

CHAPTER 4

FINDINGS AND ANALYSIS

4.1 Introduction

This chapter involves the application of methodological techniques and the analysis of gathered data to evaluate the study's variables and hypotheses. It is important to note that research analysis plays a crucial role in proposing systematic and empirical validation of the phenomenon under investigation. As stated by Rosenthal (2017), data analysis is a vital step in empirical investigation, as it gives meaning to the obtained data and facilitates deriving meaningful conclusions. Data analysis mainly contains the modification of raw data into practical information, helping to address research questions, examining the hypotheses, and formulating practical conclusions. According to Ali and Bhaskar (2016), data analysis enables researchers to analyze and validate the salient features of the data. Thus, this study also entailed a detailed data analysis, meticulously selected based on its alignment with the study's problem, questions, objectives, and hypotheses.

The data analysis in the current chapter is organized into two assessments: descriptive and inferential statistics. Descriptive statistics is based on computations of frequencies, percentages, median, standard deviations, and means, and standard deviations using the accumulated data (Andreß et al., 2013).

As highlighted by Christopher et al. (2019), descriptive statistics serve as a valuable tool for summarizing data and devising a comprehensive understanding. Also, these methodologies provide researchers with the capability to discern underlying data structures and patterns, providing profound insights into the study's variables. Besides, inferential statistics were applied to examine the proposed relationships between variables, affirm their statistical significance, and emanate generalizable conclusions. This chapter offers the results of the data analysis in both tabular and graphical formats, accompanied by elucidative narratives, thereby expanding the clarity and comprehensibility of the findings. This chapter also extends strong support to the formulation of practical, theoretical, and methodological implications by amplifying the general value of this research project.

4.2 Data Editing and Coding

According to Stinson and Fisher (1996), "Data editing and data coding involves a thorough assessment of all survey forms to determine and correct errors and omissions." Taherdoost (2021). argued that in cases of noteworthy errors, the researcher should consider excluding the relevant questionnaires from the analysis. Further, McNutt et al. (2023) suggested that if there is an error in more than 25% of questions in a survey, they should be excluded completely. This indicates that the researchers can proceed with at least 75% of the surveys and proceed to the data coding stage. In the present study, a mere 09 survey forms exceeded the 25 percent threshold for unanswered questions. Also, three screening criteria were used, implying that respondents are above 21 years of age and have experience in police service. Two of these forms, at least seven, failed to meet these requirements. Besides, the two forms contained identical responses that were further excluded. As a result, 9 out of 361

questionnaires were excluded from the study, which were further omitted from the data coding process. During the data coding procedure, the relevant data from the usable questionnaires was manually transcribed into the SPSS data file (.sav).

According to Taherdoost (2021), data coding involves assigning numerical values to different variables based on responses to certain questions. This procedure encompasses both pre-coding and post-coding techniques. In the pre-coding stage, all items were assigned numerical values. Besides, any new items identified in open-ended questions were given appropriate numerical codes. Following the completion of pre-coding, a frequency assessment was conducted to determine any variables with values falling beyond the expected range. In examples of out-of-range values, adjustments were made to the data file, including the post-coding process.

4.3 Data Screening

According to Mishra et al. (2019), it is critical to conduct data screening before performing any substantive statistical analysis. This step assures that the dataset does not contain anomalies and is adequately prepared for further examination. (Ferreira, 2020) highlighted the significance of data screening in proving the usability, validity, and reliability of information for testing causal theories. Ferreira (2020) further argued that the screening process must precede any subsequent statistical procedures. However, as it requires extra effort, it is often overlooked by researchers. As a result, unexpected results may emerge from an analysis, necessitating data manipulation, as argued by Jordans et al. (2016). Thus, it becomes critical to systematically address tasks such as rectifying missing values, recognizing outliers, testing data normality, and assessing linearity.

4.3.1 Missing Value Analysis

Salgado et al. (2016) stated that almost every research confronts the challenges caused by missing value. This challenge is especially prominent when considering potential issues such as respondent reluctance or negligence in survey participation, the risk of missing files, and the need for meticulous data recording. Considering the significant efforts in data gathering, re-starting the data-gathering process can be more demanding and, sometimes, impossible to do so. Thus, researchers usually face difficulty in proceeding to the data analysis phase when confronted with data having errors that require careful attention. The current research study examined the missing values by examining the continuous variables and the constant variables. Pigott (2001) highlighted the significance of a thorough and robust approach to handling missing data during the data-cleaning stage. This method is important in averting potentially deceitful outcomes that may arise if missing values are not managed properly.

Christopher et al. (2019) emphasized that dealing with missing values is a common challenge in datasets. Depending on the size of the missing data, it can greatly affect the accuracy and reliability of result estimations. Hence, researchers usually adopt an exhaustive data analysis strategy, focusing only on cases with complete information to mitigate this concern. The present study involved Missing Value Analysis as a vital component of the data screening process.

Pigott (2001) emphasized the importance of a rigorous approach to handling missing data during the data-cleaning stage to prevent misleading conclusions. Christopher et al. (2019) further highlighted that depending on their volume, missing values could significantly impact result estimations, necessitating careful treatment. The present study adopted a systematic approach to analyze missing values in continuous variables. The results revealed that the missing values in each continuous

variable remained well below the accepted threshold of 15% (Karpievitch et al., 2012). Specifically, the highest percentage of missing data recorded was only 0.6%, with most variables showing a mere 0.3% missing rate. Such minimal missing data suggests that the dataset maintains a high level of integrity, reducing the risk of bias and ensuring reliable statistical outcomes.

The findings further indicate that no extreme values were detected in the dataset, as all variables had zero occurrences of exceptionally high or low values. This consistency suggests that the dataset is free from significant missing values and well-structured for subsequent analysis. Given the minimal missing values and the absence of extreme cases, the data is assumed to be complete and can be analyzed without the need for extensive imputation or corrective measures. The results of the missing value analysis for continuous variables are presented in Table 4.1, confirming the robustness of the dataset and its suitability for further statistical examination.

Table 4.1: Missing Value Analysis of Continuous Variables

	Mean	Std. Deviation	Missing		No. of Extremesa	
			Count	Percent	Low	High
Gender	1.3040	.46063	1	.3	0	0
Age	1.1903	.39313	2	.6	0	0
Education	1.9432	.56705	1	.3	0	0
Religion	1.0426	.28425	1	.3	0	0
Race	1.3267	.53756	1	.3	0	0
Nationality	1.8381	1.41600	1	.3	2	0

Pertinent to a comprehensive evaluation of missing data and verification of the absence of substantial missing data that could compromise reliability, the pertinent

analysis is conducted for the constant variables (See Table 4.2 for the brief summary). The missing value analysis of the constant variables was conducted to examine the potential chances of missing values in the constant variables (Karpievitch et al., 2012).

