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Research Article

Public Opinion and it's Influence on Technology Governance in the Age of Digital Transformation

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Abstract:

This study examines how social public opinion affects technology governance in order to examine the ways in which digital transformation affects various government agencies. Our method breaks out the precise effects of digital transformation on different government departments and their contributions to overall governmental efficiency, in contrast to earlier research that frequently sees digital government as a single entity. We evaluate the extent of digital transformation in government departments from 2013 to 2023 using text analysis and empirical models, and the results show that these changes improve governmental efficiency. Our results also demonstrate how important it is to coordinate digital transformation initiatives in order to increase overall efficiency. This study not only presents a novel theoretical framework for comprehending digital government, but it also makes practical suggestions for allocating resources as efficiently as possible and planning digital projects that would advance government. For efficient analysis of the enormous volume of public debate on digital platforms, sophisticated Natural Language Processing (NLP) approaches are needed. In order to capture both contextual meanings and sequential dependencies in public opinion data, this study suggests a hybrid model that combines BERT and LSTM. The model uses LSTM (Long Short-Term Memory) to remember sequential patterns in sentiment evolution and BERT (Bidirectional Encoder Representations from Transformers) for deep semantic comprehension. The study sheds light on how public opinion influences technology policies and governance tactics by using this model to analyse case studies of AI ethics, data privacy, and platform laws.

1. Introduction

The internet has emerged as China's most potent social tool in the last several decades, thanks to its central role in facilitating communication. Modern society's structure and social ties have been transformed by the advent of the internet, an entirely novel communication technology that is centered upon information technology [1]. The percentage of Chinese internet users was 64.5% in March 2020, up from 0.05% in 1997, and the total population of internet users had increased to 904 million (from 620,000 in 1997). The number of mobile internet users increased from 79.92 millions to 897 million by 2018 end. More and more people are accessing the internet through mobile devices. March 2020 saw 255 million rural internet users, up 33.08 million from the end of 2018, making up 28.2% of the country's total users (China Internet Network Information Center, 2020). This phenomenal expansion is a direct result of the internet's role in reshaping Chinese society [2]. Governments are undergoing digital transformation as a result of rising citizen expectations and the rapid development of digital technology. Governments are expected to enhance operational efficiency and address public problems through digital initiatives, especially in these uncertain times. At the same time, governments are jumping on the bandwagon for digital economic services like banking and currencies in the hopes of launching them on a grand scale. Government digital initiatives are crucial for keeping up with changing politics, society, and technological landscapes, but people still don't fully grasp the government's role in encouraging participation and adoption [3]. According to [4], public opinion plays a significant role in society as it has the power to impact both individuals and institutions. People may make better, more informed judgments with the support of accurate and relevant data, and public opinion can impact government and organization policy and decision-making. Public sentiment can bolster or impact social and political shifts, and it can also impact societal norms and values [5]. Decisions about investments and businesses are now heavily impacted by public opinion. Public opinion may make or break a company's reputation and trustworthiness. Businesses that are paid attention to it can boost their reputation and get more trust from customers. Citizens and businesses alike would do well to keep tabs on public sentiment and work to shape it in an honest and forthright manner. Because of this, public opinion can play a significant role in shaping society for the better [6].

The Chinese government's digital transition is being accelerated by the country's fast economic growth. The rapid economic and social development in China over the last 20 years has put the government in a position of ever-increasing complexity in terms of governance. Many believe that digital transformation is the key to better government decision-making, more efficient use of resources, and higher-quality public services. The building of a digital government receives strong backing from this fast economic growth, which also improves and develops digital infrastructure, encourages technical innovation, and pushes it. Finally, there is a significant popular desire for reforming the government in China, which is in line with the establishment of a digital government. The public's faith in the government has always been impacted by the lack of transparency surrounding official matters. Government choices and actions can be better understood and monitored by the public as a result of digital transformation's increased openness [7]. Therefore, building a digital government is crucial to meeting public expectations and increasing public trust, in addition to being a necessary evil for the government.

Economic development, public demand, and national policy in China have all worked together to speed up the government's digital transformation. Data compiled by UNeGovKB shows that from 2003 and 2022, China's electronic governance Development Index increased from 0.41595 to 0.8119, representing a growth rate of 3.79% on average. It is expected that China's e-government transformation would catch up to developed nations in the near future, even though there is still a little difference compared to the developed world average of about 0.9. A distinctive growth model has emerged as a result of China's government's digital transformation, which other nations and regions can learn from[8]. With the rise of digital transformation came new problems for the traditional bureaucratic structure and the idea of vertical government, which in turn altered the way the people participated in governance and how responsive the government was [9]. Many governments have issued digital transformation policies to keep up with the rapid advancements in information technology, as well as the changing demands of modern governance and the dynamics of the environment. Furthermore, the centrality of digitization in enabling the all-encompassing reform of Chinese government administration is a point of crucial importance to the Chinese government. The government's the digital revolution of public administration is being accelerated through a number of strategic initiatives. Improving the implementation of strategic initiatives is becoming more dependent on the digital transformation of local governments. In order to drive the expansion of the digital marketplace as well as the building of Digital China, this endeavor is essential for strengthening the evolving field of the national government system and its capabilities.

