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INNOVATIVE AI TOOLS FOR DIGITAL BUSINESS TRANSFORMATION WITH A FOCUS ON DATA MANAGEMENT AND AUTOMATION OF KEY PROCESSE

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ABSTRACT

This study aims to determine whether companies' management of data and AI-driven automation contributes to operational flexibility and competitiveness, focusing on highly specialized businesses. The authors employ a global perspective using expert judgment, cross-country comparisons, compliance with international standards (ISO/IEC 27001:2022, ISO/IEC 38505-1:2021, ISO/IEC 42001:2023), and combined quantitative tools within the "Digital Transformation Integration Index" (DTII) model. Empirical research focuses on the UAE, Ukraine, and Singapore, each with distinct regulatory regimes, technical infrastructures, and organizational maturity levels. Digital capability is assessed through three factors: data governance capacity (DGC), AI automation performance (AAP), and organizational readiness for AI adoption (ORA). Results establish a hierarchy of digital maturity. Singapore achieves the highest DTII score (.94) due to robust data governance, advanced automation, and strong organizational capabilities. The UAE scores second (.815), benefiting from rapid public-sector modernization and fast AI implementation, presenting significant scaling opportunities. Ukraine's DTII score (.584) reflects improving digital skills and automation but highlights the need for enhanced infrastructure and regulation, described through a "transitive growth" model. Sectoral AAP analysis shows Singapore leading (88–95), the UAE with high but uneven performance (79–90), and Ukraine at average levels (63–78). Differences are also observed in cultural orientation toward innovation, managerial digital literacy, and institutional readiness for AI adoption, as measured by ORA. The study provides a comprehensive analytical framework to evaluate a company's or country's preparedness for digital transformation and to guide strategic priorities. Its findings can support corporate digital strategy development, enhance data management systems, streamline AI-driven workflows, and inform policies to stimulate digital economy growth, particularly in developing countries.

Keywords: *Digital Transformation, Artificial Intelligence, Information Governance, Process Automation, Planning Readiness, AI Integration, Business Analytics, Digital Strategy, Innovation, Systems, Sustainable Development.*

1. INTRODUCTION

The need for developing strategies to create capabilities and governance structures is an integral component of the overall objective of this initiative to develop an alternate approach to increasing productivity. Organisations around the globe have adopted a number of different methods of applying Artificial Intelligence (AI) to transform their organisations Organisations have created enterprise models of business as a result of the organisation's enterprisestrategy (and the enterprise strategy as a function of the business orientation). Process awareness has studied both the processes and how to utilize automated tools to assist with the changes to the processes. Integration has studied the concurrent usage of AI, Blockchain, and Cloud infrastructures as the basis of large-scale business ecosystems [1]. There is considerable conflicting evidence in the literature relating to the performance implications of digital transformations, especially when organisational readiness is low [2]. In addition, there are many organisations that are developing and implementing AI-based products prior to establishing the required managerial and/or cultural foundation to support these products. This will ultimately limit their ability to achieve the full potential [3]. In addition, the world has not resolved a number of long-standing issues relating to the quality of measurements, the reliability and quality of analytics and automation [4]. Additionally, the lack of competency models will represent a barrier to the future adoption of digital transformations and will add additional operational risk [5].Currently, researchers concur that the major impediment to the majority of organisations is the need to develop integrated data governance models and frameworks to scale AI safely [6,1].Therefore, the results of the digital transformation have varied widely depending on the geographic location and industry in which the organisation operates. That is why we selected this topic; because it represents a significant problem that will present an excellent opportunity for a research question. In general, the application of artificial intelligence (AI) typically does not result in long-term improvements in performance; however, the application of AI is often limited by institutional-level governance, process automation and readiness [7]. Although, there is a substantial body of literature focused on studying individual domains, such as automation and/or strategy, there are few examples of studies that consider the inter-domain interactions, which are common today [8,9]. There is presently a gap in the current literature pertaining to the relationships between data governance, AI automation and institutional capacity. Our motivation for undertaking this research was an applied interest in understanding how organisations can use AI technology to realise the advantages of AI within their own national environment. To achieve successful outcomes, this will necessitate the co-existence of both technical and managerial competencies to successfully deploy AI technology. In addition, organisations wish to understand where they should allocate their resources and how they can synchronise the sustainable implementation of AI technology with their national economic development objectives. Because an international environment is a good example of a transitional case study of how an organisation can adapt to a global technological shift, we therefore selected the Ukraine as our transitional case study. Companies from the Ukraine are at the forefront of the rapid development of digital skills and automation [10]. However, there is a level of governance compliance and structural constraints in terms of infrastructure capacity [11]. It is this combination, which we believe will enable us to view the Ukraine as an exemplar model to examine the regional and international variations relative to the three variables (i.e. organisational readiness; AI-based automation and data management). The goal of this research is to identify the intersection of AI-based automation and data management and organisational readiness across diverse national environments. The paper addresses a void in the literature and presents empirical evidence by investigating the three variables mentioned previously as a collective unit rather than individually. The findings of this research have implications for both theoretical knowledge and application in both business and policy, and additionally, have implications for areas of scientific inquiry.

The scope of this paper covers three areas related to AI-enabled digital business transformation: data governance, AI automation, and readiness for AI adoption in business environments. The paper does not cover all the aspects of digital business transformation, such as digital marketing, digital platforms, consumer behavior, and the digitalization of the business and economic environment as a whole. Instead, the paper aims to review the various ways in which companies and business environments create the conditions required for effective data management, AI automation, and readiness for digital transformation.

The main contribution of this paper is the development of the Digital Transformation Integration Index (DTII). This index allows for the measurement of the three different aspects of digital business transformation related to AI: data governance, AI automation, and readiness for AI adoption. The DTII contributes to the existing literature on digital business transformation in two main ways. First, the model extends previous research on the topic by considering all three aspects of digital business transformation related to AI as interconnected elements of the overall digital business transformation process. Second, the model also provides a tool that businesses can use to recognize weaknesses in their digital business transformation processes related to data and AI. Furthermore, policymakers could utilize the DTII to develop effective digital business transformation strategies for businesses and nations alike.

The problem to be solved in this dissertation is the imbalance that exists between the technology and non-technological aspects of the AI implementation in the business. While there have been numerous studies on the importance of AI automation, data governance, and digital strategy in business, these aspects have mostly been studied separately. However, there has been a lack of studies investigating the impact of data governance, AI automation, and organizational readiness on digital transformation in business.

Considering the problem to be solved in this dissertation, the following research questions will be answered:

RQ1. What is the interaction between data governance capacity, AI automation performance, and organizational readiness in the context of AI-enabled digital business transformation?

RQ2. How do the leading economies of Ukraine, UAE, and Singapore differ in terms of their digital transformation maturity?

RQ3. In what ways can the DTII model help to identify weaknesses in the AI-enabled digital business transformation in the studied countries?

The aim of this study is to demonstrate how new AI-based tools are modifying the digital transformation of businesses - specifically in relation to processing data and processes as part of this process. This paper has an objective to investigate how the variables affect the application of artificial intelligence (AI), and in addition, it also wants to compare the rate at which digital transformations occur in different countries, whether they are applicable to the degree of modification and what circumstances will enable the successful scaling of AI for companies. Despite the growing number of existing studies on the topic of AI-driven digital transformation of organizations, the available literature on the subject is fragmented. Most research has investigated aspects of AI-driven digital transformation separately, such as AI-based automation, data governance, business strategy, or organizational readiness for digital transformation. Such separate investigations limit knowledge about how these aspects of digital transformation interact within organizations and how the imbalance between these aspects affects the maturity of digital transformation within organizations. A research gap exists in the lack of studies investigating these aspects of AI-driven digital transformation as interdependent components of AI-enabled business transformation.

