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The Profound Impact of Artificial Intelligence on the Transformation of Public Management and the Improvement of the Performance of Public Services in Morocco in a Context of Modernization

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ABSTRACT

Introduction: Artificial Intelligence in Morocco is one of the important levers that continues to be used for the modernization of public administration, especially in some sectors like education, health, security, and other administrative services. However, it is a journey that can streamline processes, saving money and enhancing the quality of public services, but in fact, this is a structural challenge hindered by ethical issue (data protection, algorithmic bias and others) that must be dealt with along the path. Considering this, the aim of the current paper is to assess the strengths and weaknesses that are obstacles for the adoption of AI in the Moroccan public administration, in alignment with the State modernization agenda.

Objectives: The study tries to find out how AI influences the way public management works and how public services are delivered in Morocco. It examines the main factors that influence learning about AI, including the availability of technology, knowledge in civil servants, appropriate laws and any blockages from within the organisation. Principal component analysis and statistical tests are used to review AI's role in health and education. Finally, it provides direction for including AI in public administration, considering its ethical problems and the country's situation, to encourage improvements in the public sector.

Methods: The factors influencing AI adoption were assessed using a quantitative descriptive approach complemented by Principal Component Analysis (PCA). Between 12 October 2021 and 19 October 2021, we surveyed 150 Moroccan civil servants, managers, and experts (from relevant sectors including education, health, and public administration) using Survey Sampling International. These include technological infrastructure, human resources, socio-political issues and organizational resistance. Results were substantiated through statistical analyses (Student's t-tests, bootstrapping) and discriminant validity models (Fornell-Larcker criterion).

Results: Based on what we found, both using AI tools and automation were moderately connected to successful AI; technology infrastructure was connected strongly, demonstrating similarly powerful associations on the other utilisation end. Moreover, the effects seen from the variables are significant. For this reason, principal component analysis is the initial stage and it considers the top factors moved by some of the variables in the study, for example, both CT1 0.893 and AO3 0.843. Adopting CT and reorganising for AI has only been proven by thoroughly reviewing the organisation's data. The model, in addition, explains almost 55 per cent of the variation in AI and its values depend on the reliability of the indices. It is concluded that issues such as people being resistant to change or RGs, the availability of adequate resources and thoughtful attention to organisational culture are all points that need consideration.

Conclusions: To maximize benefits from AI in Morocco, it is imperative to invest in digital transportation infrastructure, provide training for public administration personnel, and establish an appropriate ethical legal framework. The fight against such cultural resistance and the need for algorithmic transparency are imperative. Within public services itself—especially health and education—automation of the repetitive and use of predictive analytics can change

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Research Article

the way we create public goods like better health outcomes and improved literacy skills, provided the change is inclusive of the populations served and safeguarded against systemic bias.

Keywords: Artificial intelligence, administrative modernization, public management, digital transformation, resistance to change, public policy.

INTRODUCTION

Artificial intelligence is now at the center of a multiplicity of industrial and social revolutions across the world. Its function is growing more and more central in public management, especially in developing countries; examples include Morocco, where the state hopes to modernize its administrations in order to tackle modern day challenges. In line with its vision for the modernization of public administration, Morocco has initiated a wave of reforms to integrate information and communication technologies (ICT), notably artificial intelligence, to enhance the quality and efficiency of public services. In fact, in a historical context characterized by overcoming even greater challenges, the adoption of AI in administrative processes is a unique opportunity to revolutionize public management at a global level. It would help to streamline tasks, optimize resources, reduce operational costs, and offer more responsive and personalized services to citizens. According to Garbuio and Lin (2019), AI is a growth engine it enables the creation of new business models based on automation and sophisticated data analysis, including in health care startups. This capacity to transform can be translated to the public sector, more so in sectors like health and education. Additionally, Brynjolfsson, Rock, and Syverson (2021) argue that AI and intangible technologies generate a "J-curve" on productivity, demonstrating how interventional strategic adjustments are critical to accelerating their impacts amongst public organizations.

