Applications of Artificial Intelligence in Global Diplomacy: A Review of Research and Practical Models

Article *in* Sustainable Futures · February 2025

DOI: 10.1016/j.sftr.2025.100486

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Sustainable Futures 9 (2025) 100486

Contents lists available at ScienceDirect

Sustainable Futures

journal homepage: www.sciencedirect.com/journal/sustainable-futures

Applications of artificial intelligence in global diplomacy: A review of research and practical models

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A R T I C L E I N F O

Keywords:
Artificial intelligence
Machine learning
Decision making

A B S T R A C T

The integration of artificial intelligence into global diplomacy presents opportunities and challenges that require thorough exploration. This research is crucial for understanding how AI can transform diplomatic practices, enhance decision-making, and address complex international issues. We examined AI models relevant to diplomacy, including predictive models for economic growth and data analytics for trade. Our review highlights recent advancements in AI within diplomatic contexts. Through case studies, we demonstrated AI's application in consular services, crisis management, and public diplomacy, showcasing its benefits and potential risks. We hope this paper contributes valuable insights and supports future research in AI's role in diplomacy.

1. Introduction

The rise of artificial intelligence (AI) has dramatically transformed various sectors, including international relations and global economics [1]. AI technologies have equipped governments and organizations with advanced tools to influence diplomatic decisions, shape economic policies, and optimize international trade [2]. By processing vast amounts of data, recognizing patterns, and predicting outcomes, AI enables policymakers to navigate complex geopolitical landscapes and make more informed decisions.

As AI continues to evolve, it is increasingly recognized as a dynamic and rapidly advancing field, constantly pushing the boundaries of technological innovation. Researchers and professionals alike are continually refining AI models, algorithms, and applications, which have become integral to modern technological advancements. AI's potential in international relations is vast, ranging from diplomatic decision-making to economic forecasting and trade strategy analysis. Its ability to simulate human cognitive functions has allowed AI to play an increasingly critical role in shaping global diplomacy, politics, and security [3]. Governments are now leveraging AI-driven models to enhance their capabilities in areas such as economic growth prediction, military strategy, and global competitiveness.

At its core, AI offers a powerful lens through which to reevaluate how information is processed and decisions are made in the international arena [4]. By analyzing large datasets, simulating scenarios, and learning from past experiences, AI systems provide policymakers with deeper insights into global trends and more sophisticated tools for decision-making in global diplomacies.

This paper aims to provide a comprehensive review of the current state of research on AI applications in international relations and economics. It will cover predictive models for economic growth, AI-driven decision-making tools in diplomacy, and data analytics for enhancing international trade. Additionally, the paper will explore the latest advancements, analyze experimental results from AI applications, and discuss the challenges and opportunities associated with the adoption of AI in these fields.

The contribution of this paper could be summarized as follows:

1. Examination of Practical AI Models in Global Diplomacy: This paper will explore and analyze various AI models applicable to global diplomacy. It will cover predictive models for economic

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https://doi.org/10.1016/j.sftr.2025.100486
Received 16 September 2024; Received in revised form 20 January 2025; Accepted 7 February 2025
Available online 9 February 2025

growth, decision-making tools in diplomacy, and data analytics for international trade.
2. Review of Recent Research and Innovations: The paper will provide a comprehensive review of recent research and advancements in the application of AI diplomacy. This includes the latest developments in machine learning, natural language processing, and computer vision.
3. Illustration of Case Studies and Practical Applications: The paper includes detailed case studies that illustrate the practical applications of AI in diplomacy. These case studies demonstrate how AI technologies can be utilized in consular services, crisis management, public diplomacy, and diplomatic negotiations. By examining real-world examples, the paper provides insights into the effectiveness, benefits, and potential risks associated with AI applications in various diplomatic contexts.
4. Exploration of Challenges and Opportunities: The paper will also examine the challenges and opportunities associated with the adoption of AI in global diplomacy, providing a balanced perspective for policymakers and researchers.