Government agencies, private companies, and citizens must all work together, according to experts who have come to realize in recent years, if the government is to undergo a digital revolution. The public and municipal governments are now engaging in a new dynamic as a result of digital transformation, which allows for the co-creation of value and the smooth execution of collaborative initiatives. This highlights the importance of contacts between the government and citizens in collaborative efforts and how they greatly impact the effectiveness of governance. Existing research, however, has shown conflicting results; for example, some studies have found that contacts between the government and citizens improve governance performance [10]. With machine learning, it is feasible to build a mathematical model using data, even when many of the variables are unknown in advance. As you proceed through the learning phases, which uses the training set of data to detect links and classify them, the parameters are configured. The designers select the various machine learning techniques based on the activities that need to be executed (grouping, decision tree). Typically, these techniques are grouped into three types: supervised learning by humans, unsupervised learning, and reinforcement-based unsupervised learning. Comparative trends in digital transformation over a given time period among China, the US, the EU, and India are depicted in Figure 1. The graph monitors important metrics including the uptake of AI, developments in data governance, the effectiveness of e-government, and public participation in digital projects. Due to state-led initiatives, China's use of AI and e-government services has grown rapidly, demonstrating the country's fast digital transformation. A balanced approach to digital transformation is ensured by the US and EU's consistent advancements, especially in data governance and technology legislation. India, on the other hand, is showing an upward trend, which is indicative of its growing digital infrastructure and rising public involvement in digital governance. The graphic provides insights into the dynamics of global digital governance by highlighting the various technical investments and policy approaches that influence each region's digital progress. This research delves at the ways digital transformation can boost government efficiency, which is crucial for improving performance of the public sector in this digital age. Specifically, the study builds a complete model of a production network to show how digital transformation affects efficiency in different government agencies. Everybody in the auditing community, from practitioners to lawmakers, needs this information. The findings provide practitioners with guidance on how to develop and conduct digital transformation projects, allowing them to maximize the effect of their efforts and resources. Optimizing the utilization of public monies can be achieved through policymakers using the findings to design rules that enable cooperation between departments as well as integrated digital platforms. The study provides auditors with a framework for measuring the success of digital projects, which may lead to better, more practical suggestions. As a result of fixing these problems, government services become more trustworthy and beneficial to society since they are faster, clearer, and more responsive.

2. Related Works

The related works for this paper is listed in table 1.

Table 1. *Summary on related works*

Ref	Year	Objective	Finding
[11]	2021	Digital transformation adoption can be influenced by seven separate criteria listed on the TOE: proportionate advantages, compatibility, complexity, support from top management, attitude toward change, organizational preparation, and regulatory environment. We utilized correlation analysis to look at how these things relate to digital transformation adoption.	All seven variables were positively and significantly related to digital transformation adoption, however the one with the largest correlation was attitude toward change. In addition to accurately predicting digital transformation adoption in the Saudi context, the TOE model is applicable to other sectors in Saudi Arabia.
[12]	2023	One of the factors that hastened the digitization of the public sector is the unanticipated COVID-19 epidemic, which is the primary topic of this article. In response to the COVID-19 pandemic, Situbondo Regency's Populations as well as Civil Registry Office implemented SILAO, an online portal for population management services.	This study's findings suggest that the pandemic-era public service IT system wasn't a failsafe for effective service delivery. An uninterrupted internet connection is essential for the functioning of any public service technology system. The low standard of public service has been impacted by the unpredictable power of the internet.
[13]	2019	The US E-Government Act aims to provide better oversight of the OMB's e-government projects by the federal government. Promoting e-government is the responsibility of its Office of Management and Budgeting (OMB), which will continue to collaborate with ministries to ascertain the funding requirements of each initiative.	It is crucial for promoting digital government policies through the ministry that administers the budget or set up an entirely devoted company under the ministry to ensure strong coordination and link it to the spending plan, according to the comparative case investigation of digital government operates in Korea and the US. This is from the perspective of digital the government transitions using information technology.
[14]	2020	The author examined and analyzed DT using a case study approach, focusing on pertinent events that happened during a five-year period.	According to the results, DT in government comes in waves, influencing the full administrative system from the provincial to the national level and bringing about both drastic and subtle changes as it adapts to various organizational components.
[15]	2023	The authors shed light on the general interrelationships among changes in institutions, impacts, and context aspects of digital transformation, while also explaining the implementation challenges and the impact on citizens and workers.	Several unforeseen and detrimental effects of the e-government reforms on public personnel and residents are highlighted by this study's conclusions.

[16]	2021	Goals 4 and 9 address educational growth at all levels of difficulty, industrial collaborations and improvements, and stakeholder input to the digitalization implementation process, respectively, whereas this document focuses on contextual elements.	This study adds to the existing body of knowledge on the topic of the digital revolution for social development, particularly in developing economies like Nigeria's, with the goal of achieving SDGs 4 and 9.
[17]	2024	In this research, we look at how the building of government informatization has affected the creation of digital technologies within corporations. It builds a difference-in-differences model using China's information processing and industrial pilot zones as an almost-natural experiment with government informatization building.	Government informatization construction greatly boosts business digital technology innovation, according to the empirical data. This is because it increases corporate focus on digital technologies and decreases transaction costs.
[18]	2025	In this research, we look at how digital government development affects business transformation and how to get there. An external environment conducive to corporate transformation can be created by drawing on theories of digital democracy and institutional economics, which include the building of cloud platforms, the availability of government data, and intelligent government services	These findings are supported by empirical studies on Chinese listed enterprises. In addition, businesses' internal value chains can be enhanced through the development of digital government, which effectively promotes innovation and management intelligence.
[19]	2023	The relationship between digital government development and enterprise total factor productivity (TFP) is examined empirically in this research. The moderating effect of the distribution of local government's attention is also considered.	After running the study through a battery of robustness tests including instrumental factors, one-stage lag of variables that explain things, and debiased predictive machine learning models, the researchers still came to the same conclusion: digital government development greatly enhanced enterprise TFP.
[20]	2024	We found that the digital evolution efficiency of local governments is significantly and positively impacted by government-citizen contacts at the individual level, government image, and the collaboration capacities of district-level departments.	In addition to adding to our knowledge of the processes driving local governments' digital transformation performance, these results provide helpful insights for improving policy formulation.