But this change is not simple. There are many institutional and technical obstacles facing Morocco that prevent the adoption of artificial intelligence in the public sector on a large scale. And the problems get even more complicated such as resistance to change in administrations, inadequate training of public executives, and lack of adequate technological infrastructure in some areas of the country. Certifying and regulating artificial intelligence systems are other important issues for AI systems (Namiot & Ilyushin, 2024) focusing on certifying AI systems establishes important security standards and protocols to ensure ethical use of these technologies. While Stein Smith (2024) emphasizes the role of AI on the blockchain and financial services side, perhaps a comprehensive regulatory and technological governance framework would apply beyond this particular industry and to public administration. This study explores the opportunities that AI can leverage for providing efficient public services, and it has a focus on exploring the implication for public management in Morocco. In particular, how the fusion these technologies will respond to modernization requirements and meet these particular challenges of the Moroccan administrative system?

OBJECTIVES

This study will examine the different angles of this question investigating both the opportunities presented by AI for public governance as well as the hurdles toward adoption in a developing country context. This research will examine how the integration of AI in Moroccan public administrations was initiated, that is to say, which strategies and which practices were adopted, within the framework of four key sectors: education, health, public security and basic administration services. It will also evaluate the real outcomes of this process for the quality of services for citizens and the efficiency of decision-making processes in public institutions. Finally, the study aims to provide possible recommendations to promote successful use of AI in Moroccan public sector while accounting for the socio-economic and cultural particularities of the country. In this regard, Mkik and al. (2023) explores investors' educational consumption, as it pertains to market efficiency factors that could help contextualize AI adoption through behavioral decisions by institutional actors.

METHODS

The avoiding the obstruction of the AI integrated in public services, the methodology is based on quantitative and descriptive approach. The data analysis technique used is Principal Component Analysis (PCA), this method helps to reduce the dimensionality of the data while preserving characteristics that contributes the most to its variance. It is correct because this analysis adopts the CPA to better establish the hidden relationships between the variables under study; meaning this type of analysis includes information technology infrastructure, training of civil servants, public policies, and resistance to change and how all these factors affect Artificial Intelligence adoption in public services.

This study sample includes 150 participants, consisting of civil servants, managers and experts working in Moroccan public administrations, especially in education, health and general administration. This group is selected because of their significance to the execution of digital reforms and AI within these vital sectors. The justification for this sample is both the variability of experience and perspectives that these participants can provide, and their implementation (directly or indirectly) in the digital management and transformation process. The sample also provides representative coverage of the different issues about the adoption of AI in the Moroccan context thus provides relevant outcomes that will contribute to the enhancement of public management.

Thus, Table 1 summarizes the exploratory variables and the variable to be explained identified by the literature review

Table 1. Explanatory variables and the variable to be explained in the research.

Variable	Items	Symbols	Theorists
Successful AI Adoption (TA) (Variable to Explain)	Successfully integrating AI into public services	TA1	Rogers (2003)
	Citizen satisfaction with AI powered services	TA2	Venkatesh and al. (2003)
	Measurable efficiency gains (reduction in lead times, costs, etc.)	TA3	DeLonge & McLean (2003)
Technology Infrastructure (IT) (Explanatory Variables)	IT infrastructure (servers, networks)	IT1	Nolan (1979)
	Cybersecurity of AI enabled systems	IT2	Anderson & Moore (2006)
	Big data storage and processing solutions	IT3	Gantz & Reinsel (2011)
Training of civil servants (FF) (Explanatory variables)	AI Continuing Education Programs	FF1	Eraut (2004)
	Technical skills of the teams (data analysis, algorithms)	FF2	Yates & Paquette (2010)
	Raising awareness of the ethical issues of AI	FF3	Binns and al. (2018)
Public Policy and Legislation (TTA) (Explanatory Variables)	AI friendly Legal Framework	TTA1	Brynjolfsson & McAfee (2014)
	Control mechanisms and auditing of AI systems	TTA2	Winfield & Jirotka (2018)
	Transparency of automated decisions	TTA3	O'Neil (2016)
Resistance to Change (RRA) (Explanatory Variables)	Rigid organizational culture	RRA1	Kotter (1996)
	Fear of replacing jobs with AI	RRA2	Frey & Osborne (2013)
	Lack of internal communication about the benefits of AI	RRA3	Kotter (1996)