The analysis involved computing missing values for each sub-construct to gain insights into the extent of data loss and its potential implications. The results indicated that the highest number of missing values was observed within the sub-construct "Job Satisfaction 5 (JSN5)," with 12 missing cases. This number remains well below the established cut-off threshold (Christopher et al., 2019), reinforcing the assumption that the missing data does not pose a significant threat to the reliability or validity of the dataset. Additionally, the missing values for other sub-constructs were uniformly low, with only one missing case per variable, which accounts for just 0.5% of the dataset.

Similarly, examining extreme values revealed no significant outliers that could distort the analysis. Although some variables showed minimal occurrences of high or low extreme values, they remained within an acceptable range and did not indicate any substantial data inconsistencies. Considering the minimal missing data across the constant variables, the results confirm that missing values are well-managed and do not necessitate extensive corrective measures. The dataset maintains a high degree of completeness and integrity, making it suitable for subsequent statistical analysis. The results of the Missing Value Analysis for constant variables are presented in Table 4.2, further demonstrating the robustness of the data.

Table 4.2: Missing Value Analysis of Constant Variables

	Mean	Std. Deviation	Missing		No. of Extremes ^a	
			Count	Percent	Low	High
TRE1	3.721	.855	1	.5	0	0
TRE2	4.019	.835	1	.5	7	0
TRE3	4.318	.792	1	.5	3	0

TRE4	4.059	.773	1	.5	4	0
TRE5	3.483	1.228	1	.5	4	0
TRE6	3.713	1.007	1	.5	0	0
TRE7	4.059	.773	1	.5	8	0
ETW1	3.869	.939	1	.5	11	0
ETW2	4.045	.790	1	.5	0	0
ETW3	3.696	1.081	1	.5	11	0
ETW4	4.363	.895	1	.5	0	0
ETW5	3.622	1.087	1	.5	0	0
IPS1	3.900	.965	1	.5	4	0
IPS2	4.227	.942	1	.5	09	0
IPS3	4.119	.916	1	.5	0	0
IPS4	4.000	.948	1	.5	8	0
IPS5	3.860	.939	1	.5	0	0
HRM1	3.679	1.013	1	.5	6	0
HRM2	3.6960	1.081	1	.5	9	0
HRM3	4.363	.895	1	.5	0	0
HRM4	3.926	.948	1	.5	0	0
HRM5	3.738	.933	1	.5	6	0
JSN1	3.676	1.063	1	.5	0	0
JSN2	4.119	.916	1	.5	11	0
JSN3	4.000	.948	1	.5	8	0
JSN4	3.772	.805	1	.5	0	0
JSN5	3.781	.890	1	.5	12	0
JSN6	4.164	.976	1	.5	10	0

4.3.2 Data Normality

Statistical data errors come in quantitative research, with approximately 50% of published articles containing at least one such error (Schmidt & Finan, 2018). Several fundamental statistical procedures, such as correlation, t-tests, regression, and analysis of variance, commonly referred to as parametric tests, are contingent on the belief that the data complies with a normal distribution, also known as a Gaussian distribution (Khatun, 2021). It is assumed that the populations from which the samples are derived

show a state of normality (2-5). The idea of normality holds distinct significance in the establishment of reference intervals for variables (6). It is crucial to test the normality, as a failure to meet these assumptions impedes the results and further question their generalizability. Hence, to test the normality in the current study, the following hypotheses were proposed: H1. Data is normally distributed or H0. Data is not normally distributed.

To test these hypotheses, Kolmogorov-Smirnov and Shapiro-Wilk tests were conducted. As shown in Table 4.3, the significance value of each item is individually tested, indicating significance values greater than $p > 0.05$. Consequently, it is found that the null hypothesis is accepted, and the data is normally distributed in the current research study and using parametric test would be suitable for this research.

Table 4.3: Data Normality Testing

Items	Kolmogorov-Smirnov ^a		Shapiro-Wilk	
	Statistics	Sig.	Statistics	Sig.
TRE1	.232	.078	.858	.540
TRE2	.215	.640	.841	.534
TRE3	.297	.824	.770	.517
TRE4	.216	.646	.825	.513
TRE5	.195	.637	.868	.465
TRE6	.226	.531	.879	.539
TRE7	.222	.530	.828	.536
ETW1	.271	.520	.841	.534
ETW2	.227	.509	.835	.536
ETW3	.204	.523	.860	.535
ETW4	.364	.538	.714	.539
ETW5	.198	.450	.863	.528
IPS1	.251	.519	.836	.510
IPS2	.305	.532	.775	.517
IPS3	.263	.536	.810	.468
IPS4	.238	.277	.836	.229

IPS5	.271	.327	.841	.319
HRM1	.244	.392	.839	.403
HRM2	.204	.420	.860	.416
HRM3	.364	.354	.714	.433
HRM4	.212	.273	.853	.259
HRM5	.284	.554	.830	.249
JSN1	.213	.313	.871	.298
JSN2	.263	.191	.810	.179
JSN3	.238	.209	.836	.126
JSN4	.284	.294	.837	.259
JSN5	.231	.377	.868	.339
JSN6	.304	.310	.785	.428

4.3.3 Linearity Analysis

Assessing linearity holds central importance in this study as it helped to examine the direct, linear relationship between the independent variable and the dependent variable, suggesting that variations in the independent variables lead to changes in the dependent variable (Groß, 2003). Consistent with this notion, Rosenthal (2017) emphasized that the relationship between the independent variable and the dependent variable should be linear. In this study, the linearity was assessed through the homoscedasticity test using SPSS. Notably, Casson and Farmer (2014) strongly supports employing the homoscedasticity test, arguing that the scatter plot should exhibit a linear direction rather than a curved one.

Figure 4.1 shows that the residuals of the independent variables display a linear association with the dependent variable. The scatterplot affirmed that the dataset complies with homoscedasticity rather than heteroscedasticity. Thus, linearity among the predictor and dependent variable is obtained. As a result, the presumption about homoscedasticity in the data was confirmed. Also, the Durbin-Watson value served as an indicator of the linear relationship between independent variables and the dependent

variable (Schmidt & Finan, 2018). In the present study, the computer Durbin and Watson value of 3.061 descends within the range of 2-4, representing a linear relationship between the independent and the dependent variables in the current study. In summation, the criterion of linearity in this study was duly met.

