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Exploratory Analysis of Risk Management Process of UAE Police Department

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Abstract: Risk control and management are becoming increasingly important in many organisational operations. It goes beyond the business sector to include security organisations like police departments. The fact that police officers engage in a wide range of daily activities that expose them to a variety of potentially hazardous situations Police risk management includes both physical and financial aspects. Risk identification is the first step in the risk management process, followed by risk analysis, risk evaluation, and risk treatment. According to the literature, the Dubai Police Department has no framework in place to fully manage risks and evaluate the effectiveness of police operations. Early warning systems are critical for detecting potential severe RM because police departments must rely on them to manage risks and keep track of any potential new risks. As a result, the UAE police department's risk management strategy was investigated in this paper. It classified the data collection process using exploratory factor analysis, which was a quantitative approach. A self-administered survey yielded 381 valid questionnaires from Dubai Police Department officers. The study's findings revealed that risk identification, risk analysis, risk evaluation, and risk response are the four fundamental steps of effective risk management. The Crobach Alpha test was used to assess the consistency and reliability of the data, and the result was 0.814, indicating that the data is suitable for use. Only one of the twenty indicators, which were divided into four groups for risk management, was weak according to outliers and communalities tests. The risk management process was accurately described by another 20 factors. Total variance extraction yielded a rate of 57.130 percent, which was higher than the required 50%. As a result, the risk management procedure investigated in this study may be useful for effectively managing risks in the UAE police force.

Keywords: Factor analysis, risk management, police department, UAE, Dubai

1. Introduction

Each organization deals with a variety of risks, including internal, external, strategic, and project-related risks. Hence, organizational risk management abbreviated as RM has become increasingly important in recent years, and this is true for both for-profit organizations and government agencies. Determining the best course of action involves understanding the type of risk that must be managed. An organization to manage risks need to understand and keep risk records, controls, and warranties, like fraud, health and safety, capacity, and capacity, data security, and delivery partners. While focusing on external risks, the emphasis is on significant external events. Examining the effects of the

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external events on infrastructure, financing, people, operations, and reputation is a tried-and-true method of managing external risks. The economy, deflation, terrorist attacks, severe weather, and cyberattacks are examples of external risk events.

In recent years, risk management in organizations and risk control in many operations have become more and more crucial. It is also extended to security organizations like police departments in addition to the business sector. The fact that police department employees are engaged in numerous activities each day which bring various risk situations. Police agencies must manage risks from both a physical and financial perspective. The ultimate effect of security risks may not only be felt by the general public but also by the legal system. Additionally, the burden extends beyond the confines of the police organization's risks and includes external factors that may have an impact on the nation's legal system (Archbold, 2005). In addition, police officers and departments within law enforcement organizations could become victims (U.S. Department of Labor, 2010).

Due to the development of criminal tactics, the job of law enforcement is more difficult today. The UAE faces several risks to its national security occurring from the issues like anti-money laundering, cybercrimes, counter-terrorist financing, and foreign-based offences like fraud, tax evasion, and organized crime. This emphasis the need of making adequate arrangement of risk management. The RM process begins with risk identification and progresses through risk analysis, risk evaluation, and risk treatment. Literature reveals that there is lack of framework for fully managing risks and assessing the efficiency of police operation which affects the performance of Dubai Police Department weaker. Since, police departments must rely on early warning systems to manage risks and track any future risks that may exist. It's crucial to identify potential strong RM using early warning systems. For instance, it is predictable that 10% of police officers are responsible for 90% of the problems that increase the likelihood of policing risks (Hughes et al. 2007). Using surveillance reports to inform about risks at an early stage is one of the most efficient methods for risk identification. One of the most efficient methods for producing such risk reports is early warning systems (Hall, 2002)Hence, this paper has studies risk management process adopted by police department of the UAE for managing risk in maintaining law and order situation in the country.

2. Literature Review

2.1 Risk Management

Risk management (abbreviated RM) is a systematic approach (Karim et al. 2012) to managing various risks (Musyoka, 2012). In general, a risk management system should have procedures for identifying, categorizing, and assigning risks. Strong RM systems that typically include identification, analysis, and response are required for a project to be successful so that risks can be managed when they materialize (Pellegrino et al., 2013). The goal of the RM is to anticipate problems so that risk management actions can be planned and called upon as necessary throughout the life of the project or product to reduce adverse effects on accomplishment of goals (Omwenga and Linet 2016).

The International Organization for Standardization's (ISO) defines risk as "the impact of ambiguity on things" and "harmonized activities to systematically control risks." In other words, risk management (RM) is primarily used to assess, identify, monitor, and priorities risks before applying the necessary resources in a coordinated and efficient manner. Different organisations use the continuous approach to risk management to effectively anticipate and reduce risks that have a significant impact on the project. Early and aggressive risk identification through collaboration and stakeholder involvement is a key component of effective risk management (Lark, 2015). To foster an atmosphere that encourages risk disclosure and discussion in an unrestricted and transparent manner, strong leadership is required among all pertinent stakeholders

The RM should be formally organized and integrated into the general management process used in the day-to-day management of public organizations, which is done in a particular public organization (Tworek, 2015). In public organizations, RM plays a crucial role in the processes of strategic management. A public organization can benefit from an effective RM by, among other things, lessening the uncertainty surrounding its activities and future development that stems from the environment in which it operates. Secondly, it can provide authorities and public officials with the chance to become accustomed to the fact that many phenomena are uncertain and unpredictable, to learn to act under these circumstances, and to perceive relevant risks as an inherent part of organizational functions. Besides these, it can create circumstances that enable the organization to overcome growth constraints and eliminate (or at least mitigate) the various conflicts that have been found when determining the current stage of development of the public institution (Brown & Osborne, 2013).