Due to the fact that the implementation of AI tools into organizations does not necessarily lead to the desired improvements in productivity, flexibility, and competitiveness in the business environment, it is necessary to investigate whether the companies have the data infrastructure, automation systems, and general readiness to incorporate AI tools into their management and operational processes. Thus, the study described in this paper is needed to fill this existing gap in the literature by introducing and employing the Digital Transformation Integration Index (DTII) to investigate the interaction between data governance, AI automation, and organizational readiness for digital transformation in three different countries: Ukraine, the UAE, and Singapore.

2. LITERATURE REVIEW

Beginning with the problem of Digital Transformation, the literature identifies a trend in which firms are changing how they create wealth and compete. However, the most recent studies have shifted their focus to how Artificial Intelligence (AI) supports competitive advantage. According to Reier Forradellas and Garay Gallastegui [7], the effective use and application of AI depends upon the legal frameworks and regulations of each country. Thus, researchers need to identify a way to combine and integrate two major issues, the difficulties of Digital Transformation and the need for ethical and professional ways to do business based upon the laws and regulations. However, as suggested by Rajagopal et al. [12], there is another way that researchers may contribute to further transformation within an organization: the organization itself must be culturally, operationally, and structurally transformed to allow for the logic of AI. These differing views have created an internal conflict for researchers, who are faced with seeing the biggest barriers to implementing AI in their own organizations in different manners: e.g. regulatory compliance for one group of researchers and the internal cultural, operational and structural changes required to allow for the implementation of AI in an organization for another group of researchers.

During the last decade or so, there has been a considerable amount of research into how managers can use AI to assist them in decision making. As indicated by the findings of Rane et al. [13], AI enables managers to generate data-driven strategies using the algorithms and potentially to obtain better outcomes than they would have obtained if they had not used the algorithms. Research has also illustrated that the use of AI has provided managers with several advantages in terms of forecasting and analytics as well as additional information to make financial evaluations. However, Ionescu and Diaconita [14] emphasized the role of AI in decision-making and risk assessment, but explored the implications of AI for management at a much greater level of depth. The diversity of viewpoints expressed in the literature clearly illustrate the failure of researchers to develop a comprehensive, system-wide, interdisciplinary synthesis of AI. Indeed, AI does not merely change the attributes of planning and/or analysis, but also how these activities are organized and implemented. The interaction of analytics and operations is where AI can serve as a catalyst for improving operational performance while developing new knowledge. Like the methodology approach described by Beheshti et al. [15], the authors also stated that Process GPT, a tool intended to reduce the burden of managers and enhance the transparency of processes through the automation of nonstandard events, can offer the same advantages to users of Process GPT. Similar to the methodology approach described by Beheshti et al. [15], both studies referenced organizational readiness and the human factor superficially. Consequently, there are many unanswered questions relating to the practical implementation of such systems.

A second important area that has received considerable attention in the literature is that of supply chain and value creation. For instance, Singh [16] reported that AI has a positive effect on the quality of logistics and demand forecasting. Likewise, Vărzaru and Bocean [17] reported that the use of AI has a significant effect on the innovative capacity and employee turnover of a firm. From a practical perspective, the work of Gołąb-Andrzejak [18] provides a practical element to AI-based acceleration of personalization and planning in retail services. Nonetheless, the vast majority of studies mentioned in the literature referenced above rarely take into consideration the differences between countries and therefore, the overall view remains highly fractured. Additionally, there is a dearth of research that investigates the use of AI in developing new business models. Sjödin et al. [19] suggest that the combination of the capabilities of AI, circular models and digital services will allow companies to adapt and transform in the future. However, Rane et al. [13] focused on the process by which decisions are made rather than the actual changes that are made. The authors also vary in their views on whether AI can be a strategic initiative. In this regard, Weber-Lewerenz [20] contributed to the ethics and regulatory framework, by highlighting corporate digital responsibility and user protection as key themes. However, the research is particularly weak in providing practical advice on how to implement the concepts of the research and therefore the applied utility of the research is greatly diminished. Overall, the literature analyzed in this study demonstrates that AI has enhanced the efficiency of organizations, increased innovation, and altered the rationale for decision-making. Nevertheless, there are many gaps in the literature, including the absence of comparative studies across nations, the relative paucity of studies examining AI across sectors, and the relatively superficial discussion of organizational readiness, which will be a critical determinant in assessing the degree of success in the implementation of AI. Although the existing literature was developed from theoretical models and single case studies from a specific type of business, this has led to methodological homogeneity. The empirical work undertaken to date analyzing data management and automation in integrated AI ecosystems is generally weak. The literature indicates that AI can influence the organizational logic and structure, but there are few empirical studies that examine how organizations implement AI as part of long-term sustainable operational transformations. The literature review shows that AI impacts decision making, automation, innovation, and competitiveness. However, there are some limitations to the existing research. For example, most research focuses on the technological benefits of AI while ignoring data governance and regulatory concerns. In addition, there is a lack of studies investigating how the readiness of an organization impacts the scalability of AI technologies. Furthermore, there is limited research using a comparative research method to investigate the impact of AI in different countries due to the influence that regulations, digital infrastructure, and managers' capabilities have on the outcomes of AI technologies. Thus, although the present study reflects the research that has already been conducted on the topic of AI and its impacts, it also extends that research by considering the technological, organizational, and governance impacts of AI in one model for comparison among different countries and their managers.

3. MATERIALS AND METHODS

3.1. Research Design

A comparative study with a comparative design will be used as a mixed-methods study to investigate the extent to which advanced AI tools are employed during digital transformation at three different development stages - in the UAE (rapidly transforming developing country), in Ukraine (developing country with limited development) and in Singapore (developed country). The countries have been selected based on purposeful selection criteria as it was believed they would provide a representative illustration of the types of models that may be applicable to this research. Specifically, Singapore represents a well-developed model for digital transformation that is institutionalized and heavily regulated in a very stable environment; the UAE represents a model of rapid technology adoption driven by the government and rapid development; and Ukraine represents a developing country that is still in the infancy stage of its growth, but has experienced limited growth and structural barriers to future growth. Each country has been