The primary objective of this paper is to review the impact of AI on global diplomacy. We focus on examining how AI technologies influence diplomatic decision-making, economic forecasting, and international trade analysis. Our review emphasizes recent advancements in AI methodologies, including predictive models for economic growth, decision-making tools in diplomacy, and data analytics for optimizing trade. We highlight the transformative potential of AI in shaping global diplomacy and policies. By analyzing the latest research and practical applications, we aim to showcase how AI-driven insights can enhance decision-making processes and improve strategic planning in

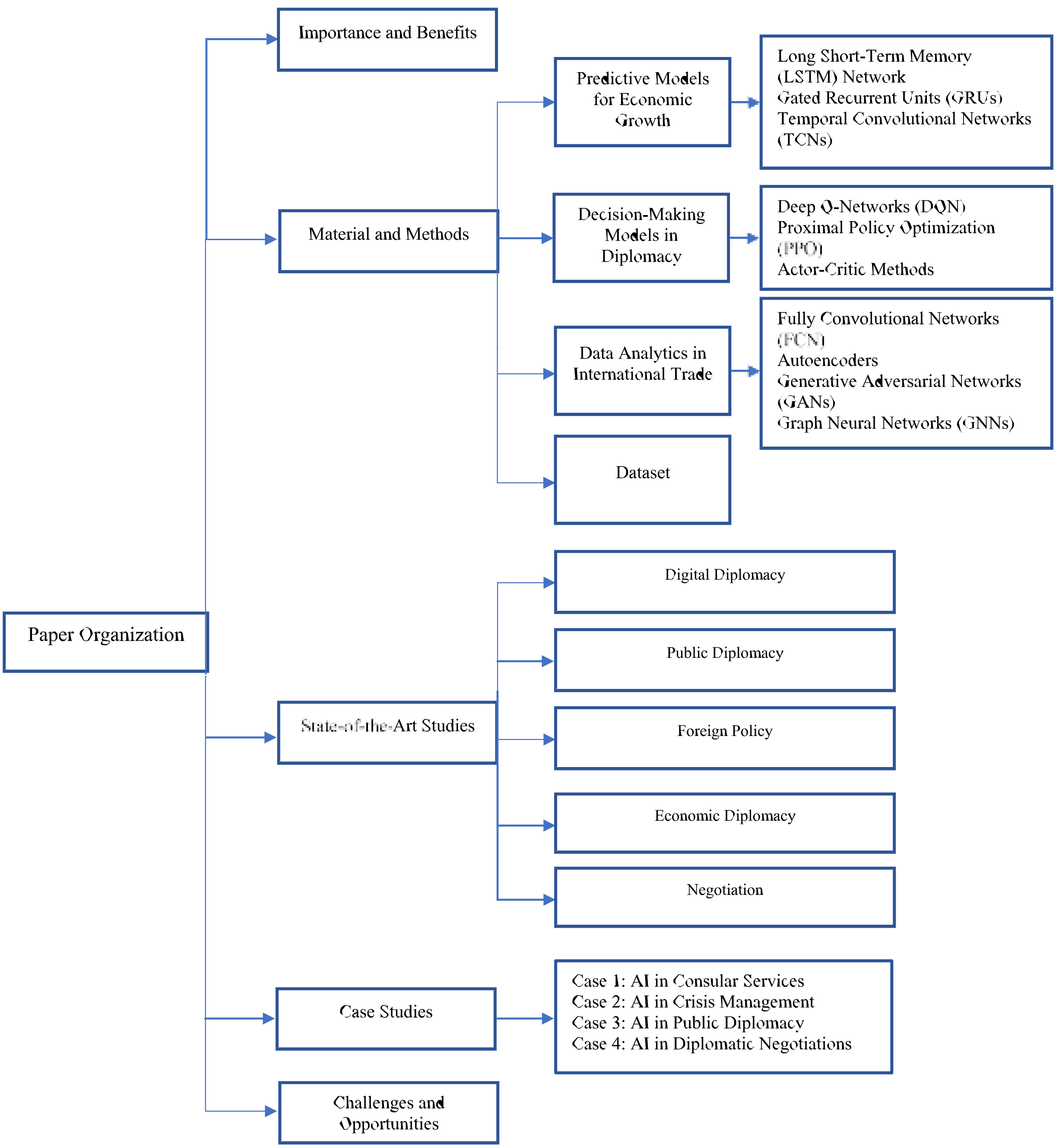

Fig. 1. A taxonomy illustrating the structure of the main topics discussed in the paper.

international contexts. Fig. 1 illustrates the key areas covered in this review, including predictive analytics, decision support systems, and data-driven trade strategies.