Table 2. *Demographic characteristics profile*

Characteristics		Freq	Percentage(%)
Gender	Male	235	45.6
	Female	270	54.0
Age	15 years under	15	2.5
	16 years to 24 years	270	55.2
	24 years to 30 years old	198	25.2
	above 30	80	15.7
Device usage freq in daily	<2h	20	4.1
	2 to 6 hrs	220	40.4
	6 to 10 hrs	200	40
no. of mobile payment apps used	0	3	0.6
	1	20	4.2
	2	330	65.2
	3	65	12.5
	4 and above	80	16.1

3. Methodology

3.1 Data method and description

This analysis makes use of data from 31 Chinese provinces between 2013 and 2023. The use of provincial-level data was justified by its strong representativeness. Given its wide geographic and demographic coverage, provincial data frequently paints a more complex picture of the region's overall progress in government digital transformation. On the other hand, city-level data may be subject to particular urban features and municipal regulations, which could introduce biases in the analysis.

Government efficiency is the study's dependent variable, and the extent of digital transformation in government agencies is its independent variable. Table 2 shows demographic characteristics profile.

3.2 Government digital transformation

Four representative government departments were chosen for this study due to their wide range of responsibilities and important positions within the Chinese political system. These departments include the Department of Education, the Dept. of civilian affairs the Department of Finance (DoF), and provincial offices of the Public Bank of China (PBoC). These departments represent several aspects of the government's operations including the creation of monetary policy, the execution of educational policies, the management of social welfare, and financial forecasting and preparation. They are in charge of important public service sectors like finance, higher learning, and civil affairs. Their selection for this study is justified by their crucial roles, which imply that their level of digital transformation may have significant implications for total governmental efficiency. The theoretical underpinnings of text analysis are found in its capacity to quantitatively analyse complicated processes by extracting important information from massive amounts of textual input through automated processing. The efficacy and dependability of text analysis have been thoroughly established, and it has been used extensively in research in social sciences, including analysis of policies, public opinion tracking, and social trend studies. The digital transformation of government is being rigorously quantified and tracked in this study with the aid of text analysis techniques, which also provide trustworthy data support for assessing its effects on government efficiency. To create the Government digital revolution index, we analysed unstructured textual data. The first step involves gathering and organising papers and policy materials about the digital transformation of government, from which we extracted relevant keywords. One We next gather the content of the "Government Information Disclosure Annual Report" from the four departments listed above, covering all 31 Chinese provinces between 2013 and 2023. In the third stage, we extract sentences that contain the keywords. In the fourth step, we use Eq. (1)a as an example, where it stands for the departments in the province and t for the year, to determine the extent of the digital revolution of the sample's departments in a certain year. The advantage of employing the proportion for appropriate sentences to analyse the government's digital transformation degree over keyword frequency text analysis is that it avoids measurement biases brought on by keyword repetition in short text segments.

GovernmentDigitalTransformationi,t
=Proportionofrelevantsentencesi,t
=wordnumberof relevant sentences i,t /totalnumberofwordsintheReporti,t . (1)

The Chinese government's transparency project, known as the "Government Information Disclosure Annual Report," requires every agency to publish an annual report outlining its information disclosure activities and progress. The department's information disclosure procedures, significant developments, particular actions done, outcomes attained, difficulties encountered, and future goals are typically covered in these reports. The goal of this approach is to encourage an open and accountable culture in people in general sector. Because these reports follow a standardised structure, we can analyse them to determine the level of digital transformation in a department and compare it to other departments. Considering text analysis's many benefits, there are certain restrictions and possible biases with this approach:

(1) Bias in keyword selection: If not thorough, it can leave out crucial details and not adequately represent every facet of the digital revolution.

(2) Subjectivity of the text: Different writers may employ different wording and vocabulary, which might increase subjectivity and complexity and possibly compromise the analysis's correctness.

(3) Context dependent status: Keywords may signify different things depending on the context, and basic frequency analysis may not fully capture their meaning. To address these problems, we used several iterations of keyword validation and screening. We made sure that the keyword selection process was accurate and comprehensive. We included subject-matter experts throughout the keyword evaluation process and drew from previously published works and policy papers. We also integrated methodologies of both qualitative and quantitative analysis. We carried out a thorough examination of particular textual material in addition to keyword frequency analysis to confirm that the text analysis results were fair. We computed the variance (VAR) of the digital revolution levels across the four departments in order to evaluate the coherence of initiatives for digital transformation within that jurisdiction. The government in the corresponding region's efforts to convert digitally are less coherent when the variance is larger.

3.3 Governance in Digital Transformer model (BERT+LSTM)

The Transformers model is a particular Deep Learning architecture that explains a natural language processing method used in (artificial intelligence (AI)). Transformers use a strong attention mechanism in conjunction with text processing to produce contextual and intricate word representations. This paradigm investigates the connections among textual phrases or objects. A variety of competitive neural sequence transduction models use the encoder-decoder structure. Based on the input symbolic representation sequence, the encoder creates a recursive representation sequence. Next the decoder generates the output a sequence of symbols starting with z. The encoder turns a stream of input symbols into a continuous representation. Then, one symbol at a time, the decoder creates an output sequence using the continuous representations that the encoder provided. In auto-regressive models, the input is used to produce the subsequent one, utilising the encoder-decoder structure.

The left and right halves display the series Transformers encoder and decoder, respectively. The fully interconnected layers used by the encoder and decoder are layers (self-attention) as well as dots (pointwise). An encoder consists of N = 6 equivalent layers. Each layer is made up of two sub-layers: the multi-head mechanisms for self-attention and the feed-forward network. The Transformers model follows this idea by using completely connected both encoder and decode layers and a self-attention stack. Normalisation of the layers and residual connections promote the flow of information. The attention function looks at how closely a particular key along with query are related to determine how many items are at danger by converting keyword-value pairings as well as queries to output. With the usage of the transformers in applications like machine translation and language modelling, natural language processing has greatly advanced.