For RM pertaining to various industries and businesses, ISO has established a number of rules (Dali & Lajtha, 2012). The most widely used set of risk management principles and practices is ISO (31000: 2009), which is based on 11 principles, processes, and structures that can be modified to meet different types of business requirements (Lark, 2015). Since its initial adoption in 2009, this standard has been used everywhere (Dali & Lajtha, 2012). A variety of industries can use the ISO (31000: 2009) standard. However, it must be noted that this standard is a voluntary effort to assist organizations of all kinds in keeping risk at a low level and not a legal framework (Lark, 2015).

The key steps in risk management are context setting, risk identification, risk analysis, risk evaluation, risk handling, communication and consultation, monitoring, and evaluation (Lark, 2015) as depicted in Figure 1.

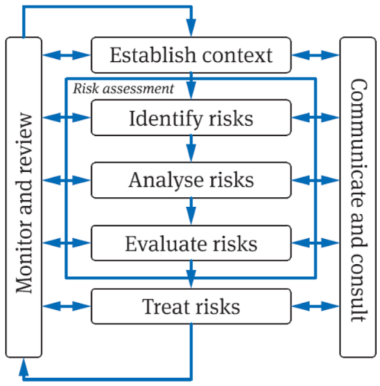

Fig. 1 - The ISO 31000:2009 RM process (Lark, 2015, p. 14)

Principles of RM as opposed to modern aid organizations' typical methods. In other words, when assessing the risks, the agency must weigh security concerns (such as change of context, incidents, kidnappings, killings, etc.) against the objectives it strives for. This is because the fundamental research change imposed by ISO 31000, which entails considering risks as an event, is particularly important for the practise of aid agencies (presence, programs, etc.). Kevin Knight (2009) pointed out that "in ISO 31000, the emphasis is changed from an event occurring, which is what it was in previous risk management guidelines, to the impact of uncertainty on goals". Every organization has strategic, tactical, and operational goals that must be accomplished. In order to do so, the organization must manage any uncertainty that could hinder the goals' accomplishment "It would be possible to adapt efficient RM structures and methods to the organization with the aid of ongoing research on the roles and responsibilities of specific organizations.

The concept of risk has many definitions, and most authors concur that it is challenging to define. To put it another way, most writers attempt to define a concept that can be easily differentiated in terms of organisation and setting. What is strong for one person may be weak for another; a threat to one manager may be a chance for another. Briefly stated, risk is a person's perception of and reaction to the unknown (Hopkins & Nightingale, 2006).

2.2 Risk Management in Public Sector

The various activities carried out by organizations engaged in public sector work are strongly correlated with the possibility of potential risks, which must first be accurately identified before being assessed, analyzed, monitored, and finally controlled. This is how RM operates as a whole (Kapuscinska and Matejun 2014). Managers in public sector organizations must look at the entire organization and have an impact on their strategies, strategies, and operations in addition to working to provide an appropriate venue for governance mechanisms (Kapuscinska and Matejun 2014). The identification of a potential risk and the highlighting of its key characteristics is a crucial step in managing a potential risk and its characteristics in a public sector organization. Risk identification uses a variety of techniques, like brainstorming. Each of them is the subject of a thorough analysis, both in terms of its likelihood and the gravity of its repercussions. In this regard, risk identification, analysis, and control must be done with great care and include details on the management practices used by the organization's various departments (Omwenga and Linet 2016).

Risk can exert an impact on a wide range of organizational functions within the public sector, including strategy, finances, human resources, technology, and the environment. Therefore, it is advised to create a template document before the risk identification stage begins, which will be a risk report once it is finished and filled out with the required data. Since specific risks can include the loss of key personnel, a significant decrease in financial and other resources, and significant interruptions in the flow of information and communication, an organizational document can be divided into characteristic areas. The aforementioned fundamental guidelines for RM implementation in public sector organizations must be understood by managers of these organizations in order to ensure that the actions taken as part of this process are carried out effectively, efficiently, and on time. Dobson & Hietala (2011) listed six essential RM conditions that should be taken into account as establishing a culture that fosters motivation and development to control risk; incorporating risk management (RM) into the overall management process; making clear links between RM and the achievement of organizational goals; and evaluating and managing contacts with outside parties are just a few of the things senior management should do to support and promote the RM process. Kapuscinska and Matejun (2014) talked about the exceptional qualities of RM in organizations in the public sector. He gave an example of how the RM concept had been applied in a particular public organization. His study's findings showed that RM in the public sector is essential, just like other businesses are in the private sector.

2.3 The Measurement of Risk Management

Risk management (RM) is the process of identifying, evaluating, and prioritizing risks (defined by ISO 31000 as the impact of uncertainty on the objectives), then utilizing resources in a coordinated and cost-effective manner to lessen, monitor, and control the likelihood or impact of unfavourable events and identifying opportunities to improve (Hubbard, 2009).