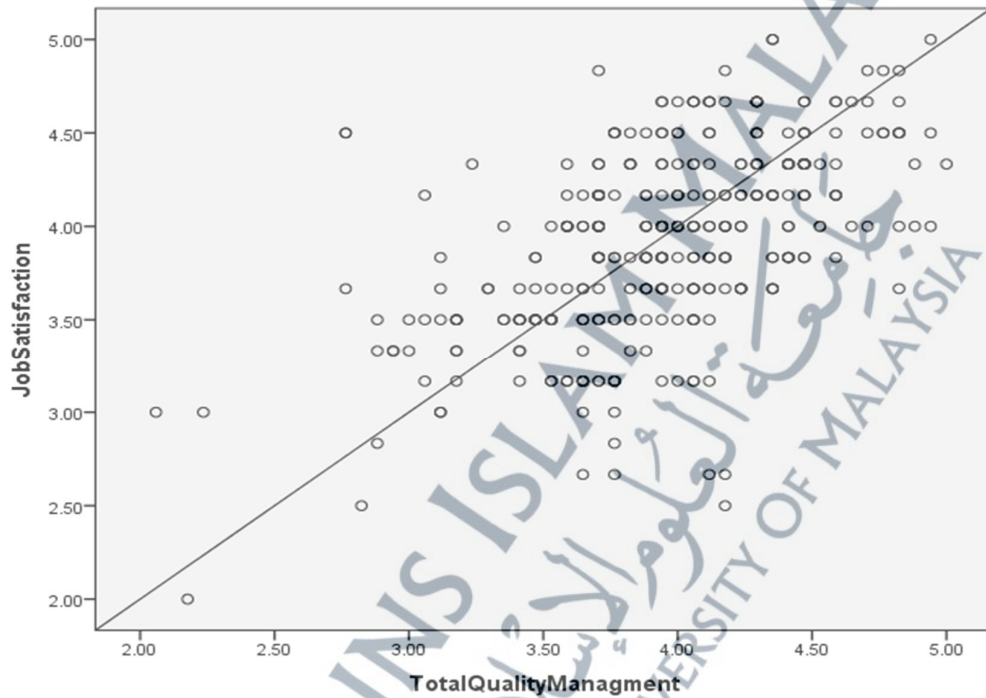


Figure 4.1: The Residuals of the Independent Variable for the Linear Association with the Dependent Variable.

4.3.4 Common Method Bias (CMB)

As this research is based on survey method, Common Method Bias (CMB) was also tested. According to Chin (2012), Common method bias (CMB) is a probable concern in survey research where data gathering relies on a single approach, like self-report questionnaires. CMB can lead to systematic errors irrelevant to the actual variables of interest. (MacKenzie & Podsakoff, 2012) argued that CMB can greatly impact the validity of study findings. Relationships between variables may emerge stronger or weaker than they truly are due to the impact of the common method bias.

Min et al. (2016) suggested that the researchers should be aware of CMB and employ strategies to mitigate its effect, i.e., using multiple methods of data collection or incorporating control variables in the analysis. By addressing CMB, researchers can improve the precision and reliability of their survey research. Thus, assessing the Common Method Bias in the current research revealed the CMB of 25.6% that is below under the threshold value 50.0% (Çizel et al., 2020).

4.4 Respondents' Demographics

The sample size for this study initially consisted of 361 respondents. However, after identifying errors during the data screening and coding process, 9 questionnaires were excluded. As a result, demographic analyses were conducted based on the data from 352 finalized questionnaires. The final response rate with 352 questionnaires remained 97.5% which was higher than the minimum threshold of 60% (Deutskens et al., 2004) Table 4.4 presents the distribution of respondents' demographics.

In terms of gender, the majority of respondents identified as male (69.6%), while 30.4% identified as female ($M= 1.62$, $SD= 2.38$). The analysis of respondents' ages revealed that 65.65% were aged 21 to 30 years, 18.2% were aged 31 to 40 years, and 16.0% were 41 years old or older ($M= 1.94$, $SD= 0.567$). Regarding educational qualifications, the study found that 67.6% of respondents held master's degrees, 19.0% held Bachelor's degrees, and 13.4% held Doctorate-level qualifications ($M= 1.04$, $SD= 0.284$).

Furthermore, the vast majority of respondents (97.7%) identified as Muslims, while 2.0% identified as atheists or having no religion, and 0.3% identified as non-Muslim ($M= 1.32$, $SD= 0.537$). In terms of race, 69.9% of respondents were Arabs (Middle Eastern/Gulf), 28.4% were South Asian and Southeast Asians, 0.9% were

White, and an equal percentage (0.9%) identified as other races (M= 1.83, SD= 1.41). Finally, 69.3% of respondents held Emirati (UAE) nationality, 10.2% held GCC nationality, 9.9% held other nationalities, and 2.8% were foreigners (M= 1.30, SD= 0.460).

Table 4.4: Respondents Demographics

Variables	Constructs	N	%	Mean	SD
Gender	Male	245	69.6	1.62	2.38
	Female	107	30.4		
Age	21-30 years	231	65.6	1.94	0.567
	31-40 years	64	18.2		
	41 or above	57	16.0		
	Bachelor	67	19.0		
Qualification	Masters	238	67.6	1.04	0.284
	Doctorate	47	13.4		
	Muslim	344	97.7		
Religion	Non-Muslim	1	0.3	1.32	0.537
	No Religion	7	2.0		
	Arab (Middle Eastern/Gulf)	246	69.9		
Race	Asian (South-Southeast)	100	28.4	1.83	1.41
	White	3	.9		
	Other	3	.9		
	UAE	244	69.3		
Nationality	Arabian	27	7.7	1.30	0.460
	Foreigner	10	2.8		
	GCC	36	10.2		
	Other	35	9.9		

Descriptive statistics were calculated to summarize the overall response patterns for the key constructs. Each questionnaire item represented the variables, including Total Quality Management (TQM), Human Resource Management (HRM) practices,

and Job Satisfaction among Ras Al-Khaimah Police Officers. As shown in Table 4.5, the mean score for TQM was 3.95 (SD = 0.48), suggesting a generally positive perception of quality management initiatives within the police department. HRM practices also received an average score of 3.88 (SD = 0.53), indicating that respondents acknowledged the presence of structured and supportive HR mechanisms, including recruitment, training, and performance evaluation. Job satisfaction had a mean of 3.92 (SD = 0.50), indicating a relatively high level of contentment and positive attitudes toward the work environment among police personnel. The moderate standard deviations across all three variables (ranging from 0.48 to 0.53) show a consistent perception among respondents, with no extreme variability. These descriptive results provide a baseline understanding of participants' perceptions and help contextualize the inferential analyses that follow, aligning with the study's objectives related to examining the interrelationships among these variables.

