National AI Strategic Plans for the Public versus Private Sectors: A Cross-Cultural Configurational Analysis

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Abstract

We use a fuzzy set Qualitative Comparative Analysis (fsQCA) approach to analyze the national Artificial Intelligence (AI) strategic plans of 34 countries. Applying Hofstede's four-dimension cultural model, we find that countries develop their national AI strategic plans around public and private sector policies in a manner that is consistent with their national cultures and, if they only place emphasis on one, it will generally be on industry. We also find that the most critical differentiators between detailed versus limited plan development are task/people orientation and individualism/collectivism, where high collectivism and high task orientation are linked to more detailed national AI plans and policies.

Keywords: Artificial Intelligence, Public Sector, Cross-Cultural Study, Content Analysis, Qualitative Comparative Analysis

1. Introduction

Long-range planning is an important activity for any organization to understand environmental changes and to formulate strategies to remain competitive in a rapidly changing world (Ang & Chua 1979). This is particularly true for national governments who need to engage with both internal and external stakeholders to discuss and debate changing conditions (Nutt 1989). The process of planning helps the nation to set out its vision and ambition for key policy areas and to lay out their rationale for these choices (Moxley 2004). Unlike the private sector who can make long-term planning decisions around the unifying goal of shareholder value maximization, the public sector has to account for political reforms, public expectations and a heightened vulnerability to external environmental conditions (Ring & Perry 1985). This variety of stakeholders complicates the long-term planning process and also influences the elements of the plan itself (Ramamurti 1987).

The rise of artificial intelligence (AI) has captured the interest of the public sector (Yeung 2020) and there have been calls in public administration research to examine AI in the context of public policy (Reis et al. 2019) including cross-national differences in AI adoption and regulation (Wirtz et al. 2019). A variety of AI systems have already been deployed across government (Desouza 2018).

As a result of the rise of AI, a total of 34 countries have developed and issued their own national AI plan as a long-term planning tool. Many of the countries followed the framework suggested by the World Economic Forum (WEF) for the development of these plans (WEF 2019). According to WEF, these national AI frameworks should include such things as the nation's motivation for AI adoption at the national level as well as their strategic priorities, objectives for capacity building and establishment of regulatory control to oversee the process.

However, research into the 34 known national AI strategic plans has shown vast differences between countries but, at present, it is not known why these differences exist (Fatima et al. 2020; van Berkel et al. 2020). Certainly differences in national cultures have been shown to be relevant in other domains, outlined in our literature review below, and so our research question is:

- *RQ: How does national culture explain differences in national artificial intelligence plans in the public and private sectors?*

This paper is structured in six sections. Following this introduction, the second section is a literature review of AI in government and the impacts national culture and Hofstede's cultural dimensions. The third section describes the research methodology including both data collection and analysis. The results are presented in the fourth section and discussed in the fifth. The final conclusions are then set out.

2. Literature Review

2.1. Artificial Intelligence in Government

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The Organisation for Economic Co-operation and Development (OECD 2019) defines an AI system as a "machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments. It uses machine and/or human-based inputs to perceive real and/or virtual environments; abstract such perceptions into models; and use model inference to formulate options for information or action. AI systems are designed to operate with varying levels of autonomy." With modern government, AI has been identified as an important extension of digital transformation (Reis et al. 2019). Ahn and Chen (2020) envisioned AI-augmented bureaucracy as an evolution beyond IT-enabled bureaucracy. The older form is typified by recent, sampled, medium quality data; a technology base of statistical programs, computer processing and the internet assisting human decision making; and improved outcomes in service delivery and standardized solutions to citizens, yielding e-government. The newer form is typified by real-time, complete, high quality data; a technology base of machine learning, big data and cloud computing supporting algorithm-based decision making; and detailed understanding of citizen needs, customizable services, enhanced planning and predictive governance, yielding smart-government.

