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Ratings of The Driving Factors for Adoption and Implementation of Artificial Intelligence in The Public Sector

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Abstract

The study constructed an estimation of the significance of driving factors that influence artificial intelligence (AI) adoption and implementation in the public sector, and accentuated a critical research area that is currently understudied. A theoretical framework, underpinned by the diffusion of innovation (DOI) theory, was developed from a mingle of the technology, organization, and environment (TOE) framework and the human, organisation, and technology (HOT) fit model. The best-worst method was used to scrutinize and rank the identified driving factors according to their weighted averages. The findings of the study pointed to privacy and security; reliability, serviceability and functionality; regulation; interpretability and ease of use; IT infrastructure and data; and ethical issues as the highest ranked driving factors for AI adoption and implementation in government institutions. The study has significant implications for policy makers and practitioners, as it would augment their perspectives on how to adopt and implement AI innovations.

Keywords: privacy and security; innovation; artificial intelligence; government; technology; best-worst method

Introduction

The current growing appetite for AI stems from its ubiquitous influence on modern human society. The omnipresence of AI technology systems is indisputable. AI technologies are becoming increasingly present in different domains and becoming increasingly competent to perform different functions. It is perceived to be cheaper, quicker and less prone to errors than the humans that it substitutes through automation (Davenport et al., 2020). Microsoft commissioned the Ernst & Young organization to survey public sector organizations in Western Europe about their adoption of AI technologies, shortly before the COVID-19 pandemic. The Microsoft study found that two thirds of public sector organizations saw AI as a digital priority. According to the study, the pandemic had sped up the adoption of AI in the public sector. It had accomplished this by pushing processes, people and services online, and these forced local, regional and national governments to lead by example. It is evident in literature that AI adoption and implementation within most segments of the public sector are lagging behind their private sector counterparts. However, this may present an unanticipated prospect. As other industries have experimented, botched, learned, and advanced their efforts with AI, government adopters can gain from the insights and finest practices garnered from these experiences. This presents a major chance for the public sector, signifying an eventual broader and speedy adoption and implementation of AI. The current momentum of AI adoption and growth has accentuated the need for a detailed study to determine the relative weights and rankings of the driving factors of its adoption and implementation in the public sector. A few studies (Davenport et al., 2020; Holzinger et al., 2021; Lauterbach, 2019; Sun & Medaglia, 2019; van Noordt & Misuraca, 2020) have discussed the driving factors of AI adoption and implementation in the public sector. However, most of these studies alleged that these factors were intertwined, and hence were silent on the relative significance of the success factors of AI adoption and implementation in the public sector. With impetus from this apparent research gap, the specific objective of this contemporary study was to determine the relative significance of the driving factors of AI adoption and implementation in the public sector using the best-worst method (BWM). The BWM was used to estimate the relative weights and rankings of the elected relevant driving factors of AI adoption and implementation by government institutions. The results of these analyses has brought insight into the actual level of importance of each selected driving factor towards the adoption and implementation of AI by government organizations.

Literature Review

It is claimed by scholars that AI technologies are able to deliver value and gains to government organizations in many ways, although there is a lack of a clear conceptualization on AI (Alexopoulos et al.,2019; Sun & Medaglia, 2019). There have been a few studies on the success factors of AI adoption and implementation in the public sector (Holzinger et al., 2021; Davenport et al, 2020; Schrader & Ghosh, 2018; Stock & Seliger, 2016; Pandey et al., 2016; Cresswell & Sayogo, 2012), but none has been found from extant literature that deals with the relative level of importance of these factors. The purpose of this inventive study was to determine the relative degree of importance of the driving factors of AI adoption and implementation in the public sector. The relevant driving factors examined in this study were identified from an extensive and meticulous literature review. The decision framework developed and used in this research originated from a blend of the technology, organization, and environment (TOE) framework (Tornatzky & Fleischer, 1990) and the human, organisation, and technology (HOT) fit model (Yusof et al., 2006), and it was underpinned by the diffusion of innovation (DOI) theory (Rogers, 1995, 2003). According to van Noordt & Misuraca (2021), AI has spread more due to increasing technological advances that improve its accessibility and availability to others. They also attribute the rapid growth of AI to the decrease in barriers, which may have previously prevented its use and development, and hinted on how governments around the world have begun to probe how AI can be used in their everyday business roles. They reasonably argued that it was necessary for the public sector to develop strategies and regulations that would allow for the simultaneous harnessing of AI's benefits, while constraining its potential risks. Their study identified well strategized and conducted procurement as a probable driving factor for the adoption of AI in government. However, although van Noordt & Misuraca (2021) discussed critical questions of how to best procure, use and regulate AI, they were absolutely silent on the relative importance of the driving factors of AI adoption and implementation in the public sector. A few other studies, such as Sun & Medaglia (2019), Holzinger et al. (2021), Davenport et al. (2020), Schrader & Ghosh (2018), Stock & Seliger (2016), Cresswell & Sayogo (2012), Karunasena & Deng (2012), Pandey et al. (2016) et cetera, have also discussed the driving factors of AI adoption and implementation but were mute on the comparative prominence of the drivers. This innovative work sought to fill the gap by developing a theoretical framework to study the driving factors of AI adoption and implementation in the public sector, with regards to the relative importance of these factors. This study was focused on the relative importance of relevant driving factors derived from literature, but not so much on the desk research discovery of another key AI driver. The antecedents to adoption of innovations in the public sector remain the same, irrespective of the kind of innovation that is introduced (Schedler et al., 2019). In this light, the known driving factors of AI adoption and implementation in the public sector, from extant literature, were discussed with respect to technological, organisational, environmental and human dimensions.