Table 4.5: Descriptive Statistics of Constructs Addressing Research Objectives

	Range	Min	Max	Mean	Std. Deviation	Variance
Total Quality Management	2.94	2.06	5.00	3.9464	.48068	.231
Human Resource Management	3.20	1.80	5.00	3.8807	.52955	.280
Job Satisfaction	3.00	2.00	5.00	3.9190	.50291	.253

4.5 Assessing the Measurement Model (Inner Model)

The current study's assessment of the measurement model followed a two-step Partial Least Squares Structural Equation Modelling (PLS-SEM) procedure suggested by Sullivan and Ford, (2019). Before initiating the first step of the measurement model

assessment, the researchers pondered on the choice between two types of factor analysis: confirmatory factor analysis (CFA) and exploratory factor analysis (EFA). EFA aims to identify the factors necessary to accurately represent the data collected for the research (C.-L. Chin & Yao, 2014). On the contrary, CFA evaluates how well the measurement items capture the underlying latent variable. CFA was selected for this study due to its capability to offer a confirmatory assessment of the measurement theory (Carlson, 2010). EFA was not used in this study because the existing factors had already been identified based on statistical findings rather than theoretical assumptions (Chin & Yao, 2014).

Notably, the decision to use Confirmatory Factor Analysis (CFA) instead of Exploratory Factor Analysis (EFA) in this study was made because the constructs and measurement instruments used were well-established and validated in previous research (Kiliç et al., 2020). These instruments had undergone strict validation in different contexts, ensuring that the identified factors were theoretically sound and applicable to the current study. Given that the purpose of the study was to confirm the structure of these pre-defined factors rather than explore new dimensions, CFA was the appropriate choice.

Furthermore, while EFA is useful for identifying factors in new or culturally distinct contexts, the instrument used here has been tested across various settings, including those with cultural differences. Thus, the need for EFA was minimized, as the focus was on confirming the stability and applicability of the existing factors in the current study's context. This approach ensured the reliability and validity of the measurement model (Pesqué-Cela et al., 2021).

Therefore, once the type of factor analysis was determined, the study considered two types of indicators: reflective and formative indicators. Since all variables under

investigation were drawn from previous research and the existing literature predominantly employed reflective indicators, the assessment focused on reflective measurement models, following the approach recommended by Carlson (2010). The initial step in the PLS-SEM analysis involved examining the reflective measurement model. As outlined by Ahmad et al. (2021), three important criteria were employed to assess the reflective measurement model: internal consistency reliability (construct reliability), convergent validity, and discriminant validity. Consequently, the first stage of testing the reflective measurement model was carried out using Smart-PLS 4.0 software, utilizing the PLS Algorithm feature.

4.5.1 Convergent Validity Assessment

Convergent validity, as described by Cheung and Wang (2017), is a rudimentary statistical concept that evaluates the degree to which different measures exhibit internal consistency, indicating consistency among different measures or indicators of a specific construct. The underlying principle of convergent validity suggests that its analysis should show a significant correlation in quantitative research. Therefore, researchers commonly use two approaches to assess convergent validity.

The first approach involves examining the correlation between scores acquired from two assessment instruments designed to measure the same construct. The second method for assessing convergent validity employs the multitrait-multimethod matrix (MTMM) approach, which entails investigating correlations among multiple constructs and measurement methods or tools (Carlson, 2010). Thus, the assessment of convergent validity in this study involved conducting Confirmatory Factor Analysis and calculating Average Variance Extracted (AVE) values. Also, the Composite Reliability of the measurement model was also evaluated.

Table 4.5 shows that most loading values exceed the cutoff value of 0.5, and the Average Variance Extracted (AVE) values exceed the threshold of 0.5 (Total Quality Management 0.643, Human Resource Management 0.745, Job Satisfaction 0.577). Furthermore, the calculation of construct reliability indicated that the Cronbach Alpha value surpassed the established cutoff of 0.7 (Total Quality Management 0.833, Human Resource Management 0.760, Job Satisfaction 0.725). Moreover, the Composite Reliability values also surpassed the threshold of 0.7 (Total Quality Management 0.871, Human Resource Management 0.854, Job Satisfaction 0.800), indicating the establishment of construct reliability in the present study. Table 4.6 provides the results of the convergent validity assessment.

Table 14.6: Convergent Validity Assessment

Variables	Items	Loads (>0.05)	AVE (>0.05)	CA (>0.07)	CR (>0.07)
	TQM1	0.724			
	TQM2	-0.015			
	TQM3	0.537			
	TQM4	0.736			
	TQM5	0.519			
	TQM6	0.639			
	TQM7	0.014			
	TQM8	0.627			
Total Quality	TQM9	0.590	0.643	0.833	0.871
Management	TQM10	0.724			
	TQM11	0.509			
	TQM12	0.461			
	TQM13	0.549			
	TQM14	0.434			
	TQM15	0.376			
	TQM16	0.627			
	TQM17	0.411			

	HRM1	0.739			
Human Resource	HRM2	0.714			
Management	HRM3	0.750	0.745	0.760	0.854
	HRM4	-0.109			
	HRM5	0.136			
	JSN1	0.598			
	JSN2	0.801			
Job Satisfaction	JSN3	0.830	0.577	0.725	0.800
	JSN4	0.022			
	JSN5	0.131			
	JSN6	0.216			

4.5.2 Goodness of Fit

As some items in the Factor Loads fell below 0.5, it was considered that they might adversely affect the assessment of the structural model. Thus, the goodness of fit was reevaluated after excluding items below the 0.5 threshold, ensuring the suitability of the data for model analysis (Chwiałkowski et al., 2018). The results revealed a Standardized Root Mean Square value of 0.178, which was below the cut-off of <0.80. Additionally, the Chi-square value remained at 1.042, below the cut-off of 3.00. The Tucker and Lewis (TLI) value was 0.904 (>0.90), and the Normed Fit Index (NFI) value was 0.899, falling within the range of 0-1. Overall, the removal of items with lower factor loads supported a good fit for the current model. Table 4.7 presents the goodness-of-fit results. Figure 4.2 displays the final measurement model after excluding loading values below the threshold. This advanced model was then employed to assess the structural model in the present research study.