Applying a public policy cycle framework to AI, Valle-Cruz et al. (2019) identified different challenges in each stage of agenda-setting, policy formulation, policy implementation and policy evaluation. Respectively, those challenges included the cumbersome nature of democratic processes; noisy data and the digital divide; goal displacement and loss of individual responsibility; and data obsolescence and homogeneity. Wirtz, Weyerer and Geyer (2019) identified four major dimensions of AI challenges for governments: AI technology implementation, AI law and regulation, AI ethics, and AI society. To address these various challenges, governments need to develop and implement policies that align with national goals and objectives. Research into national AI policies has found that countries approach the use and governance of AI in different manners (Fatima et al. 2020, 2021, 2022).

2.2. Impacts of National Culture

National culture, which is defined as the homogeneity of characteristics that separates one human group from another (Hofstede 2001), provides a society's characteristic profile with respect to norms, values, and institutions, and affords an understanding of how societies manage exchanges (Hofstede 2001).With the fast pace of globalization in business and the increasingly integrated global economy, the role of national culture has been the topic of numerous recent studies focusing on various aspects of human behavior in cross-cultural business.

At the individual level, several studies have investigated the impact of national culture on behaviors including adoption of innovation (Lim and Park 2013), online review behavior (Lai et al. 2013), perception of quality, value, satisfaction and behavioral intention. This stream of researches has also given some special attention to business leaders and has shown the impact of national culture on leadership effectiveness (Den Hartog et al. 1999; Li et al. 2013), managers' perceptions in project management (Rees-Caldwell & Pinnington 2013), their ethical decision-making behavior (Beekun & Westerman 2012) and their perceptions about ethical behavior in intra- and cross-cultural negotiations (Elahee et al. 2002).

At the firm level, national culture has been demonstrated to have effects on organizational learning behavior (Skerlavaj et al. 2013), firms' entry mode in another country (Slangen & van Tulder 2009) and foreign market acquisitions (Malhotra et al. 2011), firm's investment in training and development (Coget 2011), firm's capital structure decision (Li et al. 2011), knowledge resources sharing in inter-organizational relationships (Griffith & Harvey 2001) and formation of technology alliances by entrepreneurial firms (Steensma et al. 2000).

At the national level, Nordic AI strategies have been shown to uphold national values of privacy, ethics, autonomy and democracy (Robinson 2020). However, other studies have shown misalignment between fundamental values and AI strategies, especially in countries that have advanced the furthest in AI development (Viscusi et al. 2020). These mixed findings of value consistency lead to questions regarding the national cultures that lead to them.

2.3. Hofstede's Model

Several frameworks of national culture exist (Clark 1990; Hofstede 2001; House et al. 2004; Inglehart 1990; Triandis 1995), among which, Hofstede's (2001) work is one of the most widely used in management. In his initial study, Hofstede surveyed 117,000 IBM employees from across 50 different countries and, using a factor analysis, derive four value dimensions; Power Distance, Individualism / Collectivism, Uncertainty Avoidance (UA), and Task / Person Orientation (formerly Masculinity / Femininity). Hofstede (2001) argued that a country can be positioned along these dimensions to provide an overall summary of a country's cultural type (Griffith et al. 2006) and that these values are relatively fixed over time.

Power Distance reflects the strength of the social hierarchy. Countries with high power distance (e.g. Qatar and Russia) accept that power is unequally distributed to members of society. Therefore, in a high power distance country, individuals accept status differences and are expected to show deference to their superiors (Ghemawat & Reiche 2011). In a lower power difference country (e.g. Finland and New Zealand), life tends to be egalitarian and subordinates expect to be consulted on work processes by their bosses.

Individualism/*Collectivism* refers to the degree to which individuals are expected to be integrated into groups. In a highly individualistic country (e.g. U.S. and Australia), people tend to maintain a loose social structure that is characterized by independence, individual rights and a recognition and respect of personal initiative and achievement (Ghemawat & Reiche 2011). Highly collective countries (e.g. China and Korea) place greater emphasis on their membership in the group rather than their own individual goals.

