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Muneer Al Dwaikat [1]
Kartinah Ayupp
Yousef AhmadAlolabi

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BEYOND MONITORING: THE IMPACT OF PERFORMANCE MONITORING ON KNOWLEDGE WORKER PRODUCTIVITY

Abstract: *This study aims to present and test a new conceptual framework to study the significance of employee performance monitoring for knowledge worker productivity in the UAE construction industry. Previous research tends to overlook the mediation effects of stress and knowledge management. In this study, data is collected from 595 executives and non-executives having a minimum of three years of service tenure and a diploma or higher educational qualification from all the seven emirates of the UAE. Because of multivariate analysis, structural equation modelling is employed in the two stages of measurement model accuracy and structural links between research constructs. Research shows that employee performance monitoring directly impacts knowledge worker productivity, as well as the statistically significant impact mediating effect of stress and knowledge management on this relationship. Although stress direct effect on knowledge has a negative beta coefficient, it is still statistically insignificant. Such statistical insignificance reflects that stress does not affect knowledge worker productivity significantly. In this study, the impact of employee performance monitoring on knowledge worker productivity was established. Furthermore, this study found that stress acts as a mediator between employee performance monitoring and knowledge management, and between employee performance monitoring and knowledge worker productivity. Furthermore, this study has other theoretical, empirical, methodological, and practical contributions. This study's results will contribute to policymakers, analysts, and project managers.*

Keywords: *Employee performance monitoring, knowledge worker productivity, construction industry, stress, knowledge management.*

1. Introduction

The association between monitoring and knowledge worker productivity is a relatively understated and under-analyzed concept in human resource management. Moreover, the tools that can measure the performance of knowledge workers' productivity are challenging to use compared to the conventional tools. These workers differ from manual workers in terms of their academic qualifications, skills, and scope of work. Knowledge workers are essential for organizations to fulfil various tasks and

[1] Corresponding author: Muneer Al Dwaikat
Email: maldwaikat@yahoo.com

functions, such as devising business strategies, assessing goals, and laying out plans (Chang et al., 2015). Throughout the evaluation and monitoring of employee performance, it is also analyzed that various components such as stress, burnout, and psychological distress are limiting factors for workers' productivity.

1.1. Problem Statement

According to Palvalin et al. (2017), increasing the productivity of knowledge-workers is the distinctive problem facing management researchers and strategists in the 21st century Knowledge workers, whose responsibilities are largely unstructured and intellectual in nature, are an increasingly important segment of the workforce in the twenty-first century (Iazzolino et al., 2017). Workers' productivity and its connection to overall performance aren't well-understood in empirical investigations (Kianto et al., 2018). Research also tries to investigate the sub-dimensions of productivity, fulfilling time demands and work/task efficiency of knowledge workers, as well as their autonomy in the workplace. Previous research has inadequately discussed these sub-dimensions (Wardhani et al., 2022; Abeille et al., 2022) and are part of future directions given in those studies. Though occupational stress has been studied concerning knowledge worker productivity, it does not play any role as a mediator in the extant literature. Stress as a mediator will yield results that would change the working dynamics of the workplace. This study will provide a more in-depth understanding of how stress influences the connection between employee performance monitoring and the productivity of knowledge workers by examining their relationship. This research will use knowledge management as a mediator because there are not enough studies that investigate the mediating role that knowledge management plays on the relationship between performance monitoring and the productivity of knowledge workers. The prior investigations (e.g., Vuong et al., 2022 Yusoff et al., 2014; Adriaenssen et al., 2016) also lack depth regarding knowledge acquisition and dissemination sub-dimensions, etc., responsiveness to knowledge within the umbrella of knowledge management. Past Studies (e.g., Ramírez & Nembhard, 2004) have shown a direct relationship between employee performance monitoring and knowledge worker productivity, but mediators are not common.

1.2. Research Questions

RQ1: How do employee performance monitoring and stress affect knowledge worker productivity?

RQ2: What are the roles that stress and knowledge management play as different mediators in the interaction between employee performance monitoring and the productivity of knowledge workers?

RQ3: How does the presence of stress and knowledge management act as sequential mediators of the relationship between employee performance monitoring and the productivity of knowledge workers?

Research Objectives

1. To provide an explanation of the relationship between employee performance monitoring and the productivity of knowledge workers.
2. To provide an explanation of the direct influence that stress has on the productivity of knowledge workers as well as the role that stress plays as an intermediary in the interaction between performance monitoring and knowledge worker productivity.
3. To interpret the mediating impact of knowledge management between the relationship of performance monitoring and knowledge worker productivity.
4. To investigate the influence of stress and knowledge management working together as serial mediators in the connection between performance

monitoring and the productivity of knowledge workers.

