreasing a worker's search for knowledge through the optimal flow of knowledge that could be used for task improvisations (Constantinescu, 2009; Lee, 2001). Through these methods, knowledge sharing facilitates workers in timely responses, decision-making, and new ideas and solutions for greater customer satisfaction (Feng *et al.*, 2005; Haas and Hansen, 2007; Martinkenaite, 2011; Olander *et al*., 2016).

H2: Knowledge sharing affects knowledge worker productivity positively and statistically significantly.

Knowledge utilization facilitates a knowledge worker's capacity for task improvisation (Nisula and Kianto, 2016). However, the impact is not limited to task improvisation but also results in the mix of customers and worker's self-reflection and feedback on the quality and quantity of the task or service process and output (Martinkenaite, 2011; Nonaka and Takeuchi, 1995). This mix of self-reflection and feedback, in turn, promotes new knowledge creation. The creation of new knowledge increases the knowledge bases (Lee *et al.*, 2013). These knowledge bases and knowledge creation can be used for better task improvisation, decision-making, process improvements, and customer satisfaction (Constantinescu, 2009; Feng *et al.*, 2005; Nisula and Kianto, 2016).

H3: Knowledge utilization affects knowledge worker productivity positively and statistically significantly.

Research methods

Target population

Data were collected from knowledge workers at the headquarters of all five mobile network operator companies in the Pakistani telecom sector through a survey questionnaire. The term “knowledge workers” in this study refers to workers who have at least 16 years of formal education (university graduates) and are not involved in manual or physical jobs but knowledge work (Bosch-Sijtsema *et al*., 2009). The formal education level criterion was chosen because telecom companies recruit new university graduates (who have at least 16 years of formal education including 4-years undergraduate degree) for knowledge work jobs like engineering.

At the time of the data collection, five mobile network operator firms served the mobile network needs of 133 million users in a country of more than 200 million. These companies do not report the total number of employees in their annual reports. However, according to informal conversations with middle managers in these organizations, on average, each mobile network operator company has 500 to 600 knowledge workers at its headquarters.

The telecom sector was chosen for several reasons. First, the telecom sector is an innovation-intensive service sector that requires knowledge-intensive activities (Imtiaz *et al*., 2015). Second, employees who work at company headquarters face more innovation and thus, knowledge creation and knowledge utilization pressures as these workers respond to customers’ dynamic problems. Third, knowledge workers at company headquarters have greater autonomy than franchise employees to perform innovatively, thus allowing them to create, share, and utilize knowledge. Fourth, this sector companies recruit knowledge workers with at least 16 years of education so that the workers have higher skills and knowledge to improvise their knowledge-based tasks effectively. Finally, these telecom organizations have implemented knowledge management functions as empirical studies conducted in these organizations have suggested, thus making these organizations more relevant for data collection (Ahmad and Ahmad, 2014; Hassan, 2014).

Sampling and data collection

Data were collected through convenience sampling. Managers were indirectly accessed through personal relations. They administered survey questionnaires to knowledge workers in their firms. This kind of convenience sampling was deemed the most workable solution for collecting the data for several reasons. First, the mobile network operator companies are highly knowledge protective, and information secrecy prevails at their hearts. Second, managers can use their influence on other employees to fill in the questionnaires, and thus, ensure a sufficient number of observations. Thus, middle managers with whom the authors had direct or indirect personal relations were accessed in person. They were handed the questionnaires and were asked to use their influence on their subordinates, frontline managers, and colleagues to fill out the questionnaires. In this way, a sample of 336 usable responses was returned. Of the 336 respondents, 76.48 percent (257) were male, 91.07 percent (306) had a master's degree, while the remaining portion had higher education; 58.03 percent (195) were frontline employees, 1.78 percent (6) senior managers, and 40.17 percent (135) were middle managers.

3.3 Pre-testing

Before the survey questionnaire was distributed, it was pre-tested on a panel comprised of two knowledge management professors and three managers in the telecom organizations. The feedback and suggestions from the first round were used to improve the wording. Subsequently, the panel members were re-accessed to review the questionnaire after the suggestions and feedback had been incorporated. In the second round, all members agreed on the final version of the questionnaire.

