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# Artificial Intelligence Innovation Related Factors Affecting Organizational Performance

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**Abstract:** Organisations paid more attention to the innovations of artificial intelligence (AI) technology to improve the organizational performance. Hence, using AI-related innovations to support the organization requires understanding of factors affecting organizational performance. Thus, this paper presents the development of PLS-SEM model of AI-related innovations factors that affect the organisational performance. The study identified 21 innovation AI-related factors that were clustered into four groups namely process innovation; management capabilities; personal expertise and organization structure. The model comprised of four exogenous constructs of the innovation factors and one endogenous construct of organisational performance. The data used to develop the model was derived from 384 valid responses of a questionnaire survey amongst the employees of three government organizations in Dubai, which are Dubai Police, Dubai Electricity & Water Authority Dewa, and Emirates Integrated Telecommunications Company. The survey adopted simple random sampling technique in respondents' selection. The model was developed in SmartPLS software and was evaluated at the measurement and structural components of the model. It was found that the model has achieved its goodness-of-fit, GoF criteria of 0.596 which indicates that the model has substantial validating power. The hypothesis testing results found that three out of four relationships are significant which are having t-value and p-value above the cut-off values. The significant relationships are organization structure, personal expertise and process innovation. However, the unsignificant relationship is management capabilities affecting the organisational performance. This is due to the characteristics of the collected data which is not strong enough to establish significant relationship as what have been hypothesized. The findings are contributions to any parties that involved in the application of AI innovation to improve organisational performance.

**Keywords:** AI-related innovation factors model

## 1. Introduction

Wade et al. (2017) stated that the lack of innovation in organizations negatively affects the ability of the organizations to flourish (Wade et al., 2017). Also, the organizations that lack innovations cannot survive in an age of continuous changes (Petrie, 2011; Chamorro et al. 2018). Therefore, lacking a deep knowledge of organizational innovation does not help the organizations work in a new, complex environment (Van de Weerd et al., 2016). Public organizations have attempted to improve the innovation process alongside their internal specialists in order to improve organizational performance; however, it still in process and needs further investigation (AlQubaisi, 2017). Also, inability to exploit organizational resources is one of the most essential ideas in organizational theory (Guo et al., 2018). There are different factors that influence the use of innovation technologies in the organisations just like using

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artificial intelligent (AI) related innovations to support the organization performance. AI-related innovations and new technologies are used to influence customers to improve the organisational performance of the firm (Grgecic et al., 2015). Looking at it from the reverse side, innovative technologies aim to gain consumers which, however, requires focusing more on their values and actions during the process of planning to use any technological innovation in the organization.

An important factor related to using Al-related innovation technologies to support organization performance is the technical factor. According to Olesen (2014), the technical factors of organisations, such as different stakeholder groups, the technological features and the incongruity inside and through stakeholder groupings, are incorporated to support the organization performance. Accordingly, IT-related innovations need to focus on the technical elements in order to support the organization performance. According to Oliveira et al. (2014), the implementation of AI innovations, such as cloud computing, is influenced by technological preparedness, high managerial support and organizational size in order to succeed in utilising AI technologies to support organisational performance. Hence, using AI-related innovations to support the organizational performance requires understanding of the organization's technical capabilities to succeed in achieving better organizational performance.

Besides, the human factors might influence using AI-related technologies in the organization. Many researchers at the individual level have discussed the perspective of individuals with various target areas. According to Aggarwal et al. (2015), understanding of AI technology is seen as an influential element on using such technological innovations in the organization. Moreover, the technology skills of the system impact the actions of utilising AI-related innovations in the organisation (Aggarwal, 2015; Klaus et al., 2015; Kummer al., 2017). Accordingly, the use of AI-related innovations in the organisations might not help in enhancing the organizational performance if the human factor or the individuals' technological skills and knowledge are not taken into consideration.