Risks can originate from a number of different places, such as ambiguities in the financial markets, threats to project success and events as depicted in Figure 2 (at each stage of the design, development, production, or sustainability of the life cycle), legal obligations, credit risks, accidents, natural causes and disasters, willful attacks, ambiguities, or an unexpected causal event. Events can be divided into two categories: positive and negative. Positive events can be categorized as opportunities. The Institute for Project Management, the National Institute for Standards and Technology, actuarial associations, and ISO standards are just a few of the organizations that have developed RM standards. Depending on how the RM method is applied to security, project management, technology, groups, industrial processes, health, and public safety, the methods, definitions, and objectives change significantly (ISO Guide 73: 2009).

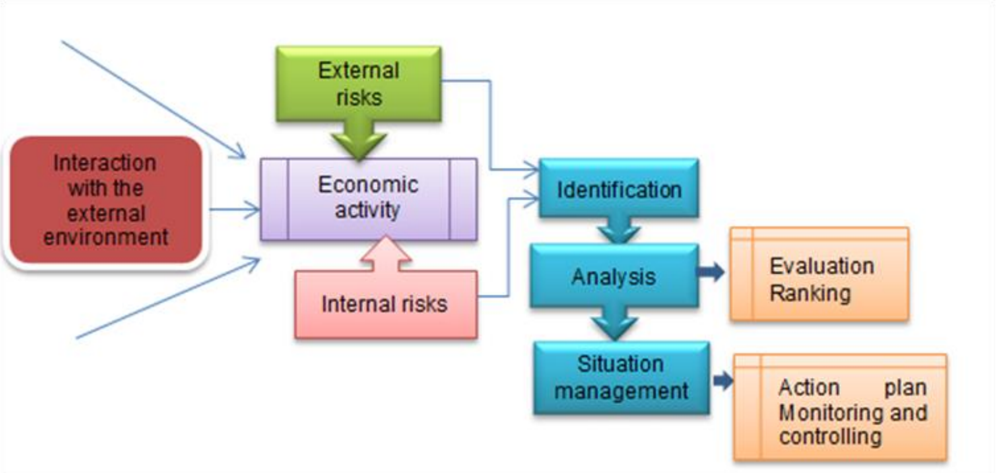

Fig. 2 - The Theory of RM (Hubbard, 2009)

2.4 Risk Identification

The project management literature frequently uses the concepts of risks and uncertainties. Despite their close resemblance, many writers distinguish these terms (Samson et al. 2009). However, it is challenging for at-risk workers to recognise and differentiate them. Regarding the use of a specific project, the definition of risk or uncertainty is frequently modified. Identifying riskis crucial (Cleden 2009). Uncertainty is an abstract measure of what we don't know. After all the potential risks have been identified, uncertainty is what is left. Since uncertainty arises from knowledge gaps that we might not even be aware of, risk must be identified prior to the creation of any projects.

The risk identification process is the first and most crucial step in RM (Banaitene & Banaitis, 2012). This implies that the goal is to obtain a perfect forecast of upcoming events when the potential sources of risk occur. The main goal of risk evaluation and risk identification is to make sure that potential risks are managed and assessed appropriately to achieve shared objectives, as it is impossible to find out or identify the very potential risks and this is not the main goal (Smith et al., 2006). As risks are constantly changing throughout the course of a project, RM is a continuous process (Potts, 2008). Karimiazari et al. (2011) argued that prior to managing risks, it is important to identify them so that new knowledge can be applied to ongoing projects.

2.4.1 Risk Analysis

The second stage of the RM process is risk analysis, which involves analysing the information gathered about the potential risk. Shortlisting the risks with the greatest impact on the project from all threats mentioned during the identification phase is another way to describe risk analysis (Cooper et al. 2005). Risk analysis is a crucial component of project management which helps to ensure that there are as few surprises as possible while your project is in progress. While it is impossible to predict the future with absolute certainty, we can use a straightforward and efficient RM process to anticipate project uncertainties and lessen their likelihood of occurring or impact. There are two method of risk analysis i.e. qualitative and quantitative which must be completed in order to increase the likelihood of a project's successful completion and decrease the consequences of those risks (Lavanya and Malarvizhi 2008). The type of risk, the scope of the project, and the specific method's requirements and criteria should all be taken into consideration when selecting a method (Ewelina and Mikaela, 2011).

Table 1 - Differences between qualitative risk analysis and quantitative risk analysis

Quantitative Risk Management	This type of analysis is centered on the quantification of risks. Statistical techniques are used in quantitative analysis to gauge the overall impact of risks on the project's outcome (Hillson, 2006)
Qualitative Risk Management	The evaluation of traits linked to individual risks is the goal of this analysis, and those traits will be given priority (PMI, 2000)