3.4 Measures

All the first-order reflective constructs were measured using items adapted from available relevant instruments on a five-point Likert scale (from 1 = strongly disagree to 5 = strongly agree). The details of the measurement scales are as follows. The scales are provided in the appendix section.

3.4.1 Knowledge management process

The three knowledge management processes were measured using the adapted CEN's (2004) "European Guide to Good Practice in Knowledge Management: Guidelines for Measuring the Knowledge Management" scale. This less used frequently scale was chosen instead of other widely recognized and used instruments (Darroch, 2003; Lee and Choi, 2003; Zack *et al.*, 2009) because not only it is based in literature (Waterman *et al*., 1980) and has been used in empirical studies (Ali, 2009; Shujahat *et al.*, 2017), but it is also used as a practical diagnostic tool by consultancy firms to assess and solve the organizations' knowledge processes problems. The exploratory nature of partial least squares-structural equation modeling (PLS-SEM) allows the effective and direct use of the less frequently used instruments with content validity. Several studies have used relatively new instruments with content validity directly in PLS-SEM (Ali *et al.*, 2017; Baumgarth, 2009; Hoffmann *et al.*, 2011; Sarstedt *et al.*, 2013; Sarstedt and Scholderer, 2010).

Knowledge worker productivity

Three dimensions were used to measure knowledge worker productivity: timeliness, work/task (knowledge) efficiency, and job autonomy. Timeliness was measured using two items adapted from Lerner *et al*.'s (2001) Work Limitation Questionnaire. Work (knowledge) efficiency was measured using three adapted items from Tangen (2005) while job autonomy at work was measured using two items adapted from Morgeson and Humphey's (2006) scale.

Measurement

This study employed PLS-SEM in SmartPLS 3.2.7 software for data analysis. The exploratory nature of the research model, small sample size, and no assumptions about the data normality were the rationales for choosing PLS-SEM (Hair *et al.*, 2017; Ringle *et al.*, 2018). Following the state-of-art guidelines for PLS-SEM (Hair *et al.*, 2016, 2017; Ringle *et al.*, 2018), all items with outer loadings higher than the 0.70 threshold value were retained while factor loadings below than 0.7 were dropped during path analysis such that their removal did not impact the content validity.

Results

Correlation analysis

The study examined the correlation matrix to examine the interconnectedness among the constructs. Table I provides the correlation among the constructs showing that knowledge management processes are highly correlated with each other and with knowledge worker productivity.

Insert Table 1 here

Measurement model assessment

Measurement model testing involved testing the following components: outer loadings, item/indicator reliability, construct reliability, and convergent and discriminant validity (Hair *et al.*, 2016, 2017; Hulland, 1999; Ringle *et al.*, 2018). The outer loadings ideal threshold is 0.7. In Table II, all the items outer loadings considered in the measurement model are higher than 0.7. Indicator reliability for an item is the square of its outer loadings. The threshold value is 0.5. Consequently, Table II shows that all the items have reliability as their corresponding threshold values exceed 0.5.

This study measured the construct reliability by checking composite reliability (Bagozzi and Yi, 1988). The ideal threshold value for the measure of construct reliability is 0.7. Table II shows that the composite reliability values are above 0.7 for the constructs, indicating adequate construct reliability. Moreover, average variance extracted (AVE) is the measure of convergent validity. The minimum threshold value for the AVE is 0.5 to establish convergent validity (Fornell and Larcker, 1981). Table II shows that each construct has an AVE value higher than the threshold value showing adequate convergent validity.

Insert Table II here

Finally, this study used the recently introduced approach (the heterotrait-monotrait (HTMT) ratio) in PLS-SEM to assess the discriminant validity. The HTMT ratio value of a set of two constructs should be less than 0.85 (the conservative value) or 0.90 (the liberal value for two constructs that are related theoretically; Henseler *et al*., 2015). Table I shows that the HTMT ratio for each set of constructs is less than the conservative value of 0.85. However, the HTMT ratio for the set of two constructs (knowledge utilization and knowledge creation) is greater than the conservative value of 0.85 but lower than the liberal value of 0.90, because the knowledge creation and knowledge utilization constructs are highly correlated theoretically (Nonaka and Takeuchi, 1995). Thus, the model has adequate discriminant validity.