Table 24.7: Goodness of Fit Results

	Obtained Values	Cutoff Value
SRMR	0.178	<0.80

Chi-square	12.042	12.041
TLI	0.904	>0.90
NFI	0.887	b/w 0-1

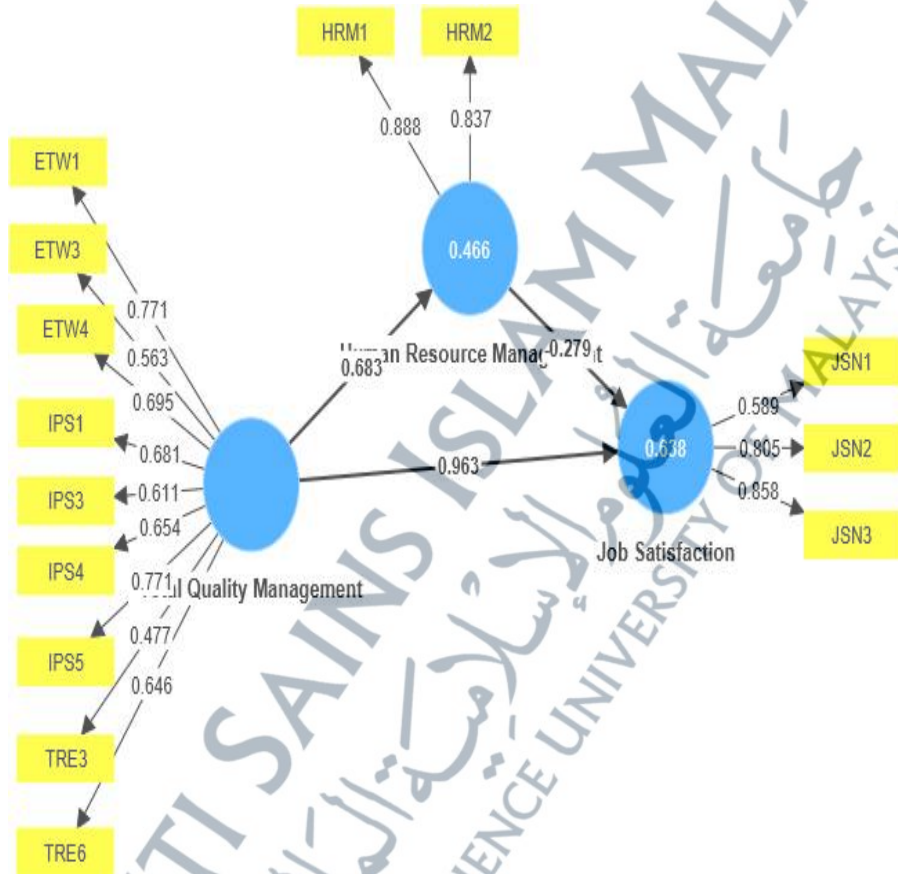


Figure 4.2: PLS - Final Measurement Model of Current Study

4.5.3 Discriminant Validity

In this study, confirming discriminant validity was essential to verify whether each indicator's loadings primarily align with their respective constructs rather than others, thereby addressing concerns regarding multicollinearity (Ringle & Sarstedt,

2016). Three established techniques were employed to assess discriminant validity within the research model: cross-loading, the Fornell-Lacker criterion, and the Heterotrait-Monotrait (HTMT) criterion. Discriminant validity was evaluated using both the Fornell-Lacker criterion (Shiu et al., 2011) and the Heterotrait-Monotrait (HTMT) criterion (Rasoolimanesh, 2022), ensuring that the confidence interval value remained below 1 (Mello & Collins, 2001). The Fornell-Lacker criterion (1981) examines the extent of shared variance among the model's latent variables, indicating that each construct should show more shared variance with its associated indicators than with other constructs in the model (Cheung & Wang, 2017). This suggests that the square root of AVE for each construct should primarily relate to its respective indicator rather than others (Rasoolimanesh, 2022). As depicted in Table 4.8, the square root of AVE for all constructs significantly exceeds correlations with other constructs.

Subsequently, the HTMT criterion was applied, with all values falling below the threshold of HTMT 0.85 (University of Cologne et al., 2013). The more stringent HTMT.90 criterion recommended by Voorhees (2016) was not utilized due to its conservative nature (Cheung & Wang, 2017). Further, HTMT inference confidence interval values, obtained through bootstrapping with 5000 subsamples, ensured that none equalled 1 for any construct (Mello & Collins, 2001). As shown in Table 4.8, all values meet the HTMT criterion, with confidence intervals well below 0.85 (University of Cologne et al., 2013). Based on the evaluations conducted using both the Fornell-Lacker and HTMT criteria (Shiu et al., 2011), it can be concluded that this study has successfully demonstrated discriminant validity.

Table 34.8: Fornell-Larker Criterion

Human Resource Management	Job Satisfaction	Total Quality Management
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Human Resource Management	0.463		
Job Satisfaction	0.378	0.359	
Total Quality Management	0.483	0.372	0.458

Table 4.9: Heterotrait-Monotrait Ratio Scale

	Human Resource Management	Job Satisfaction	Total Quality Management
Human Resource Management	0.503		
Job Satisfaction	0.668	0.608	
Total Quality Management	0.571	0.898	1.029

4.5.4 Multicollinearity Testing

Multicollinearity was further tested to determine potential correlation between independent variables. Notably, the relevant test is employed is carried out in regression-based studies as any correlations between independent variables is considered an endangering the reliability of results (Kim, 2019). The results indicated that all VIF values were below the conservative cutoff value of 3.0, confirming that no significant multicollinearity existed between the constructs. This ensures the robustness of the model and enhances confidence in the reliability of the estimated relationships. The descriptive statistics were analyzed using SPSS software (Mishra et al., 2019b), with Table 4.10 presenting the computed values for Pearson correlation coefficients, mean, standard deviation, and VIF scores. For example, "Organization focuses on providing training and educational programs" yielded a mean score of 4.31, suggesting strong consensus among respondents regarding the organization's commitment to

professional development. Similarly, the statement "Training and education positively affect our productivity" had a mean score of 3.71, further reinforcing the perceived benefits of training initiatives.

For mediator-related variables, responses reflected strong agreement, with mean values of 3.86 for "Organization motivates us to think with creativity," 3.69 for "Feel confident to share our skills and expertise while working in teams," and 4.36 for "Organization encourages teamwork for problem-solving matters." These scores indicate that employees generally perceive a supportive environment that fosters creativity, collaboration, and knowledge sharing.