We acknowledge the significant contributions of researchers and practitioners in advancing AI applications in these fields. Their work has been crucial in developing effective tools and models for managing global diplomacy. Our approach provides a comprehensive assessment of the strengths and opportunities within the realm of AI in global affairs, maintaining impartiality and focusing on both the benefits and challenges. Ultimately, we hope our findings will support policymakers and researchers in leveraging AI to navigate the complexities of the international landscape and improve global outcomes.

2. Importance and benefits

In the realm of international relations and global diplomacy, traditional methods often encounter significant limitations that impact their effectiveness [5]. One major issue is the complexity of decision-making processes. Conventional approaches frequently rely on manual analysis and subjective judgment, which can lead to inconsistencies and inefficiencies. For example, in economic forecasting and diplomatic strategy, traditional methods may struggle to accurately predict and adapt to rapidly changing global dynamics [6].

Scalability is another critical challenge. As the volume of international data increases, traditional methods can fall short in managing and analyzing large datasets. This limitation is particularly evident in economic modeling and trade analytics, where extensive data is required to understand global trends and patterns. Recent literature emphasizes the need for scalable solutions to handle the growing complexity and volume of international data more effectively [7].

Efficiency is also a major concern. The time required for manual analysis and decision-making can delay responses to economic shifts or diplomatic crises, potentially leading to missed opportunities or suboptimal strategies. AI models, with their ability to process large amounts of data quickly and accurately, address these scalability and efficiency challenges. By leveraging AI, policymakers and analysts can gain faster and more reliable insights into global economic conditions and diplomatic scenarios [8]. The importance of AI in enhancing international relations and economic strategies is well-documented. AI technologies provide powerful tools for improving decision-making in diplomacy, economic forecasting, and trade analysis. Recent studies have shown that AI-driven models can offer predictive accuracy and strategic insights that surpass traditional methods. For instance, AI models in economic forecasting have demonstrated the ability to predict market trends and economic indicators with higher precision compared to conventional approaches.

Recent advancements in AI underscore its transformative impact on international affairs. Reviews of AI applications in diplomacy highlight the role of advanced techniques, such as machine learning algorithms and predictive analytics, in improving the effectiveness of policy-making and strategic planning. These AI models not only enhance performance but also provide consistent and actionable insights across diverse global contexts.

Our study aims to deliver valuable insights into how AI can improve decision-making processes and strategic planning in international relations and global economics. By exploring the latest advancements and evaluating the practical applications of AI, we seek to demonstrate the potential benefits and implications of integrating AI into international policy and economic analysis.

3. Material and methods

In this section, we will review the practical models applied in the field of international relations and economics, focusing on how Artificial Intelligence technologies have been integrated into these domains. Fig. 2 illustrates the increasing trend in the number of research studies focusing on the impact of Artificial Intelligence on International Relations and Economics. Specifically, it presents a comparison of published papers between two time periods: from 2020 to 2022, with 15,900 studies, and from 2022 to 2024, with 16,900 studies. This upward trend demonstrates the rising interest and expanding body of research in this interdisciplinary field over recent years.

Between the years 2020 and 2022, there were approximately 15,900 research studies published globally on the topic of Artificial Intelligence and its impact on International Relations and Economics. This number increased to 16,900 between 2022 and 2024, indicating a continued rise in academic interest and research output in this area.

This trend highlights the growing recognition of AI's significance in shaping global diplomacy, international economics, and related fields. The steady increase in research publications reflects the importance of exploring AI's potential to optimize decision-making processes, enhance global trade, and address critical challenges such as cybersecurity, disinformation, and economic diplomacy.

The data underscores that AI's transformative role in international relations and economics is being increasingly explored by scholars and practitioners alike, further emphasizing the need for continued innovation and rigorous investigation in these fields.