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Research Article

Automation Opportunities (OOP) (Explanatory Variables)	Automation of repetitive tasks (data entry)	OOP1	Brynjolfsson & McAfee (2014)
	Deployment of predictive systems (preventive maintenance)	OOP2	Davenport & Kirby (2016)
	Proactive anomaly detection	OOP3	Agrafiotis and al. (2016)

RESULTS

By the table 2, data shown are statistical analyses performed for the different groups, all of them were compared using the student's t-test. In each case, the degrees of freedom (df) were 26.0, 26.7, etc. and the results were statistically significant ($p < 0.001$) for each. The mean differences (range between 2.84 and 3.18) as show that when compared show it to be very different between the groups. Effect sizes, calculated with Cohen's d, are all high, 1.96 to 2.29. This suggests that these differences are statistically significant and practically important and that each of the groups had very large effects. Each case tests the hypothesis (H_a: μ ≠ 0), indicating that the mean difference is significantly unlike zero.

Table 2. Sample Homogeneity

		Statistic	Df	p	Mean difference		Effect Size
OOP1	Student's t	26.0	150	< .001	3.07	Cohen's d	2.12
OOP2	Student's t	26.0	150	< .001	2.93	Cohen's d	2.12
OOP3	Student's t	26.7	150	< .001	3.12	Cohen's d	2.18
TA1	Student's t	26.8	150	< .001	3.12	Cohen's d	2.18
TA2	Student's t	24.2	150	< .001	2.97	Cohen's d	1.97
TA3	Student's t	28.1	150	< .001	3.18	Cohen's d	2.29
IT2	Student's t	25.4	150	< .001	3.09	Cohen's d	2.08
IT3	Student's t	24.0	150	< .001	2.86	Cohen's d	1.96
FF1	Student's t	26.6	150	< .001	3.11	Cohen's d	2.17
FF2	Student's t	25.6	150	< .001	2.84	Cohen's d	2.09
FF3	Student's t	28.1	150	< .001	3.03	Cohen's d	2.29
TTA1	Student's t	26.2	150	< .001	3.07	Cohen's d	2.14
TTA2	Student's t	26.2	150	< .001	2.93	Cohen's d	2.14
TTA3	Student's t	25.7	150	< .001	2.97	Cohen's d	2.09
RRA1	Student's t	24.2	150	< .001	2.96	Cohen's d	1.98
RR	Student's t	25.3	150	< .001	2.89	Cohen's	2.07

Journal of Information Systems Engineering and Management
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Research Article

A2						d	
RR A3	Student's t	25.0	150	< .001	3.12	Cohen's d	2.04

Note. H_a μ ≠ 0

Table 3 shows descriptive statistics for all groups (N = 150 for all tests). Mean values are between 2.84 and 3.18 suggesting that the average of scores for all groups are lying in the interval of 3.00. All median values are 3.00, indicating that the scores are distributed symmetrically with 3 in the center around which the numbers are distributed. The standard deviations (SD) vary from 1.32 - 1.53, indicating moderate variability for each group. Standard errors (SE) are between 0.108 and 0.125, which means that there are little errors estimating the mean of the population. This leads to the conclusion that the mean scores are alike within groups, however the particular scores do vary.

Table 3. descriptive statistics.