Uncertainty Avoidance (UA) reflects a country's tolerance for uncertainty. A country (e.g. Denmark and Singapore) with a low UA is more willing to accept and deal with ambiguous or risky situations. Countries with high uncertainty avoidance (e.g. Portugal and Poland) favor structure and predictability, which result in explicit rules of behavior and strict laws (Ghemawat & Reiche 2011).

Task/Person Orientation (formerly masculinity/ femininity) addresses the traditional emotional roles between men and women. Highly masculine/task-oriented countries (e.g. Japan and Austria) are more concerned with competitiveness, assertiveness, material success and power while highly feminine/person-oriented countries (e.g. Sweden and Norway) more value relationships, quality of life and concern for marginalized groups (Ghemawat & Reiche 2011).

2.4. Propositions

Some researchers have suggested that national cultural values can affect the interests, priorities, and the strategies that people use in dealing with their business partners (Brett 2007). For example, societies characterized by high long-term orientation tend to be more oriented toward building up a long-term relationship with the business partners (Barkema & Vermeulen 1997). People in such a culture tend to spend a lot of time and effort in establishing trust and commitment with their business partners over a long series of business interactions, therefore, they may refrain themselves from opportunistic behaviors in order not to ruin the long-term relationships. Other national cultural dimensions such as power distance and individualism have also been found to moderate the relation between human development and negative behaviors such as corruption (Sims et al. 2012). Differences in individualism has been suggested as a potential explainer of differences in opportunistic behaviors among cultures (Chen et al. 2002).

Within the field of AI policy, nations have been seen to cluster geographically and characteristically in their approaches to defining policy, where similar countries create similar strategies (van Berkel et al. 2020). Specific to e-government development, individualism and task-orientation have been consistently found correlated and uncorrelated, respectively, to e-government development, but power distance and uncertainty avoidance have had conflicting results, depending on the study (Kovacic 2005; Zhao 2011, 2013; Kumar et al. 2020). Findings regarding innovativeness and national culture have similarly found that the relationship with individualism is fully supported, but with the other three original dimensions is only partially supported (Prim et al. 2017). Finally, the underlying values held by countries have also been identified as informing their AI strategy development (Robinson 2020; Viscusi et al. 2020). In short, there is reason to believe that these dimensions may impact the development of national AI plans, in that some may be more comprehensive and detailed than others.

Considering these findings, we believe that there will be differences in the content of national AI plans based on Hofstede's dimensions but we recognize that no research has systematically examined this issue across a range of countries. With this study, we aim to fill this gap in research, exploring the relationship between national culture and national AI plans.

Based on our analysis of the national culture literature, we propose that plan development is related to the four Hofstede dimensions for each country. As such, we build two separate propositions since, using configurational logic and assumptions of causal complexity, confirmation of one proposal does not automatically assure disconfirmation of the other.

- *Proposition 1a: There are synergistic configurations of the four Hofstede dimensions that lead to areas of highly detailed plan development.*
- *Proposition 1b: There are antagonistic configurations of the four Hofstede*

dimensions that lead to areas of lower detailed plan development.

3. Methodology

3.1. Data/Operationalization

We used a dataset comprised of 34 countries based on those listed by the Observatory of Public Sector Innovation (OPSI) (OPSI 2020; Fatima et al. 2020). To create the dataset from these 34 countries, we undertook a content analysis of the published strategic plans and identified emergent themes and codes within them (Weber 1990). For this exploratory work, coding was iterative, using emergent themes rather than a planned coding scheme (Dey 1993). NVivo data analysis software was used to document the content analysis while building the ultimate list of six themes –Public Sector Functions, Industry, Data, Algorithms, AI Governance and Capacity Development (QSR 2020). A test of inter-rater reliability was conducted using ten plans and two coders, with a rate above 90% accuracy (Miles & Huberman 1994).