Further, organisational variables at the level of the manager, the group and business have an influence on using AI innovations in the organization. For example, the costs of change from old to new technologies have been studied from various points of view, which found that organisations might not be able to use such innovative technologies to improve their performance (van de Weerd et al., 2016). One of the major organizational variables related to using AI technologies is the team atmosphere, and scholars have found that a common goal, support for innovation, security of participatory interaction and feedback would alter cognitive perceptions and enhance using innovation technologies (Maruping & Magni, 2012; van de Weerd et al., 2016). Also, the climatic and cultural conditions at work, management and top management policy might also influence the performance of AI-related technologies in the organization (Rizzuto et al, 2014; Oliveira et al. 2014).

Moreover, social factors affecting the performance of AI innovative technologies have been examined from a variety of viewpoints at organisational level. Strong rules pressures such as laws and procedures and everyday working challenges, including the culture of work, are among the factors that inhibit the performance of innovation technologies, while social qualities such as professional readiness have a positive effect on the performance of AI innovative technologies in the organization (Choudrie & Zamani, 2016). Research have also showed that there are different external variables like business demand and strategic acceptance, and also internal considerations, such as funding for top management and group-size, which influence the performance of innovative technologies, such as AI technologies, in the organisation (Oliveira et al., 2014). Organisations have paid more attention to the innovations of AI technologies to improve organizational performance. Generally, there are different factors related to AI that might support or reduce the performance of these technologies in the organisations. These factors include technical skills, human or staff technological skills, organizational and management support for using such new innovations, and social factors such as organizational culture and strategies. These factors of AI technologies support the performance of these technologies, which in turn leads to improving organizational performance.

## 2. Data for Model

Data was collected from employees three government organizations in Dubai, which are Dubai Police, Dubai Electricity & Water Authority Dewa, and Emirates Integrated Telecommunications Company. Populations of these organizations are for Dubai Police is 17,000, Dewa is 11,000, and Du is 2,800. The survey adopted non-probability simple random sampling to select respondents from the population. A total of 384 respondents participated in the questionnaire survey and the demography of the respondents is as in table 1

**Table 1 - Respondent's demography**

| Demography | Items | Percentage |
|---|---|---|
| Age | 20 -30 years | 30% |
| | 31 to 40 years | 29% |
| | 41 to 50 years | 21% |
| | ≥ 51 years | 20% |
| Working experiences | ≤5 years | 35% |
| | 6 to 15 years | 40% |

| | | |
|---|---|---|
| | 16 to 25 years | 15% |
| | ≥26 years | 10% |
| | Manager | 12% |
| Position | Executive | 37% |
| | Worker | 51% |

The table 1 indicates that most of the respondents' age are below 50-year-old and are having working experience for more than 15 years. In term position in the organisation, most of the respondents are at executive level. This means that most of the respondents are capable and directly or indirectly involved in participating innovation activity for improving the organisation performance

## 2.1 Reliability of the Collected Data

Cronbach's alpha coefficient indicates the level of inputs' consistency given by the respondents on the factors with the range between 0 and 1 (where 0 is the lowest and 1 is the highest inside consistency). According to Sekaran & Bougie, 2016 and Souza et al., 2017, if the rates of Cronbach's alpha coefficient match or go beyond 70% (0.7), then the data is recognised as reliable. The results of the reliability test of the collected data are as in table 2

**Table 2 - Results of reliability test**

| Innovation domains | Code | Number of factors | Cronbach alpha |
|---|---|---|---|
| Process innovation | PI | 6 | 0.905 |
| Management capabilities | MC | 5 | 0.891 |
| Personal expertise | PE | 5 | 0.868 |
| Organization structure | OS | 5 | 0.877 |
| Organization Performance | OP | 4 | 0.967 |
| | Overall | 25 | 0.902 |

Based on the results in Table 2 of reliability test, it shows that the coefficients/values for four domains of innovation factors with the average value 0.885 of which it is exceeding 0.7, thus the collected data is reliable for further analysis

