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Research Article

Structural Relationship Model of Factors Affecting to The Artificial Intelligent Technology Implementation in the UAE Government Energy Sector

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Abstract

This paper presents a development of structural relationship model of factors affecting to the artificial intelligent technology implementation in the UAE government energy sector. The data used to develop the relationship was derived from questionnaire survey amongst the staffs of the UAE energy department. The model was developed and assessed using SmartPLS software. The model evaluated at measurement level based on two criteria which are convergent validity and discriminant validity and found that the model measurement has achieved the goodness-of-fit. Evaluation at the structural level is based on path coefficients (β), coefficient of determination (R^2 value), effect size (f^2), predictive relevance (q^2) and goodness-of-fit (GoF). The structural assessment found that the developed model has substantial validating power of 0.462 in representing the impact of the four groups of factors affecting the AI technology implementation. On the hypothesis testing of the model, it was found that AIT construct having the strongest influenced to the AIE construct but UEX path is not significant. The model was further verified by ten experts on the model outcomes practicality and all the experts had agreed with the model outcomes. These findings are beneficial for to academicians, researchers, practitioners and authority of UAE artificial intelligence and energy related sector.

Keywords: *Relationship Model, Artificial Intelligent, UAE, Energy Sector*

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Introduction

Energy sector encounters numerous challenges associated to growing demand, efficiency, demand patterns, changing supply and deficiency in analytics which require for optimal management. Efficiency issues are the most challenging such as the occurrence of informal associations to the power grid that resulted to huge quantity of power is neither billed nor measured. This resulting in larger carbon dioxide (CO^2) emissions as well as losses to customers to utilize energy efficiently. Other challenge in the oil and gas industry is recognizing inappropriate defects in pipelines or threading in error-prone mechanisms. These defects found at the closing stages of production line from upstream issues regarding cost budget and factory resources. Oil and gas production plants function in very dangerous surroundings and the possibility of injury is much high than conventional manufacturing surroundings. Workers in this production plants are operating under diverse environments that are likely to expose toxic fumes. Without following appropriate safety procedures, it can end up in injury and financial loss. These losses are relatively much higher when compared over the cost of implementing Artificial Intelligence (AI) in the system. By employing a computer-vision oriented system it can validate the production quality and offer deeper insight of faults in analytics. Furthermore, the AI driven defect detection able to evaluate the process and trigger any faulty.

Due to present political and social landscapes, government and business organisations are facing challenges to have an understanding on the real value of technology; the appropriate policies; investments required to unlock the potential and values of technological systems in a state. Hence with AI technology, it able to collect, store and conduct data analysis at large scale at faster rate. This will allow organizations to make improvements on the quality of the services and products which are tailored to the customer or stakeholders. Time spent for the organisation to engage in low-value responsibilities and tasks can be handled by Artificial Intelligence (AI) technology easily and this make AI technology in demand to assist the operations of an organization. Government leaders and business executives would therefore benefit from an understanding of the state of AI technology adoption in converging value and impact to the organisation, industry and the society at large.

Study by (Kwon & Zmud, 1987) revealed that with AI implementation system has a strong correlation with the productivity of an organization. (Callon & Latour, 1981) studied the causal examination to discover the impact of AI systems in the planning and coordination of a firm’s functions. It was found that the strategic implementation of AI plays a role in establishing unique and distinctive capabilities that support in gaining a competitive advantage in the marketplace. The efforts that are only achievable through the formulation and understanding of the value of these systems in the operations of a firm. While (Callon & Latour, 1981) studied on exploring of AI in the advancement of productivity in the manufacturing sector. The study revealed that the AI based systems have the capacity to enhance an organizations capacity to collect, store and conduct data analysis at an established scale in faster way. This makes improvements of the quality of the services and products tailored to address the needs of consumers. In situations where AI systems can be employed in enormous applications, the expectation is that the operational efficiency and productivity increased to a level way beyond those achieved by human resources. Future government organisations need to align the capabilities of artificially intelligent systems with high level of performance by using data-smart operations in the public sector where the policymakers concentrate on preventing rather than reacting to tragedies. In addition to this, the organisations will be seeking to provide more personalized service which can be accessed anywhere at any time (Ahn & Chen, 2017).