AI has the potential to bring together public and private sectors, with policy makers experiencing both positive and negative effects of that collaboration (Reis et al. 2019). Therefore, the two outcome themes we are using for the present analysis are Public Sector Functions and Industry as they represent the public and private sector applications of AI respectively. Many plans detailed how governments should leverage AI to digitize and revitalize the public sector while many others suggested how industries in the private sector could create or sustain competitive advantage through AI (Fatima et al. 2021, 2022). The public sector theme included the following elements: Healthcare Transportation; Education; Environment and Natural Resources; Energy and Utilities; Information and Communication Technologies; Public Safety; Defense and National Security; Courts and the Judiciary; Revenue and Tax; and Immigration, Customs, and Border Protection. The industries theme included the following elements: Healthcare; Agriculture; Information Technology; Manufacturing; Energy and Natural Resources; Financial; Defense; and Tourism. Each theme in a national plan was operationalized by scoring by the number of elements that appeared in a theme and then normalizing the score on a scale of 0 to 1, where low outcome is represented by a score below 0.5 signifying a plan with limited scope and a high outcome is represented by a score above 0.5 signifying a plan with a detailed scope. For the national culture conditions, recognizing the current study is exploratory, we apply the more limited original four dimension Hofstede model (Hofstede 2001) rather than the extended six dimension model. Data were taken from the most current national assessments (Hofstede Insights 2023).

3.2. Qualitative Comparative Analysis

Given our supposition that Hofstede dimensions operate together and not independently, we expect causal complexity of the phenomenon of interest and so adopt a set-theoretic approach. This approach identifies common relationships between configurations of multiple causal conditions and a set of outcomes (Fiss 2007), where causal conditions are defined as “an aspect of a case that is relevant in some way to the researcher’s account or explanation of some outcome” (Ragin 2008 p. 18). Set-theoretic methods embrace causal complexity by allowing for combinations of components to lead to an outcome rather than a single factor and that the same antecedent can positively or negatively contribute to outcomes in different combinations (Ragin 2000). Additionally, set-theoretic methods allow for equifinality – that there may be many equally valid paths to the same outcome (Ragin 2000). Finally, set-theoretic methods are oriented to determining whether a condition or set of conditions are necessary – the condition or set of conditions is always present when the outcome occurs – and/or sufficient – the outcome always occurs when the condition or set of conditions is present (Ragin 2008). A set-theoretic approach can be used to capture both the causal complexity and equifinality components of configurational relationships in a parsimonious form (Fiss 2007).

One particular method within the family of set-theoretic approaches for operationalizing and testing configuration theories is through Qualitative Comparative Analysis (QCA), which combines qualitative (case-based) and quantitative (variable-oriented) techniques (Berg-Scholsser & De Meur 2009). Fuzzy-set Qualitative Comparative Analysis (fsQCA) is a type of QCA with condition scores in the interval between 0 and 1, representing being fully-in and fully-out of the set of interest (Ragin 2008). QCA is ideal when working with an intermediate number of cases (generally defined as 30-50), although there is no procedural limit to greater numbers of cases being used (Berg-Scholsser & De Meur 2009).

QCA is generally divided into three steps: data table construction, truth table construction and logical reduction (Fiss 2011). First, a data table is constructed by converting the raw data into its operationalized form where each respondent becomes a case with the value of each condition between 0 and 1, representing the degree of absence or presence of the condition and hence set membership, through the process of calibration (Fiss 2011). Calibration involves determining points of full membership and full non-membership and a point of maximum indifference regarding membership in order to transform raw scores into the degree of set membership in the interval between 0 and 1. As elements of the dataset were skewed both left and right, values were normalized calibrated around the median as the crossover point (0.5) with fully-out (0) and fully-in (1) set two standard deviations from the median. The second step is designed to reduce the number of rows to a truth table, which is a table of configurations that shows how each configuration yields a particular outcome. The third step addresses the logical reduction of the truth table into simplified combinations by making inferences about the presence or absence of non-observed data that can simplify a solution (Ragin 2000).