Table 4.10: Variance Inflation Factor

	VIF	Threshold value
TRE3	1.463	
TRE6	1.654	
ETW1	2.617	
ETW3	1.59	
ETW4	1.833	
HRM1	1.348	3.0
HRM2	1.352	
HRM3	1.087	

Further, mean values of 3.67 and 3.69 were recorded for constructs related to positive relationships with top-level management and overall employee well-being, highlighting favourable perceptions regarding leadership support and workplace satisfaction. The low standard deviation values across all constructs further indicate that responses were relatively consistent, suggesting a shared perspective among participants (Marshall & Jonker, 2010).

Overall, the findings confirm that the dataset is well-structured, with no significant issues related to missing values, extreme variability, or multicollinearity. These results provide a solid foundation for subsequent inferential analyses, ensuring the accuracy and validity of conclusions drawn from the study. Table 4.9 provides a detailed summary of VIF scores, demonstrating the robustness and reliability of the dataset.

4.5.5 Descriptives of Gathered Responses

Descriptive statistics serve as concise summaries of a dataset, offering insights into its central tendency and variability. Measures of central tendency, such as mean, median, and mode, provide a sense of the dataset's typical value, while variability measures, including standard deviation, variance, minimum and maximum values, kurtosis, and skewness, reveal the spread or dispersion of the data (Mishra et al., 2019a). Table 4.10 outlines a summary of descriptive data.

The descriptive statistics indicate that employees typically have a positive perception of their organization's training, teamwork, HRM practices, and overall job satisfaction, with most means falling around 4 (agree) or slightly above. Higher means, such as 5.3 for job satisfaction with tasks, indicate stronger disagreement, suggesting dissatisfaction in certain areas. Standard deviations vary, with some items (e.g., workplace atmosphere) showing moderate consistency, while others (e.g., job satisfaction with tasks) show greater variability, indicating diverse opinions. The range and variance values confirm these variations, with higher values reflecting more dispersed responses. While employees appreciate training and teamwork, areas like recruitment processes and problem-solving strategies may need further attention.

Table 4.11: Descriptives of Responses

Items	Mean	SD	Range	Variance
My organization pays focus to provide us training and educational programs.	3.2	0.8	3.5	0.64
My organization allocates special resources to arrange training and educational programs.	4.1	0.9	4.0	0.81
My organization emphasizes training and task effectiveness.	5.0	1.2	5.5	1.44
Training and education programs positively affect us performance.	3.8	1.0	4.2	1.00
Training and education positively improve our capabilities to understand and enhance problem-solving capabilities.	4.5	0.7	3.0	0.49
Training and education positively affect our productivity	3.3	0.6	2.5	0.36
Training and education positively boost our work morale.	4.9	1.3	6.0	1.69
My organization motivates us to think with creativity.	3.7	0.9	3.8	0.81
My organization acknowledges employee's opinion in the decision-making process	5.1	1.1	4.8	1.21
We feel confident to share our skills and expertise while working in teams.	4.2	0.8	3.5	0.64
My organization encourages teamwork for the problem-solving matters.	3.9	1.0	4.0	1.00
We feel compatible both working alone and with teams.	4.8	1.2	5.2	1.44
Positive relationships with the top order individuals improve my job commitment.	3.5	0.7	3.0	0.49
Higher priority to employee wellbeing improves my job performance.	5.0	1.1	4.7	1.21
I feel confident to complete the projects in pipeline in minimum time with increased effectiveness.	4.4	0.9	3.8	0.81
I feel confident to achieve the projects submission before the deadlines.	3.6	0.8	3.2	0.64

My organization has supported me to enhance my problem-solving behavior.	4.7	1.2	5.0	1.44
HRM carefully recruits the candidates suitable to each work department.	3.4	0.7	2.8	0.49
HRM actively monitors the performance of each employee individually.	5.2	1.3	6.0	1.69
HRM individuals are mindful enough to counter any issue and its immediate solution.	4.0	0.9	3.7	0.81
HRM makes suitable choices when monitoring the employee's performance.	3.1	0.6	2.5	0.36
HRM ensure recruit process as compatible with the modern workforce requirements.	4.6	1.1	4.8	1.21
HRM ensures a consensus from workforce individuals regarding willingness to change.	3.9	0.8	3.6	0.64
All in all, I feel satisfied with my job tasks and responsibilities.	5.3	1.4	6.2	1.96
All in all, I feel satisfied towards my relations with the higher rank personals.	3.2	0.7	2.9	0.49
All in all, I feel satisfied with my relations with the teams.	4.9	1.2	5.5	1.44
All in all, I feel satisfied with the confidence given by my organization.	3.7	0.8	3.4	0.64
All in all, I feel satisfied with the workplace atmosphere.	4.1	0.9	3.9	0.81
All in all, I feel satisfied with the recruitment criteria on my organization.	5.0	1.3	5.8	1.69
All in all, I feel satisfied with the organizational strategies towards problem-solving activities.	3.8	0.7	3.0	0.49

4.6 Assessing the Structural Model (Outer Model)

To evaluate the structural model, researchers usually employ specialized tools such as Smart-PLS software or conduct PLS-SEM analysis to explore the relationships between independent variables (IVs) and the dependent variable (DV) of a study

(Ringle & Sarstedt, 2016). In PLS-based analysis, it is assumed that the data follows a normal distribution when the sample size exceeds 30, as per the Central Limit Theorem. However, this assumption can lead to Type 1 errors due to underestimation or overestimation of t-values (Barrett, 2007). To mitigate this, using a bootstrapping procedure is crucial to reduce standard errors, with a recommended subsample size of 5000 samples (Magno et al., 2022) .

In addition to examining the significance of path coefficients in evaluating the structural model within PLS-SEM, this study also incorporated other key metrics such as the coefficient of determination (R^2), the root mean square residual (SRMR), effect size (f^2), and predictive relevance (Q^2). Four hypotheses were proposed to investigate the effect of independent variables (IVs) on the dependent variable (DV), as outlined in Chapter Two. Among these, three hypotheses focused on the direct effect of independent variables (Total Quality Management and Human Resource Management) on job satisfaction. Besides, the fourth hypothesis proposed the mediating effect of the mediator (Human Resource Management) on job satisfaction.