All these AI studies indicate that AI based system has the capacity to enhance what organizations can achieve. It provides clear and compelling evidence for the need for AI implementation and development to enhance organisations. Many countries have already begun to employ artificial intelligence (AI) in the energy sector AI associated technologies permits communication among Internet of Things (IoT), smart meters, and smart grids devices. These technologies facilitate to develop transparency, efficiency and power management and this increase the usage of Renewable Energy Sources (RES). With incorporating artificial intelligence in the energy system, it has the prospective to lower energy costs, cut energy waste, and accelerate and facilitate the usage of clean RES in power grids globally. AI can develop the control, operation, and planning of power systems. Therefore, AI technologies are very much tied to the capability to offer cheap and clean energy that is necessary to growth (Tussyadiah, 2020).

United Arab Emirates (UAE) eager to exploit the benefits of AI in achieving its goals and aspiration of future smart government. Presently, the UAE government is working towards executing AI policy which could transform into an intellectual management using 100% AI dependent mechanisms by 2031. The policy involves adopting diverse kinds of AI oriented technologies which contributes in enhancing the government administration. By incorporating AI systems, it reshapes the working environment through a complete virtual workforce and automation human tasks. AI systems enable organizations to respond to the dynamic environment which demand services by the growing populations in the UAE. Besides, the implementation of AI systems provides direction to the organization towards achieving the organization's competitive advantage through the configuration of its resources within a changing environment and to fulfil the expectations of the stakeholders. This gives the UAE public sector a chance to overcome the challenges in facing different ministries and agencies that loss of public trust due to poor service delivery and corruption (Cressey *et al.*, 1998). With the capacity to collect, store and conduct data analysis at large scale in faster ways facilitated by AI technology, it allows organizations to improve the quality of services and products tailored to the needs of customers. Thus, by using AI technology, the organisation will save time and cost in giving quality to the customers. However, there are not many studies on service quality of artificial intelligence relate to UAE. Especially on the implementation of AI as a driver of future governance in the UAE. Artificial Intelligence (AI) has become one of the most effective ways of increasing efficiency and boosting productivity to the extent that there is a growing need to integrate it into the systems of large entities including government agencies (Kaplan, 2016). Hence this study intended to explore causes which drive the processes of implementing AI systems in the UAE government organizations focussing to energy sector improvement performance. This will contribute to the excellent drive to create UAE future government having robust organization function systems.

Conceptual Model

The proposed model for this study which is about the Artificial Intelligence (AI) technology implementation in UAE energy sector where it comprises of four exogenous constructs which are Technology; Human Resources; Benefit; User Expectation and one endogenous construct which is Technology Implementation. The graphical conceptual framework model is depicted as Figure xx.

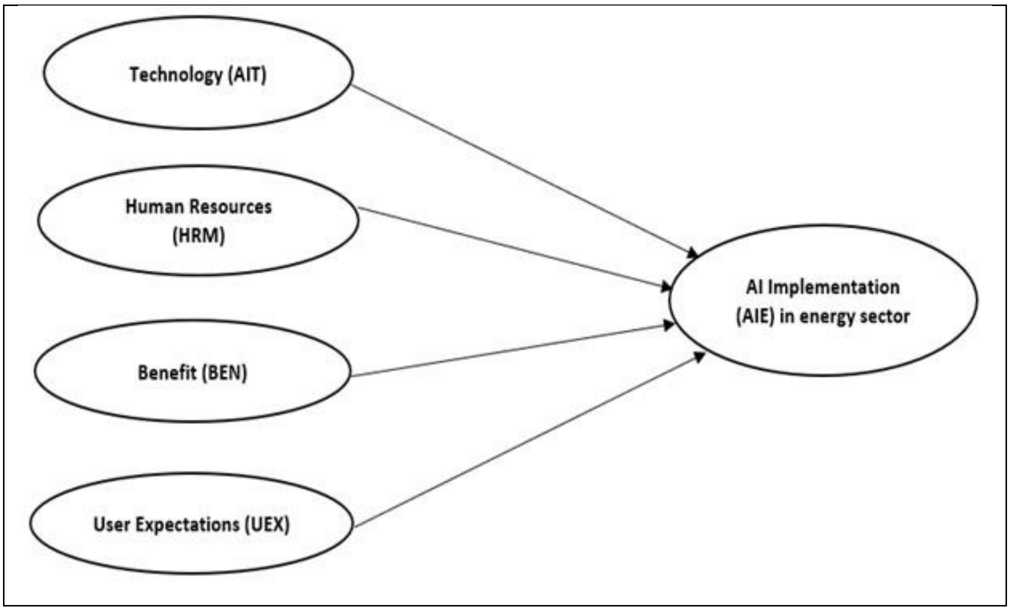

Figure 1.1: Conceptual framework

Figure 1.1 is the proposed framework or model of this research which was developed based on the reviewed literature. This untested model with four independent construct variable and one dependent construct variable and postulated hypotheses for this model is as follow;