2. Literature Review

In their systematic literature review, De Sordi et al. (2020) synthesized the concept of the knowledge worker as the one whose work is defined by the continuous, organized, and dominant expansion of organizational knowledge via the exploration mechanism. It distinguishes knowledge workers from those with pre-existing knowledge [information workers] whose primary responsibility is to exploit organizational knowledge. The knowledge worker is capable of information gathering, analysis, and application (Turriago-Hoyos et al., 2016). In order to find the taxonomy of widely accepted categories or dimensions for evaluating the productivity of knowledge workers, Ramrez and Nembhard (2004) conducted a comprehensive and systematic analysis of the literature spanning more than sixty years. This was done in order to find the answers to their research questions. They came to the conclusion that the overall factors that contribute to the productivity of knowledge workers are as follows: volume, cost, and profitability; timeliness or time demand; autonomy; efficiency; quality; efficiency; customer satisfaction; creativity or innovative behaviour; a successful project; responsibility; and the importance of knowledge; as well as the knowledge worker's perception of productivity and absenteeism. Previous studies have used either two or three components, depending on the nature of the investigation (Ramirez and Nembhard, 2004; Shujahat et al., 2022). The timeliness or time needs, the efficiency of knowledge, and job autonomy are the three dimensions that can be used to quantify the productivity of knowledge workers in this study. These dimensions are based on the setting of the study itself. The researcher who conducted this study came to the conclusion that the concept of knowledge management consists of four sub-dimensions after reading Gold et al. (2001). These aspects are known as 1) the acquisition of knowledge, 2) the transformation of knowledge, 3) the application of knowledge, and 4) the protection of knowledge. Performance monitoring is categorized as a third-order formative construct according to Stanton (1997). It is further separated into two second-order formative constructs, which are monitoring behaviour and supervisor traits Figure 1. Monitoring behavior is further segregated into three first-order reflective sub-dimensions: justification, process control, and consistency. Supervisor characteristics are classified into three first-order reflective constructs: trust, expertise, and job performance knowledge.

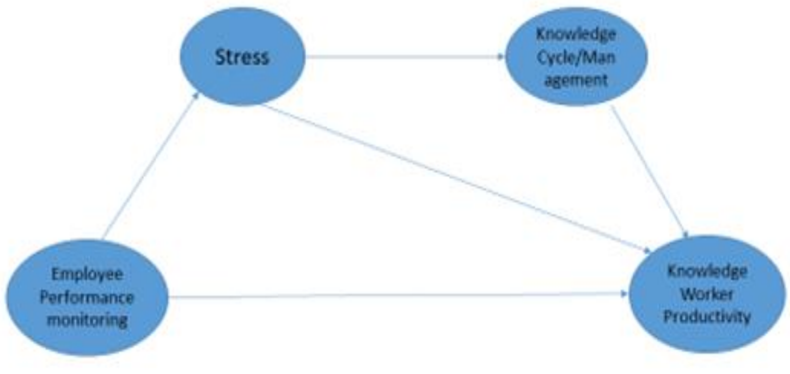

Figure 1. Conceptual Model

2.1. Hypotheses Development

The quantitative study by Chandra et al. (2020) of 163 private sector employees found that technological spatial intrusion (e.g., cameras or other technical monitoring) is deeply dependent upon being seen as productivity-enhancing alternatively as a privacy violation. Wells et al. (2007) came to the conclusion that employees will react more positively to EPM if managers and human resource development professionals carefully frame the reasons for monitoring and feedback in terms that are constructive and developmental while they were researching the aftereffects of EPM. The currently available research makes no mention of performance monitoring on the productivity of knowledge workers. It is for this reason that the following hypothesis is proposed:

H1: Employee Performance monitoring positively affects knowledge worker productivity.

According to the findings of research conducted on academic staff by Ekienabor (2016), when higher levels of stress are present in an environment without any managerial concern for a solution, it results in lower employee performance, which risks the reputation of the organization and results in the loss of a skilled employee. These investigations, which empirically proved an inverted U-shaped association between arousal (stress, anxiety, etc.), and performance, are supported by the Yerkes–Dodson law. The fact that there is very little research on how stress affects the productivity of knowledge workers in the construction sector is made abundantly clear by the conversation that came before it. On the basis of the debate up to this point, the following hypothesis can be formulated:

H2: Stress negatively affects the knowledge worker productivity.

The technologically advanced business environment of today equates performance monitoring with electronic performance monitoring, and the research show that the role of electronic performance monitoring on stress is clear (Amick & Smith, 1992, Kolb & Aiello, 1996). The detrimental impact that stress has on knowledge management is brought to light in the research conducted by Marques et al (2019). They came to the conclusion that a strong positive association existed between organizational stress and disengagement from information sharing, as well as a relationship between stress and maturity in the management of knowledge. Therefore, the following is proposed as a hypothesis:

H3: Stress mediates the relationship between employee performance

In the preceding paragraph, the effect of stress on knowledge management has been established with the help of studies. However, such studies have a context other than the construction industry of the UAE. Hence there is a need to check the effect of stress on knowledge management in the context of the UAE construction industry. To continue with the discussion loop, there are research in the current body of literature (e.g., Kianto et al., 2018) that ponder the effect that knowledge management has on the productivity of knowledge workers. However, the research that was carried out by Kianto et al. (2018) against the backdrop of five different mobile network carriers. There is a compelling requirement to test the effect of knowledge management on knowledge worker productivity in the UAE construction industry in order to establish the reliability of the impact. This is due to the fact that the dynamics of the construction industry may be different from those of mobile network operators. Keeping in view the discussion above, the mediating role of knowledge management between stress and knowledge worker productivity is essential, and hence the following hypothesis may be formulated:

H4: Knowledge management mediates the relationship between stress and knowledge worker productivity.