In recent years, there has been a significant surge in research

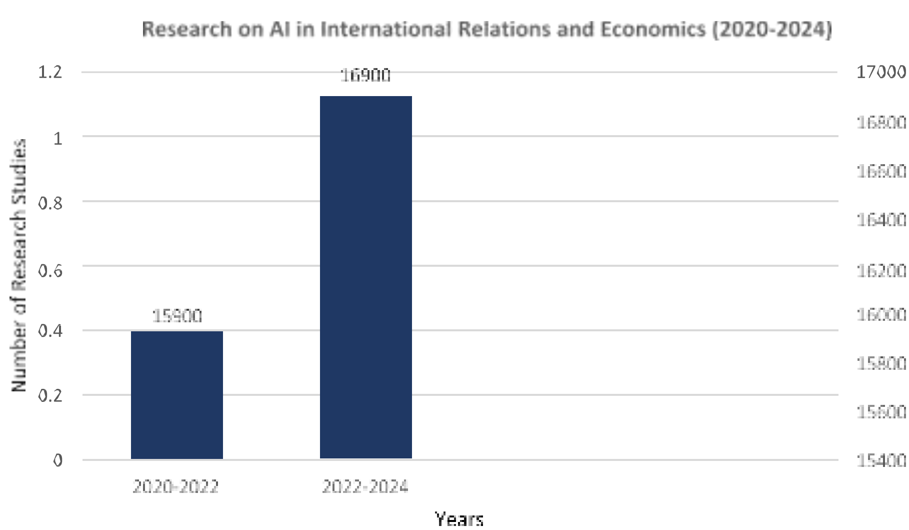

Fig. 2. Distribution of research studies in AI in international relations and economics.

examining the impact of artificial intelligence on international relations and economics. By 2023, it is estimated that several hundred academic papers and reports have been published globally, exploring various facets of AI's role in shaping global dynamics. These studies delve into AI's application in economic diplomacy, international crisis management, political and economic forecasting, cybersecurity, and even conflicts and warfare. Researchers have particularly focused on AI's implications for global trade, international governance, and conflict resolution, emphasizing both its transformative potential and the challenges it introduces [9].

For instance, AI has been studied for its ability to predict future outcomes in international supply chains and optimize trade networks. Additionally, significant attention has been given to issues related to synthetic data, data quality, and privacy concerns, particularly within the context of global trade. Moreover, recent publications have addressed critical issues such as AI's role in countering disinformation and managing the risks associated with deepfakes, which pose considerable threats to international political stability. The challenges of transparency, ethical implications, and the development of advanced technologies like autonomous weapons systems have also been recurring themes in this body of research, highlighting the complexity of integrating AI into the international arena.

3.1. Predictive models for economic growth

Predictive models for economic growth are crucial tools in analyzing and managing economic dynamics. These models enable analysts and decision-makers to forecast economic trends, market fluctuations, and the effects of economic policies using historical and current data. In the rapidly evolving global economy, advanced predictive models, particularly those employing deep learning techniques, provide enhanced capabilities for accurate forecasting. These models are designed to simulate and predict various aspects of economic growth, such as Gross Domestic Product (GDP), inflation rates, and economic output. By leveraging historical data and sophisticated algorithms, they help in understanding complex economic patterns and making informed decisions. The use of predictive models is integral for evaluating policy impacts, assessing market conditions, and strategizing economic development.

Fig. 3, covers the general process of applying predictive models to economic growth. It includes steps from data preparation and model selection to evaluation and deployment, applicable across various types of predictive models.

In this section, we will explore advanced predictive models used in the field of economic growth. In the realm of sequential data analysis, several advanced models have been developed to address the limitations of traditional Recurrent Neural Networks (RNNs) [10] and enhance their ability to capture temporal dependencies. These models include Long Short-Term Memory (LSTM) Networks [11], Gated Recurrent Units (GRUs) [12], and Temporal Convolutional Networks (TCNs) [13]. Each of these models introduces unique mechanisms and innovations that improve performance in handling complex sequential tasks.