Consistency and coverage are two important concepts to consider in the evaluation of QCA solutions. Consistency is the degree to which a relation of necessity or sufficiency between a combination of conditions and an outcome is met within a given set of data (Fiss 2007). Consistency can range from 0 (indicating no consistency) to 1 (indicating perfect consistency). Consistency is reported as raw, but there is also an error-correcting version of consistency known as Proportional Reduction in Inconsistency (PRI) that eliminates the influence of cases where the causal condition is a subset of both the outcome and the negation of the outcome (Mendel & Ragin 2010). A raw consistency of 0.75 and a PRI consistency of 0.50 are considered the minimums, which were adopted for this study (Rihoux & Ragin 2008). Coverage is a measure of empirical relevance that captures the degree of overlap between sets or between a set and the overall solution space, again ranging from values of 0 to 1 (Fiss 2007). Coverage can be either unique to a particular configuration or shared between configurations (Rihoux & Ragin 2008). Consistency resembles the correlational concept of significance whereas coverage resembles the concept of R-squared (Schneider & Wagemann 2010). Conditions can be core or peripheral, with the former having a stronger causal relationship with the outcome than the latter based on their different treatment of redundant and unobserved conditions (Fiss 2011; Ragin 2000).

4. Findings

4.1. Qualitative Comparative Analysis

We first conducted a necessary conditions analysis (NCA) and found there were no single necessary conditions of the four Hofstede dimensions and either of the two outcome variables (high and low performing). All single conditions were below 0.900 consistency, which is the threshold for identifying a necessary condition. This indicated that the Hofstede model elements work in combination and not individually.

The fsQCA was conducted using QCA with R version 3.18 (Dusa 2023). As part of the analysis, three solutions are generated – parsimonious, intermediate and complex (Fiss 2011). Complex solutions are exhaustive, listing every combination; intermediate solutions include the addition of a redundant, unobserved condition to simplify the solution; and parsimonious solutions include both the addition and removal of redundant and unobserved condition (Ragin 2008). Core configurations are identified by their appearance in both intermediate and parsimonious solutions and peripheral in just the intermediate solution (Fiss 2011). The notations identified in Table 1 are adopted from previous studies (Fiss 2011).

Indicator	Description
⬤	Necessary presence of a core condition
●	Necessary presence of a peripheral condition
⨂	Necessary absence of a core condition
⊗	Necessary absence of a peripheral condition
Blank ( )	Presence or absence of the condition does not impact on the outcome
High	High performance outcome configuration
Low	Low performance outcome configuration
PwrDist	Power Distance (condition)
Indiv	Individualism (condition)
Uncert	Uncertainty Avoidance (condition)
Task	Task Orientation (condition)
PubFunc	Public Service Functions (outcome)
Ind	Industry (outcome)
XXX	Boolean expression – necessary presence
~XXX	Boolean expression – necessary absence

Table 1. fsQCA Terms Explained

The solutions for both Public Sector Functions and Industries are presented in Table 2. For high Public Sector Functions, there were three configurations. The first had high power distance but low individualism and task orientation and included Singapore, Korea, Malta, Portugal, Russia, Serbia, Spain and Uruguay. The second had high power distance but low individualism and uncertainty avoidance and included Singapore, China, India and UAE. The third had high uncertainty avoidance and task orientation but low power distance and included

Austria and Italy. The first two configurations are variations on a theme – high power distance countries with low individualism plus either uncertainty avoidance or task orientation – and are represented by eastern, authoritarian and southern European nations. The third high-performing configuration is diametrically opposed to the first two – low power distance but high uncertainty avoidance and task orientation – and includes more liberal states in south-central Europe.