Qualitative Risk Analysis: Collecting pertinent risk information is the first step in the risk evaluation process. This information may be historical data obtained from the provider's prior experience. They also discuss the modelling of risk uncertainty, in which the likelihood of occurrence is determined by the likelihood and possible financial repercussions. The next step is to evaluate the overall impact of these risks. Qualitative risk evaluation techniques describe the likelihood and consequences of risk using descriptive scales. Rapid assessments are conducted using these relatively easy methods in small and medium-sized projects (Cooper et al., 2005). (Heldman, 2005). This approach is frequently used when there is a lack of digital data, access to it is restricted, and there are limited time and financial resources (Radu, 2009). According to Cooper et al. (2005), the main goal of qualitative methods is to prioritise potential threats in order to identify those that will have the greatest impact on a project. By concentrating on these threats, projects will be more effective overall (PMI, 2004). The project's dimensions and goals are reflected in the complexity of the scales (Cooper et al., 2005) and definitions (PMI, 2004). A current risk evaluation can be used to determine the current state of risk because risks may change throughout the life of a CLP (Cooper et al., 2005). One of the common way of explaining risks is use of risk matrix to describe the level of risk. It classifies risk as low, medium and high level of risk (Ismail et al. 2014) which is computed based on occurrence and significant level of the measured indicators to descriobe the importance level of the risks (Memon et al. 2018; Alameri et al. 2021). Winch (2010) lists a probability and impact matrix as one of the most popular techniques for identifying risk sources. This matrix is depicted in Figure 3. Risks are categorised according to their impact and likelihood of happening. This enables you to rank the project's risks according to how easy or difficult they are to manage. Figure 3 illustrates how high to low quality scales can be used to estimate known unknowns and subjectively assess known ones (Winch, 2010).

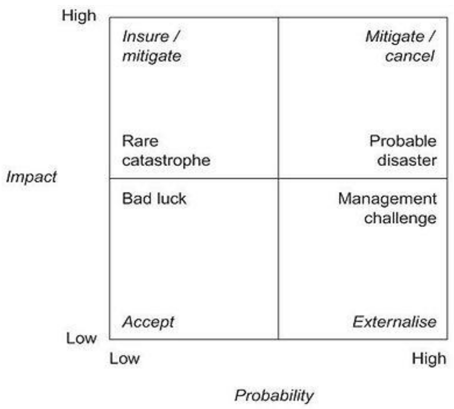

Fig. 3 - Probability and impact matrix (Winch, 2010)

Quantitative Analysis: A lot of analytical work is required for quantitative methods. The benefits and results of the method of choice should be contrasted with the efforts made. Small projects, for instance, might only need identification and risk-based precautions, whereas larger projects might need more thorough investigation. Due to the amount of resources required, including sophisticated software and qualified personnel, they are more appropriate for medium and large projects (Heldman, 2005). The impact of each risk on the high and low end of the spectrum as well as the likelihood that it will be achieved are determined through quantitative risk evaluation. An evaluation of effects and the creation of lists for further investigation of identified risks are frequent components of a qualitative risk assessment (Zou et al., 2007). A correlation between the effects of the two types of analysis should be included in the risk assessment at the individual level (Schieg, 2006). When quantifying risk, it is possible to estimate the impact and probability of a specific risk. The effect of the risk on the project's goals is evaluated while taking into account both the positive opportunities and outcomes as well as the negative threats and outcomes. It's crucial to clarify and ascertain the likelihood and effects of a specific project. As a foundation for further analysis, the risk matrix method can also be used with a chance and an effect. Quantitative analysis clearly shows that high-priority assessments are high-risk threats and that the likelihood is high-risk and may call for an immediate response, whereas low-level threats may be more controlled and only receive attention when it is necessary.

2.4.2 Risk Evaluation

Risk evaluation seeks to identify and rank potential risk situations (Schieg, 2006). In the literature, risk evaluation generally takes one of two approaches: quantitative and qualitative data. The second approach is based on interviews and the brainstorming technique, whereas the second approach is based on data (Banaitene & Banaitis, 2012). Prior to using a qualitative approach, it is essential that the most important likely risk factors are accurately quantified in advance and then analysed. Exposure to potential risks may cause a number of people to experience delays, decreased productivity, and increased operating costs. Project failures frequently cause delays in other projects because resources can be shared among several projects. Delays can also be brought on by subcontractors (Schatteman et al., 2008). Quantitative risk analysis is also viewed as an optional component by many companies, whereas qualitative risk evaluation is a required component for all projects being studied Hillson (2004).

2.4.3 Risk Response

The final stage of the RM process outlines the steps that should be taken in response to the identified threats and hazards. The risks determine the strategy and method that is used (Winch, 2002). Winch (2002) contends that risk can be controlled more effectively as lower it is. Winch (2002) also discusses how quickly operation in the common case informs the public in addition to these kinds of reactions. Until the necessary information is available to minimise the risks, this can be avoided. This course of action, which is held here and criticises the risk, is known as "deferred decision" (Ewelina and Mikaela, 2011). Hillson(2004) defined the following steps as priority schemes for choosing response strategies The dimensional process of risk management is shown in Figure 4.