Long Short-Term Memory (LSTM) Network. Long Short-Term Memory (LSTM) networks represent a significant advancement in the realm of Recurrent Neural Networks (RNNs), specifically designed to address the challenges associated with learning long-term dependencies in sequential data. LSTMs have become a cornerstone in the field of sequence modeling, offering a robust solution for tasks where capturing information over extended periods is crucial.

The key innovation of LSTMs lies in their ability to maintain and manage a memory cell that can store information over long sequences. Traditional RNNs often struggle with the vanishing and exploding gradient problems, which make it difficult to learn from data far in the past. LSTMs overcome these limitations by incorporating a set of

1. Input: Economic Data
- Gather historical economic data (e.g., GDP, inflation rates, etc.)
- Collect additional relevant features (e.g., market indicators, policy changes)

2. Preprocessing
- Clean the data: Handle missing values, outliers, and inconsistencies
- Normalize or standardize the data if required
- Split data into training, validation, and test sets

3. Model Selection
- Choose appropriate predictive models based on the data and problem (e.g., ARIMA, VAR, DSGE, Machine Learning models, Neural Networks)
- For each model type, define necessary parameters and configurations

4. Model Training
- Train the selected models using the training dataset
- For machine learning models, tune hyperparameters using the validation dataset

5. Model Evaluation
- Evaluate model performance using the test dataset
- Use appropriate metrics (e.g., Mean Absolute Error, Root Mean Squared Error) to assess accuracy

6. Forecasting
- Generate predictions using the trained models
- Aggregate forecasts from different models if applicable

7. Analysis
- Analyze the results and compare performance across models
- Interpret the forecasts in the context of economic growth and decision-making

8. Refinement
- Refine models based on performance analysis
- Update models with new data as it becomes available

9. Reporting
- Document the methodology, results, and insights
- Provide recommendations based on model forecasts

10. Deployment (if applicable)
- Integrate the model into decision-support systems or tools for continuous forecasting
- Monitor model performance over time and make adjustments as necessary

Fig. 3. Workflow for predictive models in economic growth analysis.

specialized gates that regulate the flow of information into and out of the memory cells. This architecture allows LSTMs to preserve important information and selectively update it based on the input data and previous memory, making them particularly effective for tasks such as time series forecasting, speech recognition, and natural language processing.

Fig. 4 illustrates LSTM structure. According to this figure, an LSTM network consists of several essential components:

1. **Memory Cells**: These cells serve as the core of the LSTM architecture, designed to retain information across time steps. They provide a stable mechanism for preserving data over long sequences, enabling the network to capture long-range dependencies.
2. **Gates**: LSTMs utilize three types of gates to control the information flow:
   - **Forget Gate**: This gate determines which information from the memory cell should be discarded. It uses the previous hidden state and the current input to generate a forget vector that regulates which parts of the memory cell are updated or retained.
   - **Input Gate**: The input gate controls the extent to which new information is added to the memory cell. It combines the previous hidden state with the current input to produce an input vector, which influences the amount of new information incorporated into the cell.
   - **Output Gate**: This gate decides what information from the memory cell should be output to the next layer or the final prediction. It creates an output vector based on the current memory cell state and hidden state, determining which information is passed forward.
3. **Cell State**: The cell state is a vector that flows through the network, updated by the input and forget gates. It acts as the network's memory, holding information across multiple time steps and facilitating stable gradient flow during training.

Mathematically, the operations of LSTMs involve computing the forget gate $\{f_t\}$, input gate (i_t), output gate (o_t), as well as updating the cell state (C_t), and hidden state (h_t). These computations ensure that the network can effectively manage and utilize memory over long sequences.

LSTMs have demonstrated their effectiveness in various applications. In natural language processing, they are employed for tasks such as language modeling, machine translation, and text generation. In time series analysis, LSTMs excel at predicting future values based on historical data. They are also used in speech recognition and video analysis, where understanding temporal patterns is essential.

Gated Recurrent Units (GRUs). Gated Recurrent Units are a type of Recurrent Neural Network architecture. GRUs were developed as a simpler alternative to LSTM networks, with the aim of addressing some of the same challenges related to learning long-term dependencies in sequential data while reducing computational complexity.