## 3. Assessment of Model's Measurement Component

The model was generated in SmartPLS software using the collected data as figure 1. Then this model comprises of two components namely measurement and structural components. At the measurement component level, it is evaluated based on the indicator reliability, convergent validity, and discriminant validity to achieved the fitness criteria of the component (Rahman, et.al., 2022)

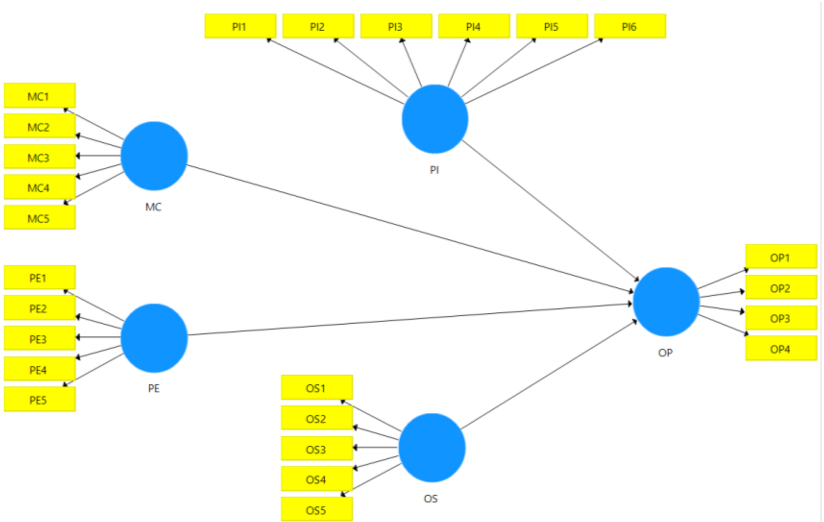
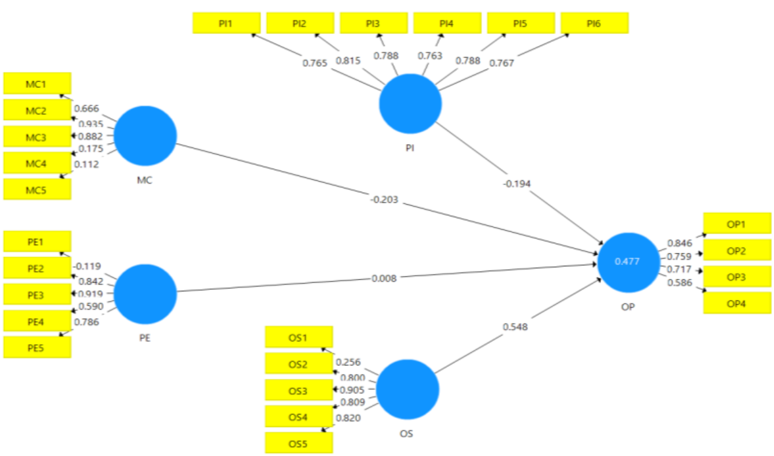
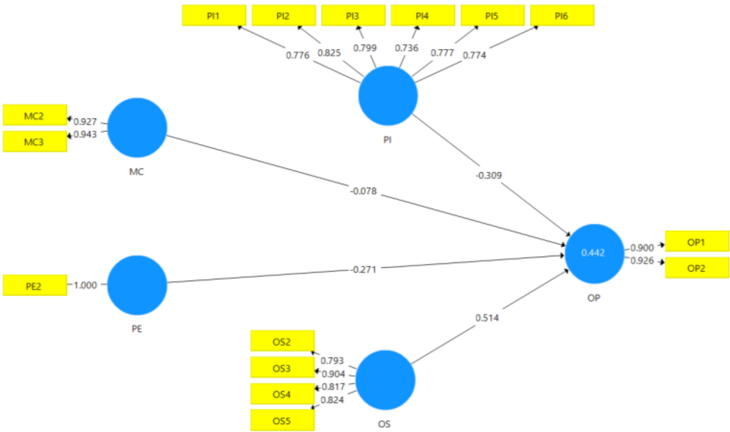



**Fig. 1 - The constructed model**




First iteration




Final iteration

**Fig. 2 - The initial and final iterations of the model**

Based on the figure 2, four iterations were conducted until the model achieved the fitness criteria. It indicates that several of the factors were deleted to ensure that the model achieved the criteria. The deleted factors are as in table 4.