The discussion in setting Hypotheses H3 and H4 hints toward another possible serial mediation effect: the effect of employee performance monitoring on stress, then the impact of stress on knowledge management, and the impact of knowledge management on knowledge worker productivity. Studies correlate EPM with increased stress (Amick & Smith, 1992; Smith et al., 1992; Aiello & Shao, 1993; Ravid, 2022). The effect of stress on knowledge management is also discussed in the extant literature (e.g., Ford et al., 2015; Marques et al., 2019). In conclusion, the influence of knowledge management on the productivity of knowledge workers is also examined in studies such as the one conducted by Kianto et al (2018). Haas and Hansen (2007) and Iranzadeh and Pakdelbonab (2014) study are two examples of the many research that have empirically investigated the link between knowledge management and the productivity of knowledge workers. The serial mediation effect may be proven by connecting the dots, and it is in this impact that stress and knowledge management take on the function of serial mediators in employee performance monitoring and knowledge worker productivity.

H5: Stress and knowledge management serially mediate the relationship between employee performance monitoring and knowledge worker productivity.

3. Methodology

It is evident from Tables 1 and 2 that Dubai accounts for the highest number of companies and the largest number of employees in the construction sector in UAE, followed by Abu Dhabi.

Note: The data in Table 1 in the appendix is taken from the Ministry of Human Resources and Emiratisation and UAE official open portal data, and it shows the distribution of the number of construction companies in UAE, emirate wise Number of Employees in the Construction Sector by Emirate, UAE, 2019.

Table 1. Number of Construction Companies by Emirate, UAE, 2019

Emirate	Number of Companies
Abu Dhabi	16,540
Dubai	23,226
Sharjah	10,560
Ras Al-Khaimah	3,922
Fujairah	2,101
Ajman	7,012
Umm Al Quwain	1,001
Total	64.362

Note: Table 2 in the appendix is taken from the Ministry of Human Resources and Emiratisation and UAE official open portal data. It shows the distribution of the number of construction workers in the UAE, emirate-wise.

Table 2. Number of Employees in the Construction Sector by Emirate, UAE, 2019

Emirate	Percentages	Number of Employees
Abu Dhabi	25.62%	420,654
Dubai	52.89%	868,433
Sharjah	11.42%	187,508
Ras Al-Khaimah	2.60%	42,808
Fujairah	1.71%	28,122
Ajman	4.93%	81,094
Umm Al Quwain	0.79%	13.105
Total	100%	1,641,724

Probability sampling requires a sampling frame, a list of all the population elements, and their contact details (Sekaran & Bougie, 2016). Although the researcher tried his best to obtain all of the UAE's construction workers, this became practically impossible. Companies keep their employees' records strictly confidential, and it was not possible to obtain such an exhaustive list of the elements in the population and contact details. Owing to such s situation, the researcher opted for non-probability sampling. Bryman and Bell (2011) stated that the non-probability sampling approach is a broad concept that encompasses all sampling methods conducted in the absence of any sampling probabilities procedure. Nevertheless, non-probability sampling is prevalent in studies, especially in the market analysis, where the research conducted is without the sample framework (Saunders et al., 2012). Quota sampling is used to ensure that representatives of all construction workers located in seven emirates are a part of this examination (see Table 3). On the other hand, purposive sampling ensures that the sampling unit's basic requirements are fulfilled.

Table 3. Quota Distribution of sample size into the Seven Emirates

Emirate	Percentage	Number of Respondents
Abu Dhabi	25.62%	127
Dubai	52.89%	263
Sharjah	11.42%	57
Ras Al-Khaimah	2.60%	13
Fujairah	1.71%	8
Ajman	4.93%	25
Umm Al Quwain	0.79%	04
Total	100%	497

For each quota selected from seven emirates of UAE construction companies, the researcher seeks to search individuals who can and will offer relevant information by nature of expertise or understanding (Bernard, 2002). It includes finding and recruiting persons or a bunch of people who are experienced and very well aware of a topic of concern (Cresswall et al., 2011). For this reason, employees who are knowledgeable and experienced in the construction industry are selected as subjects for this study. For this particular study, the sample unit specifies the construction workers in the United Arab Emirates construction companies with a diploma or higher qualification. The minimum age of these construction workers should be 21 years with three years of experience or more in the relevant industry. This specific segment is selected for comprehending the effect of performance monitoring on the knowledge worker productivity.