(i) H_1: AIT has significant relationship with AI technology implementation

(ii) H_2: HRM has significant relationship with AI technology implementation

(iii) H_3: BEN has significant relationship with AI technology implementation

(iv) H_4: UEX has significant relationship with AI technology implementation

Measurement evaluation of the model

Confirmatory Factor Analysis (CFA) is to assess measurement model. In CFA, any item that does not fit the measurement model due to low factor loading should be removed from the model. Fitness of a measurement model is indicated through certain Fitness Indexes. If the items deletion exceeds 20% of total items in a model, then the particular construct is deemed to be invalid [failed confirmatory]. CFA could be run for every measurement model separately or run the pooled measurement models at once. In evaluating PLS-SEM measurement model, the model was examined through indicator reliability or factor loading, convergent validity, discriminant validity (Fornell-Larcker criterion and cross loading) (Hair *et al.*, 2017).

3.1 Convergent validity

After the model has been constructed, the reliability and convergent assessment was conducted by iteration processes 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. Convergent validity is assessed by examining the construct reliability include Cronbach's alpha (α) and Composite Reliability (CR) and Average Variance Extracted (AVE). However, composite reliability is a new style to measure scale reliability overall and is preferred with CFA. On the other hand, Cronbach alpha is an average measure of internal consistency and item reliability. It is preferred when EFA is used for factor extraction (Hair *et al.*, 2017). If in case the AVE value less than 0.5 but CR value is more than the acceptable level of 0.6, the convergent validity of the construct is still adequate (Hair et al., 2012).

According to Hair *et al.* (2017) that any indicators having low factor loading less than 0.5 can be deleted simultaneously for the following iterations. For constructs convergent validity, the results of Cronbach's alpha (α) and Composite Reliability (CR) are considered acceptable. However, 3 out of 4 groups of constructs found are having Average Variance Extracted (AVE) below than 0.50 of acceptable criterion. Hence, the deletion and the iteration processes are continuing alternatively until the output values achieved or fulfilled construct's reliability and validity of evaluation criterions. The smallest factor loading is removed through one at a time approach for each iteration process. Thus, the final values for convergent validity are generated from the model and are as displayed Table 1.1.

Table 1.1: Final model results

Name of construct	Construct code	Convergent Validity	
		CR ≥ 0.7	**AVE ≥ 0.5**
AI technology acceptance and adoption	AIE	0.770	0.532
Technology	AIT	0.809	0.515
Cost benefit	BEN	0.765	0.520
Human resources	HRM	0.782	0.548
User expectation	UEX	0.857	0.669

Table 1.1 shows that the Composite Reliability (CR) for all constructs are above 0.70 and the Average Variance Extracted (AVE) values are above 0.5. Hence, the evaluation of convergent validity values of the measurement component is above the cut-off values.

3.2 Discriminant validity results

The term discriminant validity is a validation technique that tests can be invalidated by too high correlations with unrelated tests. Principally, discriminant validity is concerning the degree to which latent variable differs from other latent variables. The discriminant validity means that the measuring items of a construct measure what they expected to measure. Discriminant validity assumes that items should correlate higher among them than they correlate with other items from other constructs that are theoretically supposed not to correlate. Hence, this study uses two approaches to examine discriminant validity which are cross-loading and Fornell–Larcker criterion (Urbach Frederik, 2010).

3.2.1 Cross loading

Cross loading is another approach to evaluate model discriminant validity. It measures the correlation of the particular items with all constructs within the model including the construct they are required to reflect. The criterion is that an item should load more highly to the construct it is required to reflect than to the other constructs in the model (Chin, 1998; J. F. Hair et al., 2017). In this study, cross loadings were performed by checking the generated values of correlation coefficients for all the 16 indicators against the all the constructs (4 exogenous and 1 endogenous) as shown in Table 1.2.