The primary innovation of GRUs lies in their streamlined gating mechanisms, which combine the functionality of LSTM gates into a more compact structure. This design choice helps to simplify the network architecture while maintaining similar performance benefits. Fig. 5 illustrates GRUs structure. According to this figure, GRUs consist of two main gating mechanisms: the update gate and the reset gate. These gates control the flow of information into and out of the network, facilitating the learning of long-range dependencies and the management of temporal data.

1. **Update Gate:** The update gate determines how much of the past information (from the previous hidden state) needs to be retained and how much of the new information (from the current input) should be incorporated. This gate essentially blends the old and new information, allowing the network to adjust its memory dynamically based on the input sequence.
2. **Reset Gate:** The reset gate controls how much of the past information should be forgotten. It decides the extent to which the

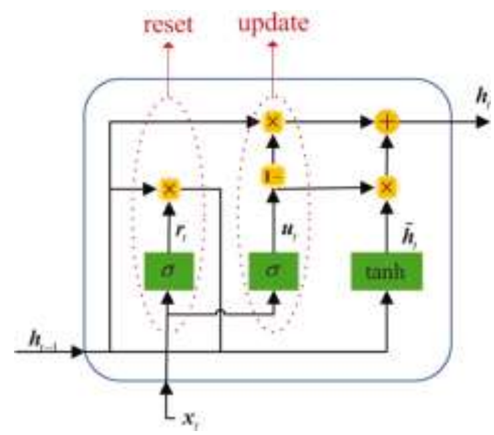

Fig. 5. An GRUs architecture from [15].

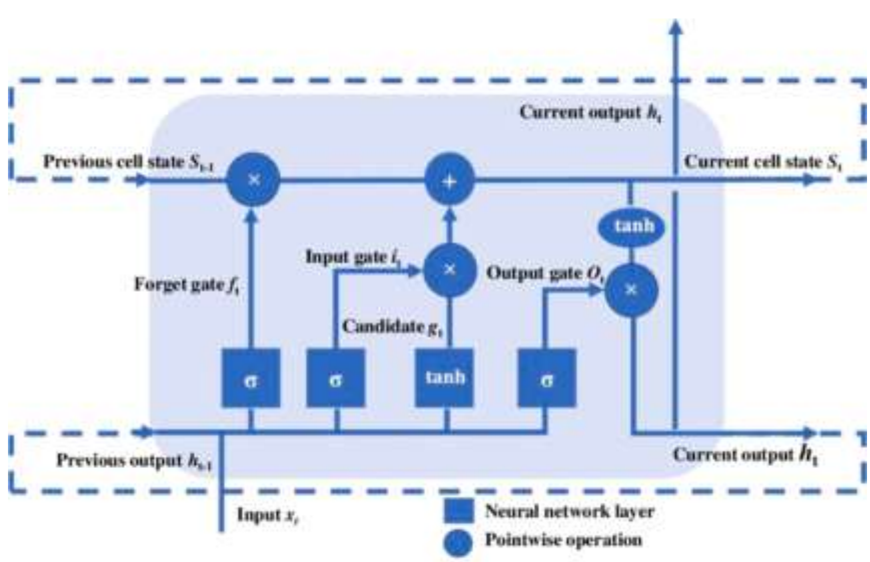

Fig. 4. An LSTM architecture from [14].

previous hidden state should be discarded or reset when processing the current input. This gate helps the network to focus on relevant parts of the sequence while ignoring less important information.

The operations of GRUs can be expressed mathematically as follows: GRUs offer several advantages, including fewer parameters compared to LSTMs due to their simpler gate structure. This reduced complexity often translates to faster training and inference times, making GRUs a more efficient choice for applications where computational resources are constrained. Despite their simplicity, GRUs have been shown to perform comparably to LSTMs in many tasks, such as natural language processing, time series forecasting, and sequential data analysis.

Temporal Convolutional Networks (TCNs). Temporal Convolutional Networks (TCNs) represent a modern approach to sequence modeling that leverages the strengths of convolutional neural networks (CNNs) in handling temporal data. This network offers a compelling alternative to recurrent architectures like Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) for tasks involving sequential or time-series data.