In this study, the minimum sample size required has been determined with the help of a G-Power analysis. Using the sample-to-item ratio is the standard method for determining the appropriate size of a study's sample population. In light of recent advancements, it has been suggested that researchers make use of power analysis in order to determine the appropriate size of their samples (Hair et al., 2018; Hair et al., 2017; Hair et al., 2019; Kline, 2016; Ringle et al., 2018; Uttley, 2019). The optimal ratio should not be lower than 5 to 1 (Gorsuch, 1983; Hatcher, 1994; Suhr, 2006). According to Bentler and Chou (1987) and Bollen (1989), five to ten observations per estimated parameter are required in SEM. Following the authors' advice mentioned above in this section, the researcher decided to have 7 cases per observed variable (item) to attain a reasonable sample size. Hence in this study, the total number of items is 71. When 71 items are multiplied by 7, this comes to a total of 497 respondents. Respondents are engaged in this study via a validated, self-managed survey as an information-gathering tool. Tashakkori and Teddlie (2003) mentioned that a self-managed survey is a type of device that helps to attain self-reporting information from participants. Partial least squares structural equations are used in this thesis (PLS-SEM). The model's formative constructs are the most important reason to use PLS-SEM (Hair et al., 2017). In order to handle formative constructs, the covariance-based SEM algorithm must be used. Formative constructs in the model are the most important reason to use PLS-SEM (Hair et al., 2017). The covariance-based SEM technique cannot handle formative constructs.

Researchers use a technique known as Partialing Out of Marker Variables in the PLS Model (PLS) to control CMB (Podsakoff, Mackenzie, and Podsakoff, 2003). An endogenous construct's R2 value was determined by drawing a hypothesized model using Smart PLS software. Once the marker variable on the endogenous construct had been removed, the R2 value was recalculated. As a result of this comparison, we found that 0.560-0.568 = 0.08 was a difference in R2 between the endogenous construct before and after adding the marker variable. After removing the marker variable, an R2 difference of 0.018 was detected in the endogenous construct, which is not statistically significant. This study supplied another clue to the lack of a significant common method bias. Table 4 cross-tabulates three demographic variables: age, education, and marital status. The cross-tabulation reflects that the largest group of respondents are master's degree holders in the age bracket of 31-40. The smallest number of respondents belongs to the age bracket of above 60. This data division is as per the requirements of the construction industry in the UAE. The harsh weather requirements demand that most workers belong to a relatively younger age bracket. The genuineness of data can also be gauged from the simple fact that moving up the age bracket reveals more married respondents than single persons.

Table 4. Cross Tabulation of Age, Marital Status, and Education

Age, Education, and Marital Status				**Age**				
				21-30	**31-40**	**41-50**	**51-60**	**Above 60**
Education	Diploma	Marital Status	Single	53	36	4	0	3
			Married	12	18	9	1	4
	Bachelors or equivalent	Marital Status	Single	23	19	9	2	0
			Married	29	67	43	20	3
	Masters or equivalent	Marital Status	Single	8	10	7	6	1
			Married	8	28	45	18	4
	Ph.D./ Doctor of Business	Marital Status	Single	4	6	3	0	1
			Married	3	14	17	11	15
		Total		140	198	137	58	31

4. PLS-SEM Analysis

4.1. Measurement Model for First-order Reflective Constructs

Measurement model estimate of first-order reflective models begins with examining indicator loadings. According to the accepted standard for indicator loadings, the percentage of variance explained by a construct for an indicator should be at least 0.708. (Hair et al., 2019). The second step in evaluating a measurement model is to assess its internal consistency reliability. PLS-SEM researchers frequently refer to Jöreskog's (1971) composite reliability (CR) as the gold standard. The greater the CR value, the more reliable the system is. Between 0.70 and 0.90 is acceptable to excellent. Data with a redundancy index greater than 0.95 is considered invalid by Diamantopoulos et al (2012). Correlation values above 0.95 are undesirable because they reflect correlations between error components that are exaggerated. Because unweighted items are included in Cronbach's alpha, it is a less exact measure of internal consistency dependability. McNeish (2017), in his trend-setting article titled "Thanks Coefficient Alpha, We'll Take It From Here," asserted that Cronbach's alpha is with glitches based on impractical assumptions. On the other hand, items are weighted in composite reliability, thereby resulting in higher reliability values.

The next step in the examination of reflecting measurement models is to evaluate their convergent validity. Convergence validity is a measure of how well a model's variables can be explained by the model as a whole. The average variance extracted (AVE) is the metric that is used to evaluate the convergent validity of a concept. AVE, also known as the average value across all tests, is determined by using the squared loadings of each and every construct; in order for AVE to be judged acceptable, it must be at least 0.50. According to Hair and his colleagues, an AVE number of 50 percent suggests that the construct accounts for fifty percent of the variance in the items (Hair et al., 2019). Outer loadings, composite reliability, and average variance are all shown in Table 6 (see below). External loadings are within acceptable limits in Table 5, as are composite reliability and AVE.