Table 1.2: Indicators cross loadings

No.	Indicators	Constructs				
		AIE	AIT	BEN	HRM	UEX
1	AIE2	**0.621**	0.255	0.32	0.183	0.163
2	AIE6	**0.846**	0.429	0.304	0.319	0.356
3	AIE8	**0.704**	0.276	0.394	0.27	0.345
4	AIT1	0.319	**0.668**	0.3	0.136	0.292
5	AIT3	0.33	**0.76**	0.135	0.137	0.213
6	AIT5	0.311	**0.757**	0.092	0.002	0.248
7	AIT9	0.322	**0.68**	0.156	0.032	0.305
8	BEN1	0.367	0.237	**0.692**	0.153	0.329
9	BEN4	0.277	0.191	**0.718**	0.352	0.257
10	BEN6	0.336	0.085	**0.753**	0.421	0.321
11	HRM1	0.18	0.02	0.293	**0.631**	0.142
12	HRM3	0.282	0.041	0.392	**0.824**	0.187
13	HRM5	0.313	0.153	0.255	**0.752**	0.093
14	UEX5	0.353	0.313	0.324	0.106	**0.874**
15	UEX7	0.185	0.193	0.28	-0.087	**0.705**
16	UEX9	0.404	0.357	0.417	0.307	**0.863**

Table 1.2 shows that the cross-loading values of the indicators within the latent construct are higher (as signified with bold font) as compared with values to other latent constructs of the model. For example, the AIE construct has three indicators with each indicator having greater loading value with its construct as compared with the other constructs. Therefore, these items discriminately belong to the AIE construct which definitely not to another construct. This case is similar to the other constructs' indicators. Hence, it demonstrates that the discriminant validity of model is attained.

3.2.2 Fornell-Larcker

Fornell-Larcker criterion compares the AVE square root values with the latent variable correlations. This approach states that the construct shares more variance with its indicators than with any other construct. The analysis Fornell-Larcker is valid if the square root of AVE in each latent construct is bigger than its highest correlations among the latent construct. In Fornell-Lacker criterion, when weak indicators are deleted in stages it will improvises the errors of Average Variance Extracted (AVE) of latent constructs to an acceptable level (Hair et al., 2014; Leguina, 2015). Finally, the square root of AVE value of the model reached the adequacy of discriminant validity criterion as in Table 1.3.

Table 1.3: Fornell-Lacker criterion

Construct	**Construct**				
	AIE	**AIT**	**BEN**	**HRM**	**UEX**
AIE	**0.729**				
AIT	0.448	**0.717**			
BEN	0.46	0.239	**0.721**		
HRM	0.361	0.108	0.418	**0.74**	
UEX	0.409	0.369	0.424	0.185	**0.818**

The bolded values in the Table 1.3 represent the 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. After conducting the measurement model evaluation, there is no more deletion of indicator and the final model is as Figure 1.2.

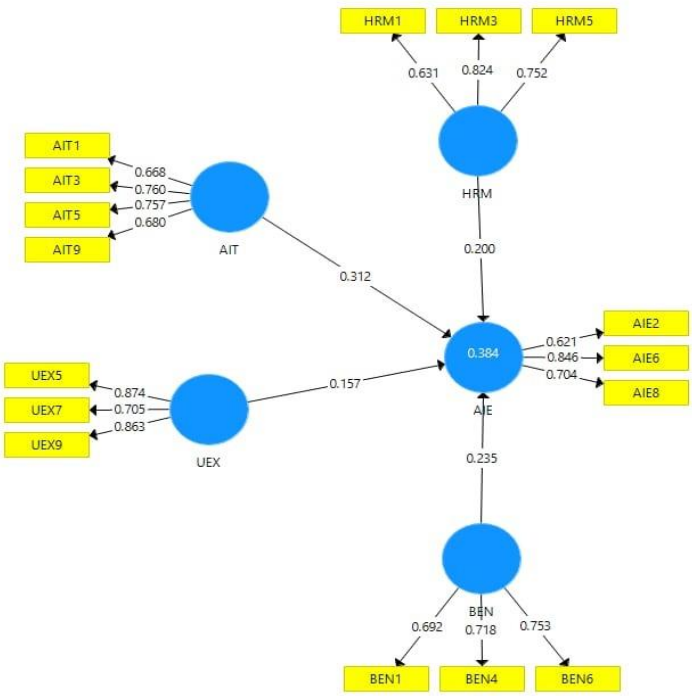

Figure 1.2: Graphical of the final model

Figure 1.2 show the graphical of the final model after conducting the measurement evaluation on the model. Hence, it can be deduced that the model has achieved measurement evaluation goodness-of-fit. The following process is to evaluate the structural component of the model.