For path coefficients analysis, three significance levels were considered: 1 percent ($\alpha = 0.01$), 5 percent ($\alpha = 0.05$), and 10 percent ($\alpha = 0.10$). Critical values of 1.645 and 1.28 were used for two-tailed and one-tailed tests, respectively, for $\alpha = 0.01$ (Ringle & Sarstedt, 2016). Similarly, critical values of 1.96 and 1.645 were employed for two-tailed and one-tailed tests, respectively, for $\alpha = 0.05$ (Bagozzi & Yi, 2012). For $\alpha = 0.10$, critical values of 2.58 and 2.33 were applied for two-tailed and one-tailed tests, respectively. Furthermore, (Magno et al., 2022) strongly advocated for conducting initial analyses using PLS path modelling to evaluate hypothesized path models for direct effects, followed by subsequent analyses including mediation effects.

4.6.1 Coefficients of Determination R^2

Before assessing the relationships proposed in the structural model, the Coefficient of Determination R^2 examines the predictive power of independent variable in the current research study (Ferreira, 2020). In other words, the Coefficient of Determination R^2 was utilized to examine the extent to which independent variable (Total Quality Management) causes variation in the dependent variables (Human Resource Management and Job Satisfaction) in the current research study. Table 4.12 indicates the results of the Coefficient of Determination R^2 , showing 73.6% of variance in the variable “Human Resource Management” and 50.3% of variance in the Job Satisfaction. Based on Ringle’s suggestion, the R^2 exceeding the threshold value of 20.0% is considered as acceptable in management sciences research. The value 0.736 and 0.503 are considered substantial for the current research study.

Table 4.12: Coefficient of Determination R^2

Variables	R^2	Strength
Human Resource Management	0.736	Substantial
Job Satisfaction	0.503	Substantial

4.6.2 Effect Size (f^2)

Effect size (f^2) was examined to quantify the magnitudes of relationships among variables in the current research study (Kraft, 2020). The effect size of Total Quality Management in its relation to Human Resource Management and Job Satisfaction was examined. Thus, the effect size of Total Quality Management on Human Resource management remained $f^2 = 0.688$, and the effect size of Total Quality Management on Job Satisfaction remained $f^2 = 0.169$. According to Lorah (2018), effect size $d = 0.2$ is considered as small, $d = 0.5$ indicates a medium effect size, and $d = 0.8$ is considered as

large effect size. Thus, this study acquired effect sizes that both are far greater than 0.8 (Samartha & Kodikal, 2018), indicating a large effect size. Table 4.13 represents the findings of effect size in the current study.

Table 4.13: Effect Size (f^2) Results

Predictor Variable	Dependent Variable	R^2 Included	R^2 Excluded	f^2	Effect Size
Total Quality Management	Human Resource Management	0.668	0.446	282.313	Large
Total Quality Management	Job Satisfaction	0.571	0.326	169.128	Large

4.6.3 Predictive Relevance Q^2

According to Samartha and Kodikal (2018), Predictive Relevance, or Q-square, implies predictive power in modelling. It evaluates whether a given model holds predictive significance, where values surpassing 0 show a favorable outcome. Another pertinent metric, Q^2 , especially measures the endogenous constructs' predictive relevance. When Q-square values exceed zero, the model effectively reconstructs values and maintains predictive relevance, highlighting its capability to make significant predictions. Also, when a Q^2 value exceeds zero, it further highlights the model's predictive utility. Researchers can use the Blindfolding procedure within the Smart-PLS framework to establish the Q-square value. This approach helps evaluate the model's predictive quality and general prediction effectiveness. Thus, results revealed the predictive relevance of Total Quality Management $Q^2 = 0.724$ and Human Resource Management $Q^2 = 0.519$. Based on the criteria provided by (Akter & D'Ambra, 2011) Q^2 near to zero 0 means lack of or absence of predictive relevance while, near to 1 or higher means strong predictive relevance. The current study indicated the predictive

relevance for each construct is strong. Table 4.14 shows the results of predictive relevance Q^2 in the current research study.

Table 4.14: Predictive Relevance (Q^2)

Predictor Variable	Q^2	RMSE
Total Quality Management	0.724	0.205
Human Resource Management	0.519	0.114

4.6.4 Testing the Direct Relationships

First, the direct relationships proposed in the first three hypotheses were tested. In the H1 of the study, a direct effect of Total Quality Management on Job Satisfaction among Ras Al Khaimah police officers was examined. Results showed a significant effect of Total Quality Management on Job Satisfaction with the Beta Coefficients $\beta=0.907$, t -value 13.005, and significance value $p < 0.000$, indicating the H1 of the study is strongly supported. The H2 of the study examined the effect of Total Quality Management on the Human Resource Management in the Ras Al Khaimah police officers. With the with the Beta Coefficients $\beta=0.858$, t -value 16.802, and significance value $p < 0.000$, H2 of the current research study is also supported. Finally, the third hypothesis proposed a significant effect of Human Resource Management on the Job Satisfaction of the Ras Al Khaimah police officers was analyzed. Results showed the Beta Coefficients $\beta=0.-0.244$, t -value 8.280, and significance value $p < 0.000$, demonstrating that H3 is also supported by the path analysis.

Notably, the path among Total Quality Management and Job Satisfaction remained the strongest among all (0.907), followed by Total Quality Management and Human Resource Management (0.858), the path between Human Resource Management and Job Satisfaction remained weakest (-0.244) among all. Table 4.13

indicates the results of hypotheses testing concerning direct effects, while figure 4.15 shows the final structural model of the current research study.

Table 4.15: Path Analysis of the Direct Relationships

Hypotheses	β	t	M	VIF	SD	P	99% Confidence Intervals	
							Lower	Upper
Total Quality Management → Job Satisfaction	0.907	13.005	3.91	1.000	0.502	0.000	0.507	0.687
Total Quality Management → Human Resource Management	0.858	16.802	3.88	1.793	0.529	0.000	0.650	0.822
Human Resource Management → Job Satisfaction	-0.244	8.280	3.91	1.036	0.502	0.000	0.293	0.476