	N	Mean	Median	SD	HIMSELF
OOP1	150	3.07	3.00	1.45	0.118
OOP2	150	2.93	3.00	1.38	0.113
OOP3	150	3.12	3.00	1.43	0.117
TA1	150	3.12	3.00	1.43	0.117
TA2	150	2.97	3.00	1.50	0.123
TA3	150	3.18	3.00	1.39	0.113
IT2	150	3.09	3.00	1.49	0.122
IT3	150	2.86	3.00	1.46	0.119
FF1	150	3.11	3.00	1.44	0.117
FF2	150	2.84	3.00	1.36	0.111
FF3	150	3.03	3.00	1.32	0.108
TTA1	150	3.07	3.00	1.44	0.117
TTA2	150	2.93	3.00	1.37	0.112
TTA3	150	2.97	3.00	1.42	0.116
RRA1	150	2.96	3.00	1.50	0.122
RRA2	150	2.89	3.00	1.40	0.114
RRA3	150	3.12	3.00	1.53	0.125

The table 4 displays the output of a PCA (principal component analysis) based first cleaning. FF, OOP, RRA, TA, and TTA all describe the magnitude of individual factors or components Greatness, so a better understanding of FF tables, and all of these panels in the ISQ as a whole can contribute to understanding the strength of the association between variables in FF or any other measure to the components. For example, FF factor has very high correlation with variables FF1, FF2, FF3 with coefficients respectively of 0.893, 0.850, and 0.843. Similarly, the coefficients of OOP1, OOP2, OOP3 display high coefficients (OOP1 = 0.841, OOP2 = 0.826, OOP3 = 0.843), indicating good correlation with its factor. And so on and so forth for the other variables like Q1O1, Q4O2 and RRA and TTA just showing the [COLUMN NAME] -> [FACTOR PAIR] relationship in the purification process. In this way, the table helps us to visualize how each of the different variable combinations are placed in the overall CPA schema.

Table 4. PCA: First Purification

	FF	IT	OOP	RRA	YOUR	TTA
FF1	0.893					
FF2	0.850					
FF3	0.843					
OOP1			0.841			
OOP2			0.826			
OOP3			0.843			

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Research Article

Q1O1			0.834	
Q1O2			0.812	
Q1O3			0.811	
Q4O1	0.754			
Q4O2	0.900			
Q4O3	0.894			
RRA1		0.780		
RRA2		0.782		
RRA3		0.842		
TTA1				0.803
TTA2				0.876
TTA3				0.884

The table 5 summarizes the item bootstrapping results, which serve to evaluate the robustness of the relationships between the variables and factors. Here, for each one, the observed sample (O) value is compared to the sample mean (M) and sample standard deviation (STDEV) which is an estimate of coefficient stability. T statistics (|O/STDEV|) quantify how substantial the relationships are, while the P-values provide better insight for estimating the chance of occurrence of the effects. While all the relationships are highly significant given P values of 0.000, this does not indicate that none of the relationships are due to chance. The T stat of 38.137 for the relationship of FF1, FF shows a strong association. Likewise, the association between Q4O2 and IT is subjected to very high T statistics (53.321), and the association between Q4O3 and IT is subjected to the same phenomena (49.142) which implies the very strong association of these associations. The average samples have values that are similar to the original samples, which shows that the results are stable. The low standard errors also confirm this is not a noisy model, and therefore the relationships between the variables and factors are statistically significant, as listed in the table above.

Table 5. Bootstrapping of items.

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
FF1 <- FF	0.893	0.892	0.023	38.137	0.000
FF2 <- FF	0.850	0.845	0.034	25.076	0.000
FF3 <- FF	0.334	0.332	0.107	3.134	0.002
OOP1 <- OOP	0.841	0.839	0.030	28.486	0.000
OOP2 <- OOP	0.826	0.826	0.029	28.962	0.000
OOP3 <- OOP	0.843	0.843	0.028	29.999	0.000
Q1O1 <- TA	0.834	0.835	0.027	30.905	0.000
Q1O2 <- TA	0.812	0.810	0.039	20.690	0.000
Q1O3 <- TA	0.811	0.811	0.034	24.198	0.000
Q4O1 <- IT	0.754	0.751	0.042	17.860	0.000
Q4O2 <- IT	0.900	0.899	0.017	53.321	0.000
Q4O3 <- IT	0.894	0.893	0.018	49.142	0.000
RRA1 <- RRA	0.780	0.779	0.032	24.493	0.000
RRA2 <- RRA	0.782	0.783	0.037	21.040	0.000
RRA3 <- RRA	0.842	0.842	0.025	33.559	0.000
TTA1 <- TTA	0.603	0.605	0.069	8.798	0.000