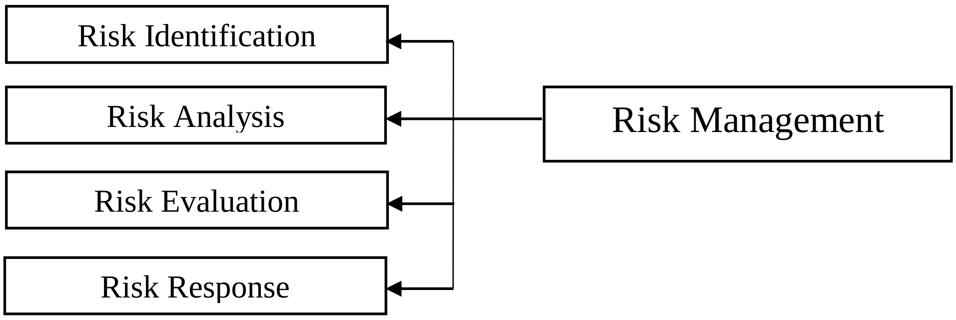

Fig. 4 - The dimensional model of risk management

3. Research Methodology

The process of collecting and analysing data is referred to as research methodology. There are three research methods: quantitative, qualitative, and mixed-mode (Bachayo et al. 2022). This study used a quantitative methodology. Quantitative research aims to investigate and test theories as well as to explain phenomena by demonstrating that they are based on theoretical premises (Oberiri, 2017). The deductive interpretation model is the foundation of quantitative methods in the humanities. Quantitative research looks for results that can be used to quantify the issue and understand its prevalence for a larger population. Methods for collecting quantitative data are typically structured data collection methods or survey methods such as online surveys, paper surveys, polls taken on mobile devices, in-person interviews, and phone interviews. Since surveys are among the best and most widely used data collection tools, this study used surveys to gather data using self-administered questionnaires. Self-administered questionnaires can be delivered to respondents by mail or in person. The primary statistical analyses were employed with the help of Statistical Package for the Social Sciences (SPSS) Version 21.0 to run reliability testing and factors analysis.

The internal consistency of the questionnaire is used to validate the reliability of the questionnaire, so it is important that each paragraph in the question be consistent with the description of the construct. Cronbach's alpha is a commonly used measure of reliability in scientific studies with quantitative data. When the value of Cronbach's alpha is 0.70 or higher, it is considered to be a reliable indicator in social science studies. Factor analysis is a statistical method used to compare groups of survey-taker responses to see if they share more similarities than differences. This dimensionality analysis of the survey items looks at how various survey questions relate to one another (Leandre et al., 2012; Tabachnick & Fidell, 2013; Kline, 2016; Bandalos, 2018). This technique was developed for the express purpose of unveiling the underlying dimensions of collections of achievement test items (Mulaik, 1987). In the realm of constructs, factor analysis is useful for establishing the probability that a given set of items collectively measures said construct. Two broad types of factor analysis are exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) (Knekta et al., 2019). Using EFA, one can look for hidden patterns in a dataset (Knekta et al., 2019). As a result, EFA can clarify the connections between various concepts and constructs and contribute to the creation of new theories. Early on in the development of an instrument, EFA is appropriate. The researcher can identify survey items that don't empirically fit the intended construct and should be eliminated by using EFA. Additionally, EFA can be used to investigate the instrument's dimensionality.

4. Results and Discussion

4.1 Data Collection

400 police officers working for the Dubai Police Department were given a questionnaire to fill out in order to gather data. 381 valid questionnaires were received in response to that with a response rate of 95.25 percent as summarized in Table 2.

Table 2 - Survey response rate

Questionnaire response	Frequency	Rate
Number of questionnaires distributed	400	100.00%
Valid questionnaires	381	95.25%
Incomplete/Blank questionnaires	19	4.75%

As can be seen in Table 2, there were 19 incomplete surveys that were omitted from the final count. This study's response rate is above 50%; thus, the data collected are adequate for extrapolating the results. If surveyed responses are less than 50 percent, as Bryman and Bell (2015) point out, it is possible that the study's findings will not be representative of the population as a whole. Prior to data analysis, these responses were used for a demographic analysis. The processes and methods that give researchers access to the study sample's dimensions are referred to as demographic analysis. The demographic data gathered for this study shows a sample of police officers from Dubai police departments, and Table 3 details various demographic traits.

Table 3 - The demographic profile of the respondents

Demographics	Level	Frequency	Percentage (%)
Gender	Male	318	83.46
	Female	63	16.54
Age	20-29 years	109	28.61
	30-39 years	131	34.38
	40-49 years	77	20.21
	50-59 years	53	13.91
	≥ 60 years	11	2.89
Academic Qualification	Bachelor	278	72.97
	Master	90	23.62
	PhD	13	3.41
Work Experience	1-5 years	61	16.01
	5-10 years	131	34.38
	10-15 years	120	31.50
	> 15 years	69	18.11

Table 3 shows that there are more men than women employed by the Dubai Police Department, with employees aged 30-39 having the highest employment rates and employees older than 60 having the lowest employment rates, or 2.89 percent. According to academic qualification data, the majority of employees in Dubai police departments hold bachelor's degrees, while the minority holds only PHDs. This outcome suggests that the police department in Dubai has a sufficient level of education. According to the results, employees with middle occupational experience (5–10 years) make up the highest percentage of the workforce, while new hires (1–5 years) make up the smallest percentage (16.10).

4.2 Data Reliability

The reliability coefficient is a gauge of each item's internal consistency, showing how closely the items in this study are related to one another. Cronbach (1951) states that the alpha reliability coefficient can take on a value between 0 and 1, with higher values indicating more trustworthiness. Alpha value 0.70 or higher is considered statistically significant (Cronbach, 1951; Sekaran & Bougie, 2013). The reliability test result for the data showed that Cronbach's Alpha Coefficient value is 0.814, indicating that the data collected is very good and reliable for further analysis.