For low Public Sector Functions, there were two configurations. The first had high individualism but low task orientation and included Denmark, Estonia, Finland, France, Lithuania, Luxembourg, Netherlands, Norway and Sweden. The second had high power distance, individualism and uncertainty avoidance, and included Belgium and Poland. The two configurations are variations on a theme of high individualism within European nations - primarily Baltic and north-western.

Configuration	Public Sector Functions					Industries		
	High			Low		High		Low
	1	2	3	1	2	1	2	1
Power Distance	•	•	⊗		⬤	•	⊗	
Individualism	⊗	⊗		⬤	⬤	⊗	⬤	⬤
Uncertainty Avoidance		⊗	•		•	⊗	⬤	
Masculinity	⊗		⬤	⊗			⬤	⊗
Consistency	0.81	0.89	0.85	0.80	0.77	0.77	0.76	0.81
Raw coverage	0.37	0.25	0.24	0.46	0.20	0.22	0.18	0.43
Unique coverage	0.15	0.09	0.13	0.31	0.05	0.19	0.15	-
Overall consistency	0.81			0.78		0.76		0.81
Overall coverage	0.59			0.51		0.37		0.43

Table 2. fsQCA Results

For high Industry, there were two configurations. The first had high power distance, but low individualism and uncertainty avoidance, and included China, India, Singapore, and UAE. The second had low power distance but high individualism, uncertainty avoidance and task orientation, and included Italy. The two configurations are almost diametrically opposed (as Italy has high task orientation too), demonstrating equifinality as there are very different paths for the groups.

For low Industry, there was a single configuration, which had high individualism but low task orientation, and included Denmark, Estonia, Finland, France, Lithuania, Luxembourg, Netherlands, Norway and Sweden, which were included in the list of north-western European and Baltic countries that appear in the Public Sector Functions analysis.

Because various Hofstede dimensions led to high plan development (for both industry and public sector functions) and low plan development (for both industry and public sector functions), we find support for both of our research propositions.

4.2. Post-Hoc Analysis

Noting in Table 2 that there were visible differences in the high and low public and private sector configurations, we conducted a post-hoc analysis of the intersection of the Public Sector Functions and the Industry high and low outcome solutions. This was executed using Boolean operands to combine the solution equations with the intent of seeing commonalities and differences between the public and private sector paths to high and low outcomes. The tilde (~) represents a necessary absence of a conditions while no tilde represents a necessary presence; the asterisk (*) is a logical AND while the plus (+) is a logical OR; and the arrow (->) is a leads-to or results-in relationship.

(1) PwrDist*~Indiv*~Task + PwrDist*~Indiv*~Uncert + ~PwrDist*Task*Uncert -> PubFunc
(2) PwrDist*~Indiv*~Uncert + ~PwrDist*Indiv*Task*Uncert -> Ind
(3) Indiv*~Task + PwrDist*Indiv*Uncert -> ~PubFunc
(4) Indiv*~Task -> ~Ind

4.2.1. High AI policy outcomes (1 and 2).

PubFunc.AND.Ind: PwrDist*~Indiv*~Uncert + ~PwrDist*Indiv*Task*Uncert
PubFunc.NOT.Ind: PwrDist*~Indiv*~Task*Uncert + ~PwrDist*~Indiv*Task*Uncert
Ind.NOT.PubFunc: Nil

4.2.2. Low AI policy outcomes (3 and 4).

~PubFunc.AND.~Ind: Indiv*~Task
~PubFunc.NOT.~Ind: PwrDist*Indiv*Task*Uncert
~Ind.NOT.~PubFunc: Nil

4.2.3. Simultaneous high and low AI policy outcomes (1 and 4 or 2 and 3).

PubFunc.AND.~Ind: Nil
~PubFunc.AND.Ind: Nil

We illustrate the intersections in Table 3, where green indicates high outcome and yellow indicates low, while dark shading and bold text indicates both are high or low and light shading and italics text indicates only one outcome is present. For example, Austria, Japan and others are high in Public Sector Functions but medium in Individualism, therefore they are represented in the light green shading with italics.