Identification of the Driving Factors of AI Adoption and Implementation in the Public Sector

The decision framework developed in this study emanated from a blend of the TOE framework and the HOT fit model, and it was propped by the DOI theory. This framework was used to explore the weights and rankings of the driving factors that significantly impact the adoption of AI in the public sector. The new model categorized the driving factors of AI adoption and implementation in the public sector into technology, organisation, environment and human dimensions (see Table 1). Within each of these dimensions, there were driving factors that were recognized and selected by an amalgamation of literature from preceding studies and perceptions of AI industry experts. The literature garnered from preceding studies, for the identification and selection of relevant AI driving factors for this contemporary study, has been comprehensively reviewed in the next four subsections of this section of the chapter. The literature review was thematically arrayed according to the dimension to which an identified and chosen driver belonged.

Technological Dimension

According to De Vries et al. (2016), to ease the adoption of innovations, they should be regarded as easy to use, and to try out and compatible with the values of the organization. According to Rogers (1995, 2003), compatibility with the existing values and practices is the extent to which innovation is visible as consistent with existing morals, experiences, and needs of prospective adopters. An innovation that is not compatible with the ideals and custom of a target group would not be sustainable. Also, ethical concerns of a target group of an innovation, such as data security and privacy issues, should be thoroughly addressed for it to succeed. Privacy is the protection of sensitive information. Privacy is hinged on how data is used and governed, whilst security focuses on protecting data from theft for profit and destructive attacks (Abouelmehdi et al., 2018). Sufficient privacy and security can foster the adoption and implementation of AI in the public sector. Furthermore, AI innovations should be serviceable, functional, and easy to use without ambiguities. A very important success factor of AI adoption and implementation in the public sector, especially in the healthcare sector, is the ease of use and interpretability of models that help in the decision making processes during diagnosis and treatment (Thesmar et al., 2019). The Intelligent interpretation of AI models is an imperative success factor to the implementation of AI by governments. Accessibility and availability of the technological innovation (van Noordt & Misuraca, 2021) is also vital to its adoption and implementation in the public sector.

Organisational Dimension

Employee competence is a vital driving factor for the adoption and implementation of AI in the public sector. Competence of staff refers to the ability of employees in an organisation to espouse new business approaches to perk up performance and boost competitive advantage. A competent employee is a precious human resource who consistently seeks solutions to emerging business issues and takes advantage of looming prospects using contemporary technologies (Nilashi et al. 2016). The cost of training and consultancy is another critical driving factor for the adoption and implementation of AI in the public sector. This includes the cost incurred for enhanced training of staff in the use of new technologies related to AI for its proper implementation and exploitation, and the cost of investment in terms of consultancy (Stock & Seliger, 2016). Service collaboration between the various public actors concerned with AI is also a key driving factor for its adoption and implementation in the public sector. Healthier collaboration and consultations between stakeholders drives a public organisation to an excellent technological solution (Morse, 2010). An organisation's in-depth understanding of their own IT infrastructure, data, and capabilities facilitates their adoption and implementation of AI (Edler et al., 2006; Edquist et al., 2000). The ability of an organisation to successfully strategize and conduct AI procurement contracts is also a probable driving factor for the adoption and implementation of AI in that public organisation (van Noordt & Misuraca, 2021). Government and top management can support the adoption and implementation of AI in the public sector by providing the required internet facility at subsidized rates to public institutions (Bonczek et al., 2014). Organizational culture is also a key driving factor for the adoption and implementation of AI in the public sector. A cultural change is required as organizations are now being converted into smart factories. Due to automation, the roles of organizations will change and pave the way for decentralization and a shift of duties and responsibilities (Broring et al., 2017). Quality of life, quality services and service equity are collectively influential driving factors for the adoption and implementation of AI in the public sector. Public service should have a positive effect on the quality of life of citizens. It should impact their security, health, satisfaction et cetera (Cresswell & Sayogo, 2012). With regards to quality, AI services should be prompt with the provision of relevant, precise and accurate service and information to citizens (Karunasena & Deng, 2012). Also, for AI to be adopted and implemented in the public sector, there should be service equity in the sense that citizens should be equally treated irrespective of their gender, religion or race (Pandey et al., 2016).