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selected based on four main criteria of Digital Maturity, Rigidity of Regulatory Frameworks in Place at the Time of Study, Level of Development of Digital Transformation, Establishment of Data Governance and Intensity of Deployment of AI-Driven Automation Systems. Overall, each country has formalized data and technical standards for its ecosystems in the case of Singapore; rapid development of digital transformation solutions through governmental action in the case of the UAE; and an irregular and fragmented digital transformation implementation environment in the case of Ukraine. Therefore, we can study three unique digital transformation architecture models: The Integrated Maturity Model (Singapore) and The Accelerated Expansion Model (UAE), and The Transitional Hybrid Model (Ukraine). In addition to providing illustrations of varying degrees of digital maturity and data governance; the countries also represent varying degrees of regulatory environments; and they utilize AI-driven automation systems at differing levels. The investigation of this study was both theoretical, empirical and comparative. The study took place from 2022 through2025. We initially attempted to complete an analytical review of all prior relevant research studies and governmental reports/policy papers regarding the AI-driven Digital Transformation of the three selected countries. The global standards that were used to develop the methodology for this study include: ISO/IEC 42001:2023 for the management of artificial intelligence; ISO/IEC 27001:2022 for information security/cybersecurity; ISO/IEC 38505-1:2021 for data governance; NIST Artificial Intelligence Risk Management Framework (AI RMF 1.0). In developing the methodology for this study, organizational preparedness, data management practices, and trustworthy AI-based automation, as outlined in the referenced frameworks, have been incorporated. The three digital transformation processes that are contained within this study are interdependent. The first process involves the development of an architectural structure (data management) that contains: the data systems structure, data quality, data security, and data interoperability. The framework of the data governance framework that will be used for evaluation purposes is directly connected to the structure of the metadata developed during the secure development of information-management practices and the development of secure practices and protocols to ensure compliance with both ISO/IEC 27001:2022 [21], and ISO/IEC 38505-1:2021 [22]. The second process involves the use of AI to automate business processes using AI as predictive analytics for systems/platforms to support and enhance workflow, and to use machine-learning-based decision-support tools and operational-AI models. Three additional processes are involved when investigating these systems/platforms. These are: AI Management and Risk Management as per I.SO/IEC 42001:2023 [23] and NI.ST AI RMF [24], and the level of readiness of an organization to implement AI-based solutions. This process is far from simply having the ability to manage the technology or possessing a digital culture. Neither are required to be evaluated or considered - nor is the flexibility of your internal systems and their support. The assessment of the structure of your culture is equally important as to whether you will be able to successfully implement a new solution. A comparative context was created by recognizing that the developmental process for a technological advancement process is vastly different among countries. Ukraine is an example of a transitional model for the implementation of AI. Technology adoption occurred relatively quickly, however, inconsistently across the country. Although technology has become entrenched in numerous regions, other regions have minimal adoption of technology due to either insufficient infrastructure or lack of regulatory support for the technology. In addition, there are also barriers to technology adoption that may relate to less tangible organizational issues. The UAE is the exact opposite of Ukraine in regards to implementing AI this is a model of implementation that is being led by the state as part of their national strategic plan and national data management regulations to assist in transitioning from manual to automated processes for both commercial and administrative processes. Singapore is once again the "gold standard" of AI adoption. In Singapore, AI is no longer something new and experimental in organizations; rather, AI is now simply another part of their business. Consequently, AI adoption in corporate governance has evolved into several habitual practices. Empirical data collected from companies in the manufacturing, retail, finance, logistics, and service sectors in all three countries (i.e., Singapore, Australia, and Ireland), were collected to provide the evidence base for this research [25-27]. The sample consisted of companies that are developing an ecosystem for AI (i.e., initial stages), and companies that have already developed an ecosystem for AI. This allowed for the identification of three levels of transformation: basic, intermediate, and advanced. The empirical research design used to obtain the evidence was complex, however, it enabled a thorough understanding of how data management technologies can be integrated with AI-based automation, and how companies can establish the necessary infrastructure to support the integration of these technologies. Additionally, the adoption of international standards [23-26], and the use of transparency, in our methodological approach will enable the systematic analysis and comparative study of the technological and managerial aspects in each country.

3.2. Conceptual Framework

The assessment of the new AI-enabling tools that support digital transformations in organizations were conducted using the AI.-Enabled Digital Transformation Assessment Model (ADTAM). The ADTAM is an integrated model that is used to measure the relationship between the three categories of digital transformation (i.e., Data Governance, Artificial Intelligence-Enabling Automation, and Organization's Capability to Leverage these Technologies). The ADTAM was constructed based on international standards such as I.SO/IEC 42001:2023 for the management of artificial intelligence systems [23], I.SO/IEC 27001:2022 for information security [21], ISO/IEC 38505-1:2021 for data governance [22]. Each element of the ADTAM represents the major elements of digital transformation as reported by both academic researchers and regulatory bodies; i.e., a solid base for a company's data infrastructure; the capability to deliver effective AI solutions; and an organization's capability to utilize, and scale new technologies. Each element of the ADTAM represents the main element of several conceptual models of AI-driven change. For instance, data serves as the basis for the automation process and the environment within an organization determines whether or not an organization utilizes the output of the AI to assist with their daily operations.

There are three constructs that were considered essential to this study and represent the technological and managerial dimensions of current digital transformation. These constructs are: Data Governance Capacity (DGC); AI Based Automation Performance (AAP); and Organizational Readiness for AI (ORA). Collectively, DGC, AAP, and ORA represent the capacity of businesses in Ukraine, UAE, and Singapore to build and grow out AI-based solutions.

Data Governance Capacity (DGC) represents the essential criteria for data quality, consistency and security. The DGC construct is used to evaluate an organization's ability to develop, preserve, and protect their Information Systems. Further, the DGC construct is used to determine the degree to which an organization trusts the integrity and availability of their Information Systems and whether there is interoperability among all platforms. Additionally, the model includes compliance with ISO/IEC 27001:2022 and ISO/IEC 38505-1:2021 to enable (informed) secure management of data and responsible management of data. Thus, the greater the rating indicates that organizations are better equipped to perform analytics, machine learning and automated decision making.

AI-Based Automation Performance (AAP) is a method of evaluating to what extent an organization has utilized AI-solutions in their business processes. Examples of solutions that were evaluated include Intelligent Workflow Automation, Predictive Analytics, Demand Forecasting, and Machine Learning Models used in finance, manufacturing, logistics, and service operations. The indicators of performance for AAP include accuracy, scalability, latency, explainability, and compliance to tenets of risk reduction established in I.SO/IEC 42001:2023 and NI.ST AI RMF. Generally speaking, AAP demonstrates how much AI improves productivity and the cost savings produced from the implementation of AI in an organization's operational performance. ORA deals with an organization's institutional, managerial and cultural preparedness to adopt and scale AI-based solutions. An organization's digital expertise of their employees, an organization's culture of innovation, the availability of programs, and the adaptability of an organization's administrative structure are part of ORA. The answer to the question posed by ORA is, do the organization have the internal conditions to accept, absorb and responsibly handle automated systems due to rapid technological changes? The logical coherence of the three areas is clear; i.e., productive automation is possible when the organization has quality data, and that data is secured in terms of integrity and security for all data, and the organization is able to integrate AI results in their strategic planning so that they consider the impact of AI to the business, management and organization as a whole. The structural logic of the ADTAM model is shown in Table 1.

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Table 1: The AI-enabled digital transformation assessment model (ADTAM) structure

Component	Symbol	Focus of Analysis	Method of Measurement	Interpretation
Data Governance Capacity	DGC	Data Quality, Data Integrity, Security, Compliance with ISO/IEC 27001:2022 & ISO/IEC 38505-1:2021	Documentation Audit, Expert Scoring, Compliance Checklists	Indicates the level of maturity of data systems and readiness for AI Integration
AI Automation Performance	AAP	Efficiency and Reliability of AI-Based Automation and Analytics	Performance Metrics, Precision/Recall Analysis, Risk-Compliance Evaluation	Shows the Technical Ability for Intelligent Automation and Optimization
Organizational Readiness for AI	ORA	Digital Competences, Managerial Flexibility, Innovation Culture	Surveys, Interviews, Organization Diagnostics	Reflects the Institutional Ability to Adopt and Support AI-Driven Transformation

Source: developed by the author based on [23–26]