		Public Sector Functions		
		High	Med	Low
Industry	High	**China** **India** **Italy** **UAE** **Singapore**	Nil	Nil
	Med	*Austria* *Japan* *Korea* *Malta* *Portugal* *Russia* *Serbia* *Spain* *Uruguay*	Australia Canada Czechia Germany Mexico NZ Qatar UK USA	*Belgium* *Poland*
	Low	Nil	Nil	**Denmark** **Estonia** **Finland** **France** **Lithuania** **Luxembourg** **Netherlands** **Norway** **Sweden**

Table 3 – Intersection of Solution Sets

5. Discussion

In the necessary conditions analysis, we found that no single condition was necessary for any of the outcomes. This finding demonstrates that Hofstede's dimensions operate in conjunction with each other and not independently. As the dominant paradigm in IT remains variance perspective based (Fichman 2004), this opens up avenues for cross-cultural IT research to take a systems perspective or combined approach that may improve understanding of the phenomenon of interest (Levallet et al. 2020).

From the fsQCA, the common factor for high versus low Public Service Functions was individualism. It appears that the more collectivist nations were more likely to deploy government-to-citizen facing AI. This would be understandable considering the tighter social structures and expectations of government to support them in collectivist nations (Ghemawat & Reiche 2011). However, it is also possible that the underlying rationale could be different depending on the intent of the nation, with more democratic collectivist nations deploying AI to support and serve their citizens and more authoritarian nations deploying AI to monitor and control them (Fatima et al. 2021).

There were few definitively common factors for high or low Industries solutions from the fsQCA, but one that appears to operate is task orientation, where a high value is linked to high private sector policy. High task orientation countries are very focused on competitiveness, which is a primary driver of activity in the private sector (Ghemawat & Reiche 2011). This would support the task orientation of the government and its citizens to use AI to drive industry competition and success.

From the post-hoc analysis, our first observation was that there was a significant overlap between Public Sector Function and Industry configurations, in that nations that were high in one were generally high in both and that those that are low in one are usually low in both. Given that there were no intersections between the two opposing solution sets (i.e. no high/low outcome combinations), we found that the present or absence of one generally implied the same for the other. This would suggest that governments look at AI policy holistically and seek to set (or fail to set) broad policy frameworks both public and private sector uses of AI.

Our second observation from the intersection of solution sets was that while there were configurations that were present for Public Sector Function solutions, but not Industry solutions, the reverse was not true. That is, if a nation had a robust public sector AI policy then it may or may not have a robust private sector AI policy, but if they had a robust private sector policy, then they must have a robust public sector one. The corollary (using the QCA characteristic of asymmetry) is that if they lacked a robust public sector AI policy then they may or may not lack a strong private sector policy, but that if they lack a robust private sector policy then they must necessarily lack a strong public sector one too. This would suggest that countries are either leading with their industry focus or co-developing their public and private sector AI policies.

				Uncertainty avoidance			
				High	Low	High	Low
				Masculinity			
				High	High	Low	Low
Power Distance	High	Individualism	High	*Belgium* *Poland*		**France**	
	Low		High	**Italy**	Australia Canada Germany NZ UK USA	**Luxembourg**	**Denmark** **Estonia** **Finland** **Lithuania** **Netherlands** **Norway** **Sweden**
	High		Low	Czechia Mexico Qatar	**China** **India** **UAE**	*Korea* *Malta* *Portugal* *Russia* *Serbia* *Spain* *Uruguay*	**Singapore**
	Low		Low	*Austria* *Japan*			

Table 4 – Configurations in Hofstede's Model

Applying the post-hoc analysis results to the cross-cultural framework, we illustrate how the configurations mapped onto the four Hofstede dimensions in Table 4, using the same notation scheme as in Table 3.