Environmental Dimension

It has been widely acknowledged that AI has many advantages for public governance. However, the development of AI and its tools for the public sector is still emerging and faces organizational, managerial, political, and legal challenges (Sun & Medaglia, 2019). There are challenges like quality of input data, manipulation of data, governance of the system, and liability in the setting up and use of AI (Holzinger et al., 2021). Pressure from competition, especially from the private sector, is a key factor within the environmental context which can manipulate the adoption and implementation of AI in the public sector. Regulation is another imperative factor which can influence AI adoption. AI adoption and implementation in the public sector is affected by statutory rules and regulations. According to Lauterbach (2019), the bureaucratic rules set by regulators lead to increased AI costs and choke innovation paths. Human societies are ruled and regulated by legislative entities. Hence, it is essential to clarify and classify an AI application scheme and its users to settle on the responsibility hubs in case of faults (Vellido, 2019).

Human Dimension

In the human context, it is believed that creative leadership is needed for the successful deployment of an innovation. According to De Vries et al. (2016), an individual within an organization, no matter their position in the hierarchy, may be seen as the informal leader of an important factor in the innovation process. Also, Satisfaction of a customer is a crucial factor within the human context which can influence AI adoption and implementation in the public sector. Since AI is still relatively new, it would be prudent to foresee the ethical issues that might become visible once it expands and control these problems in advance (Lee & Park, 2018). According to Schrader & Ghosh (2018), proper ethical engagement between humans and technology is fundamental to AI development.

Dimensions	***Factors***	***References***
Technological (TL)	Compatibility (TL1) Privacy and security (TL2) Reliability, serviceability, and functionality (TL3) Interpretability and ease of use (TL4) Accessibility and availability(TL5)	De Vries et al. (2016), Rogers (1995, 2003), Abouelmehdi et al. (2018). Thesmar et al.(2019), van Noordt & Misuraca (2021).
Organizational (OG)	Competence of staff (OG1) Cost of education and training of staff (OG2) Service collaboration (OG3) IT infrastructure and data (OG4) Procurement management (OG5) Government and top management support (OG6) Organizational culture (OG7) Quality of life, quality services and service equity (OG8)	Nilashi et al. (2016), Stock & Seliger (2016), Morse (2010), Edler et al., (2006), Edquist et al. (2000), van Noordt & Misuraca (2021), Bonczek et al. (2014), Broring et al. (2017), Cresswell &Sayogo (2012), Karunasena & Deng (2012), Pandey et al. (2016).
Environmental (ET)	Competitive pressure (ET1) Regulation (ET2) Clarity of legal issues (ET3)	Sun & Medaglia (2019), Holzinger et al (2021), Lauterbach (2019), Vellido (2019).
Human (HM)	Creative leadership (HM1) Satisfaction (HM2) Ethical issues (HM3)	De Vries et al. (2016), Lee & Park (2018), Schrader & Ghosh (2018).

Source: authors' own construct

Table 1: A theoretical framework on the driving factors (DFs) of AI adoption and implementation in the public sector.

Research Methodology

The research modelling framework proposed in this study encapsulated the paths to prioritising the driving factors of AI adoption and implementation in the public sector, using the BWM. The BWM was used to determine the relative significance of each dimension and driving factor of AI adoption and implementation in the public sector. This was done by comparing the best dimension (most important) to the worst (least important) initially, and then comparing the other dimensions to the worst afterwards using a linguistic scale for the pair wise comparison. A synonymous procedure was then performed to rank the identified and selected driving factors according to their perceived degree of significance (see questionnaire).