**Table 4 - Outer/factors loading of the model**

| | Initial iteration | | | | | Final iteration | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **MC** | **OP** | **OS** | **PE** | **PI** | **MC** | **OP** | **OS** | **PE** | **PI** |
| MC1 | 0.666 | | | | | Deleted | | | | |
| MC2 | 0.935 | | | | | 0.927 | | | | |
| MC3 | 0.882 | | | | | 0.943 | | | | |
| MC4 | 0.175 | | | | | Deleted | | | | |
| MC5 | 0.112 | | | | | Deleted | | | | |
| OP1 | | 0.846 | | | | | 0.900 | | | |
| OP2 | | 0.759 | | | | | 0.926 | | | |
| OP3 | | 0.717 | | | | | Deleted | | | |
| OP4 | | 0.586 | | | | | Deleted | | | |
| OS1 | | | 0.256 | | | | | Deleted | | |
| OS2 | | | 0.800 | | | | | 0.793 | | |
| OS3 | | | 0.905 | | | | | 0.904 | | |
| OS4 | | | 0.809 | | | | | 0.817 | | |
| OS5 | | | 0.820 | | | | | 0.824 | | |
| PE1 | | | | -0.119 | | | | | Deleted | |
| PE2 | | | | 0.842 | | | | | 1.000 | |
| PE3 | | | | 0.919 | | | | | Deleted | |
| PE4 | | | | 0.590 | | | | | Deleted | |
| PE5 | | | | 0.786 | | | | | Deleted | |

| | | |
|---|---|---|
| PI1 | 0.765 | 0.776 |
| PI2 | 0.815 | 0.825 |
| PI3 | 0.788 | 0.799 |
| PI4 | 0.763 | 0.736 |
| PI5 | 0.788 | 0.777 |
| PI6 | 0.767 | 0.774 |

Table 4 shows the factors loading of the model at initial and final iteration until the model has achieved the construct reliability and validity and also discriminant validity. A total of 10 factors were deleted after four iterations were conducted and left with 15 factors

## 3.1 Indicator Reliability

Once the model has been constructed, the processes started by conducting iteration on the model using ***PLS Algorithm*** function to calculate the model criteria's estimates. The assessment of the indicator reliability depends on examining the factor loading values. The modelling evaluation is carried out by consecutive iterations and deletion of item/variable until and also checking for achievement of criteria threshold. At the final iteration/modelling, the model has achieved indicator reliability criteria threshold values as displayed in table 5.

**Table 5 - Indicator reliability and validity**

| | MC | OP | OS | PE | PI |
|---|---|---|---|---|---|
| MC2 | **0.927** | -0.217 | -0.009 | 0.143 | 0.390 |
| MC3 | **0.943** | -0.245 | 0.023 | 0.193 | 0.371 |
| OP1 | -0.218 | **0.900** | 0.395 | -0.058 | -0.444 |
| OP2 | -0.234 | **0.926** | 0.456 | -0.086 | -0.501 |
| OS2 | -0.009 | 0.313 | **0.793** | 0.340 | -0.196 |
| OS3 | -0.008 | 0.471 | **0.904** | 0.405 | -0.252 |
| OS4 | 0.062 | 0.370 | **0.817** | 0.441 | -0.243 |
| OS5 | -0.014 | 0.385 | **0.824** | 0.422 | -0.226 |
| PE2 | 0.181 | -0.080 | 0.481 | **1.000** | 0.134 |
| PI1 | 0.278 | -0.328 | -0.127 | 0.201 | **0.776** |
| PI2 | 0.296 | -0.376 | -0.250 | 0.038 | **0.825** |
| PI3 | 0.269 | -0.453 | -0.122 | 0.124 | **0.799** |
| PI4 | 0.248 | -0.326 | -0.313 | -0.003 | **0.736** |
| PI5 | 0.312 | -0.415 | -0.278 | 0.108 | **0.777** |
| PI6 | 0.459 | -0.484 | -0.217 | 0.143 | **0.774** |

Table 5 indicates that all the left-over indicators/variables in the model are having factor loading equal or more than 0.5 which is above cut off value for the factor loading.