The core idea behind TCNs is to apply convolutional operations along the temporal dimension of sequences. Unlike traditional RNN-based models, which process data sequentially and may struggle with long-term dependencies, TCNs utilize convolutional layers that can efficiently capture temporal patterns across entire sequences in parallel. This approach allows TCNs to leverage the benefits of convolutions, such as translation invariance and parallel processing, while effectively modeling temporal dependencies.

Fig. 6 illustrates TCNs structure. According to this figure, key components of TCNs include:

1. **Dilated Convolutions:** TCNs employ dilated convolutions to increase the receptive field of the network, allowing it to capture long-range dependencies without increasing the computational cost significantly. Dilated convolutions introduce gaps (or dilations) between the filter elements, enabling the network to aggregate information from a larger temporal window while maintaining efficiency.
2. **Residual Connections:** TCNs use residual connections between convolutional layers to facilitate the learning of deeper network architectures. These connections help to mitigate the vanishing gradient problem by allowing gradients to flow more easily through the network during training. Residual connections also contribute to improved performance and faster convergence.
3. **Causal Convolutions:** In TCNs, causal convolutions are used to ensure that the output at any given time step depends only on the current and past inputs, and not on future inputs. This characteristic is crucial for maintaining the temporal integrity of the data and ensuring that predictions are based on information available up to the current time step.

TCNs have shown promising results across various applications, including time series forecasting, speech synthesis, and video analysis. Their ability to process entire sequences in parallel, coupled with the use of dilated and residual convolutions, makes them well-suited for handling long-term dependencies and complex temporal patterns efficiently.

3.2. Decision-making models in diplomacy

In the realm of international relations, decision-making models play a crucial role in understanding and predicting the behavior of nations and policymakers. These models are designed to simulate and analyze the strategic choices made by states and actors in the context of diplomacy, conflict resolution, and international negotiations. By leveraging various computational and analytical techniques, decision-making models provide valuable insights into how decisions are made, the potential outcomes of different strategies, and the implications for global diplomacy.

Decision-making models in diplomacy can be broadly categorized into several types, each offering different perspectives and methodologies for analyzing diplomatic interactions:

1. **Game Theory Models:** Game theory provides a formal framework for analyzing strategic interactions between multiple actors. In the context of diplomacy, game theory models are used to study scenarios such as negotiation processes, conflict resolution, and alliance formation. These models help to identify equilibrium strategies, predict outcomes, and assess the impact of different actions on the overall balance of power.
2. **Agent-Based Models:** Agent-based models simulate the behavior of individual agents (e.g., countries, diplomats) within a system. Each agent operates based on specific rules and strategies, and their interactions lead to emergent behaviors and outcomes. Agent-based models are particularly useful for studying complex diplomatic scenarios where multiple actors with varying preferences and capabilities interact.
3. **Decision Trees:** Decision trees are used to map out the possible decisions and outcomes in a structured manner. In diplomatic decision-making, decision trees help to visualize the different choices available to policymakers and the potential consequences of each choice. This approach facilitates a systematic analysis of the decision-making process and aids in identifying optimal strategies.
4. **Markov Decision Processes (MDPs):** MDPs provide a mathematical framework for modeling decision-making in situations where outcomes are partly random and partly under the control of

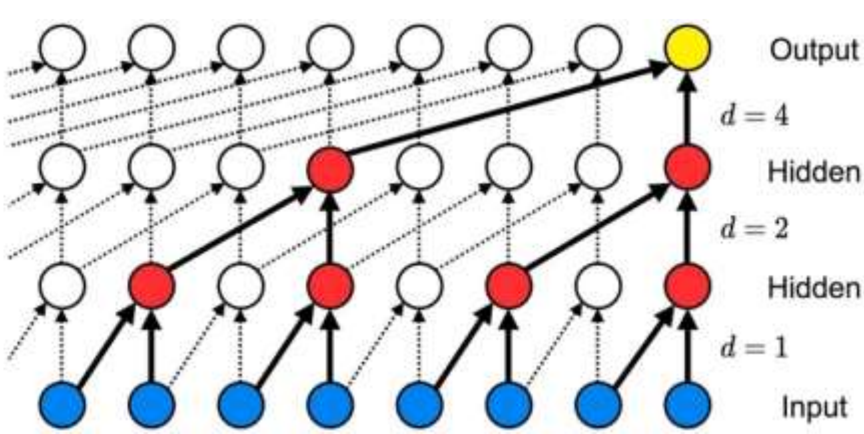

Fig. 6. An TCNs architecture from [16].

the decision-maker. In diplomacy, MDPs can be used to model scenarios with uncertain outcomes, such as negotiations and conflict management, by considering the probabilities of various states and actions.