Best-Worst Method (BWM)

According to Wang et al. (2019), the BWM is a multi- criteria decision-making model which estimates the weights of criteria by employing two vectors of pair wise comparisons between the most important and the least important criteria. According to Rezaei (2016), the following steps are involved in determining the weights of criteria using the BWM (see Figure 1):

Step 1: Finalisation of decision criteria

A set of decision criteria are identified and extracted from an intensive search of literature, and experts' opinions and recorded as *{C1, C2 . . . Cn}* for *n* main criteria. In this study, the decision criteria were the driving factors of AI adoption and implementation in the public sector.

Step 2: The best (most important) and worst (least important) criteria are selected.

At this stage, the expert selects the most important and least important criteria from the pool of identified decision criteria in Step 1 based on his/ her opinion.

Step 3: A matrix is developed by determining the pair wise comparison between the most important criterion and the other decision criteria. The objective of this step is to determine the preference of the most important criterion to the other decision criteria by using a linguistic scale for the BWM having scores from 1 to 9. The linguistic scale is shown in Table 2. The outcome of the pair wise comparison of the best criterion and other decision criteria is expressed by a 'best-to-others' vector as follows:

$$DB = (dB1, dB2, \ldots, dBn)$$

Where *dBj* represents the preference of the most important criterion *B* over a criterion *j* amongst the decision criteria, and *dBB* = 1

Step 4: The 'others -to-worst' matrix is developed by conducting a pair- wise comparison of the other decision criteria against the least important criterion using the linguistic scale for BWM shown in Table 2. The outcome of comparison of the other decision criteria to the worst criterion is expressed as follows:

$$DW = (dW1, dW2, \ldots, dWn)^{q}$$

Where *dWj* represents the preference of the criterion *j* amongst the decision criteria in Step 1 above the least important criterion *W*, and *dWW* = 1.

Step 5: Computing the optimal weights (*p1**, *p2** . . . *pn**)

Weights of criteria are determined such that the maximum absolute differences for all criterion *j* are minimised over the following set {*|pB – dBjpj|*, *|pj – djW pW|*}.

A minimax model can be formulated as:

$$\min \max j\{|pB - dBjwj|, |pj - djWwW|\}$$

Subject to:

$\sum_j pj = 1$ .... (1)

$pj \geq 0$, for all criterion j.

Model (1) can be solved by converting it into the following linear programming problem model:

$$\text{Min } R^L$$

Subject to:

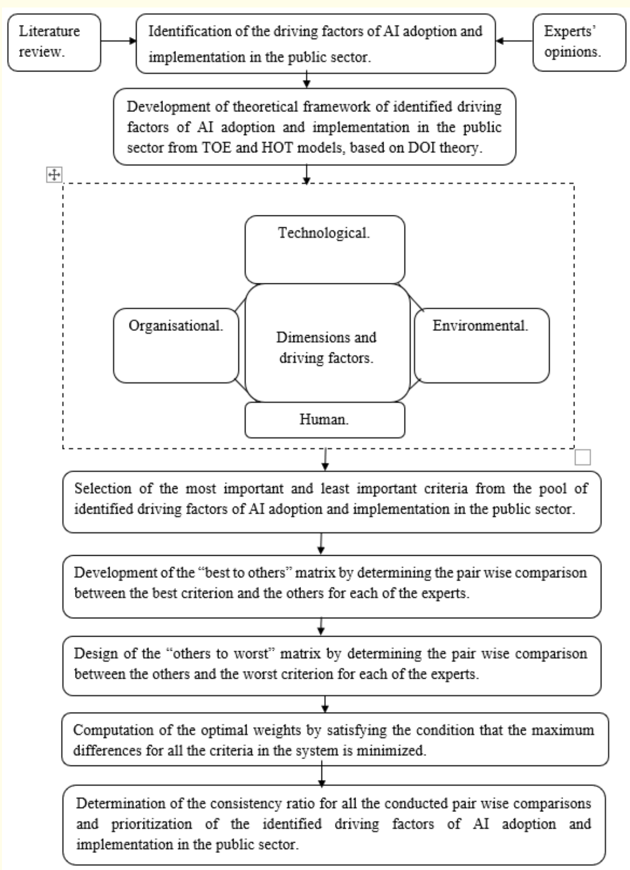
$$|pB - dpj| \leq R^L, \text{ for all criterion } j$$

$$|pj - dpW| \leq R^L, \text{ for all criterion } j$$

$$\sum_j pj = 1$$

$pj \geq 0$, for all criterion j..(2)

Solving the linear model (2), will result in optimal weights ($p1^*, p2^* \ldots pn^*$) and optimal value R^L. Consistency (R^L) of comparisons also needs to be estimated. A value nearer to zero is more desired for consistency (Rezaei , 2016; Wang et al., 2019).