Table 5. Outer Loadings, Composite Reliability and Average Variance Extracted for First Order Reflective Constructs

Constructs	**Items**	**Outer-Loadings**	**Composite Reliability**	**Average Variance Extracted**
Knowledge Management Acquisition	KMA1	0.795	0.88	0.552
	KMA2	0.693		
	KMA3	0.747		
	KMA4	0.773		
	KMA5	0.696		
	KMA6	0.747		
Knowledge Management Application	KMAP1	0.736	0.876	0.541
	KMAP2	0.696		
	KMAP3	0.783		
	KMAP4	0.687		
	KMAP5	0.726		
	KMAP6	0.781		
Knowledge Management Conversion	KMC1	0.735	0.884	0.559
	KMC2	0.764		
	KMC3	0.727		
	KMC4	0.749		
	KMC5	0.752		
	KMC6	0.756		
Knowledge Management Protection	KMP1	0.767	0.865	0.516
	KMP2	0.757		
	KMP3	0.658		
	KMP4	0.7		
	KMP5	0.747		
	KMP6	0.676		
Knowledge Worker Productivity Autonomy	KWPA1	0.72	0.877	0.588
	KWPA2	0.779		
	KWPA3	0.78		
	KWPA4	0.775		

	KWPA5	0.777		
Knowledge Worker Productivity Efficiency	KWPE1	0.652	0.824	0.54
	KWPE2	0.763		
	KWPE3	0.759		
	KWPE4	0.759		
Knowledge Worker Productivity Timeliness	KWPT1	0.728	0.827	0.545
	KWPT3	0.694		
	KWPT4	0.786		
	KWPT5	0.742		
Monitoring Behavior Consistency	MBC1	0.732	0.803	0.577
	MBC2	0.801		
	MBC4	0.743		
Monitoring Behavior Justification	MBJ1	0.802	0.851	0.656
	MBJ2	0.84		
	MBJ3	0.786		
Monitoring Behavior Process Control	MBPC1	0.715	0.802	0.505
	MBPC2	0.742		
	MBPC3	0.759		
	MBPC4	0.618		
Supervisor Characteristics Expertise	SCE1	0.794	0.912	0.634
	SCE2	0.839		
	SCE3	0.802		
	SCE4	0.756		
	SCE5	0.807		
	SCE6	0.78		
Supervisor Characteristics Job Performance Knowledge	SCJPK1	0.723	0.896	0.633
	SCJPK2	0.805		
	SCJPK4	0.814		
	SCJPK5	0.79		
Supervisor Characteristics Trust	SCT1	0.703	0.876	0.587
	SCT2	0.79		
	SCT3	0.77		
	SCT4	0.816		
	SCT5	0.747		
Stress	STR2	0.742	0.85	0.535
	STR3	0.765		
	STR4	0.742		
	STR5	0.832		

Table 6 shows the discriminant validity of all the first-order reflective constructs in the model. The researcher in this thesis opted for the more rigorous approach of following the criteria of HTMT0.85 for establishing discriminant validity among constructs. All the HTMT values are below the threshold of HTMT0.85, and hence discriminant validity has been established.

Table 6. Discriminant Validity via HTMT Ratios

Constructs	KMA	KMAP	KMC	KMP	KWPA	KWPE	KWPT	MBC	MBJ	MBPC	SCE	SCJPK	SCT
KMAP	0.838												
KMC	0.846	0.829											
KMP	0.835	0.848	0.845										
KWPA	0.656	0.548	0.614	0.613									
KWPE	0.642	0.582	0.622	0.622	0.706								
KWPT	0.66	0.631	0.655	0.632	0.64	0.839							
MBC	0.4	0.318	0.399	0.378	0.535	0.462	0.427						
MBJ	0.694	0.592	0.592	0.666	0.757	0.704	0.701	0.578					
MBPC	0.427	0.326	0.394	0.404	0.382	0.349	0.318	0.849	0.492				
SCE	0.602	0.533	0.534	0.605	0.696	0.508	0.506	0.611	0.785	0.507			
SCJPK	0.62	0.532	0.527	0.598	0.764	0.533	0.534	0.582	0.821	0.478	0.834		
SCT	0.624	0.57	0.578	0.61	0.721	0.585	0.575	0.621	0.873	0.483	0.849	0.821	
STRESS	0.243	0.218	0.231	0.219	0.346	0.283	0.253	0.281	0.311	0.141	0.443	0.412	0.43

4.2. Measurement Model for Second-Order Formative Constructs

Formative measurement models were examined to see if the formatively assessed construct was highly linked with the reflective measure of the same construct. 'Redundancy analysis is another name for this type of study (Chin, 1998). The name "redundancy analysis" comes from the fact that the model's content is repeated in both the formative and reflecting constructs. Formative indicators that have a strong correlation with the construct of interest are more likely to be accurate than those that do not. While 0.80 is ideal, but at least 0.70 and higher is recommended, for the convergent validity assessment, is recommended (Hair et al., 2017). It was stated in the research design phase and included in the collection of data for conducting redundancy analysis. The construct's essence is summarised by the global item (Sarstedt et al., 2013). The conceptual model has four second-order formative constructs: behaviour monitoring, supervisor characteristics, productivity of knowledge workers and knowledge management. Table 8 shows the results of redundancy analysis for all four constructs. The path coefficients' values are above 0.700, establishing the second-order formatively measured constructs' convergent validity.