## 3.2 Convergent Validity

The convergent validity is assessed by examining the construct reliability include Cronbach's alpha (α) and Composite Reliability (CR) must be greater than or equal to 0.70, and Average Variance Extracted (AVE) should greater than 0.50. Then for convergent validity of the constructs of the model, the values are as presented in table 6.

**Table 6 - Convergent validity values**

| | Cronbach's Alpha | Composite Reliability | Average Variance Extracted (AVE) |
|---|---|---|---|
| **MC** | 0.857 | 0.933 | 0.875 |
| **OP** | 0.801 | 0.909 | 0.833 |
| **OS** | 0.855 | 0.902 | 0.698 |
| **PE** | 1.000 | 1.000 | 1.000 |
| **PI** | 0.873 | 0.904 | 0.611 |

Table 6 shows all the values are above the threshold criteria. Where the Cronbach's alpha (α) and Composite Reliability (CR) for all constructs are above 0.70 and the Average Variance Extracted (AVE) values are more than the cut-off value of 0.5. Hence, the evaluation of the indicator reliability and convergent validity values of the measurement model are above the criteria cut-off values.

## 3.3 Discriminant Validity

Discriminant validity can be carried out in two approaches which are cross-loading technique and Fornell-Larcker criterion technique. Cross-loading technique makes comparisons between the AVE square root values with the latent variable correlation value. Thus, this study accepted Fornell–Larcker and cross-loading criterion in inspecting the discriminant validity of the measurement model. Finally, the square root of AVE value of the model reached the adequacy of discriminant validity criterion as in Table 7.

**Table 7 - Fornell-Lacker criterion**

| Constructs | MC | OP | OS | PE | PI |
|---|---|---|---|---|---|
| **MC** | **0.935** | | | | |
| **OP** | -0.248 | **0.913** | | | |
| **OS** | 0.008 | 0.468 | **0.835** | | |
| **PE** | 0.181 | -0.080 | 0.481 | **1.000** | |
| **PI** | 0.406 | -0.519 | -0.276 | 0.134 | **0.782** |

Table 7 represent the bolded square root of AVE and non-bolded values represent the inter-correlations value between constructs. It is indicated that all off-diagonal elements are lower than square roots of AVE. Hence, confirming that the model had achieved criterion of discriminant validity of the measurement model.

**Table 8 - Results of cross loading**

| | Constructs | | | | |
|---|---|---|---|---|---|
| **Factors** | **MC** | **OP** | **OS** | **PE** | **PI** |
| MC2 | **0.927** | -0.217 | -0.009 | 0.143 | 0.390 |
| MC3 | **0.943** | -0.245 | 0.023 | 0.193 | 0.371 |
| OP1 | -0.218 | **0.900** | 0.395 | -0.058 | -0.444 |
| OP2 | -0.234 | **0.926** | 0.456 | -0.086 | -0.501 |
| OS2 | -0.009 | 0.313 | **0.793** | 0.340 | -0.196 |
| OS3 | -0.008 | 0.471 | **0.904** | 0.405 | -0.252 |
| OS4 | 0.062 | 0.370 | **0.817** | 0.441 | -0.243 |
| OS5 | -0.014 | 0.385 | **0.824** | 0.422 | -0.226 |
| PE2 | 0.181 | -0.080 | 0.481 | **1.000** | 0.134 |
| PI1 | 0.278 | -0.328 | -0.127 | 0.201 | **0.776** |
| PI2 | 0.296 | -0.376 | -0.250 | 0.038 | **0.825** |
| PI3 | 0.269 | -0.453 | -0.122 | 0.124 | **0.799** |
| PI4 | 0.248 | -0.326 | -0.313 | -0.003 | **0.736** |
| PI5 | 0.312 | -0.415 | -0.278 | 0.108 | **0.777** |
| PI6 | 0.459 | -0.484 | -0.217 | 0.143 | **0.774** |