3.4 BERT

The application of deep learning framework that describes a natural language analysing technique used in artificial intelligence (AI) is the Transformers model. Transformers create complex and contextual word representations by combining text processing with a powerful attention mechanism. The relationships between textual phrases or just objects are examined by this paradigm. The encoder-decoder structure is used in many competitive neuronal sequence transduction models. The encoder generates a recursive representation sequences based on the input graphical representations sequence. The decoder then produces a series of symbols beginning with z as the result. An input stream of symbols is transformed into an ongoing process representation by the encoder. The decoder then uses the continuous interpretations that the encoder supplied to generate an output sequence, one symbol at a time. Auto-regressive models use the encoder-decoder structure to generate the input of the previous one.

The encoder and decoder for the series Transformers are shown in the left and right portions of Figure 1, respectively. Both layers (self-attention) and dots (pointwise) are fully interconnected layers that are utilised by the encoder and decoder. N = 6 comparable layers make up an encoder. The feed-forward network and the multi-head techniques for self-attention are the two sub-layers that comprise each layer. By utilising a self-attention stack and fully connected encoder and decoder layers, the Transformers model adheres to this concept. Information flow is facilitated by layer normalisation and residual connections. By translating keyword-value pairings and queries to output, the attention function determines how closely a given key and query are related to calculate how many things are at risk. Processing natural language has significantly improved with the use of transformers in applications such as language modelling and machine translation.

3.5 Mathematical Formulation

The transformer encoder, a key part of BERT, processes input tokens using self-attention. The following is a mathematical description of the self-attention mechanism:

$$\text{Attention(Q,K,V)=softmax}(\frac{Qk^T}{\sqrt{dk}})\text{V} \qquad (2)$$

Where,

- Q(Query),K (Key), and V (value) are the input matrices.
- d_k is the dimension of the key vectors.

BERT employs many self-attention heads to record various context elements:

$$\text{MultiHead(Q,K,V)= Concat }(head_1,head_2……,head_h)W^O \qquad (3)$$

Where each head is computed as:

$$head_i = \text{Attention(Q}W_i^Q\text{,K}W_i^k\text{, V}W_i^V) \qquad (4)$$

Here, W_i^Q,W_i^k,W_i^V are the learned projection matrices for the i-th head.

3.6 Construction of LSTM model

The gradient vanishing and exploding problems that traditional RNNs have when dealing with long sequence data have been addressed by LSTM (Long Short-Term Memory), a specialised type of RNN (Recurrent Neural Network), although its full potential is still unrealised in a number of ways. For problems like prediction of time series and language modelling, the majority of existing research focusses on using LSTM alone or in combination with traditional optimisation techniques. However, especially in the field of educational technology, these endeavours frequently fail to consider the complex interactions among model architecture, the hyperparameter decision-making, and real-world application situations. The absence of investigation into novel optimisation techniques designed especially for LSTM in the larger context of personalised learning paths is one significant research gap. Even while they can be somewhat successful, traditional optimisation techniques might not be able to pinpoint the ideal hyperparameters and model setups needed for extremely complex tasks like forecasting student behaviour in various educational environments. The necessity for more sophisticated, adaptive optimisation techniques that can dynamically adapt to the subtleties and complexity of educational data is highlighted by this constraint. By presenting a novel method that uses transformation model to optimise LSTM models especially for the goal of creating and improving individualised learning routes for English learners, the innovation suggested in this research aims to close these gaps. This integration offers a workable solution to the established problem of creating really customised educational experiences in addition to being a methodological leap in machine learning optimisation. BERT enables the LSTM model to extract the most insightful trends from learners' behavioural data by dynamically adjusting LSTM hyperparameters and possibly changing the model architecture itself. This ultimately results in the creation of highly effective, adaptive, and deeply personalised learning paths. In LSTM networks, an input xt is received at every time step t, wherein t=1,2,…. The LSTM unit then processes this input along with its own internal condition from the previous step in time to generate an output ht. Long-term dependencies in the sequence data are preserved by the LSTM thanks to this repeating procedure. The expression used to calculate ht is:

$$i_t = \lambda(W_{ix}x_t + W_{ih}h_{t-1} + W_{ic}c_{t-1} + b_i) \quad (5)$$
$$f_t = \lambda\left(W_{fx}x_t + W_{fh}h_{t-1} + W_{fc}c_{t-1} + b_f\right) \quad (6)$$
$$o_t = \lambda(W_{ox}x_t + W_{oh}h_{t-1} + W_{oc}c_{t-1} + b_o) \quad (7)$$
$$c_t = f_t c_{t-1} + i_t\sigma(W_{cx}x_t + W_{ch}h_{t-1} + b_c) \quad (8)$$
$$h_t = o_t\sigma(c_t) \quad (9)$$

A number of gates in the LSTM unit are essential for controlling the information flow:

The input gate (it) regulates the amount of fresh input data (xt) that can be used to update the memory cell's state (ct). The input gate determines the necessary update level by considering both the current input xt and the prior hidden state ht−1. The sigmoid function, which squashes the output to a range between 0 and 1, is the activation function σ commonly used here. This gives you fine-grained control over the update. The forget gate (ft) controls which information from the previous memory cell state ct−1 should be kept, in contrast to the input gate, which concentrates on incoming data. In order to determine which portions of the prior memory are significant enough to retain,
this gate similarly uses the sigmoid function, evaluating both xt and ht−1.