For integrated assessment, the study calculates the Digital Transformation Integration Index (DTII) (1):

$$DTII = (0.40 \times DGC) + (0.35 \times AAP) + (0.25 \times ORA) \quad (1)$$

Delphi-AHP weights of the majority of experts confirm that Data Governance is the greatest enabler; followed by Automation Performance; and finally Organizational Readiness. We therefore relied on the rationales in the ISO/IEC 38505-1:2021 (Governance Principles) and the NIST AI Risk Management Framework (secure data infrastructure is the key to creating the trust required for AI). The ratio is thus justified. In addition to the prior quantitative evaluation of the use of AI Data Management Tools, Automation Technology and Organizational Readiness for transition to digital systems, we also attempted to find additional qualitative assessments from experts about the significance of these components. Therefore, we selected fifteen experts with experience in AI Systems, Data Management, Cyber Security, and Transition Process (greater than ten years) from Ukraine, the UAE, and Singapore all having extensive knowledge in their respective areas of expertise to create a wide breadth of knowledge base for us to use as a basis for providing an objective, well-rounded and comprehensive evaluation; we then collected information from those experts over the course of three rounds using the Delphi Methodology in the months of March through May 2025; to protect the anonymity of our participants and to ensure that all participating countries were treated equally, this research was conducted in a controlled environment. The experts responded to two questionnaires, one questionnaire dealt with Technology Factors, while the other dealt with Managerial Factors, using a 5-point Likert Scale. However, by the time of the third round of surveys, the experts had achieved a high consensus as to the comparative significance of the technology and managerial factors. Using AHP (Analytic Hierarchy Process), we calculated the relative weight of the three main dimensions in the model. In order to further verify our methodology and to see whether there exists a reasonable degree of consistency in the opinions of the experts, we applied the Kendall Concordance Coefficient ($W = 0.84$). Generally speaking, when you use a common metric to measure the extent of each country's readiness for AI:

– ≥ 0.75. – The country has well-established integration with AI and well-established Data Management Practices.

– 0.50–0.74. - The country has average AI-readiness; AI tools are being partially utilized.

– < 0.50. - The country is at the early stages; The country lacks both technological and managerial maturity.

The analytical framework described above has been used as a means to provide insight into how ready Ukraine, UAE, and Singapore are for an AI based digital transformation as well as how Data Management, Automation Systems, and institutional capabilities can relate to one another and influence the rate and quality of the digital transformation process. As expected, each country has its own particular puzzle to solve.

3.3. Methods of Data Collection and Analysis

The objective of this multi-phase mixed-methods study was to develop methodological consistency by combining quantitative modeling with qualitative institutional and technological analysis of data governance and organizational capability. The process of moving from data identification to validation of the resulting findings was accomplished through a series of three sequential phases. Phase One utilized a systematic documentation approach; a variety of credible documents relevant to the study were obtained from the Nations States examined in this research, but the sample size of the documents was limited to those that contained measurable indicators of Artificial Intelligence (AI) use in relation to Data Governance and Organizational Capability. Phase Two, the Quantitative Component, was a correlation testing and regression modeling analysis of the relationships among the three primary AI constructs (digital transformation; Data Governance Maturity (DGM); and AI-enabled Automation Intensity (AAI); and Organizational Readiness for AI (ORA)). Standardized β-coefficients of Pearson's correlations were calculated to determine the strength and direction of the statistically significant relationships observed in each of the three country-specific models. Further, VIF diagnostic and residual analysis (VIF < 3.) were used to evaluate the predictor variables that contributed to the differences in the quality of fit of the model among the three country-specific models. This type of analysis was used because it allows for the assessment of linearity among the constructs and the predictive capability of the models to determine if variation in either data governance or automation can be used to explain variation in organizational readiness. Additionally, the reliability of the developed model was assessed utilizing regression diagnostics that evaluated the degree of multicollinearity present in the model (lower multicollinearity.). K-means clustering was also used to classify the digital transformation regimes of the three nation-states under study (Ukraine, the United Arab Emirates (UAE), and Singapore) into three potential models based on the level of AI integration. Based on the cluster analysis results, Singapore was determined to be a highly integrated nation-state that has high levels of automation and therefore fell into one specific cluster. Conversely, the UAE was identified as a rapidly growing nation-state that is focused on innovation and therefore was categorized as another cluster. Ukraine was determined to be a transitional nation-state that is experiencing modernization and transformation of its infrastructure. Cluster analysis was chosen over alternative analytical techniques because it allows researchers to discover clusters within a dataset without prior knowledge of the existence of such clusters, thereby allowing researchers to have greater objectivity when determining national models relative to other models. The qualitative components of this study involved document and strategic policy analysis, industry case studies, and national digital strategy framework analysis. Document and strategic policy analysis was done to examine documents and policies relevant to the implementation of artificial intelligence. Industry case studies were performed to gather examples of organizations that utilize AI. National digital strategy framework analysis was performed to analyze the national digital strategies of the countries under study. The document pool was developed based on the following inclusion criteria: (1) the document was an official or peer-reviewed document; (2) the document included AI-specific metrics; and (3) the document was by sector related to manufacturing, finance, retail, and public services. Developing a document pool based on the above criteria helped reduce the risk of selection bias and enabled comparative analysis. The data used in this study were obtained from official sources (the Ukrainian Ministry of Digital Transformation, the UAE Artificial Intelligence Office, and the Singapore Smart Nation and Digital Government Office) and from corporate digitalization reports. International best practices were also analyzed using ISO/IEC 42001:2023, ISO/IEC 27001:2022, ISO/IEC 38505-1:2021, and the NI.ST AI RMF. The data collection method used for the semi-structured interview component included a pre-established format that elicited information concerning the respondent's experiences with data governance, the respondent's perceptions of the barriers to AI adoption, and the effect of automation on the organization's productivity, as well as indicators of organizational readiness. The selection criteria for the respondents included (1) managerial responsibilities for AI-related projects; (2) at least five years of industrial experience; and (3) previous involvement in digital change initiatives. Thematic coding was used to analyze the interview data and thematic analyses were performed using priori categories (data governance, adoption performance, and readiness factors). The interview transcripts were independently coded by two coders. When any disagreement occurred between the two coders, consensus was achieved. The intercoder reliability was Cohen's κ = .82 which is indicative of substantial agreement. The empirical aspects of this research project were divided into three phases from January 2023 to October 2025: Phase I: Systematic review and mapping of documentation and associated technologies in manufacturing, finance, retail, and public service sectors (January 2023-June 2023); Phase II: Surveys and semi-structured interviews with digital transformation managers, data governance officers, and AI architecture specialists (July 2023-May 2024); and Phase III: A Delphi expert panel study with AHP weighting (June

2024-October 2025). The phase-based design of this research project allowed for the qualitative findings of the research project to inform the development of quantitative models and provided expert validation of the findings to increase clarity. The validity of the research findings from this study were analyzed through Kendall's W = 0.84 and a boots trapping resampling (α = .05, n = 500) process. Bootstrapping validation also provided additional support for the robustness of the regression results as well as for cross-country comparison purposes. The data were validated with Kendall's W = 0.84 and bootstrapping resampling (α = .05, n = 500).

A triangulation method that included IT, organizational, and regulatory perspectives was utilized to increase the depth of the understanding of how the dynamic nature of digital adoption impacts the national models of digital transformation in Ukraine, the UAE, and Singapore.

3.4. Technical and analytical Environment

Our analysis has been conducted entirely digitally. We have used the commercial analytical software and Python 3.12 for all of our work. The main programs we have used to analyze our data are: Pandas, to add columns to a table based upon the value of existing columns; NumPy, to perform statistical operations (Arrays); SciPy, to perform various scientific functions (e.g., hypothesis testing); Scikit-learn, to perform Machine Learning (K-means Clustering and validate cluster assignment).