Variable name	Dimensions	Factors	Average Cronbach Alpha
Risk management	Risk Identification	5	0.814
	Risk Analysis	5	
	Risk Evaluation	5	
	Risk Response	5	

4.3 The Outliers

Data points known as outliers differ significantly from the rest of the observations. An outlier is a value that deviates significantly from the other values in the dataset. This can be the result of experimental error or measurement inaccuracy; the latter is occasionally removed from the data set. An outlier is a value that differs significantly from the other values in a random sample of a population. As a result, insufficient outlier detection and analysis could result in significant problems in statistical studies (Moore and McCabe 1999). If there are any outliers in the data set, IBM-SPSS circles them to show that they won't have an impact on the analysis. Extreme outliers, on the other hand, are marked by SPSS with a star to highlight a potential issue with the data set that could harm the analysis. The differences in risk management between outliers and normal values are shown in Figure 5.

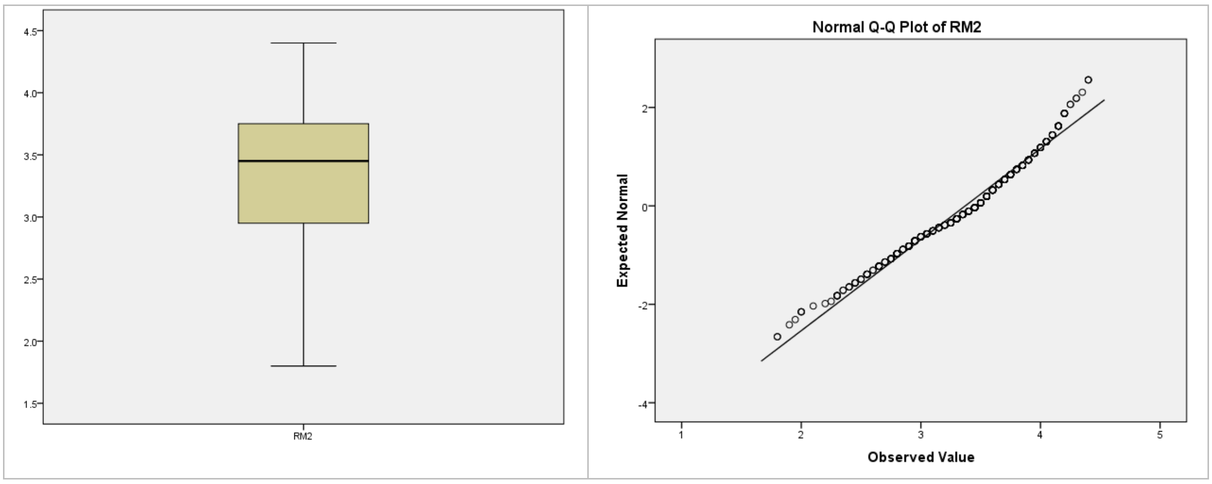

Fig. 5 - Outliers in the dataset of variables

Figure 5 depicts a graph that contains a few non-extreme outliers, which are represented by circles. The dataset associated with the variable is therefore statistically valid. As a result, the outliers' tiny size discrepancies are not a sign of a bad dataset. The dataset for each variable is finally suitable for additional analysis.

4.4 Exploratory Factor Analysis (EFA)

To organise the observed variables (questionnaire indicators) in relation to particular dimensions, exploratory factor analysis (EFA) is used. EFA was run based on principal component analysis. Principal component analysis is a mathematical procedure that converts a set of correlated indicators into a smaller set of uncorrelated indicators known as principal components (Zainun et al. 2014). Communalities, KMO and Bartlett's Test, total variance explained, and rotated component matrix were all included in the EFA analysis.

4.4.1 KMO and Bartlett’s Test

In EFA, the first analysis is a Bartlett's test. When the significance level is less than 0.05, the empirical data is suitable for EFA. Kaiser-Meyer-Olkin (KMO) evaluates data quality using a coefficient based on the Kaiser-Meyer-Olkin Measure of Sampling Adequacy. When this coefficient is "excellent > 0.9, Very good > 0.8, Good > 0.7, Fine > 0.6." the quality of the data is excellent. Thus, it is suggested that KMO > 0.6 be taken as an indicator of trustworthiness for EFA data. Furthermore, KMO should be statistically significant if the sample data are adequate and conform to the data (Cerny and Kaiser 1977). Table 4 shows the results of KMO and Bartlett's Test.

Table 4 - KMO values in the Bartlett's test

Variable name	KMO	Sig.	Data Quality
Risk management	0.849	0.000	Very good

The output in Table 4 can be evaluated, and it shows that the empirical data connected to each variable is significant (Sig. =0.000 0.05) and fits the EFA (KMO > 0.000). Sofroniou and Hutcheson (1999) provide support for the idea that a KMO value in the range of 0.7 to 0.9 is regarded as a good indicator for data fit in factor analysis.