Note: Table 7 in the appendix shows the results of redundancy analysis, and all the values of path coefficients are above the minimum threshold of 0.700.

Table 7. Second-Order Constructs Convergent Validity

	MBG	**SCG**	**KMG**	**KWPG**
MB	0.757			
SC		0.763		
KM			0.785	
KWP				0.800

4.3. Assessing the Collinearity Issues

When it comes to determining weights and statistical significance, high degrees of collinearity between formative indicators are critical. In practise, high collinearity levels can have a significant impact on the results of an analysis in two ways. There are a number of ways in which collinearity affects the standard errors and the ability to demonstrate that the estimated weights are statistically different from zero. It is recommended to use the variance inflation factor (VIF) to determine how closely the formative indicators are related to each other. Severe collinearity concerns are indicated by structures with VIF values greater than 5. (Hair et al., 2019). VIF values for all second-order constructions in the model are shown in Table 8.

Table 8. Collinearity Diagnostics for Second-Order Formative Constructs

Second-Order Constructs	VIF Values
KMA	3.064
KMAP	3.042
KMC	3.002
KMP	2.732
KWPA	1.489
KWPE	2.107
KWPT	1.952
MBC	1.578
MBJ	1.219
MBPC	1.52
SCE	3.283
SCJPK	3.376
SCT	3.258

There is no evidence of multicollinearity across first-order constructs because all values fall below the maximum criterion of 5.

Note: Table 8 in the appendix shows no multicollinearity issues among second-order constructs as VIF values are below the maximum threshold of 5.0.

4.4. Outer Weights Significance and Relevance

In the third step, the researcher evaluated the weights of the indicators and their statistical significance. The researcher used the bootstrapping approach based on the non-parametric nature of PLS-SEM to assess for statistical significance (Chin, 1998). To test for statistical significance, the use of a bias-corrected confidence interval is something that Hair et al. (2017a) suggested adopting for the bootstrap distribution. For the purpose of constructing confidence intervals, Aguirre-Urreta and Rönkkö (2018) suggested using the percentile technique. If the confidence interval contains a zero, this indicates that the result is statistically insignificant. Brand experience, relationship quality, and customer citizenship behaviour are all shown in Table 10 with their respective weights, p-values, and bias-corrected confidence intervals.

Note: Table 9 in the appendix indicates outer weights, T-statistics, P values, and bias-corrected confidence intervals of the second-order constructs. Non-Presence of zero in the upper and lower bound of class intervals indicate the statistical significance of outer-weights.

Table 9. Outer weights, T-statistics, P values, and class intervals

	Beta Coefficient	Standard Error	T Statistics	P Values	Bias Corrected CI	
					2.50%	97.50%
KMA -> KM	0.478	0.079	6.045	0.000	0.318	0.628
KMAP -> KM	0.130	0.065	0.177	0.001	0.146	0.476
KMC -> KM	0.320	0.081	3.967	0.000	0.156	0.472
KMP -> KM	0.289	0.090	3.211	0.001	0.115	0.471
KWPA -> KWP	0.678	0.056	12.077	0.000	0.567	0.787
KWPE -> KWP	0.198	0.066	2.980	0.003	0.062	0.323
KWPT -> KWP	0.287	0.060	4.796	0.000	0.173	0.407
MBC -> MB	0.326	0.034	9.651	0.000	0.259	0.391
MBJ -> MB	0.655	0.032	20.291	0.000	0.592	0.718
MBPC -> MB	0.268	0.035	7.678	0.000	0.194	0.331
SCE -> SC	0.379	0.026	14.636	0.000	0.325	0.427
SCJPK -> SC	0.321	0.025	12.995	0.000	0.272	0.369
SCT -> SC	0.368	0.021	17.197	0.000	0.327	0.409

4.5. Measurement Model for Third-Order Formative Constructs

In the conceptual model, employee performance monitoring (EPM) is the only third-order formative construct. The two dimensions are monitoring behavior (MB) and supervisor characteristics (SC). This third-order formative construct is assessed on the same pattern as second-order formative constructs. The steps are assessing for convergent validity, collinearity diagnostics, and outer weights significance. For redundancy analysis, the correlation (path coefficient) of the formatively measured construct EPM is checked with a global item of the same construct, i.e., EPM. Path coefficient value of 0.745 suggests the existence of convergent validly for EPM. Collinearity issue is checked with VIF values. Collinearity diagnostics are applied only to the 3rd order construct of employee performance monitoring. The researcher was able to conclude that EPM does not have collinearity difficulties because the threshold value of 5.00 was met. There are values below the maximum threshold of 5.0 for the sub-dimensions of monitoring behaviour and supervisor characteristics (Hair et al., 2017). MB and supervisor characteristics (SC) are shown in Table 10 with their respective VIF values (SC).