We converted our original, raw, unedited data (agency and corporate reports) to a "usable digital format", and manually entered every item of information in the reports into our database. Furthermore, we coded relevant text in the reports utilizing our designated indicators. We also normalized values for all numbers where applicable, and organized our databased on the use of each company at different levels of Artificial Intelligence (AI). To determine the level of automation (digitalization) of the organizations, their preparedness to automate, as well as their management and processes, panels were created with Matplotlib, Seaborn and Power BI / Tableau Public. This research is based on country level data about digitalization (the Annual Reports of the Ministry of Digital Transformation in Ukraine; the Office of Artificial Intelligence in the UAE; the Smart Nation Program in Singapore.) and the values for organizational regulation and weighing of the studied companies that was conducted by means of a Delphi-AHP method. Structured PDFs of national documentation, including source references, date of publication, and relevancy to the sector of study, were also incorporated into our Excel database. Expert evaluations were also entered into anonymous CSV files containing unique identifiers for the experts.

Each stage of data processing was carried out in compliance with I.SO/IEC 38505-1:2021 and ISO/IEC 27001.:2022. Secure transmission methods were used between each system. The reliability of the process was confirmed by running the complete analytical pipeline (multiple runs) on a system that had no external influence on the results. The same DTII scores and cluster assignments were generated for each run of the pipeline, confirming the consistency of the model throughout this study. Finally, the authors developed Python scripts as Jupyter Notebooks and ran the identical scripts on another workstation with the exact same versions of the software libraries. The identical results were generated on both systems. In addition to operating the analytical pipeline, all of the activities associated with the research project were coordinated with a Git repository, allowing the researchers to confirm the verifiability of the data, their traceable nature, and their verifiable origins. Thus, it was possible to unify quantitative models, expert opinions, and policy analyses within a single technical framework to gain a deeper understanding of how data management, AI-based automation, and an organization's willingness to transform can affect a country's trajectory of digital transformation.

4. RESULTS

4.1. Data. Governance Maturity Assessment for Countries Implementing AI-Driven Digital Transformations

There were many different factors for the experts to think about when assessing their confidence in the pieces of evidence documented in the official documentation of the findings of their respective industries. For instance, a Singaporean expert believed that "metadata functions perfectly", however, according to the documentation, it was stated that "it works well." Although the documentation of the Ukrainian systems appeared to be very organized and had a full account of all processes and procedures for each system, it was clear through the interviews with the subject matter experts of the industry, that there were systems missing some of the required processes to protect the integrity of the data, as a result, I made a few minor errors myself, to give a better idea of how much the data reflected the actual reality of the situation.

The DGC. Values for the three countries are illustrated in Figure 1. The five sub-indicators

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(data quality, data integrity, data security, metadata and compliance with ISO) were normalized. Normalizing the various metrics and transforming the raw values into a comparable format allowed us to make cross-country comparisons. Even though normalizing the metrics was a relatively boring task, it was the only practical method for making cross-national comparisons using realistic and/or reliable data instead of compiling a list of convenient numbers for each country. Overall, Singapore displayed high consistency across most of its areas; UAE presented high levels of performance on the majority of the dimensions but in an inconsistent manner; and, Ukraine was found to exhibit a mixed profile of maturity with some areas exhibiting higher levels of maturity than would normally be expected, and other areas displaying lower levels of development than what is typically seen. As such, these differences in maturity profiles indicate that the maturity levels of national data governance systems vary by country and can impact the ability of a country to pull up AI-driven digital transformations.

It should be noted that the DGC values for the three countries were determined using the Expert Survey methodology and the reports from organizations, as well as by conducting a basic check against the requirements of the two International Standards IvSO/IEC 27001:2022 and ISO/IEC 38505-1:2021 to determine the level of maturity of the National Data. Governance Systems as they "pull up" AI driven digital transformations.

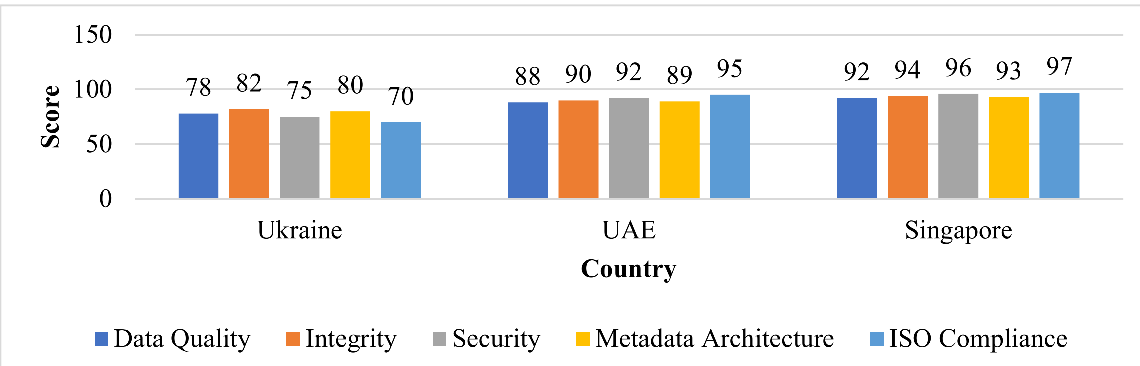

Figure 1: DGC Score for Each Country in This Study of; Ukraine, UAE, Singapore
Source: developed by the author based on expert evaluation and standards [23–26]

To summarize, we would characterize the profiles of the Ukrainian, Emirati and Singaporean Data Governance Committees (DGCs), based on their performance according to the five selected indicators, derived from the five components and scaled from 0 to 100 for Ukraine, the UAE, and Singapore, as follows: Ukraine has a medium-advanced profile regarding data management. On the other hand, when looking at individual categories, the success of Ukraine's digitalization strategy is evident, particularly in "Data Quality" (72), "Metadata Architecture" (68) and "Data Integrity Indicator" (63) which is placed somewhere in the middle, and a low in "Security" (55) and "ISO Compliance" (52) due to short comings in the fields of cybersecurity law and international standards compliance. Therefore, although the balance in Ukraine's profile is apparent, it can be inferred that progress was not achieved equally in all sectors. The UAE possesses very high values for almost all of the parameters analyzed and presents itself as the most consistent and reliable of the three case studies presented here. The UAE's top two indicators - "Security" (88) and "ISO Compliance" (91) - show the Government's commitment to protecting data through its strict data protection legislation and the application of a robust Digital Governance Model. Similarly, the UAE's high scores for "Data Quality" (84), "Data Integrity" (82), and "Metadata Structure" (86) demonstrate that the country's technical and regulatory frameworks work in synergy to support its leadership position in terms of Data Governance. Singapore presents the highest overall score among the three countries that were analyzed, and as anticipated, there was no prior expectations about it before starting this study. Besides having the best scores in "Security" (95), "ISO Compliance" (94), and "Data Quality" (92), Singapore also holds the first place globally in using Metadata Architecture (90) and Data Integrity (89) to achieve a homogeneous approach to establishing a Data Governance Framework. The UAE has the second-highest total score and demonstrates a relatively balanced configuration. Even though it has demonstrated significant development growth, Ukraine's configuration is less balanced compared to Singapore and the UAE and will require improvements so that it is more aligned with

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"Security" and "ISO" standards. Therefore, the empirical results reported here provide a solid base for this research project to evaluate how each level of data governance affects a country's ability to implement digital transformation and how effective AI-based systems are at national level.

4.2. The performance of AI automation in the four major sectors – finance, manufacturing, retail and logistics - is examined in this report to assess the AI automation performance (A.A.P.) across three countries, namely, Ukraine, UAE and Singapore

This report examines how well AI automation has performed in the four major sectors finance, manufacturing, retail and logistics and compares the AI automation performance (AAP) in these four major sectors across three countries Ukraine, UAE and Singapore. It is historically in the four major sectors that algorithm-based solutions and automated workflow processes have had the most positive operational impacts. The performance of AI automation in the four major sectors was evaluated through the use of documentation relating to technical aspects of the companies studied; an evaluation by experts; and confirmation of compliance with both the international standard of ISO/IEC 42001:2023 and the National Institute of Standards and Technology's (NIST) AI Risk Management Framework. Each sector included evaluations in the three main categories of model accuracy, scalability and operational reliability. For each sector, our evaluation resulted in a clear and sometimes surprising view of the degree of maturity of the national AI automation level. The Sectoral AAP Index for the three countries is shown in Figure 2. The index includes metrics representing accuracy, scalability and operational reliability, and is normalized on a 0-100 scale.