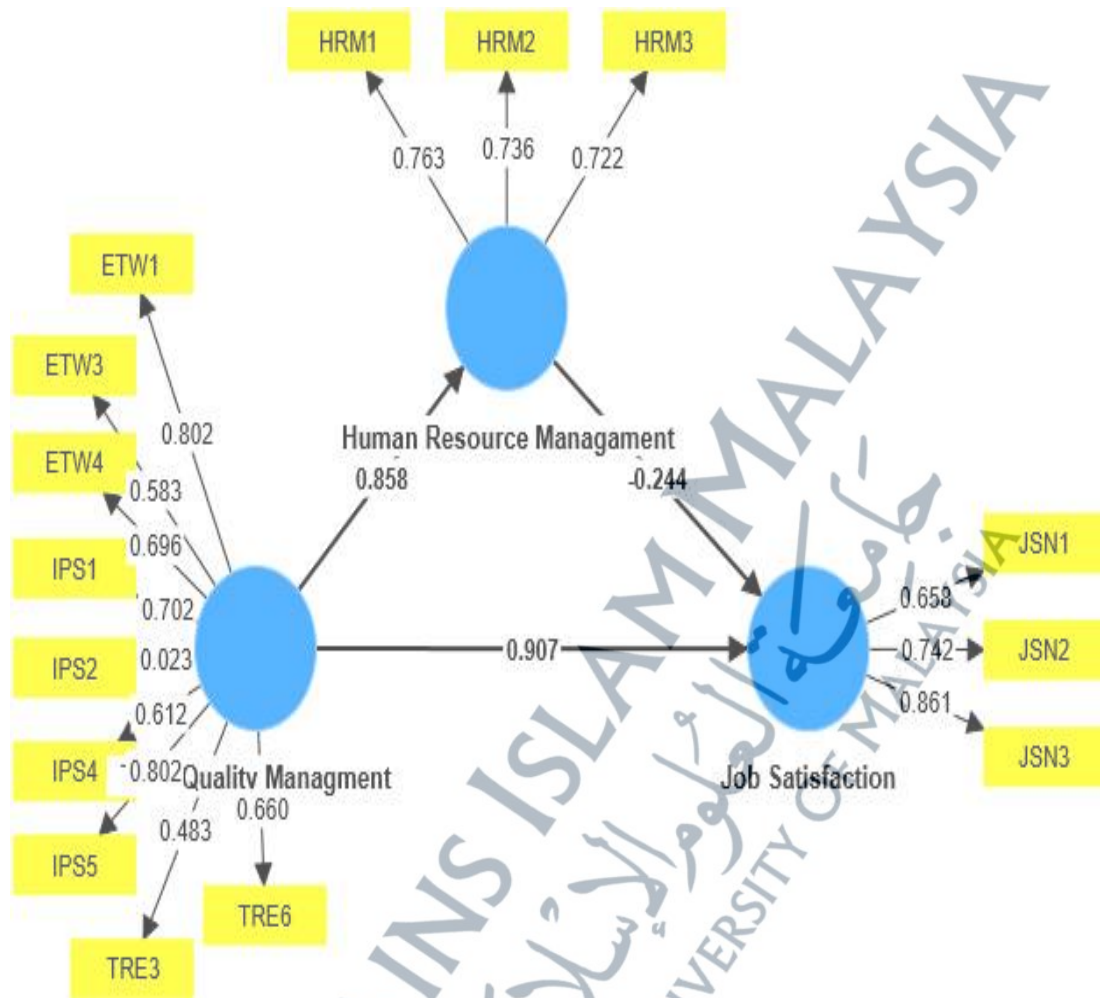


Figure 4.3: Final Structural Model Indicating Path Values and P-values.

4.6.5 Testing the Indirect Relationship

A mediator variable is aimed at affecting the direct relationships between independent variable and the dependent variable(s). The objective of a mediator variable in research is to help ascribe the background mechanism or procedure through which an independent variable (IV) affects a dependent variable (DV). Thus, the mediating effect of Human Resource Management on the relationship between Total Quality Management and Job Satisfaction was examined using the Smart-PLS. Results showed that the direct effect of Total Quality Management on the Human Resource

Management ($\beta= 0.668, p < 0.000$) and Job Satisfaction ($\beta= 0.543, p < 0.000$) is significant, that further leads to the significant mediation of Human Resource Management on the relationship between Total Quality Management and Job Satisfaction with the path value $\beta= 0.042$, significance value $p < 0.000$, and indirect value 0.028. Figure 4.4 shows the results of mediation analysis indicating path values and significance values obtained concerning the mediation analysis.



Figure 4.4: PLS- Results of Mediation Analysis

4.7 Summary of the Research Findings

A total of four hypotheses were proposed and tested in the current research study out of which first three were based on assuming direct relationship while the fourth one proposed mediating effect. Analysis revealed that all the hypotheses are supported and

validated by the research findings. Table 4.16 provides a summary of hypotheses testing results in the current research study.

The results suggest that Total Quality Management (TQM) is crucial in shaping Job Satisfaction and Human Resource Management (HRM) practices within Ras Al-Khaimah Police in the United Arab Emirates. Also, HRM was found to significantly affect Job Satisfaction, supporting its critical role in employee well-being and workplace effectiveness. The mediation analysis further affirmed that HRM is a significant intermediary between TQM and Job Satisfaction, emphasizing its significance in translating quality management initiatives into improved employee satisfaction.

These results highlight the relationship between organizational management practices and employee outcomes, implying that effective implementation of TQM enhances HRM strategies and contributes to job satisfaction among law enforcement personnel. This has practical implications for policymakers and organizational leaders aiming to improve workplace dynamics and employee engagement.

Table 4.16: Summary of Hypotheses Testing Results

Hyp.	Proposition	Supported
H1.	Total Quality Management has a significant effect on Job Satisfaction among Ras Al-Khaimah Police Officers in the United Arab Emirates	Yes
H2.	Total Quality Management has a significant effect on Human Resource Management among Ras Al-Khaimah Police Officers in the United Arab Emirates.	Yes

- | | | |
|------------|--|-----|
| H3. | Human Resource Management has a significant effect on Job Satisfaction among Ras Al-Khaimah Police Officers in the United Arab Emirates. | Yes |
| H4. | Human Resource Management media the relationship between Total Quality Management and Job Satisfaction among Ras Al-Khaimah Police Officers in the United Arab Emirates. | Yes |
-

4.8 Chapter Summary

In this chapter, an extensive analysis was conducted using a combination of descriptive statistics and inferential statistics (Structural Equation Modelling), providing useful discernment into the relationships among the variables under study. The descriptive statistics showed a clear overview of the central tendencies within the dataset, illustrating key characteristics of the observed variables. Further, applying SEM allowed a more in-depth exploration of the complex interplay between the constructs. Through SEM, both the measurement and structural models were tested, providing a holistic understanding of the underlying theoretical framework. Thus, the findings supported the proposed hypotheses, establishing the relationships posited in the conceptual model. The mediator variable (HRM) played a critical role in explaining the mechanisms through which the independent variable affected the dependent variable. This mediation analysis provided a subtle understanding of the complex ways and processes involved.