Memory Cell (ct): Long-term dependencies are

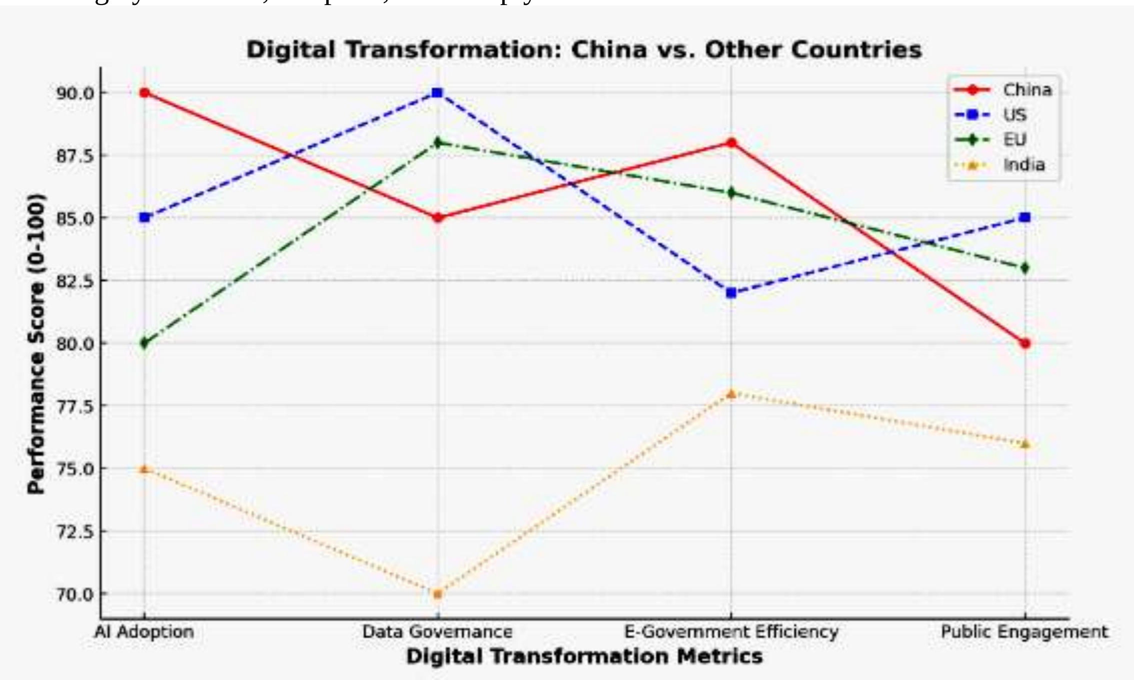

Figure 1. *Digital Transformation among different countries*

preserved in the memory cell, which is the LSTM unit's central storage component. The outputs of the input and forget gates are used to update it. In particular, it adds a modified version of the current input, xt, scaled by the input gate it, after first forgetting a piece of its former state, controlled by ft. In order to ensure that only pertinent knowledge is retained, this method blends forgetting the past with incorporating the present. Output Gate (ot): This last gate regulates the amount of the internal storage space state (ct) that is visible to the outside world as the state that is hidden (ht). It is calculated using the sigmoid. function and both xt and ht−1 as inputs, same like the input as well as forget gates. However, it shapes the unit's contributions to the subsequent layer or the ultimate output by regulating the flow of information out of the cell rather than directly managing the input into the cell state. The LSTM unit overcomes the constraints of conventional RNNs in handling dependence on long-range by combining these gates with nonlinear activating functions and measured summation of inputs to learn complicated temporal patterns from sequential data. The LSTM is a potent tool for jobs involving time-series analyses, language modelling, and other sequential prediction challenges because of its gated control structure and selective forgetting and remembering capabilities

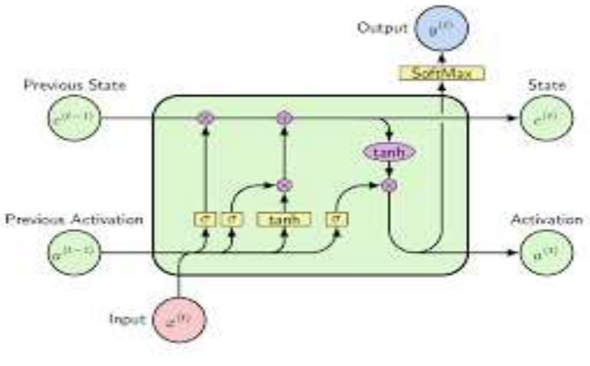

Figure 2. *LSTM unit structure*

3.7 Benefits of BERT +LSTM:

In the digital age, the BERT + LSTM hybrid model is a very useful tool for examining social public opinion and how it affects technology governance. While LSTM measures sentiment changes over the years, BERT collects deep meanings of context from news, social media, and public discussions. This makes it perfect for tracking misinformation, anticipating opinion trends, and tracking public reactions to policy. In addition to facilitating real-time public monitoring and improving sentiment analysis accuracy, this combination aids policymakers in anticipating governance difficulties by gaining insight into changing social concerns. Its capacity to handle sequential data sets it apart from conventional models, guaranteeing data-driven choices for long-term technological governance. Figure 2 is LSTM unit structure and figure 3 shows proposed model.