Table 8 shows that the cross-loading values of each indicator within its latent construct are higher (as signified with bold font) as compared with values to other latent constructs of the model. Each item outer loading is greater than its value in the other constructs. It demonstrates that the discriminant validity of model is attained. Hence, it can be concluded that the measurement model had achieved model goodness-of-fit criteria.

## 4. Structural Assessment

The structural component assessment involved path relationship strength, coefficient of determination, predictive relevance of the model, goodness-of-fit (GoF) and hypotheses of the paths

## 4.1 Strength of Path Relationship

According to Hair *et al.* (2019), path coefficients is measured with beta (β) value that reflect is the strength of the path or relationship between exogenous and endogenous constructs with values approximately between –1 and +1 (values can be smaller/larger but usually fall in between these bounds). Path coefficients values close to +1 represent strong positive relationships and vice versa for negative values that are usually statistically significant. The closer the estimated coefficients are to 0, the weaker are the relationships. The generated path coefficients or beta values of the model are extracted from the software and tabulated as in table 9.

**Table 9 - Beta values of the paths**

| Exogenous constructs | Endogenous construct [OP] | Rank of path strength |
|---|---|---|
| MC | -0.078 | 4 |

| | | |
|---|---|---|
| OS | 0.514 | 1 |
| PE | -0.271 | 3 |
| PI | -0.309 | 2 |

Table 9 shows that beta values of four relationships. According to Hair et al. (2017), β value should be above 0.1 regardless its signage either positive or negative. Thus, economy construct (ECO) is having the strongest while organisational and management construct (OAM) is the frailest relationship to the sustainable solar energy success project construct (SSES).

## 4.2 Coefficient of Determination

Coefficient of determination is also known as $R^2$ which can be viewed as the combined effect of the exogenous variables on endogenous variables of the model. The R2 values ranges from 0 to 1 with value closer to 1 representing complete predictive accuracy. This study adopted the R2 threshold value by Cohen (1988) which R2 value of 0.26 is considered as substantial, R2 value of 0.13 is regarded as moderate, and R2 value of 0.02 is considered as weak. The R2 value for this model is extracted from the final model generation using PLS Algorithm function in SmartPLS software which is equal to 0.442 and considered as substantial effect.

## 4.3 Predictive Relevance of the Model

Predictive relevance is by measuring on $Q^2$ values that quantify the variances between the omitted and the predicated data points (Chin, 1998; Tenenhaus et al., 2005). By applying the blindfolding iteration process, the $Q^2$ values can be generated as in table 10.

**Table 10 - Generated predictive relevance (Q2)**

| Construct | Sum of Squares of Observations (SSO) | Sum of Squares of Errors (SSE) | Predictive relevance, $Q^2$ (=1-SSE/SSO) |
|---|---|---|---|
| MC | 312 | 312 | |
| OP | 312 | 205.856 | 0.34 |
| OS | 624 | 624 | |
| PE | 156 | 156 | |
| PI | 936 | 936 | |

According to Cohen, (1988) as the rule of thumb, it states that if the $Q^2$ value is equal and more than 0.02 but less than 0.15 then it indicates that the respective exogenous construct is having small predictive relevance, for $Q^2$ value is equal or more than 0.15 but less than 0.35, it indicates that the respective exogenous construct is having medium predictive relevance, for $Q^2$ value is equal and more than 0.35 then it indicates that the respective exogenous construct is having large predictive relevance (Hair *et al.*, 2017). Thus, based on the generated results in table 10, the model has achieved medium predictive relevance. This means that the exogenous constructs have medium predictive relevancy on to the endogenous construct.