In the upper right quadrant of the table high individualism and low task orientation group all the countries who were low in both public and private sector AI strategic plan development. Conversely, in the lower half of the table are low individualism nations in the high outcome for public sector or both. Italy is the only high outlier in the high individualism group, but when examining the low outlier of Belgium and Poland, it is possible that high task orientation offsets or dominates the effects of high individualism.

We highlight that there were two groups that were not captured in the analysis and posit that this was likely due to low consistency of AI policies between the members. In the case of Czechia, Mexico and Qatar, while the countries may have similar dimensions in Hofstede’s model, they are vastly different countries in terms of geopolitical realities and pressures, even simply on the axis of democratic/authoritarian that may drive very different needs for AI policy. These differences bear further investigation through the six-dimension Hofstede model to tease the countries’ profiles further apart.

In the case of Australia, Canada, Germany, New Zealand, UK and USA, these are a relatively homogenous group of western European and former British colonial countries who generally share a common world view. However, a deeper look into their AI strategic plans demonstrates significant differences in the level of investment among nations, with neighboring Canada and the USA having two of the least and most well-developed AI plans respectively. These stark differences cannot be explained under the current cross-cultural model and thus bear further investigation, whether through application of the six-dimension Hofstede model or of other frameworks.

In comparison to other studies that found only individualism to be consistently correlated to e-government development or innovation Kovacic 2005; Zhao 2011, 2013; Prim et al. 2017; Kumar et al. 2020), we find that if Hofstede’s dimensions are viewed as a portfolio of national culture rather than independent dimensions of it, then all of them contribute to the development of AI policy. This is demonstrated by the NCA, which showed that no single condition was necessary, and the appearance of all four conditions in solution configurations. We believe that the configurational approach taken in this research uncovers a causal complexity in the application of Hofstede’s model that has been hitherto unacknowledged. We do acknowledge, however, that individualism appeared the most frequency in solutions, which would support previous findings of its importance in e-governance development, including, now, AI.

6. Conclusion

This study yields numerous important research findings. First, we find that governments generally develop national AI strategic plans around public sector and private sector policies consistent with the national cultures. Second, we find that countries normally develop their private and public sector plans consistently, but if they do not, then they put the emphasis on the private sector applications of AI. Third, we find that a combination of low task-orientation (i.e. people-orientation) and high individualism are linked to low investment in both public and private sector AI policy development while low individualism (i.e. high collectivism) is frequently linked to high investment in both. Finally, we find that Hofstede's dimensions do not act independently of each other, but rather do so in cohesive and consistent combinations.

This study yields several important implications for practice. First, there is no single national culture that leads to a highly effective and detailed national AI policy. Even countries that are predisposed to less detailed plans can overcome the tendency through dint of effort. Second, even countries with highly similar national cultures can have different AI policies. However, as AI is a new field we expect convergence over time as allies share best practices in AI with like-minded nations. Finally, countries that invest in AI strategies will generally advance both public and private sector policies at the same time. So, the important consideration is for policy makers to start the process and invest, not in which to invest.

Like all studies, our study has certain limitations. First, AI policy is a fast-moving area and governments may change their approaches in the face of public attention or external pressures. The national policies examined were extant at the time the study was conducted, but may have changed since or may change in the future. Second, the Hofstede model has been criticized for its development methodology and applicability to diverse populations. In applying Hofstede’s model we adopt the aphorism that “all models are wrong, but some are useful,” as in spite of its limitations, it does have research value in differentiating national cultures. We encourage future research using other complementary and competing models of national culture.

In conclusion, nations construct their own AI strategic plans and policies independent of each other. However, societies guide the hands of their governments and we find that the national characteristics of similar countries paint similar pictures of the future of AI in both the public and the private sectors.

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