4.4.2 Communalities

Communalities, one of the primary measurements in factor analysis, are the subject of the second analysis in EFA. Communalities show that all measured indicators belong to one variable and have a common correlation (Tabachnick & Fidell, 2007). Ideally, the community magnitude is less than 0.30. In general, a recommended item factor loading is greater than the 0.30 cut-off value (Hair 2009). In statistics, if a lot of the observed variables have communality magnitudes below 0.30, there may be problems with those particular variables that require additional investigation or omission due to their shaky correlation with the other observed variables. The communalities of the variable magnitudes are shown in Table 5.

Table 5 - Communalities of variables

Variable name	Communalities' range	Weak communalities (≤ 0.30)
Risk management	0.161 – 745	1

It is clear that most items connected to each construct share a fair amount of similarities with other indicators within a given variable. One of the indicators, though, has a low communality value. While other communalities provide a good fit of data, this indicator is weak and should be dropped. Table 6 displays the communalities' full tables.

Table 6 - Communalities of variables

Variable Code	Extraction
Risk Analysis_1	.575
Risk Analysis_2	.675
Risk Analysis_3	.741
Risk Analysis_4	.705
Risk Analysis_5	.590
Risk Identification_1	.603
Risk Identification_2	.598
Risk Identification_3	.604
Risk Identification_4X	.161
Risk Identification_5	.687
Risk Response_1	.647
Risk Response_2	.614
Risk Response_3X	.555
Risk Response_4	.608
Risk Response_5	.667
Risk Evaluation_1	.702
Risk Evaluation_2	.745
Risk Evaluation_3	.741
Risk Evaluation_4	.673
Risk Evaluation_5X	.695

Extraction Method: Principal Component Analysis.

4.4.3 Total Variance Explained

The percentage or degree of variation explanation by each conceivable dimension is displayed in the output of the total variance explained table. The explained variation is a statistic that quantifies how much a theoretical model contributes to the variation of a specific set of data. The size of the eigenvalue reveals how much variance in the original variables each dimension is able to explain. The percentage of variance (percent) shows how much of each dimension's variance is accounted for by the total variance across all dimensions (Achen, 1990). This percentage shows how much of a given dimension accounts for the variance in the variable. Table 7 details the overall variance explanation's outcome.

Table 7 - Total Variance Explained of variables

Variable name	Dimensions	Percentage explanation	EFA dimensions	Redundant dimensions
Risk management	1. Risk Identification 2. Risk Analysis 3. Risk Evaluation 4. Risk Response	57.130%	5	1

Table 7 i.e. explanation of total variance's output reveals that risk management is linked to four dimensions (1 redundant dimension). The redundant dimensions should be removed, it should be noted. Cross-loading indicators, also known as weak factor loading (0.40), are present in this dimension. Also preferred to be 50.00 percent was the cut-off variance explanation of each variable by all dimensions scored Eigen values 1.0. The explained variance of risk management is greater than 50.00 percent, as shown in Table 7. The explained details of variance are listed in Table 8.

Table 8 - Total Variance Explained

Component	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.547	27.734	27.734	3.220	16.098	16.098
2	2.511	12.556	40.290	2.893	14.464	30.562
3	1.924	9.622	49.913	2.708	13.538	44.100
4	1.518	7.589	57.502	2.606	13.030	57.130
5	1.087	5.434	62.935	1.161	5.805	62.935

Extraction Method: Principal Component Analysis.

4.4.4 Rotated Component Matrix

The researcher calculates the loading of the observed variables (items) on the corresponding dimensions of the rotated component matrix. The output of the total variance explained is used to derive these parameters. The dimensions and their corresponding indicators can be sorted with pinpoint accuracy by rotating the factors. Indicators are the variables that were observed and measured during data collection. The first step is to identify the indicators which have been observed to have a low correlation with the selected dimension. Thus, indicators with factor loadings below 0.4 are disregarded because they cannot be related to any of the dimensions. Likewise, the rest of the analysis does not include things that are loaded on multiple dimensions. The general rule is that a variable needs to have a rotated factor loading of +0.4 on one of the dimensions for it to be considered significant for the study (Hair et al., 2017). The significance of an observed variable (item) is typically determined by a loading greater than 0.4. (Comrey & Lee, 1992). In addition, if the factor loading is high, then the variable being measured is a good proxy for that factor. Items that are heavily weighted toward a single factor will also support the validity and single dimensionality of the measures (Cortina, 1993, Ahire & Devaraj, 2001). The grouping of dimensions and the quantity of redundant indicators are also shown in Table 9.

Table 9 - Rotated component matrix of variables

Risk management	Number of indicators	Number of EFA indicators	Omitted indicators	Lowest Factor loading	Highest Factor Loading
Risk Identification	5	4	1	0.709	0.774
Risk Analysis	5	5	0	0.692	0.824
Risk Evaluation	5	4	1	0.788	0.846
Risk Response	5	4	1	0.754	0.794

Table 9 reveals that risk management is linked to 4 dimensions (3 omitted indicators). These indicators either have weak factor loading (0.4) or cross factor loading (loading on multiple factors). Table 10 contains all of the tables for the variables' rotated component matrices, and Figure 6 displays the scree plot results.