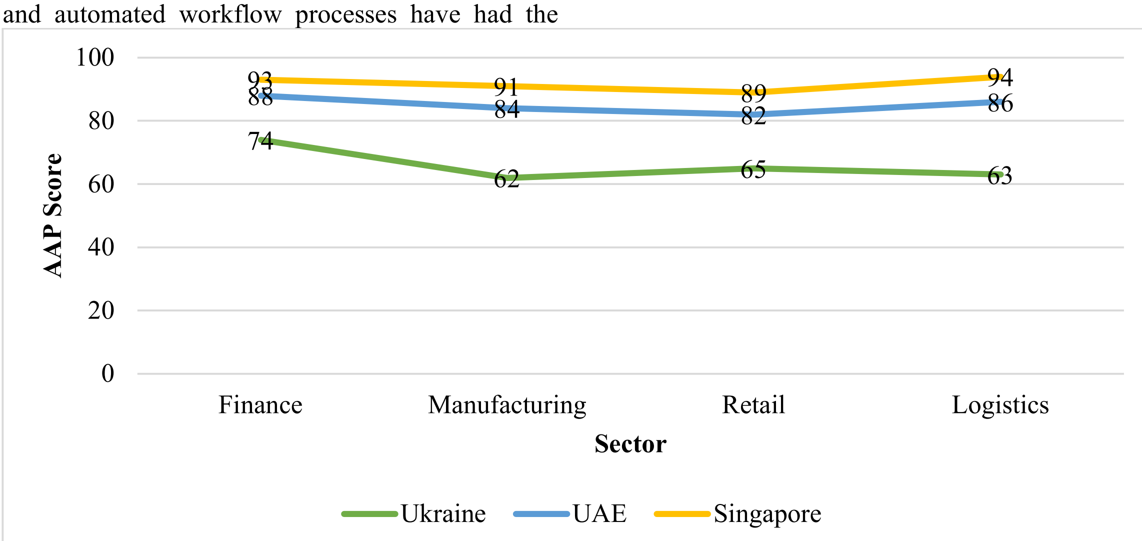

Figure 2: Sectoral AI Automation Performance Index (AAP) in Ukraine, UAE, and Singapore
Source: developed by the author based on [25-27] and expert evaluation

The results reflected in Table 2 were also expected. Singapore ranked number one globally in the AI Automation Index (AII). Singapore's AII was ranked from 88 to 95 across all sectors, with the highest rating from the financial services sector (95). There is a direct relationship between the use of advanced risk assessment technologies and the implementation of ISO/IEC 42001:2023 standards and the rating of 95 received by the financial services sector. The ratings for the manufacturing sector (92) and the logistics sector (90) reflect the widespread and consistent implementation of artificial intelligence (AI) into their processes. There is no evidence of "gaps" or "holes" in either process.

While the UAE has performed well, the consistency of the performance has been lacking (79-90). In this case, the logistics sector was the leader (90) as they have been testing autonomous vehicle routes, smart ports and other automated processes routinely. The finance (88) and retail (84) sectors have shown a high level of reliability in their use of AI automation, however, the manufacturing (79) sector is still under-going modernization and the transition to using AI in control systems has been occurring but not to the extent desired.

In assessing the countries' levels of AI adoption, the Ukraine is considered a transitional model - scoring 6.3 to 78. The financial services sector appears to be the strongest sector (78) as the continued growth of Ukraine's fintech will help positively affect the growth of AI adoption in the country. Both the retail (72) and manufacturing (69) sectors show a moderate level of automation - both have limitations due to infrastructure. The logistics sector was rated as the lowest (63) in the overall assessment - indicating that the country has yet to begin implementing AI and does not have the capabilities to perform predictive analysis. The variation in the degree of AI adoption among these countries demonstrates how the degree of AI adoption can vary significantly depending on the degree of AI adoption in various sectors, the compliance with regulatory requirements and the quality of the underlying infrastructure of each country.

4.3. Organizational Readiness for AI (ORA), and Institutional Capability

Organizational readiness for Artificial Intelligence (AI) encompasses several aspects. These include employee's digital competencies, the internal infrastructure to foster an environment for innovation, manager adaptability and the organizations' capacity to incorporate AI into daily business processes and strategic planning. Our results indicated considerable differences among Ukraine, UAE and Singapore with respect to AI-readiness based on our analysis of the survey responses from managers, system architects, and data management specialists.

These differences could be identified from the combined responses of both surveys (e.g., overlaying). The country profiles generated, differed in degree of digital competency, as well as in degree of innovative culture, availability of training programs to scale AI, and the extent of institutional support necessary to deploy large-scale AI-based systems; these are summarized in Table 2.

Table 2: Organizational AI Readiness (ORA) Indicators by Country

ORA Indicator	Ukraine	UAE	Singapore
Digital Skills Index	0.62	0.78	0.91
AI Training Availability	0.55	0.82	0.94
Innovation Culture Strength	0.58	0.80	0.93
Governance Flexibility	0.60	0.83	0.95
Data Governance Maturity	0.54	0.81	0.96
Structural Adaptability	0.57	0.79	0.92
Managerial Digital Literacy	0.59	0.84	0.93
AI Integration Capability	0.52	0.77	0.90
Investment Stability	0.50	0.88	0.94
Cross-sector Collaboration	0.48	0.75	0.89

Source: developed by the author based on expert evaluation and standards [23–26]

While there is certainly evidence of a developing ability of individual Ukrainians to develop their own AI capabilities(e.g. Digital Skills = 62 and Managerial Digital Literacy = 59) there is also a developing disconnect between the capabilities of institutions and the capabilities of individual innovators. While the ability of institutions in Ukraine to facilitate the development of new innovations seems to be hindered by structural barriers (48 for inter-sectoral cooperation and 50 for investment stability) it is clear that these systemic barriers will "tear apart the innovation cycle." Thus, the current readiness profile of Ukraine is fragmented due to this large gap in capability. The UAE represents a completely different picture of its readiness profile - and one that is both significantly more favorable and more balanced: 75-88. It is clear that the UAE has developed a thoughtfully and strategically implemented plan to rapidly implement digital transformation within the country through the actions of the state. As such, the investment stability (88), managerial digital literacy (84) and management flexibility (83) all represent a form of "nodal support" in the innovation ecosystem, and support/encourage the development and growth of the other components of the ecosystem. Additionally, the results indicate that the UAE has achieved unexpectedly high levels on two dimensions (AI Training Availability [0.82] and Data Governance Maturity [0.81]) that would normally seem contradictory to its history as an AI adopter; however, the development of a nationally sponsored capacity-building program through the government's centralization and a well-defined regulatory environment has supported the successful adoption and scaling of AI in the UAE.