Structural evaluation of the model

Previous has shown that the measurement model has being assessed for its fitness and found that it has achieved the stipulated criteria which are convergent and discriminant validity. Then the following step is to assess the structural model. This involves examining relationship between dependent variables with independent variables. The relationship is a set of one or more dependent relationships linking the hypothesized model's constructs representing the interrelationships of variables between constructs (J F Hair et al., 2010; Hair Jr. et al., 2017). Structural model of a study assesses the relationships among latent variables representing the underlying theory of the study using several criterions that are hypothesis testing, path coefficients (β), coefficients of determination (R^2), effect size (f^2), predictive relevance (q^2) and goodness-of-fit (GoF).

3.3 Path's strength [extract from to final model]

Path coefficients also known as beta (β) value is the strength of the path or relationship between exogenous and endogenous constructs. It examines the impact strength of independent variables toward the dependent variables. According to Hair *et al.* (2017), path coefficients have standardized 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. For this study, path coefficient is checked from the final model and the generated values are as depicted as Table 1.4.

Table 1.4: Ranking of path strength

Path	Beta values [β]	Rank on path strength
AIT → AIE	0.312	1
BEN → AIE	0.235	2
HRM → AIE	0.200	3
UEX → AIE	0.157	4

Table 1.4 shows the beta values of path in the model. Ranking of path is based on the beta value where path having highest beta value is ranked the first. In this case AIT path is the strongest influence to AIE.

3.4 Model predictive accuracy [extracted from final model]

Coefficient of determination (also known as R^2) can be viewed as the combined effect of the exogenous variables on endogenous variables. This criterion measure of the model's predictive accuracy by evaluating the overall effect size and variance explained in the endogenous construct for the structural model (Ramayah *et al.*, 2018). The R^2 values ranges from 0 to 1 with value closer to 1 representing complete predictive accuracy (Hair Jr. et al., 2017). Basically, R^2 value should be high enough for the model to have a minimum level of explanatory power (Urbach Frederik, 2010). Then recommended R^2 values should be equal or greater than 0.10 in order for the variance explained of a particular endogenous variable to be considered adequate. However, this study adopted the R^2 threshold value by Cohen (1988) which R^2 value of 0.26 is considered as substantial, R^2 value of 0.13 is regarded as moderate, and R^2 value of 0.02 is considered as weak. Hence, based on the final figure the R^2 value is 0.384 at the endogenous construct of AIE. This implies that the four exogenous constructs are substantially explained with 38.4% of the variance in AIE endogenous construct.

3.5 Impact of exogenous on endogenous [running PLS algorithm]

Evaluation on the impact of exogenous on endogenous is conducted using effect size technique. The technique evaluates coefficient of determination (R^2) values of endogenous construct due to the change in R^2 value when a specified exogenous construct is omitted from the model has a substantive impact on the endogenous construct (Hair *et al.*, 2017). The process of generating R^2 value is by *running the PLS algorithm* on the final model. After R^2 values have been generated the effect size (f^2) is calculated using formula suggested by (Chin, 1998) is given as follows;

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}} \qquad (5.1)$$

where;

f^2 = effect size

$R^2_{included}$ = R^2 value of the endogenous construct where all exogenous construct is included from the model

$R^2_{excluded}$ = R^2 value of the endogenous construct when a selected exogenous construct is excluded from the model

The rule of thumb state that the effect size values of 0.02, 0.15 and 0.35 are represent small, medium and large effect sizes respectively (Cohen, 1988). When an exogenous construct is deleted from the path model, it changes the value of the coefficient of determination (R^2) and defines whether the removed exogenous construct has a significant influence on the value of the endogenous construct. Since there are four exogenous constructs then it required four iterations process to determine effect size value for this model as in Table 1.5.

Table 1.5: Effect size (f2)

Exogenous construct	$R^2_{included}$	$R^2_{excluded}$	f^2	Status
AI Technology	0.384	0.305	0.128	Small effect
Human resource management	0.384	0.351	0.054	Small effect
Benefit	0.384	0.350	0.055	Small effect
User Expectation	0.384	0.366	0.029	Small effect

Table 1.5 shows the effect size values for all the exogenous constructs. The results indicate all the constructs are having small effect size more than cut-off value of 0.02 as specified by Cohen (1998).