Structural model assessment

The structural model evaluation consisted of the following steps: assessment of the structural relationship in the model for multicollinearity assessment, hypotheses testing, regression, f^2 effect size, and Q^2 predictive relevance (Chin, 1998; Hair *et al.*, 2016, 2017; Ringle *et al.*, 2018). The measure for multicollinearity assessment was the variance inflation factor (VIF) for which the threshold value is less than 3. Table III indicates that all exogenous constructs have VIF values less than 3, thus indicating no multicollinearity issue in the structural model.

Insert Figure I here

Next, the hypotheses were tested using the path coefficients and their significance levels. The results shown in Table III and Figure I suggest that knowledge creation (β=0.30, p<0.05) and knowledge utilization (β=0.455, p<0.05) enhance knowledge worker productivity statistically significantly. Thus, H1 and H3 are supported. In contrast, the results suggest that knowledge sharing does not enhance knowledge worker productivity statistically significantly (β=0.114, p>0.05). Consequently, H2 is not supported.

Insert Table III here

The R^2/regression value for knowledge worker productivity is 62.2 percent, a substantial value (Hair *et al.*, 2017; Figure I). This suggests that taken together, the three knowledge processes explain 62.2 percent variation in knowledge worker productivity. Moreover, 0.35, 0.15, and 0.02 are the threshold values of the f^2 effect size for large, medium, and small effect sizes, respectively (Hair *et al.*, 2017). The f^2 effect sizes for knowledge creation (0.094), knowledge sharing (0.021), and knowledge utilization (0.202) represent small and medium effect sizes, thus, indicating that although knowledge creation impacts knowledge worker productivity statistically significantly, omitting knowledge creation from the model does not have a large effect on knowledge worker productivity (Table III). In contrast, knowledge sharing is not a statistically significant predictor of knowledge worker productivity, although the effect size has a small value above zero (Table III). Finally, using the blindfolding procedure, the Q^2 value for knowledge worker productivity is 0.342 which is considerably above than the threshold value of 0. This value indicates the predictive relevance of three exogenous constructs for knowledge worker productivity.

Multi-group analysis

To understand the contextual association between knowledge management and productivity, this study conducted multi-group analysis (MGA) of three demographic factors (gender, formal education level, and managerial position; Hair *et al.*, 2017). Table IV shows that there are non-statistically significant gender differences (male-female) for the effects of knowledge management processes (knowledge creation (β=0.085, p>0.05), knowledge sharing (β=0.310, p>0.05), and knowledge utilization (β= 0.070, p>0.05)) on knowledge worker productivity. Similarly, non-statistically significant formal education differences between knowledge workers (a taught master's degree-M.Phil. degree) for the effects of knowledge management processes (knowledge creation (β=0.153, p>0.05), knowledge sharing (β=0.168, p>0.05), and knowledge utilization (β=0.061, p>0.05)) on knowledge worker productivity were noted. Finally, the differences in managerial positions were also computed. There were only nine responses from strategist managers. Therefore, this small sub-group was suppressed automatically by SmartPLS 3.2.7, and only group differences between frontline managers and middle managers were computed. Non-statistically significant differences for managers (frontline-middle) for the effects of knowledge management processes (knowledge creation (β=0.052, p>0.05), knowledge sharing (β=0.088, p>0.05), and knowledge utilization (β= 0.007, p>0.05)) on knowledge worker productivity were found.

Insert Table IV here

Discussion

This study postulated that knowledge management is likely to increase knowledge worker productivity statistically significantly. The results show that knowledge creation and knowledge utilization impact knowledge worker productivity statistically significantly, but in contrast to expectations, knowledge sharing does not exert a statistically significant impact. The results are discussed in more depth as in the following.

The results show that knowledge creation has a positive and significant effect on knowledge worker productivity. These results confirm findings in previous studies (Bosch-Sijtsema *et al*., 2009; Iranzadeh and Pakdelebonab, 2014). Many definitions of knowledge work and knowledge worker productivity (Bosch-Sijtsema *et al*., 2009) consider knowledge creation and knowledge utilization the two main processes and activities in knowledge work that increase knowledge worker productivity. The service sector in general and the telecom and IT sectors in particular are considered dynamic and knowledge-intensive. This dynamism, for example, in the form of customers' dynamic problems and demands, pushes knowledge workers to continuously acquire and create new knowledge that can then be used to generate solutions for greater customer satisfaction.