Ukraine and the UAE readiness profiles differ substantially. For example, the readiness profile of Singapore presents a very narrow range between the lowest and highest readiness scores (i.e. 89-96). This demonstrates a "compression" of high value readiness into a single dimension, as a result of three synergistic contributors (individual skills, organizational adaptability, and institutional support) working together to foster growth in an ecosystem. The highest values were found in Data Governance Maturity (96), Governance Flexibility (95), and AI Training Availability (94). These high values indicate that there exists a strong institutional model of governance of digitally-enabled environments in Singapore. The values of Digital Skills (91) and AI Integration Capability (90) also demonstrate that Singapore exists in a stable learning environment to sustain technology within an organization. Thereby providing a means of supporting and promoting these elements in a business environment. Therefore, Ukraine is presently situated in the developmental zone where we expect to find growth potential and systemic obstacles to that growth; the UAE has developed to a mid-range high level of readiness and is capable of leveraging national strategies and investments to support that growth; and Singapore has established an operational AI ecosystem in which growth occurs naturally with virtually no barriers to scale.

4.4. Integrated Digital Transformation Integration Index (DTII) and Country Profiles

The DTII (Digital Transformation Integration Index) is a combined index measuring the 3 main elements of the national digital capability, i.e., Data Governance Capability (DGC), AI Automation Potential (AAP), and Organizational Readiness for AI (ORA). We assigned the relative weights to DGC, AAP, and ORA at 0.40, 0.35 and 0.25 respectively in order to ensure that the infrastructure, operational and institutional variables are somehow equally weighted; we had to do so because this was the only way the index would be able to measure "the potential" of the system as well as its scalability. The DTII profiles of the three countries presented in table 3 show three very distinct types of transformation pathways. Each one has its own value in relation to the degree of digital maturity of the country as well as the speed of its innovation process.

Table 3: Digital Transformation Integration Index (DTII) and Its Components

Country	DGC	AAP	ORA	DTII
Ukraine	0.58	0.60	0.56	0.584
UAE	0.80	0.83	0.82	0.815
Singapore	0.93	0.95	0.94	0.943

Source: developed by the author based on aggregated indicators [23–26]

While the Digital Transformation Index (DTI) shows that countries have achieved different levels of digital maturity, the countries analyzed here clearly show similar trends. The DTI for Ukraine is 584, and therefore is classified as "systems in motion". While the process is underway, the DTI profile is still relatively "stretched", since Ukraine has made some progress, but the DTI for Ukraine is still less than 6. However, although the average of the AAP (60) and ORA (56) are each less than 6, the DGC (58) has increased in value over time; which implies that there are a variety of opportunities in which Ukraine may develop its digital transformation and that there are multiple ways that AI and digital governance are asymmetrically connected. In contrast, the UAE has a much higher DTI (815) and is thus an example of a "balanced" and "fast" innovation model. The UAE's level of automation (83) and governance level (80) are very close to the level of organization's readiness to quickly and efficiently implement the use of AI. Singapore has the highest concentration of all of the countries examined, with all of the component values ranging from 93 to 95; and, therefore, all of the layers of the infrastructure and operational and institutional elements are functioning in tandem.

Therefore, it should come as no surprise that the DTII score for Singapore is 943 (i.e., you are at a high level of digital transformation maturity; and, therefore, you are likely to experience fewer frictional costs than hiccups). A triad of countries can be identified by combining the two models. These countries include Ukraine – a transitional model where growth in opportunity will occur simultaneously with inequality in both institutional and infrastructural development; the UAE – a high speed innovation regime whose infrastructure has been developed through investment and rapid implementation; and, Singapore – an integrated high-level of maturity model whose governance, automation and organizational readiness are perfectly synchronized. The DGC scores also support these findings. Specifically, Singapore is a fully institutionalized system; the UAE is a country with a robust regulatory regime; and, Ukraine is a country that is developing but, is doing so in an uneven manner, particularly as it pertains to security and iso compliance. Therefore, the AAP dynamics also support the same conclusions. Specifically,

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Singapore remains consistent in all of the categories; the UAE is high, but heterogenous; and, Ukraine is a transitional model with the potential for growth anchored in its infrastructure.

Additionally, the differences were even greater due to the ORA scores: Singapore represents a highly competent system; the UAE represents a model that is supported by both the political and financial systems; and, Ukraine represents a country that possesses emerging expertise, but barriers exist within its governance structure. Thus, the DTII translates these results into three national models: Singapore is a high-integration model; the UAE is a high-speed innovation model; and, Ukraine is a transitional model of expansion/progress, at a slow pace. These results collectively provide evidence for the argument that governance, automation, and organizational capabilities are interdependent factors that determine the effectiveness and scalability of national digital transformations.

5. DISCUSSION

As stated in the previous study, a company cannot just add AI to their current business model, it is necessary for these three layers - Data Governance Maturity (DGCM), Automation Performance (APP), and Organizational Readiness (OR) - to be interconnected for AI to assist in moving their business model forward. Brem et al. [28] have proposed that in order to scale Artificial Intelligence (AI) it will be necessary for AI to include both data analysis and an organizational structure in one unified system. The relevance of this study to the Singapore context appears particularly high given the high level of DTII (94) and the fact that the three DTII subscales had almost identical values; this supports the relationship between data and governance decision making identified by Sjödin et al. [29] in the context of continued innovation. Additionally, the study has found something new; in a mature environment, the impact of having a high level of ORA on the index is larger than the impact of having a high level of AAP. This implies that institutional capability tends to weigh heavier than technology. Conversely, in the UAE, a "high velocity" was observed; high APP(88), ORA (82) and a somewhat lower DGC (79). Our findings provide partial support for Czvetkó et al.'s [30] conclusion that industrial AI can be quickly deployed with a medium level of institutional maturity given an effective BPM environment. We added a new layer of complexity to this nuance in our research; a DGC that is too low will limit the DTII's ability to be integrated into the DTI, and therefore will lower the overall index independent of the degree of automation. A multi-story building (many floors) built on top of an unstable foundation will be unstable, likewise a large scale AI system that does not have a stable governance structure will be unstable. Lastly, Ukraine represents a transition model. The DGC in Ukraine = 68; AAP = 72; ORA = 61. It is easy to see the large difference between the indicator. This is in line with the opinion of Paramesha et al. [31] about the fact that developing countries use AI primarily in the fields of application (e.g., finance, analytics) and less so in structural transformations. We however found a further result: in reality, the limited range of values of ORA constrains the index much more than would normally be expected by the literature. The development of a culture of innovation, modernization opportunities, and the fragmentation of DTII take place irregularly. Therefore, the elevated level of AAP in Ukraine supports the research of Odonkor et al. [32], who were able to link the AI tools to the digital infrastructure development. Nevertheless, the evidence provided here shows that automation alone is insufficient. Governance and cooperation are needed because, otherwise, there is no system. Overall, the comparison of the country pairs illustrates a common trend: DTII is not the sum of its components, but rather a system where the least capable part of the system brings the rest of the system down. Thus, it appears to support the view of Bialialow et al. [33] that a harmonized regulatory framework, organizational systems and technological applications will be necessary for the successful transition to a digital economy. For example: lack of strong ORA in Ukraine; absence of standardization of DGC in UAE; full coordination in Singapore. This is in accordance with the views of Ortina et al. [34] to some degree regarding the opinion that the adoption of international standards will provide effectiveness. On the other hand, the UAE paradox is clear: high APP does not necessarily mean high DTII; this is caused by the level of regulatory compliance. Finally, the study defines a new framework for evaluating how DGCM, APP, and ORA are important for determining digital transformation paths in three extremely different national contexts. And most importantly, it points out: there are several ways to achieve this [35-37], but only when governance, automation and organizational abilities exist to enable the connection.

The results of this study are in line with previous studies showing how AI can contribute to innovation in business models, optimizing business processes, and making decisions based on data. Previous studies have all pointed to AI's contribution to innovation management,

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servitization of digital products and services, automation of business processes, and decision-making. However, the findings of this study show that the automation capabilities of AI do not necessarily determine the digital transformation maturity of a country. All three countries showed that their digital transformation maturity depended on their data governance and readiness to adopt digital transformation within their countries and industries.