3.6 Predictive relevance [running blindfolding]

Predictive relevance is to predict how well the data points of indicators in the final model. Predictive relevance (q^2) is about evaluating the magnitude of R^2 value of the model. The predictive relevance is based on Q^2 values which measure the differences between the omitted data points and the predicated ones (Chin, 1998; Tenenhaus *et al.*, 2005). The Q^2 values are generated from blindfolding iteration process. Blindfolding is built on a sample reuse technique that every 7th omission distance data point as suggested by Hair *et al.*, (2012) is omitted in the endogenous construct's indicators and estimates the parameters with the remaining data points (Hair *et al.*, 2017). Blindfolding process generates two different types of Q^2 values that are cross-validated communality (CVC) and cross-validated redundancy (CVR). However, this study PLS model only used cross-validated redundancy value as suggested by Hair *et al.* (2017) that CVR has already includes the key element of the path model, the structural model, to predict eliminated data points. The formula for calculating predictive relevance (q^2) by Cohen (1988) is given by the following equation.

$$q^2 = \frac{Q^2_{included} - Q^2_{excluded}}{1 - Q^2_{included}}$$

where;

q^2 = predictive relevance

Q^2_{included} = value of the endogenous latent variable where all the exogenous construct variables are included in the model

Q^2_{excluded} = a selected exogenous construct is excluded from the model

The blindfolding iteration process was conducted to all the exogenous constructs and the predictive relevance q^2 was generated and calculated to each of the process and the results are as in Table 1.6. The rule of thumb state that if the q^2 value is 0.02, 0.15, 0.35 then it indicates that the respective exogenous construct is having small, medium, large predictive relevance to the model respectively (Cohen, 1988).

Table 1.6: Predictive relevance (q2)

Exogenous construct	**Q^2_{included}**	**Q^2_{excluded}**	**q^2**	**Status**
AI Technology [AIT]	0.166	0.126	0.048	Small predictive relevancy
Human resource management [HRM]	0.166	0.153	0.016	No predictive relevancy
Benefit [BEN]	0.166	0.153	0.016	No predictive relevancy
User Expectation [UEX]	0.166	0.167	-0.001	No predictive relevancy

The predictive relevance (q^2) results show that only AI Technology construct is having q^2 values of 0.048 which indicates the construct has small relevancy while others construct have no predictive relevancy.

3.7 Goodness-of-Fit [calculation]

Goodness-of-fit (GoF) index proposed by (Tenenhaus *et al.*, 2005) is the geometric mean of the average communality (AVE) and the model's average coefficients of determination (R^2) value. The GoF value is in range between 0 and 1 which can be categorised into small ($GoF \geq 0.1$), medium ($GoF \geq 0.25$) and large ($GoF \geq 0.36$) validating power (Wetzels *et al.*, 2009) as baseline values for validating the PLS model globally. Hence, GoF index of a model can be calculated manually using the following formula (Wetzels *et al.*, 2009):

$$GoF = \sqrt{\overline{AVE} \times \bar{R}^2}$$

where;

GoF = goodness-of-Fit

AVE = average communality

R^2 = coefficients of determination

In PLS path modelling, a cut-off value for AVE is ≥0.5 and R^2 (small: 0.02; medium: 0.13; large: 0.26) proposed by Cohen (1988) are adopted to calculate the GoF. 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 1.7.

Table 1.7: Calculation of GoF

Constructs	Square root of AVE in construct validity and reliability	R^2 values
AIT-exogenous	0.515	-
BEN-exogenous	0.520	-
HRM-exogenous	0.548	-
UEX-exogenous	0.669	-
AIE-endogenous	0.532	0.384
Average value	**0.5568**	**0.384**

For this model, the average of AVE for endogenous variable is 0.579 and the average R^2 for all dependent variables is 0.219. Thus, the calculated, $GoF = \sqrt{0.5568 \times 0.384} = 0.462$. This indicates that the model is fit and having medium global validating power.

3.8 Hypothesis testing [bootstrapping]

Hypothesis testing is conducted using a bootstrapping technique on the final model. In this technique 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 for significance testing of the structural path (Wetzels *et al.*, 2009). Once the bootstrapping procedure is completed, the path coefficients values were generated. However, this study considered p-values for the hypothesis testing and the values are as shown in Table 1.8.