The results also indicate that knowledge sharing has a positive but non-statistically significant effect on knowledge worker productivity although with a small effect size f^2. These results contradict those in Iranzadeh and Pakdelebonab's (2014) study that showed a positive and significant effect of knowledge sharing on employee task efficiency and are in line with Haas and Hansen's (2007) results. In definitions of knowledge work and knowledge worker productivity, creation and application of knowledge are considered critical antecedents of knowledge worker productivity and knowledge work (Bosch-Sijtsema *et al*., 2009; Turriago-Hoyos *et al*., 2016). The lack of a statistically significant direct association between knowledge sharing and productivity might be because knowledge sharing has an indirect impact on productivity through impacting other knowledge processes (Nonaka and Takeuchi, 1995). This discussion also points out future research avenues that some knowledge processes (e.g., knowledge creation) might mediate the association between knowledge sharing and productivity.

The results further indicate that knowledge application has a positive and statistically significant effect on knowledge worker productivity. These results are in line with Iranzadeh and Pakdelebonab (2014) who found a similar effect of knowledge utilization on employee task efficiency. Lee *et al*. (2013) reported that when new knowledge is created and implemented, it replaces previous knowledge and helps to solve novel dynamic problems within the prevalent knowledge-intensive service sector (the telecom sector here). Consequently, knowledge application yields an increase in knowledge workers' ability to solve novel problems, ambidexterity, and innovation performance.

This study also conducted a multi-group analysis for three subsamples (gender, formal education level, and managerial position) to explore statistically significant group differences, if any, for the relation between knowledge management processes and knowledge worker productivity. The results indicated that the differences in gender (male and female), formal education level (a taught master's degree and M.Phil./M.S. degree, a more research-intensive master's degree), and managerial position (frontline managers and middle managers) were not statistically significant. The non-statistically significant differences between male and female knowledge workers indicate that there are no significant glass-ceiling dynamics that could impede female knowledge workers' participation in comparison with male knowledge workers in knowledge management activities to increase their productivity. Similarly, there are non-significant statistical differences for knowledge workers with Master (16 years of formal education) and M.Phil. (research-oriented 18 years of formal education) Degrees. Many definitions of knowledge worker characterize knowledge workers by their formal education (Bosch-Sijtsema *et al*., 2009). Therefore, once knowledge workers possess formal education, then they are more likely to use their knowledge and skills as lifelong deeper learner for creating and acquiring new knowledge to increase productivity. Finally, results indicated that the intragroup differences in managerial positions (frontline and middle managers) were not statistically significant. These results indicate that whatever the knowledge workers' managerial level, it is mandatory for them to generate and utilize the knowledge as input as part of their knowledge worker jobs.

Conclusions

This study addressed the effects of knowledge management processes on one of the most critical issues in contemporary organizations, knowledge worker productivity. The research context was the five mobile network operator companies in the Pakistani telecom sector, which is the most knowledge-, service-, and innovation-intensive sector within the country. Although there is much empirical evidence of the influence of knowledge management on organizational-level variables, few studies have examined the relation between knowledge management and individual-level performance issues such as knowledge worker productivity.

The key finding of this study is that irrespective of gender, formal education level, and managerial position, knowledge creation and knowledge utilization stimulate knowledge worker productivity. Therefore, this study suggests a novel benefit of knowledge management as a source and an antecedent of increasing knowledge worker productivity. Moreover, the results indicate that knowledge sharing is not a statistically significant determinant of knowledge worker productivity. Knowledge sharing might impact knowledge worker productivity through affecting other knowledge processes.