Another contribution of this study is explaining why some countries with the best implementations of AI experience less digital transformation than other countries with similar AI implementations. For example, while the UAE has some of the best automation implementations of AI, their data governance and readiness to undergo digital transformation limits their digital transformation maturity. Ukraine had a lower potential for automation, but due to their fragmented data governance and readiness to embrace digital transformation, their DTII score is relatively low. Singapore has the highest digital transformation maturity score, but not because of their automation implementations of AI, but their data governance and readiness to embrace digital transformation. Thus, this study makes an additional contribution to the literature by providing an overview and explanation of how digital transformation maturity requires the development of technological, governance-related, and organizational capabilities.

Finally, the additional contribution of this research is the development and use of the DTII model to measure digital transformation maturity in countries. Most previous studies focused solely on the tools and processes that countries used to automate their AI implementations. However, this model demonstrates the imbalances between the three components of digital transformation maturity and how they impact a country's digital transformation maturity score.

6. LIMITATIONS AND THREATS TO VALIDITY

The criteria that were used to assess the validity of the DTII model were chosen in relation to the research objectives and the structure of the DTII model itself. The main factors that should have an impact upon the reliability, comparability, and interpretation of the DTII model were assessed to determine its validity. Thus, the criteria for assessing validity included the selection of the countries to be evaluated, the means of measuring the DTII model, the construct validity of the DTII model, the comparability of the model across the countries in the study, and the stability of the research model over time.

Several threats to the validity of the DTII model can be recognized and named. One such threat to validity is the potential impact of the selection of only three countries to be evaluated. While those three countries were selected to represent different models of digital transformation, it is still possible that the results of the study cannot be generalized to other developing or even developed digital economies. Second, the potential impact upon validity of utilizing experts to score the various ORA indicators. While methods like Delphi-AHP methods, Kendall's W, and bootstrapping were used to increase the reliability of the experts' scores, the judgments of the experts may still have contained some bias. Third, the structure of the DTII model indicates a threat to the construct validity of the model. While the model utilizes indicators related to data governance, AI automation, and organizational readiness, it does not incorporate other potential indicators of digital transformation.

Fourth, the external validity of the model could be threatened by the fact that the results of the study were limited to the three countries that were assessed. Thus, the results may not be applicable to other countries. Fifth, the temporal validity of the model may be threatened by the fact that the study is based cross-sectionally. In other words, the study did not measure the changes to the factors over time, but only provided an assessment of the digital transformation in the countries during the time period in which the study was performed. Thus, these threats to validity do not invalidate the results of the study, but they do indicate the limits on the interpretation of those results.

7. CONCLUSIONS

In the case of this research, the results represent an overall consistent assessment of a country's ability to develop its digital transformation (DT) capacity. A developed country's DT capacity is defined by its ability to manage data, the successful implementation of AI automation and the readiness of an organization to scale its intelligent systems.

The newness of the DTII model lies in the fact that for the first time the three components of DT capacity Data Governance Capacity (DGC), AI Automation Potential (AAP) and Organizational Readiness (ORA) are represented in a single conceptual framework that measures the maturation of the three DT components separately rather than as a sum total. Thus, the DTII model captures the distortions within a country's ecosystem which may occur in its transition toward DT.

The data demonstrated a strong correlation between country DT capability as measured by DT II in an international comparison of DT capabilities. Singapore ranked first, in terms of DT capabilities and demonstrated the most system-consistent DT capability among all of the countries analyzed. In addition to demonstrating high degrees of system consistency across its DGC indicators (security-95, ISO-94, metadata-90), and AAP indicators (all were about 88-95), all of which correlated well with ORA (0.91-0.96), Singapore also demonstrated that it had a completely automated DTII (0.943) that functioned on the ORA dimension and achieved the highest DT capability rank.

The UAE was at the opposite end of this spectrum. It was traveling in a completely opposite direction and was experiencing great success due to government programs which have produced a "high-speed" model. The UAE had a high degree of DGC (82–91) and a high rate of increase in AI-automation (AAP 79–90) directed at logistics and corporate applications and an ORA (0.75–0.88) indicating that management and investments acted as accelerators. When all of the above factors were combined, a DTII of .0.815 was obtained, which indicated a rapidly increasing environment.

Ukraine represents a different model or path. Here, a hybrid growth model - one area of development is progressing at a higher rate than the others and then slows down - is being used. While DGC (52–72), AAP (63-78) and ORA (0.48-0.62) vary to a large extent so that fragmentation is apparent, there has been some growth in human capital and there is still a significant amount of opportunity for the structure constraints (i.e., infrastructure to regulation) to inhibit the further development of DT. In addition, the DTII value of 0.584 indicates current capability and a coherent logic framework will need to exist to maintain the capability.

Overall, the DTII model can assist business in defining their digital architecture and defining their data governance policies and assessing the potential for automated processes. Additionally, the DTII model can support government agencies in creating and supporting specific programmatic support initiatives, enhance cyber-resilience, and build human capital for AI. Ultimately, the study results show that the actual maturation of DT is dependent as much upon establishing regulatory coherence as it is on the establishment of robust infrastructure and organizational capacities. These three elements are the determinants of whether a country can sustainably scale AI technology over the long-term.

The novelty of this study lies in the use of the DTII model to assess AI-enabled digital transformation. Unlike many existing methods to evaluate digital transformation that focus on technological aspects of AI implementation, the DTII model considers three aspects of digital transformation: data governance, AI automation, and organizational readiness. These aspects make it possible to determine not only the level of digital development of an organization but also the imbalances within its digital transformation that limit the scalability of its AI systems.

The impact of this research includes both scientific and practical dimensions. Scientifically, the study contributes to the existing literature by providing a framework for comparing AI-enabled digital transformation in various countries. Additionally, the model can be used in practice by organizations to better understand their digital transformation capabilities and by policymakers to create strategies that enhance the digital transformation process. Overall, this research presents a critical view of the various aspects of AI-enabled digital transformation and clarifies that the successful implementation of such transformations depends on more than just the implementation of AI technologies. Other capabilities, such as digital governance and digital transformation, must be developed alongside AI technologies for successful digital transformation to occur.

8. STRENGTHS, WEAKNESSES, AND FUTURE RESEARCH DIRECTIONS

The strengths of this research study are inherently linked to its research objective. The first strength of this research is the creation of an integrated model (DTII) that assess the three elements of digital transformation: data governance, AI automation, and organizational readiness. Another strength of this research is the comparison of three different countries to identify the various paths that the studied nations have experienced in their digital transformation process. Finally, the use of internationally recognized criteria for assessing digital transformation based on ISO/IEC and NIST recommendations represents another area of strength for this research study.

The weaknesses of this study relate to the limitations of the research. The first weakness of this study is the limited number of countries that were assessed in this research study. The second weakness of this research study is the use of expert-based weights for the criteria in the DTII model, despite efforts to use Delphi-AHP procedures to weight those criteria. The third weakness of this research study is that there are no data regarding digital transformation maturity collected over time, which limits the research study's ability to determine how that maturity changes over time.

Future research can expand upon this study by evaluating additional countries that utilize different regulatory and economic environments. Additionally, future studies can attempt to assess the DTII model at the level of individual companies. Another area for future research studies would be to gather longitudinal data on the digital transformation maturity of the nations studied in this research, which would help to reveal the impacts of improvements to the three elements of digital transformation. Finally, future versions of the DTII model can be created that incorporate additional evaluation criteria and indicators of digital transformation maturity beyond those used in this study.

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