Table 10 - Rotated Component Matrix

	Component				
	1	2	3	4	5
Risk Analysis_3	.824				
Risk Analysis_4	.791				
Risk Analysis_2	.762				
Risk Analysis_5	.726				
Risk Analysis_1	.692				
Risk Evaluation_3		.846			
Risk Evaluation_2		.841			
Risk Evaluation_1		.825			
Risk Evaluation_4		.788			
Risk Identification_5			.774		
Risk Identification_3			.754		
Risk Identification_2			.735		
Risk Identification_1			.709		
Risk Response_3X			-.514		.510
Risk Response_5				.790	
Risk Response_1				.778	
Risk Response_2				.761	
Risk Response_4				.754	
Risk Evaluation_5X					-.807
Identification_4X					

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

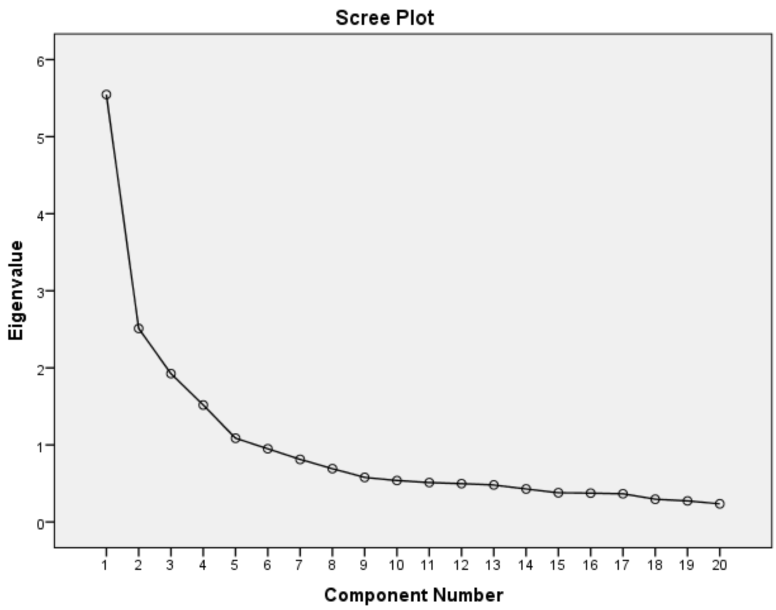

Fig. 6 - Scree Plot

4.4.5 Central Tendency Measures

Central tendency statistics (mean, standard deviation, skewness, and Kurtosis) are used to understand the overall mean value for each variable as well as the level of agreement on each item. Descriptive analysis is useful for figuring out which survey questions were most strongly supported by respondents. Descriptive statistics are used to describe the fundamental features of a dataset. They provide concise summaries of the sample and the metrics. The "centre" of a set of response value distributions can be thought of as a rough estimate of the distribution's central tendency. There are three types of estimating the central tendency. Popular methods for estimating the centre of a distribution include (Mean). Dispersion, on the other hand, describes how values are scattered around the central tendency. Range and standard deviation are two common measures of dispersion. To determine how far individual responses were outside the mean, we calculated their standard deviation.

The following scale was used to rate the respondents' overall impressions: Somewhat true responses fall in the 2.45–3.45 range, moderate agreement in the 3.45–4.45 range, and full agreement in the 4.45–5 range. This average fluctuates from a low of 1-1.44 (extreme disagreement) to a high of 1.45-2.44 (moderate degree of disagreement). The validation threshold was set at a mean score of 2.9, meaning that if a variable received a mean score of 2.9 or higher, it would be considered "agreed". Descriptive statistics for each variable are presented below. The skewness measure was developed to assess the degree of symmetry or, more precisely, the lack of symmetry between results. It is a method for assessing the degree of asymmetry in a data set. Distinguishing between values at either end of the tail is possible. Distributions that are perfectly symmetrical have a skewness of zero. A symmetrical distribution or set of data looks the same when viewed from either side of the centre point. Data are roughly symmetrical when the skewness is between -0.5 and 0.5. Data are significantly skewed if the skewness is between -1 and -0.5 (negatively skewed) or 0.5 and 1 (positively skewed) (positively skewed). The author used Kurtosis to see if their primary data had a heavy or light tail in comparison to a normal distribution of responses. It is generally accepted that a normal univariate distribution can have asymmetry and kurtosis values between -2 and +2. (George and Mallery 2010). Table 11 displays the descriptive statistics centrifugal force analysis results.

Table 11 - Descriptive Statistics of constructs

	N	Min.	Max	Mean	St. Deviation	Skewness	Kurtosis
Risk management	381	1.80	4.40	3.37	0.54	-0.49	-0.28

Data in Table 11 can be read to discover that the magnitude of the mean values is 3.37, indicating that the data is largely symmetrical.

5. Conclusion

This paper focused on studying the risk management process adopted by the police department of the UAE. It used exploratory factor analysis to categorize the process where data collection involved quantitative approach. Self administered questionnaire resulted in obtaining 381 valid questionnaire from the officers working in Dubai Police Department. Results obtained in the study revealed that effective risk management follows four essential steps as risk identification, risk analysis, risk evaluation and risk response. The data was checked for consistency and reliability with the help of Crobach Alpha which was 0.814 showing that the data is satisfactory to use. Among the 20 indicators classified in 4 groups of risk management only 1 indicator was weak as identified during outliers and communalities tests. Other 20 factors were strong to describe the risk management process. Total variance extraction reported 57.130% extraction which was above 50% as required. It means that the risk management process investigated in this study can be useful for managing risks in police department of the UAE effectively.

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