Source: authors' own construct

Figure 1: Research modelling framework.

Data Collection

To facilitate the conduct of this research, a questionnaire was designed and used to collect data from experts with a minimum of five years of professional management and decision-making experience in the Ghanaian AI sector. This was done to ensure the accuracy of data garnered since the experts were deemed to be sufficiently knowledgeable to effectively complete the survey. The experts were purposefully selected from the realms of computer science and engineering, national security and identification, police/military intelligence and medical units, academia and quaternary medical research in the AI sector of Ghana. They were assured of the confidentiality of their reports in order to allow for effective model building and profound observation (Nilashi et al., 2016). The experts were designated mid-level and above ranking executives, hence their responses sufficiently represented the AI sector (Fu et al., 2006).

To conduct the survey, several steps were undertaken to maximise the rate of response and minimise response bias amongst the experts from the selected public sector AI organisations. Initially, a pilot study was done by sending copies of the google form questionnaire designed for this study to three researchers through emails and interviewing three experts face- to - face to provide feedbacks for a review. The three researchers who participated in the pilot study were a female and two males who hold PhD degrees and had at least seven years of research experience in computer science and engineering. Also, the experts who participated in the pilot study had managerial experience of at least five years in the Ghanaian public AI sector. Based on the feedbacks from the pilot study, the questionnaire was modified and copies were emailed to twenty-five experts (see Appendix A for questionnaire link). Five experts each were selected to represent the five different roles of the participants as illustrated in Table 2. A follow- up on the respondents was done via phone conversations and personal visits (Yang et al. 2018). Eventually, sixteen completed copies of the questionnaire were received out of the twenty-five that were emailed to the experts, a response rate of 64%. This response rate was considered suitable for efficient analysis, and to yield reliable findings, according to the BWM used in this study that does not require a large sample size to provide precise and consistent results (Wang et al., 2019; Rezaei, 2016).

Demographic Summary of Respondents		
Characteristic	***Number of Respondents***	***Percentage of Sample (%)***
Gender		
Male	9	56%
Female	7	44%
Education		
Master degree	5	31%
Doctorate degree	11	69%
Years of experience		
5–10	10	62.5%
Above 10	6	37.5%
Roles		
Computer scientist/Engineer	3	18.75%
National security/National	3	18.75%
identification authority director	3	18.75%
Police/Military intelligence director	3	18.75%
Police/Military/ Quaternary medical director	4	25%
University lecturer		

Linguistic Scale for Pair Wise Comparison in BWM.	
Linguistic attributes	***Scores***
Equally important	1
Equal to moderately more important	2
Moderately more important	3
Moderately to strongly more important	4
Strongly more important	5
Strongly to very strongly more important	6
Very strongly more important	7
Very strongly to extremely more important	8
Extremely more important	9

Source: authors' own construct

Table 2: Demographic summary of respondents, and linguistic scale for pair wise comparison in BWM.

Results and Discussion

Starting with the first step of the BWM, the dimensions and driving factors of AI adoption and implementation in the public sector that were identified and selected from an extensive review of extant literature were evaluated by the decision-makers using questionnaires. A simple mean method was used to select the variables that were above the arithmetic mean and analysis of the results at this stage indicated that all the identified dimensions and driving factors were accepted with no auxiliary inclusions. Therefore, inclusiveness of relevant data was ensured and content validity was confirmed.

Calculation of the Weights of Driving Factors (DFs) using BWM

After the finalisation of the DFs of AI adoption and implementation in the public sector, their weights were calculated using the BWM. The data garnered from the experts via the completed questionnaires were analysed using the BWM-Solver, a Microsoft Excel based software that is used for BWM analysis. For this study, sixteen experts performed the selection of the most important and least important criteria from the pool of identified driving factors for the main dimensions as well as subcategory criteria. Subsequent to selecting the most important and least important criteria, the experts were requested to give preference ratings of the best criteria to other criteria and other criteria to worst criteria for the main dimension's criteria, as well as subcategory criteria. The preference ratings of the first expert, Expert 1, for the main category criteria, as well as subcategory criteria are illustrated in Table 3.