To the best of the authors' knowledge, no study has empirically tested the impact of different knowledge management processes on knowledge worker productivity while controlling for demographic factors. Previous studies were not as conclusive because of knowledge worker productivity measurement issues, contradictory findings, explicit data collection from knowledge workers and the knowledge-intensive service sector, and the lack of consideration of demographic factors as control variables, among other issues. Therefore, this paper provides a new contextual and conclusive understanding of the antecedents of the productivity of a key segment of today's workforce: knowledge workers. Furthermore, as in the literature on knowledge-related issues, Pakistan, and more generally, the South Asian context, has received scant attention, this paper extends the current knowledge management debate to a relatively unexplored geographic and cultural context.

Practical implications

This study proposes to practitioners that similarly to how scientific management was used to increase manual worker productivity, knowledge management toolkit can be used to foster knowledge worker productivity irrespective of gender, managerial position, and formal education level. More specifically, knowledge management processes and knowledge workers' propensity to (Atapattu, 2018) and engagement in knowledge management processes (Butt et al., 2018) are crucial for fostering knowledge worker productivity irrespective of gender, managerial position, and education level. Knowledge management processes and knowledge workers' engagement in and propensity to knowledge management processes can be supported by knowledge management practices that are considered conscious managerial interventions. Knowledge management practices can be categorized into ten practices (four knowledge-based HRM practices, information technology, work/task organization, strategic management of competence and knowledge, learning mechanisms, knowledge protection, and supervisory work; Inkinen *et al.*, 2015). Therefore, managers must explore and use the idiosyncratic knowledge management practices that suit their organizations to foster knowledge processes and knowledge workers' engagement in and propensity to knowledge management processes that, in turn, can facilitate knowledge worker productivity. Finally, workers with different types of knowledge and formal education should be recruited as such diversity can increase workers' engagement in and propensity to knowledge management processes to yield a higher level of productivity.

Limitations and future research directions

The limitations are as follows. First, this study had a cross-sectional design. Second, this study disregarded knowledge processes interrelationships (Nonaka and Takeuchi, 1995) while testing the hypotheses. Therefore, future studies may consider the case study research design to consider interrelationships as knowledge processes are qualitative at large and intertwined. Third, the geographic scope of the data collection was limited to the Pakistani telecom sector, which poses significant limitations in generalizing the results to other contexts. Finally, the convenience sampling is also a limitation.

In addition, the study recommends the following research avenues. First, the impact of knowledge management infrastructure or knowledge management practices on knowledge worker productivity should also be tested. Second, the 62.2 percent variance in knowledge worker productivity is explained by knowledge management processes. Future studies should explore and test other factors that could explain the unexplained variance.

Acknowledgements

The authors are thankful to Professor Paul Louis Iske, School of Business and Economics, Maastricht University, Netherlands, two anonymous reviewers, and Editor-in-Chief for their cooperation and developmental feedbacks.

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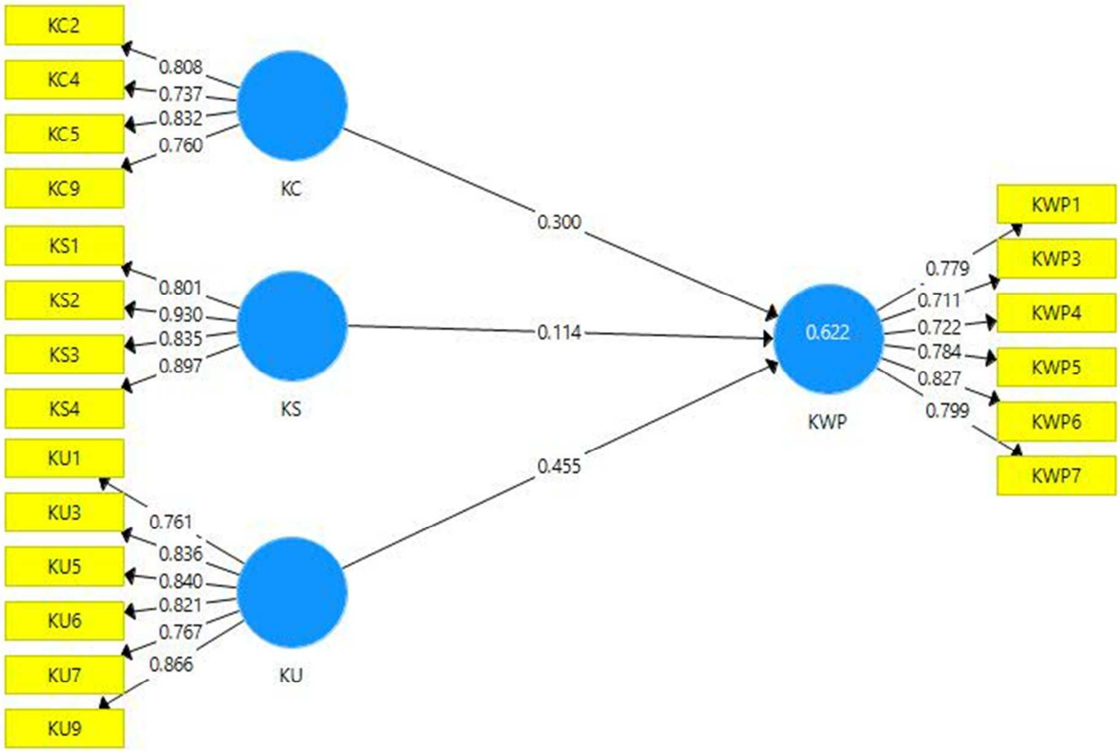
Figure I. Research strucutral model