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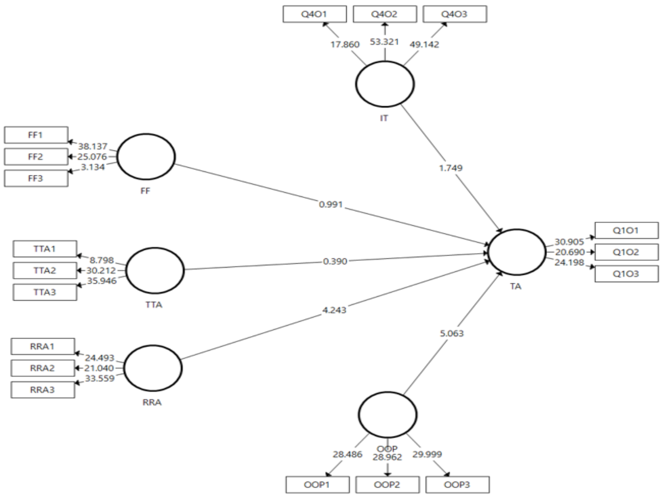
Research Article

TTA2 <- TTA	0.876	0.872	0.029	30.212	0.000
TTA3 <- TTA	0.884	0.882	0.025	35.946	0.000

The figure 1 shows the final purified analysis model which illustrates the relationship strengths of the observed relationships between latent variables and their indicators which were observed via SEM. Unobserved constructs like FF, OOP, RRA, TTA, TA and IT are connected to their observational variables (FF1, FF2...), and the causal or correlative effect between them is shown as paths with arrows. The numerical figures under the arrows e g 38.137 53.321 are the T statistics, providing a measure of the strength and significance of these relationships. Having a high value indicates that the relationships between the variables is significant and robust. For example, FF is very strongly related to its FF1, FF2 and FF3 indicators just like TTA and RRA are to their own factors. The model has been designed to investigate relationships between variables and how each latent factor is affected by its indicators, highlighting an archetype of the overall structure, post-purification.

Figure 1. Final conceptual model (after purification).



The next table 6 contains R Square and R Square Adjusted values for the TA variable. The R Square displayed is 0.547, which means that 54.7% of the variance of the TA variable is explained by the model, indicating a moderate relationship between TA and the independent variables. In contrast, R Square Adjusted is lower, at 0.538, which considers the number of variables in the model and adjusts for the risk of a "bicycle" model. The small difference between the two values indicates that the model is comparatively stable and the adjustment of the explanatory variables is moderate. That said, both measures suggest that the model explains a sizeable, yet moderate, proportion of the BP variance while also attaining a good fit.

Table 6. R square and R square adjusted.

R Square	**R Square Adjusted**
0.547	0.538

Table 7 shows the results of discriminant validity for the Fornell-Larcker criterion, which is applied to measure how much each latent variable is different from the others in a model. On the diagonal of the table, are shown the square root of the values of R Square of each latent variable representing the variance shared with itself. That is, example, the square root of the FF is 0.738, suggesting that FF accounts for approximately 54.5% of its variance. The other values on the outside of the diagonal represent latent variable correlations. According to the Fornell-Larcker criterion, for a latent variable to have discriminant validity, the square root of this latent variable's R square (on the diagonal) should be greater than the correlations with this variable and others. For

Journal of Information Systems Engineering and Management
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Research Article

instance, the square root R Square of TA is 0.819, and is larger than its correlations with those of FF (0.541), IT (0.604), OOP (0.669), and RRA (0.634), indicating that TA has discriminant validity with respect to the other variables. While certain variables are shown to correlate highly with one another, like IT and FF (0.746), or RRA and TTA (0.656), those levels aren't as high as the square root of the R square value concept, showing enough distinctiveness between the variables. Thus, the Fornell-Larcker criterion suggests acceptable discriminant validity of the latent variables in this model in general.