Table 11 Collinearity Diagnostics for Third-Order Formative Construct

Indicators	VIF
MB	1.875
SC	1.875

Note: Table 10 in the appendix shows the variance inflation factor for the sub-dimensions of MB and SC, which form the third-order construct of EPM.

4.6. Outer Weights Significance and Relevance

The bootstrapping method was quite helpful in determining whether or not the outer weights were significant and relevant. For the purpose of determining whether or not outside weights are significant, the bootstrapping method was applied to draw 5,000 subsamples. The results of the various statistical tests, including bias-corrected confidence intervals, standard errors, T-statistics, and p-values, are presented in Table 11.

Note: Table 11 in the appendix indicates outer weights, T-statistics, P values, and bias-corrected confidence intervals of the second-order constructs. Non-Presence of zero in the upper and lower bound of class intervals indicate the statistical significance of outer-weights.

Table 11. Outer weights, T-statistics, P values, and class intervals

Path Relationships	Beta Coefficients	Standard Errors	T Statistics	P Values	Bias Corrected CI	
					2.50%	97.50%
MB -> EPM	0.243	0.067	3.613	0.000	0.110	0.368
SC -> EPM	0.819	0.056	14.661	0.000	0.706	0.923

4.7. Structural Model Assessment

This study adhered to the suggestions that Hair et al. (2019) given for the standard evaluation of the structural model. Collinearity diagnostics (inner VIF value), the coefficient of determination (R2), significance and size of path coefficients (statistics), effect size (f2), and the cross-validated redundancy measure based on blindfolding (Q2) and effect size were all components of the structure model evaluation steps (q2).

4.7.1 Collinearity Diagnostics (Inner VIF values)

The collinearity assessment needs to be

completed first before the structural model can be evaluated. Examining formative measurement approaches is analogous to the process that we are going through now. Exogenous construct latent variable scores are utilized to obtain VIF values in partial least squares regression. If the VIF is greater than 5, it's time to worry about collinearity (Hair et al., 2019). All of the model's latent variables are listed in Table 12, along with their VIF values. Since none of the exogenous variables had values more than 5, collinearity between them is not an issue in this investigation.

Table 12. Inner VIF Values in the Structural Model

Constructs	KWP
EPM	1.758
KM	1.587
ST	1.166

Note: Table 12 in the appendix shows the inner VIF values for the structural model. The maximum threshold value of 5.0 is the benchmark, and all inner VIF values are well within the specified limit.

4.7.2 Assessment of the Significance of Structural Model Path Coefficients

Direct Effects

Since in this study, the model type is second-order reflective-formative. Therefore, the disjoint two-stage approach is used for finding out the significance of path coefficients via bootstrapping. Based on the findings, the two-stage technique is presented here in two distinct forms for consideration. Ringle et al. (2012) refer to one variety as the embedded two-stage technique, whilst Becker et al. (2012) term the second form the fragmented two-stage approach. Both of these names refer to the same form. Disjoint techniques, on the other hand, are based on the lower-order components of a higher-order construct, whereas embedded approaches are based on the opposite (Cheah et al., 2019). The existing literature does not suggest any amplifying reasons for the preference of one approach over the other. Table 12 analyzes the statistical significance of path coefficients via bootstrapping procedure for direct effects in the model. t-values greater than 1.65 (one-tail testing) and p-values less than 0.05 indicate that H1 is supported. An examination of bias-corrected confidence intervals further supports this conclusion because H1's bias-corrected confidence interval does not include zero. The bias-corrected confidence interval for hypothesis H2 (Stress -> Knowledge Worker Productivity) includes zero. Consequently, the researcher came to the conclusion that it had a negligible impact (Hair et al., 2017a). Table 12 shows that the results support H1 and H2. H2 on the other hand, isn't even an option. In H1 monitoring the performance of employees has a direct bearing on the amount of work produced by knowledge workers. The productivity of knowledge workers is negatively affected directly by stress, as stated in Hypothesis 2. The evidence does not support hypothesis 2, which states that stress has a negative relationship with the productivity of knowledge workers but that the statistical significance of such an influence has not been shown.

Mediation Effects

The first indirect effect (H3) is the mediation link of EPM ->ST ->KM. The second mediation effect (H4) is the serial mediation effect ST -> KM ->KWP. The third mediation effect (H5) is EPM-> ST -> KM ->KWP. The last mediation link (H6) is EPM->ST -> KWP. Table 13 and Table 14 depicts all specific indirect effects necessary for performing mediation analysis. The data supports hypotheses H3, H4, and H5. Hypothesis H6 is not supported.