An identical process of the BWM survey, as described in the paragraph above, was performed by all the experts who took part in this study. This was done to estimate the performance ratings of the main category and subcategory DFs of AI adoption and implementation in the public sector. The entire weights of the DFs for both the main category and subcategory were obtained using Equation (1). All the aggregated weights were computed by applying the data sourced from the sixteen experts to Equation (2), and estimating the mean using the simple average technique. The entire results of the evaluation process, facilitated by the BWM-Solver, are evinced in Table 3. The degree of significance of a DF is revealed by its ranked position in the table. The global ranks of the recognised DFs, shown in the table, were calculated by multiplying the preference weights of the respective DF's dimension with the individual weight of the DF.

Main Category DFs				
Best to Others	***Technological (TL)***	***Organisational (OG)***	***Environmental (ET)***	***Human (HM)***
Best criteria: Technological (TL)	1	3	5	3
Others to Worst			***Worst criteria: Environmental (ET)***	
Technological (TL)			5	
Organisational (OG)			3	
Environmental (ET)			1	
Human (HM)			2	

Technological (TL) Subcategory DFs					
Best to Others	***TL1***	***TL2***	***TL3***	***TL4***	***TL5***
Best criteria: TL2	3	1	3	3	3
Others to Worst	***Worst criteria: TL1***				
TL1	1				
TL2	5				
TL3	3				
TL4	3				
TL5	3				

Organisational (OG) Subcategory DFs								
Best to Others	***OG1***	***OG2***	***OG3***	***OG4***	***OG5***	***OG6***	***OG7***	***OG8***
Best criteria: OG4	3	3	2	1	3	3	3	3
Others to Worst	***Worst criteria: OG2***							
OG1	3							
OG2	1							
OG3	2							
OG4	3							
OG5	2							
OG6	3							
OG7	3							
OG8	2							

Environmental (ET) Subcategory DFs			
Best to Others	***ET1***	***ET2***	***ET3***
Best criteria: ET2	3	1	3
Others to Worst	***Worst criteria: ET1***		
ET1	1		
ET2	5		
ET3	3		

Human (HM) Subcategory DFs			
Best to Others	***HM1***	***HM2***	***HM3***
Best criteria: HM3	3	2	1
Others to Worst	***Worst criteria: HM1***		
HM1	1		
HM2	3		
HM3	5		

Aggregate Weights of Main and Subcategory DFs for all the Experts.					
Main category DFs	***Weights of main category DFs***	***Subcategory DFs***	***Weights of subcategory DFs***	***Global weights***	***Ranking***
Technological (TL)	0.466	TL1	0.085	0.040	10
		TL2	0.396	0.185	1
		TL3	0.255	0.119	2
		TL4	0.170	0.079	4
		TL5	0.094	0.044	9
Organisational (OG)	0.259	OG1	0.059	0.015	18
		OG2	0.130	0.034	12
		OG3	0.180	0.047	7
		OG4	0.232	0.060	5
		OG5	0.112	0.029	13
		OG6	0.110	0.028	14
		OG7	0.084	0.022	17
		OG8	0.093	0.024	16
Environmental (ET)	0.172	ET1	0.143	0.025	15
		ET2	0.600	0.103	3
		ET3	0.257	0.045	8
Human (HM)	0. 103	HM1	0.133	0.014	19
		HM2	0.333	0.035	11
		HM3	0.534	0.055	6

Source: authors' own construct

Table 3: Pairwise comparison of main category and subcategory DFs by Expert 1, and aggregate weights of main and subcategory DFs for all the experts.

Ranking of the Dimensions of the DFs for AI Adoption and Implementation in the Public Sector

As evinced in Table 3, the results pointed to the technological dimension as the most significant dimension for AI adoption and implementation in the public sector. It is also exuded in the table that the organisational, environmental and human dimensions followed respectively in order of importance. From the results, it can be construed that the driving factors that are related to the technological context are extremely important and should be adequately sure-fired for the success of AI adoption and implementation in the public sector. The organisationally related DFs were the next in level of importance, with regards to the adoption and implementation of AI in the public sector. The environmental context filled the third position, whilst the human context was ranked least amongst the main category dimensions. AI managers must be encouraged to be in conformity with these DFs to promote the adoption and implementation of AI in the public sector.