Table 1.8: Path analysis results of the structural model

Path	P values [≤ 0.050]	Significant level
AIT→AIE	0.003	Significant
BEN→AIE	0.028	Significant
HRM→AIE	0.039	Significant
UEX→AIE	0.150	Not significant

From the results in Table 1.8, it indicates that the strength and the level of significance of the structural model. Hypotheses testing results can be summarised as follow;

(i) H_1: AIT has significant effect to AIE

(ii) H_2: HRM has significant effect to AIE

(iii) H_3: BEN has significant effect to AIE

(iv) H_4: UEX has no significant effect to AIE

It also indicates that three paths are significant and with AIT construct having the strongest influenced to the AIE construct. However, UEX path is not significant and this is the reflection from the data collected from the respondents that thought UEX is that not son significant to AIE in UAE energy sector. According to Hair *et al.*, (2017), less significant path relationships generated from SmartPLS software is due to low quality of input data derived from respondents in establishing the relationships.

Model verification

The expert's verification was conducted through physical interviews assisting with structured questionnaire of the model's outcomes. A total of 10 experts are having more than 10 years of working experiences in UAE energy sector were selected for this verification process. The demography of the experts is shown in Table 1.9.

Table 1.9: Profile of experts

Expert's position	Years' experience in energy sector	Highest academic qualification
Project Manager	25	Degree
Project Manager	31	Degree
Senior executive	25	Master
Project Manager	16	Master
Director	17	Master
Project Director	28	Degree
Senior executive	25	Degree
Senior engineer	17	Master
Senior engineer	15	Master
Senior executive	21	Master

Table 1.9 indicates that all the experts are in the higher management hierarchy of their organisations where majority of them are director, project manager, senior executive and senior engineer. Holding high position in the organisation indicates that these experts have high level of understanding regarding the AI implementation in energy sector. These experts have minimum working experience of 15 years and maximum experience of 31 years for working in energy sector in UAE. This indicates the eligibility of the experts' working experiences for this verification process. Hence, with all the attributes attained by the experts as in the table 5.14, it can be deduced that the experts are eligible to respond this verification survey to determine whether the model outcomes are relevant to current practice in UAE energy sector. The selected experts were interviewed to explain the model and its outcomes. The experts were required to tick their agreeability of the ranking of the path relationship as in the table. The results of this experts' verification are as in Table 1.10.

Table 1.10: Results of experts' verification on the model outcomes

Experts	**Rank of group's factors affecting AI implementation in UAE energy sector**			
	Rank 1 AI Technology [AIT]	**Rank 2** Benefit [BEN]	**Rank 3** Human Resource Management [HRM]	**Rank 4** User Expectation [UEX]
E1	√	√	√	√
E2	√	√	√	√
E3	√	√	√	√
E4	√	√	√	√
E5	√	√	√	√
E6	√	√	√	√
E7	√	√	√	√
E8	√	√	√	√
E9	√	√	√	√
E10	√	√	√	√

Table 1.10 indicates that all the experts agreed with the model outcomes where technology is the dominant factor in influencing the Artificial Intelligence (AI) implementation in the UAE energy sector. Then follow by the benefit factor, human resources and finally the user expectation factors. Hence, it can be deduced that the final objective of this study has been achieved as all the 10 experts has agreed with the model outcomes which is suitable to the UAE energy sector environment.

Conclusion

This paper presented the development of PLS-SEM model of relationship between factors affecting Artificial Intelligence (AI) technology implementation in the UAE government energy sector. The PLS model consist of 4 independent constructs and 1 dependent construct with four hypotheses. At the measurement evaluation, the model has undergone 10^{th} iterations process before achieving convergent and discriminant validities criterions. For structural evaluation, the model was evaluated and found that it achieved the overall model of fit known as GoF with the value of 0.462. In term of hypothesis testing, three of the paths had significant impact toward the endogenous construct. Only UEX construct was found not significant to AIE in UAE energy sector according to the respondents' data. AIT was found the strongest path to AIE indicating that technology is the most affecting factor to the AI technology implementation in the UAE government energy sector. The model was verified by 10 experts on the outcomes of the model and all the experts agreed with the outcomes. Hence, the model was verified by the experts. These findings are beneficial for to academicians, researchers, practitioners and authority of UAE artificial intelligence and energy related sector.

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