3. Results and Discussions

Social public opinion on technology Governance

Public opinion on technology governance has improved over the past year, according to the figure 4, sentiment trend study, with negative sentiment falling from 30% to 18% and positive sentiment increasing from 55% to 72%. This implies that increased public trust has been facilitated by effective policy implementations, more openness, and more stringent restrictions. A steady group of people who are either uninvolved or undecided is indicated by neutral sentiment. The attitude swings are consistent with important governance choices including platform accountability measures, data privacy legislation, and AI restrictions. In order for policymakers to successfully modify governance initiatives and proactively address public concerns, our research emphasises the significance of real-time public mood tracking utilising AI-driven models such as BERT + LSTM. The accuracy comparison of several NLP models for public sentiment analysis reveals that BERT + LSTM (90%) is the most successful as it combines the deep contextual knowledge of BERT with the sequential data processing capabilities of LSTM, which makes it perfect for sentiment trend monitoring. Due to its pre-trained embeddings, BERT alone (85%) performs well but lacks sequential memory, whilst XGBoost (82%) and CNN (80%) exhibit reasonable accuracy. CNN is good at identifying local word patterns but has trouble with long-term relationships. SVM (75%) has the lowest accuracy because of its limits in handling complicated sentiment fluctuations, whereas LSTM alone (78%) performs respectably but lacks BERT's extensive contextual characteristics. According to these findings figure 5, deep learning models—especially transformer-based architectures like BERT—perform better in sentiment analysis than conventional machine learning models, which makes them more appropriate for technology governance's real-time surveillance of public opinion. The precision analysis in figure 6, shown as a percentage, demonstrates how well various NLP algorithms identify public opinion about technology governance. Because it can capture both sequential dependencies (LSTM) and deep contextual meaning