Table 7. Discriminant Validity according to Fornell-Larcker Criterion.

	FF	IT	OOP	RRA	YOUR	TTA
FF	0.738					
IT	0.746	0.852				
OOP	0.593	0.671	0.837			
RRA	0.535	0.588	0.610	0.802		
YOUR	0.541	0.604	0.669	0.634	0.819	
TTA	0.570	0.580	0.606	0.656	0.519	0.799

The table 8 summarizes the reliability metrics of the measured variables in the research, such as: Cronbach's Alpha, rho_A, Composite Reliability and Average Variance Extracted (AVE). Results demonstrate that the majority of the latent variables possess a high internal consistency, with Cronbach's Alpha values larger than 0.7, such as FF (0.897) and IT (0.810) suggesting strong reliability. Rho_A behaves similarly, with high scores for FF (0.891) and IT (0.833). With respect to the Composite Reliability, all latent variables, except for RRA (0.844) and TTA (0.837), present values greater than 0.7, indicating a good ability of the factors to explain the variance of the indicators. For AVE, most variables show an acceptable value above 0.5 except FF (0.544) and TTA (0.638), which also surpasses the threshold but with a fraction slightly less than 0.5. These results, in summary, indicate that the model has broad reliability, with quality indicators that are measurable and fall within acceptable parameters.

Table 8. Indicators of Research Reliability.

	Cronbach's Alpha	**Rho-A**	**Composite Reliability**	**Average Variance Extracted (AVE)**
FF	0.897	0.891	0.759	0.544
IT	0.810	0.833	0.888	0.726
OOP	0.786	0.787	0.875	0.700
RRA	0.726	0.742	0.844	0.643
YOUR	0.755	0.756	0.860	0.671
TTA	0.708	0.775	0.837	0.638

The table 9 demonstrates the variance Inflation Factor for different items which is an indicator for checking the multicollinearity of a model. A high VIF indicates high intercorrelation among the items, which can create problems of redundancy for the data. In this table, I give you the range of VIF ranging between 1.013 (FF3) and 2.464 (Q4O2). Generally, rule of then in many situations' states that FIV >5 or 10 means there would be multicollinearity but here, they are less than 3 in all cases, which indicates that there is no alarming multicollinearity in this model. As an illustration, Q4O2 has a VIF of 2.464, which is fairly high but acceptable. As another example, the value of FF3 (1.013) or RRA1 (1.321) is relatively low. In further summary, the FIVs demonstrate no concerning multicollinearity among the elements of the model, and linkages between the variables are sufficiently separate so as not to detrimentally affect coefficient estimation.

Journal of Information Systems Engineering and Management
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Research Article

Table 9. Presentation of the item VIF

Composite Reliability	Average Variance Extracted (AVE)
FF1	1.588
FF2	1.595
FF3	1.013
OOP1	1.670
OOP2	1.545
OOP3	1.771
Q1O1	1.578
Q1O2	1.534
Q1O3	1.460
Q4O1	1.440
Q4O2	2.464
Q4O3	2.257
RRA1	1.321
RRA2	1.541
RRA3	1.498
TTA1	1.166
TTA2	1.959
TTA3	1.846

To perform the fit of the saturated model and the estimated model, the table 10 summarizes several indicators that verify the quality of the fit. The values of SRMR (0.075) were equal in both models and below the threshold of 0.08 that indicates a good overall fit between model and observed data. As with d_ULS (0.959), d_G equals 0.425 and shows that the distance between the truth data and the model estimation is stable. The appropriate goodness-of-fit test is the Chi-Square (646.381), which is locked between two linearly independent models that demonstrate that the estimated model fits the saturated model well, which means that the overall quality of fit to all models is high. NFI (0.735) finally acceptable, but slightly lower than 0.8 threshold indicates a good fit. Overall, the fitted model provided us a good enough fit relative to the saturated model.