(KC= Knowledge Creation; KS=Knowledge Sharing; KU=Knowledge Utilization; KWP=Knowledge Worker Productivity)

Table I. Correlations analysis and HTMT ratios for discriminant validity

Set of the two constructs	Correlation value	HTMT ratio
KS→KC	0.577	0.662
KU→KC	0.766	0.896
KU→KS	0.615	0.677
KWP→KC	0.714	0.842
KWP→KS	0.567	0.624
KWP→KU	0.755	0.845

(KC=Knowledge Creation; KS=Knowledge Sharing; KU=Knowledge Utilization; KWP=Knowledge Worker Productivity)

Table II. Evaluation of measurement model

Indicators	Outer loadings	Item reliability	Composite reliability	AVE
KC2	0.808	0.652	0.865	0.616
KC4	0.737	0.543		
KC5	0.832	0.692		
KC9	0.760	0.577		
KS1	0.801	0.641	0.924	0.752
KS2	0.930	0.864		
KS3	0.835	0.697		
KS4	0.897	0.804		
KU1	0.761	0.579		
KU3	0.836	0.698	0.923	0.666
KU5	0.840	0.705		

KU6	0.821	0.674		
KU7	0.767	0.588		
KU9	0.866	0.749		
KWP1	0.779	0.606	0.898	0.595
KWP3	0.711	0.505		
KWP4	0.722	0.521		
KWP5	0.784	0.614		
KWP6	0.827	0.683		
KWP7	0.799	0.638		

(KC=Knowledge Creation; KS=Knowledge Sharing; KU=Knowledge Utilization; KWP=Knowledge Worker Productivity; AVE=Average Variance Extracted)

Table III. Structural model

Hypothesis	**Relationship**	**Path Coefficient (O)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**	**VIF**	**Effect size (f^2)**	**Predictive relevance Q2**
H1	**KC→KWP**	0.300	0.057	5.263	0.000	2.530	0.094	0.342
H2	**KS→KWP**	0.114	0.060	1.915	0.056	1.680	0.021	
H3	**KU→KWP**	0.455	0.062	7.309	0.000	2.713	0.202	

(KC=Knowledge Creation; KS=Knowledge Sharing; KU=Knowledge Utilization; KWP=Knowledge Worker Productivity)

Table IV. PLS-Multi-Group Analysis (gender, higher education, and managerial position)

Relationship	**Path coefficients difference (male-female)**	**p-value difference (male-female)**	**Path coefficients difference (master-M.Phil.)**	**P-value (master-M.Phil.)**	**Path Coefficients difference for managers (frontline-middle)**	**P-value difference for managers(frontline-middle)**
KC→ KWP	0.085	0.231	0.153	0.869	0.052	0.670
KS → KWP	0.310	1.000	0.168	0.916	0.088	0.842
KU → KWP	0.070	0.272	0.061	0.311	0.007	0.519

(KC=Knowledge Creation; KS=Knowledge Sharing; KU=Knowledge Utilization; KWP=Knowledge Worker Productivity)