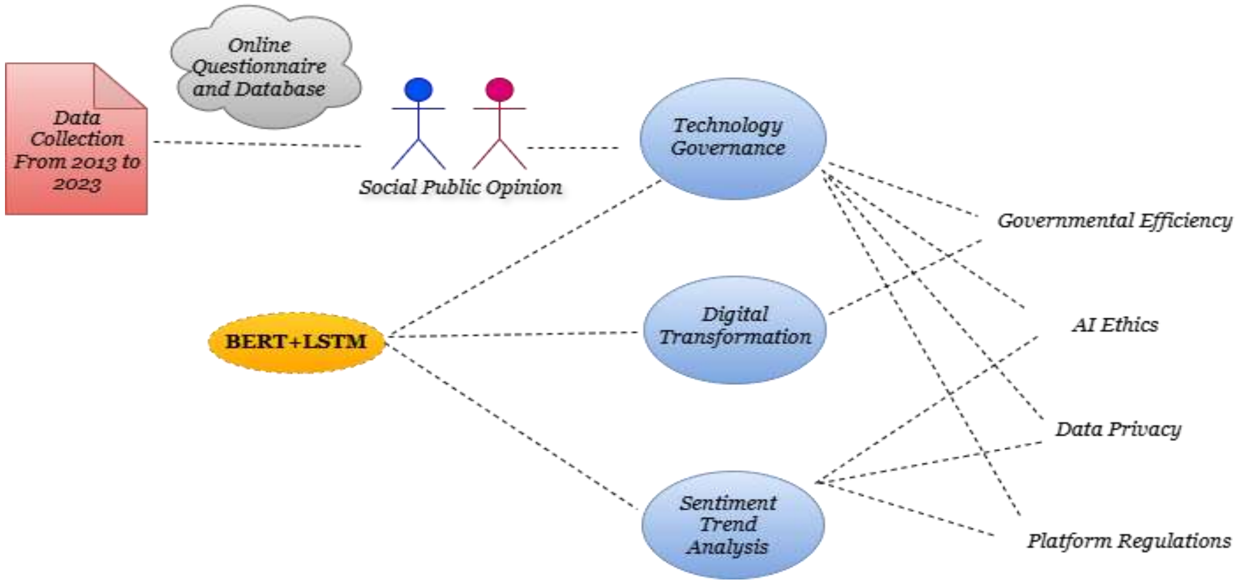

Figure 3. *Proposed Model*

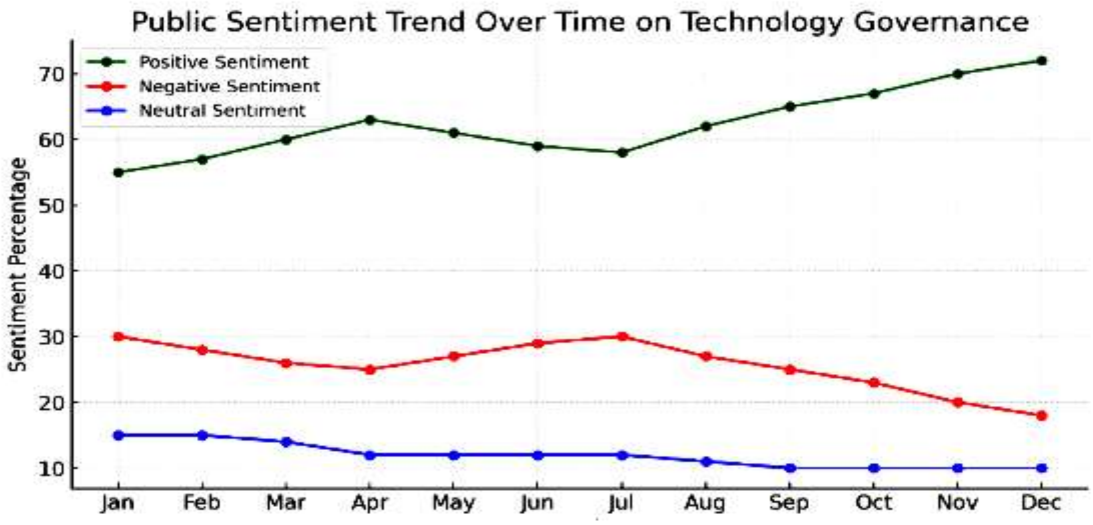

Figure 4. *Social public opinion about the data transformation*

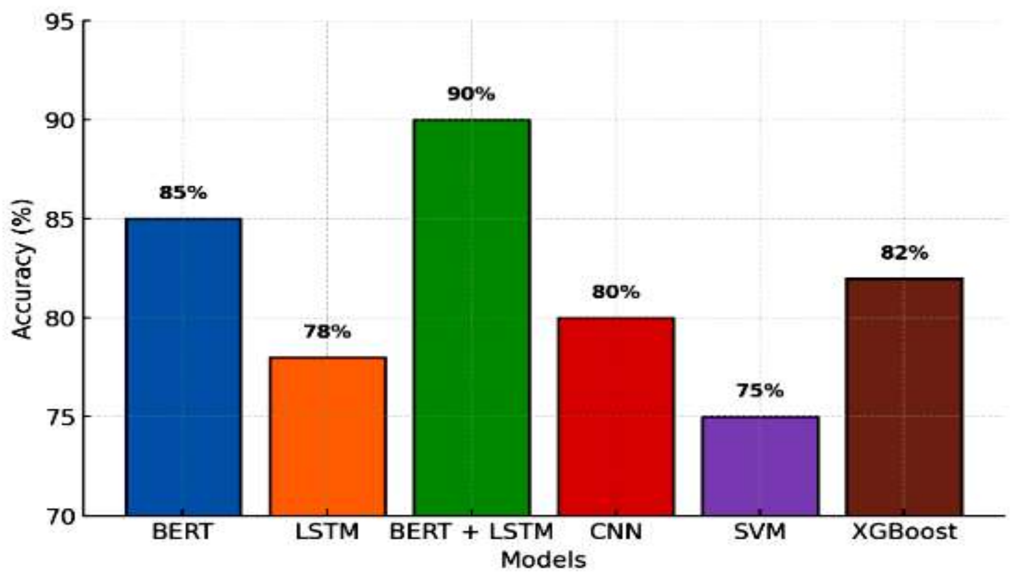

Figure 5. *Accuracy of the existing and proposed model*

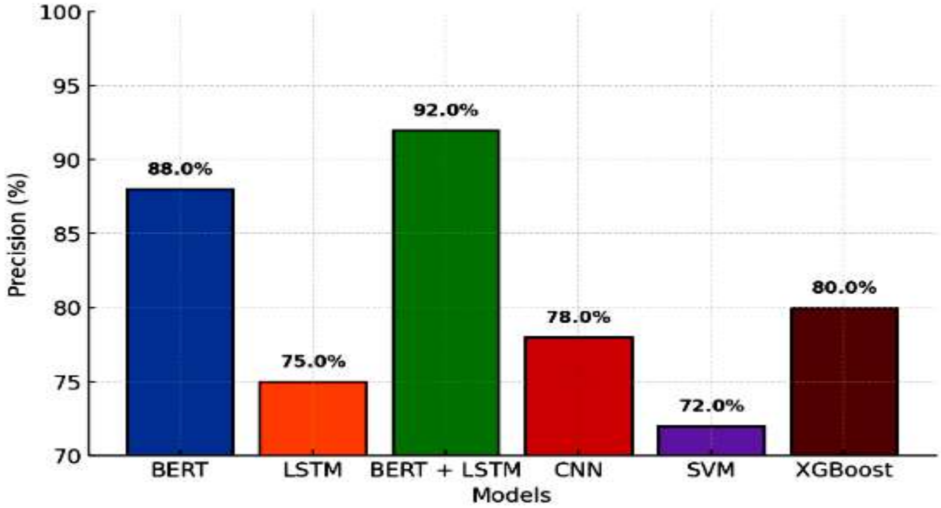

Figure 6. *Precision of the existing and proposed model*

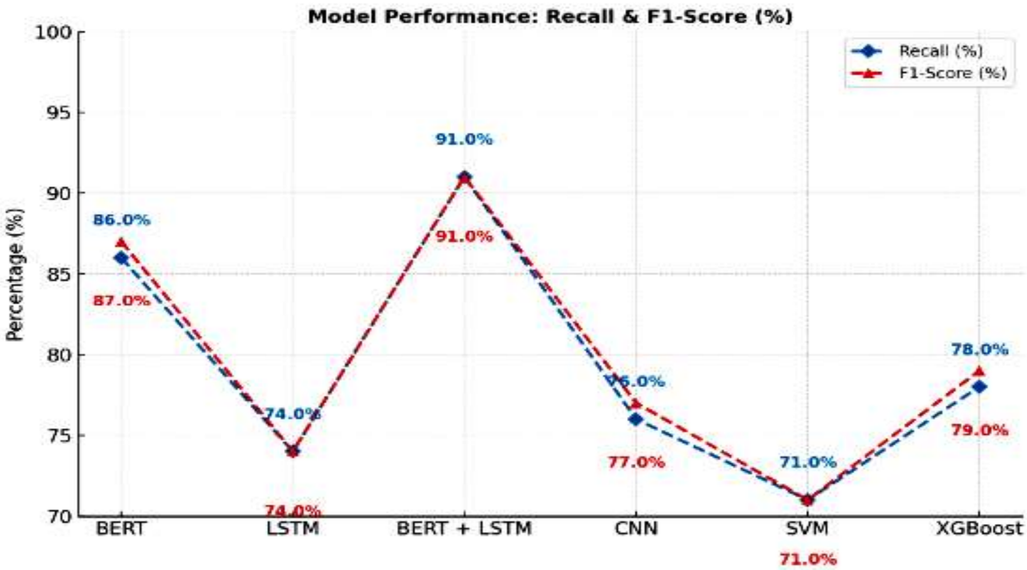

Figure 7. *Recall and F1-Score of the existing and proposed model*

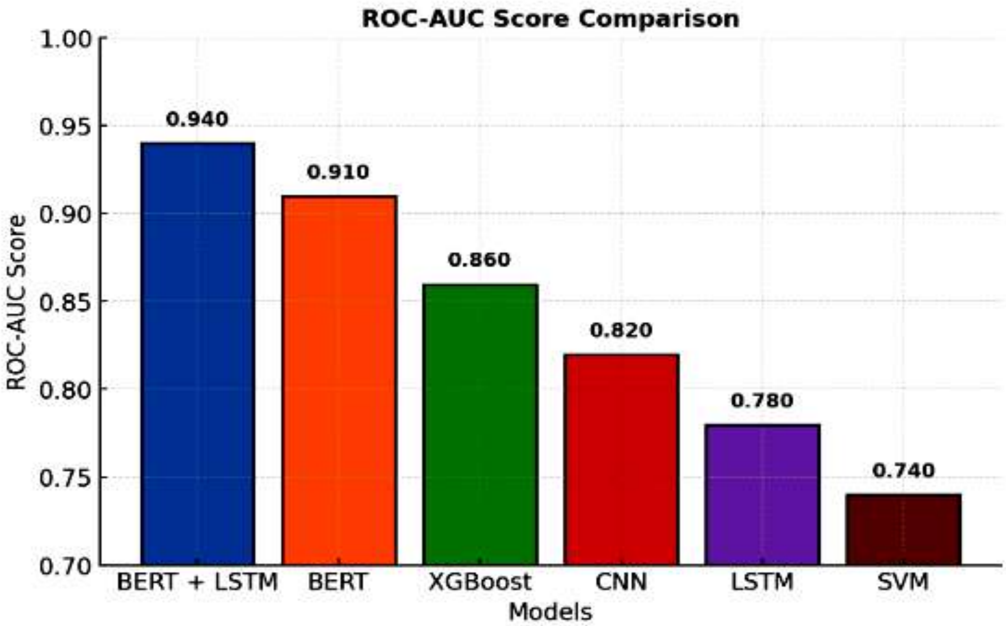

Figure 8. *ROC-AUC of the existing and proposed model*

(BERT), BERT + LSTM (92%) has the lowest number of false positives and the best accuracy. Due to its absence of sequential learning, BERT by itself (88%) performs well as well but trails somewhat behind. Because systems rely on feature-based learning rather than in-depth contextual knowledge, XGBoost (80%) and CNN (78%) exhibit middling accuracy, suggesting that they could misclassify some feelings. The two models with the lowest accuracy, LSTM (75%) and SVM (72%), struggle to accurately distinguish subtle sentiment fluctuations. According to our investigation, deep learning models—especially transformer-based architectures like BERT—perform better than conventional machine learning models when it comes to precisely detecting sentiment in intricate public debate.

Recall and F1-Scores (%) for several NLP models in sentiment analysis are clearly compared in Figure 7. BERT + LSTM (91%) continuously beats other models, proving that it can capture sentiment trends with balanced categorisation and good recall. Despite lagging significantly because it lacks sequential learning, BERT alone performs well (86% recall, 87% F1-score), aided by its rich contextual awareness. CNN (76-77%) and XGBoost (78%) perform moderately, suggesting that although they are capable of accurately classifying attitudes, they do not have the sophisticated language comprehension of transformer-based models. The lowest scores are shown by LSTM (74%) and SVM (71%), which reflects their difficulties in precisely capturing sentiment changes. With recall in blue and F1-score in red, the new colour scheme enhances clarity and makes it simpler to discern model performance. In comparison to conventional machine learning techniques, our results confirm that hybrid deep learning models—in particular, BERT-based architectures—offer better sentiment analysis capabilities. An essential assessment statistic for classification models is the ROC-AUC curve, figure 8 shows how well the models can distinguish between sentiment classes at different threshold levels. To illustrate the trade-off between accurately recognising positive cases and reducing false alarms, it compares the True Positive Rate (TPR) versus the False Positive Rate (FPR). The performance of several models in differentiating across sentiment classes is visualised by the ROC-AUC score comparison. With the greatest ROC-AUC score of 0.94, the BERT + LSTM model demonstrates its better capacity to distinguish between positive and negative feelings. With the help of its contextual word representations, the BERT model (0.91) comes in second. The intermediate performance of CNN (0.82) and XGBoost (0.86) indicates that they may not have deep contextual comprehension, but they do capture significant sentiment information. The weakest performers in terms of successfully separating sentiment classes are LSTM (0.78) and SVM (0.74). These findings demonstrate that hybrid deep learning models perform better on sentiment classification tasks than conventional machine learning techniques, especially transformer-based architectures.

4. Conclusions

The influence of digital government building on corporate intelligent transformation is examined in this study. It examines how digital government is being built using institutional economics and digital governance theory. According to the report, digital government fosters cloud platform development, open government data, and AI applications in government services, hence fostering an atmosphere that is conducive to intelligent transformation. Additionally, it implies that the development of digital government lowers the costs of institutional transactions, freeing up resources for businesses to invest in more fruitful endeavours like AI applications. The Chinese government has made the development of AI and digital government a top priority, providing a solid basis for empirical study.This dissertation explores the impact of digital transformation on the effectiveness of technology governance in the public sector. It reveals that the impact of digital growth on performance varies based on a department's position within the broader technological influence and its ability to improve public perception. The study suggests optimizing digital transformation resource allocation. The research aims to maximize the total impact of digital transformation on governmental efficiency and emphasizes the importance of systemic thinking in building a digital government. The study suggests that a coordinated system of digital governance capabilities is crucial, as outlined in China's "Guidelines on Strengthening the Construction of a Digital Government." However, the study has limitations, such as its focus on a specific time period and group of Chinese government agencies and lacks a comprehensive examination of coordination methods or challenges. Future research could broaden the scope of this study.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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