Table 13. Statistical significance of Path Model Coefficients (Direct Effects only)

Paths	Beta Coefficient	Standard Error	T Statistics	P Values	Bias Corrected CI		Decision
					2.50%	97.50%	
H_1: EPM -> KWP	0.429	0.048	9.003	0.000	0.329	0.518	Supported
H_2: ST -> KWP	-0.046	0.032	1.403	0.161	-0.108	0.017	Non-Supported

Table 14. Specific Indirect Effects

Paths	Beta Coefficient	Standard Error	T Statistics	P Values	Bias Corrected CI		Decision
					2.50%	97.50%	
H_3:EPM -> ST -> KM	0.084	0.025	3.360	0.001	0.039	0.134	Supported
H_4:ST -> KM -> KWP	-0.086	0.021	4.178	0.000	-0.127	-0.046	Supported
H_5:EPM -> ST -> KM -> KWP	0.033	0.010	3.173	0.002	0.015	0.054	Supported
H_6:EPM -> ST -> KWP	0.017	0.013	1.367	0.172	-0.007	0.043	Not-Supported

Coefficient of Determination (R2)

The R2 and adjusted R2 values for each of the endogenous constructs that are accounted for in the conceptual model are presented in Table 15, which can be found below. When determining the value of adjusted R squared, the number of predictors that are included in the model is one of the factors that are taken into account. Even though it can be used to eliminate bias toward composite models, the adjusted coefficient of determination, also known as R2adj, is always going to be lower than R-squared. Another name for R2adj is R-squared adjusted.

Table 15. Coefficient of Determination (R^2) and Adjusted R^2

	R Square	**R Square Adjusted**
KM	0.05	0.048
KWP	0.56	0.558
ST	0.142	0.141

Note: Table 15 in the appendix indicates R2 and adjusted R2 for all the endogenous variables in the conceptual model.

Effect Size (f2)

f2 explains why R2 changes when an exogenous component is removed from the model. Cohen claims the following: (1988), A f2 value of 0.02 represents a tiny influence, but f2 values of 0.15 and 0.35 represent medium and big effects, respectively. Because of the increased sample size, a significant p-value is more likely to be found. That is why using solely the reported p-values for analysis could put a halt to future study (Sullivan & Feinn, 2012). Monitoring the performance of employees has a modest effect size (0.238) on the productivity of knowledge workers, as seen in Table 16. It has a medium effect size (0.214) on the productivity of knowledge workers, as well. An employee's level of stress is moderately affected by performance evaluations, with an effect size of 0.166. Finally, stress had just a 0.053 and 0,004 impact on knowledge management and knowledge worker productivity, respectively.

Table 16. Effect Size (f^2)

	KM	**KWP**	**ST**
EPM		0.238	0.166
KM		0.214	
ST	0.053	0.004	

Note: Table 16 in the appendix indicates the effect size (f2) of all exogenous variables on endogenous variables in the model.

5. Conclusion

The purpose of this section is to explain and emphasize the study's distinctive contributions. By combining, innovating, and expanding on the notions of stress and knowledge management, this study adds to theory development from a variety of disciplines. Kolb and Aiello (996) inspired the development of a single-dimensional stress model. This study established a negative correlation between stress and knowledge worker output through the evaluation of hypothesized path linkages. However, stress does mediate in the relationship between employee performance monitoring and knowledge management. Knowledge management, which works as a mediator in stress and knowledge worker productivity, has statistical significance. It means knowledge management does establish an indirect route between stress and knowledge worker productivity. The serial mediation effect of stress and knowledge management in the relationship between employee performance monitoring and knowledge worker productivity has been shown to have statistical significance. This conclusion can be drawn from the fact that the effect has been shown to have both. Extending expectancy theory in the context of employee performance monitoring and knowledge worker productivity is another way in which the theoretical contribution is made. This is ultimately a step forward in the process of further developing theories in worker productivity that are supported by empirical evidence. The findings of this study lend credence to the findings of Kianto et al. (2019), who discovered a significant connection between knowledge management and the productivity of knowledge workers. According to previous studies conducted by Kianto et al. (2019) and Sahibzada et al., one can draw the conclusion that knowledge management has a beneficial impact on the productivity of knowledge workers. This finding is in line with the findings of the aforementioned data (2020). As a result, further research into knowledge management is warranted. This work makes methodological contributions because of the diverse research designs, different sampling procedures, improved measurement scales and PLS-SEM with variance-based structural equation modelling.

Implications and recommendations for Further Research

An important conclusion for those responsible for developing and implementing an employee performance management strategy is that this study provides the first concrete evidence of the impact of such a strategy. In addition, those interested in the promotion of knowledge management will benefit from the findings of this study. It's important to note that the implications of this study go beyond policymakers to include building sector managers and academics.

The mixed-method research approach could help collect detailed responses and descriptions about respondents' feelings and attitudes for further research. Further, a longitudinal study for a better understanding of human behavior may yield different and more insightful research results. Finally, a Multi-Group Analysis (MGA) of respondents from different regions could be more instrumental in highlighting employee performance monitoring differences among different population segments.

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Muneer Al Dwaikat
UNIMAS
maldwaikat@yahoo.com
ORCID 0000-0001-7577-2951

Kartinah Ayupp
UNIMAS
akartinah@unimas.my
ORCID 0000-0003-0097-7156

Yousef Ahmad Alolabi
UNIMAS
y.olabi@gmail.com
ORCID 0000-0002-9503-6844