Global Ranks of the DFs

Table 3 exudes the global rankings of the DFs for AI adoption and implementation in the public sector. The top six DFs under the global ranks, which represent about the top 30% of DFs, belong to all the four dimensions considered in this study. These top DFs are privacy and security; reliability, serviceability and functionality; regulation; interpretability and ease of use; IT infrastructure and data; and ethical issues. The results of the study suggest that privacy and security was the highest ranked DF for the attainment of the objective of driving AI adoption and implementation in the public sector. Privacy is hinged on how data is used and governed to protect sensitive information, whilst security focuses on protecting data from theft for profit and destructive attacks (Abouelmehdi et al., 2018). The second most significant DF in the ranking hierarchy was reliability, serviceability and functionality. This denotes a dependable, properly working and easy to use AI service without ambiguities. It means the simpler an AI technological innovation is, the higher its probability of adoption by public organisations. Regulation was also a highly ranked DF in this study. Regulation denotes the bureaucratic rules set by regulators to control the deployment of AI technology in the public sector. These bureaucratic rules may lead to increased AI costs and choke innovation paths (Lauterbach, 2019). The next most important DF, interpretability and ease of use, means the ease with which a user understands what the output results from the AI innovation system means. This DF is especially significant in the public healthcare sector, for example, the national military and police hospitals, as well as the national quaternary medical and research centre located on the campus of the University of Ghana in Accra. As explained by Thesmar et al. (2019), a very important success factor of AI adoption and implementation in the public sector, especially in the healthcare sector, is the ease of use and interpretability of models that help in the decision making processes during diagnosis and treatment. IT infrastructure and data was the fifth ranked most important DF for AI adoption and implementation in the public sector according to this research. IT infrastructure and data denotes an organisation's in-depth understanding of their own IT infrastructure, data, and capabilities. This understanding by organisations facilitates their adoption and implementation of AI (Edler et al., 2006; Edquist et al., 2000). The sixth ranked DF, ethical issues, include data privacy and security issues, and envisages the ethical issues that might become visible once AI expands, since it is still a relatively new innovation. It is prudent to foresee the ethical issues that might become visible once AI grows and control these problems in advance. An appropriate ethical engagement between humans and technology is vital for AI development (Schrader & Ghosh, 2018; Lee & Park, 2018).

Ranking of the DFs within Each Dimension

Technological DFs

The findings of this study evinced that privacy and security had the highest rank in this dimension. As comprehensively discussed in the preceding paragraphs, privacy is the protection of sensitive information and security focuses on protecting data from theft for profit and destructive attacks. This implies that managers and other actors in public sector AI management could be more disposed to AI patronage if sufficient privacy and security could be provided. The next ranked key factor in this dimension was reliability, serviceability and functionality, which have been duly discussed in the preceding section. The next three ranked DFs in this dimension, in order of importance, were: interpretability and ease of use; accessibility and availability; and compatibility respectively.

Organisational DFs

IT infrastructure and data was the highest ranked DF within the organisational dimension. The next seven DFs, ranked in order of their significance to AI adoption and implementation in the public sector, were: service collaboration; cost of education and training of staff; procurement management; government and top management support; quality of life, quality services and service equity; organizational culture; and competence of staff respectively.

Environmental DFs

This dimension had regulation as the highest ranked DF. Regulation signifies the administrative rubrics set by regulators to control the disposition of AI technology in government institutions. According to Lauterbach (2019), these official rules may lead to increased AI costs and choke innovation paths. Henceforth, this study proves that milder rules that are neither ambiguous nor belligerent make conditions better for AI adoption and implementation in the public sector. The next most important DF in this context was the clarity of legal issues, an issue which is akin to regulation. The third ranked DF in this dimension was competitive pressure.

Human DFs

The results of this study projected that ethical issues made up the highest ranked DF in this dimension. This was followed by satisfaction as the second ranked most important DF of AI adoption and implementation in public institutions, in the human dimensional context. The last ranked DF in this dimension was creative leadership.

Theoretical and Practical Implications

The study significantly contributes to the theory and practice of adopting and implementing AI technology in governments. From a theoretical perspective, the theoretical framework based on the TOE and HOT models, and the DOI theory, aids in understanding the limited areas that when concentrated on can attain governmental AI objectives. From the TOE and HOT theoretical viewpoints, the adoption and implementation of AI by governments is influenced by driving factors categorized into technological, organisational, environmental and human (TOEH) dimensions. Theoretically, through the lenses of the TOE and HOT models, this study enacts a proliferation in the level of variance explained on the drivers of AI adoption and implementation in the public sector in a distinctive fashion by using the BWM.