Table 10. Model Saturation and Estimation.

	Saturated Model	Estimated Model
SRMR	0.075	0.075
d_ULS	0.959	0.959
d_G	0.425	0.425
Chi-Square	646.381	646.381
NFI	0.735	0.735

DISCUSSION

Using a quantitative and descriptive approach, this research aims to explain the (factors) that determine the uses of artificial intelligence (AI) in the public sector in Morocco, in order to identify the main determinants for the adoption of AI in public services in the Moroccan context. - Using PCA, we were able to visually explore latent correlations between core components the likes of technical infrastructure, training for civil servants/public policy, resistance to change, etc. Now Being AI in crackdown on required point is, the above factors are characteristics of AI in implementation and their relation provides us important indication of the future AI technology used in public service which is beneficial for us. On tech adoption opening of tech infra is one of the major utilities point for the successful

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Research Article

adoption of AI, study further showed. However, with many of the infrastructures in Morocco being still nascent, particularly in rural regions, the access to an equal playing field with digital technologies is a sore point. Training and upskilling civil servants, also critical if AI is to be deployed in the most effective way, the study said. A workforce of public servants, many of whom have little direct experience working with advanced technologies, will need continued professional development in data science, AI tools, and digital governance if they are to meaningfully engage with AI.

Public policy and legal compliance became major drivers of AI adoption as well. Additionally, it was reiterated that regulations need to be put in place that protect the rights of citizens, and particularly their data protection and privacy, while enabling innovation. The study concluded that in delivering public service, Morocco has an insufficient legal framework that does not meet the ethical, legal and social issues arising from the use of AI behind the delivery of public service. The AI algorithms need to be transparent and the decision-making process needs to be accountable to make AI trusted and readily adopted by general masses. Among these barriers, revealing public fear of AI, and resistance to change in administrative practices stuck on one of heaviest. This kind of resistance should be dealt with by having a strong change management plan in place in the form of awareness campaigns, and nurturing the belief of the employees about the advantages of AI.

They utilized several strong reliability indicators to evaluate the quality of the data. As measured by Cronbach's Alpha and rho-A, internal consistency was satisfactory, indicating that the variables included in the analysis were reliable and consistent from sample to sample. We observe that the links between the respective variables were stable in the bootstrap results, providing more confidence that the relationships we are observing are not merely samples generating an artifact but are representative of some population trend. This was confirmed by model fit analyses and demonstrated the fit of the estimated model to capture the key relations in the utility space between the high-level factors driving AI adoption. These findings confirm that the model developed in this study appropriately and reliably represents the future research could be deepened through developing the analyses behind externalities such as government policy, political will, and citizen activism. These dimensions would provide a bigger picture on the adoption of AI and may help foster a favorable environment of AI usage by the public services. Investigate the roles of political actors, like policymakers and influencers in AI-related decisions, and people's perceptions and trust in AI, to understand the social impacts of the adoption of AI.

However, while this study carries certain advantages, some limitations can also be acknowledged. The research applied to a sample of public servants working as managers and experts in the education, health and general administration sectors, hindering its generalizability across sectors and also geographic settings. They did not include public services like transportation, justice and social services, which might face a different set of A.I. issues. Also, the subjective & behavioral dimensions of adoption of AI may be hard to perceive due to statistical bias. Integrating qualitative approaches. interviews and/or case studies — would give a better understanding of why certain barriers can become facilitators of the adoption of AI at the micro level.

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