## 4.4 Goodness-of-Fit (GoF)

GoF index is for assessing the global validity of a model. It is the geometric mean of the average communality (AVE) and the average coefficients of determination ($R^2$) value of the model (Hair, Ringle & Sarstedt, 2011). The GoF value of the model should be in the range between 0 and 1. If the value is equal or more than 0.1 but less than 0.25, the model can be categorised as having small validating power; if the GoF value is equal or more than 0.25 but less than 0.36 then it can be categorised as having medium validating power and for GoF value equal or more than 0.36, the model is considered having high/large validating power (Wetzels *et al.*, 2009; Akter *et al.*, 2011). Hence, GoF index of a model can be calculated manually using the following formula:

Goodness-of-fit, $GoF = \sqrt{\overline{AVE} \times \bar{R}^2}$ (1)

where;

*AVE* = average communality

$R^2$ = coefficients of determination

Hence, for this model the average of AVE for the entire construct variable and the $R^2$ for all dependent constructs variables as in Table 11.

**Table 11 - Calculation of GoF**

| All Constructs | Values from the final model | |
|---|---|---|
| | AVE | $R^2$ value |
| MC | 0.875 | 0.442 |
| OP | 0.833 | |
| OS | 0.698 | |
| PE | 1.000 | |
| PI | 0.611 | |
| Average | 0.803 | |

The average of AVE for endogenous variable is 0.803 and the average $R^2$ for all dependent variables is 0.442. Thus, the calculated, *GoF* = 0.596. This indicates that the model is having global large/high validating power.

## 4.5 Hypothesis Testing

Hypothesis testing for this model is conducted using bootstrapping function of the SmartPLS software. The bootstrapping method is basically the derivation of the sample from the sample. In this procedure, a large number of 5000 resamples are taken from the original sample with replacement to give bootstrap standard errors, which in turn gives approximate T-values and P-value for significance testing of the structural path (Hauser, Ellsworth, & Gonzalez, 2018; Gamil, Y. and Abdul Rahman, I., 2020). The generated t-values and p-values for the hypothesis testing for this study's model are shown in Table 12.

**Table 12 - Results of bootstrapping**

| Hypothesis | T Statistics (\|>1.96\|) | P Values (<0.05) | Comments |
|---|---|---|---|
| MC -> OP | 1.19 | 0.234 | Not significant |
| OS -> OP | 7.368 | 0 | Significant |
| PE -> OP | 3.796 | 0 | Significant |
| PI -> OP | 4.334 | 0 | Significant |

The hypothesis testing results show that three out of four relationships are significant which are having t-value and p-value above the cut-off values. The significant relationships are Organization structure, Personal expertise and Process innovation. However, the unsignificant relationship is Management capabilities affecting the organisational performance. This is due to the characteristics of the collected data which is not strong enough to establish significant relationship as what have been hypothesized.

## 5. Conclusion

This paper has presented the development of PLS-SEM model of AI-related innovations factors that affect the organisational performance. The study identified 21 innovation AI-related factors that were clustered into four groups namely process innovation; management capabilities; personal expertise and organization structure. The model comprised of four exogenous constructs of the innovation factors and one endogenous construct of organisational performance. The data used to develop the model was derived from 384 valid responses of a questionnaire survey amongst the employees of three government organizations in Dubai, which are Dubai Police, Dubai Electricity & Water Authority Dewa, and Emirates Integrated Telecommunications Company. The survey adopted simple random sampling technique in respondents' selection. The model was developed in SmartPLS software and was evaluated at the measurement and structural components of the model. It was found that the model has achieved its goodness-of-fit, GoF criteria of0.596 which indicates that the model has substantial validating power. The hypothesis testing results found that three out of four relationships are significant which are having t-value and p-value above the cut-off values. The significant relationships are Organization structure, Personal expertise and Process innovation. However, the unsignificant relationship is Management capabilities affecting the organisational performance. This is due to the characteristics of the collected data which is not strong enough to establish significant relationship as what have been hypothesized. The findings are contributions to any parties that involved in the application of AI innovation to improve organisational performance.

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