The findings of the study suggest that privacy and security; reliability, serviceability and functionality; regulation; interpretability and ease of use; IT infrastructure and data; and ethical issues can foster the adoption and implementation of AI innovation in the Ghanaian public sector. These findings are in line with the study by Abouelmehdi et al. (2018), with regards to prudent data usage and governance, and protection from theft for profit and destructive attacks. Data governance is built by knowing who owns the data and what the data rights entail; who is allowed to collect what data; what the rules are for data aggregation; and what the rules are for data rights transfer (Medhora, 2018). Furthermore, Medora (2018) also supports the importance of ensuring data integrity by securing against biases, inaccuracies and mistakes. However, contrary to studies by Nilashi et al., (2016) and Stock & Seliger (2016), the findings of this contemporary research indicate that employee competence, and cost of education and training of staff are relatively not highly crucial to the adoption and implementation of AI in public organisations in Ghana. This may be attributable to the fact that AI technologies are usually user friendly and less likely to be complicated, and hence need neither technical education nor expertise to use. Also, this study contradicts the postulations of Broring et al. (2017) on the level of importance of organisational culture when adopting and implementing a social innovation.

Concisely, this research corroborates some studies on the driving factors of AI adoption and implementation in the public sector. However, this research approach and context differ from previously published documents on the subject. For this inventive work, a theoretical framework based on the TOE and HOT models, and underpinned by the DOI theory, was used to study the driving factors which influence the adoption and implementation of AI in the public sector of Ghana. The developed theoretical model for this study may be applied by any AI firm to classify its organisational success factors according to their importance rankings.

Managerial Implications

The findings of this study present a comprehensive and profound understanding to managers on effective measures to be taken for the adoption and implementation of AI in the public sector. The research is especially helpful to managers of public sector AI organisations in developing countries such as Ghana, Kenya, Nigeria, and other African nations where there are comprehensive data protection laws, which share some elements found in the European Union's general data protection regulation. Managers may adopt the modelling framework of this study, and focus more on improving technologies and developing data protection regimes for better adoption and implementation of AI by public institutions. Significantly, this study would assist public managers to highlight the highly ranked driving factors of AI adoption and implementation, and focus on them with dedicated resources.

Conclusion

The application of the TOE and HOT theoretical frameworks for this study heightened the level of variance explained on the driving factors of AI adoption and implementation by government institutions. In the shade of the TOE and HOT models, underpinned by the DOI theory, this study proposed a comprehensive research framework that was relevant to the context of Ghana's government AI adoption and implementation programme. It is envisaged that this would afford a better understanding of the diffusion of AI technologies and address issues pertaining to its use in the public sector. The results of this study show that the integration of AI innovation into the Ghanaian government sector is still in its early stage, characterized by a slow rate of usage.

Four main dimensions of technology, organisation, environment and human contexts were conceptualized to significantly affect the general adoption and implementation decision of AI in the public sector. Subsequently, this study has revealed the value of the developed composite framework for identifying the most significant driving factors that influence governmental use of AI. When compared to the traditional concepts, this model is a more reliable tool for categorisation of the drivers of AI adoption and implementation in the public sector.

This research was partially based on the perceptions (experts' opinions) of AI managers in the Ghanaian public sector, which may be characterised with biased judgment and ambiguity. In future research, fuzzy logic may be applied to reduce the uncertainty in experts' opinions (Orji & Wei, 2016). Also, in future, success factors of AI adoption in other sectors such as transportation, healthcare and financial technology may be investigated by using the theoretical framework developed in this work. Similarly, the research modelling framework may be modified to take up other multi-criteria decision methods such as the analytical hierarchy process (AHP) and the technique for order preference by similarity to ideal solution (TOPSIS). A wider perspective of this contemporary work may be carried out by garnering data from a bigger pool of experts in the public sector AI institutions of other countries. Furthermore, a comparative study may be done by either comparing diverse modelling frameworks on the subject theme, or comparing findings of public sector AI institutions of different countries, or comparing findings from diverse public sector AI institutions in the same country.

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Appendices

Appendix A

Questionnaire link: https://docs.google.com/forms/u/0/d/e/1FAIpQLSdY_n9XurssjuCIkz9295nRz5ZugSvLnzeQWyxjG0yZOlLP6A/form Response