5. **Multi-Criteria Decision Analysis (MCDA):** MCDA is a method for evaluating and prioritizing multiple conflicting criteria. In the context of diplomacy, MCDA helps policymakers assess different options based on various factors such as political, economic, and strategic considerations. This approach supports a more comprehensive analysis of trade-offs and helps in making informed decisions.

Fig. 7 outlines a general approach for implementing decision-making models in diplomacy, capturing the essential steps involved in setting up, running, and analyzing such models.

In this section, we will explore several common and advanced decision-making models used in the field of diplomacy. In the realm of strategic interactions and international relations, several advanced models have been developed to address the complexities of diplomatic decision-making and enhance our understanding of strategic behavior. These models include Deep Q-Networks (DQN) [17], Proximal Policy Optimization (PPO) [18] and Actor-Critic Methods [19]. Each of these models introduces unique mechanisms and innovations that improve performance in handling complex decision-making tasks.

Deep Q-Networks (DQN). Deep Q-Networks (DQN) mark a significant advancement in reinforcement learning by combining traditional Q-learning techniques with the power of deep neural networks. Introduced by DeepMind in 2013, DQNs address the limitations of conventional Q-learning, particularly in handling complex, high-dimensional state spaces.

In traditional Q-learning, the objective is to learn an optimal action-value function $Q(s, a)$ which represents the expected reward of taking action a in state s and then following the optimal policy. However, maintaining a table of Q-values becomes impractical when dealing with large state and action spaces. This is where DQNs make a substantial difference. Instead of using a Q-table, DQNs utilize a deep neural network to approximate the Q-value function. This network is capable of managing high-dimensional input spaces, such as those found in video games or robotic control tasks.

Fig. 8 illustrates DQNs structure. According to this figure, a key innovation in DQNs is the use of experience replay. During training, experiences consisting of state, action, reward, and next state are stored in a replay buffer. Instead of learning from sequential experiences, which can lead to instability, mini-batches are sampled randomly from this buffer to update the Q-network. This approach helps to break the temporal correlations between consecutive experiences and stabilizes the learning process.

Another crucial component of DQNs is the target network. This separate network provides stable Q-value estimates during training. The target network is periodically updated with the weights of the main Q-network. This mechanism helps to address the instability that arises from the moving target problem, where the Q-values being estimated change as the network learns.

The core of a DQN is a CNN that approximates the Q-value function. The network takes the state representation as input and outputs Q-values for each possible action. The training objective is to minimize the difference between predicted Q-values and target Q-values, which are computed using the Bellman equation. Specifically, the target Q-values are calculated as:

$$y = r + \gamma \cdot \max_{a'} Q_{target}(s', a') \tag{1}$$

where r is the reward, γ is the discount factor, s' is the next state, and a' represents possible actions in the next state.

1. **Initialize model parameters**
   - Define agents (countries, diplomats)
   - Specify interaction rules and preferences
   - Set initial conditions and states
2. **Define decision-making strategies**
   - For Game Theory:
     - Set up the game matrix or utility functions
     - Compute equilibrium strategies
   - For Agent-Based Models:
     - Define agent behavior rules
     - Simulate agent interactions and update states
   - For Decision Trees:
     - Build the decision tree structure
     - Evaluate outcomes for each decision path
   - For Markov Decision Processes:
     - Define states, actions, and transition probabilities
     - Solve the MDP to find optimal policies
   - For Multi-Criteria Decision Analysis:
     - Identify criteria and weights
     - Evaluate options based on criteria
     - Rank options and select the best one
3. **Run simulations or analyses**
   - Execute the model to simulate decision-making scenarios
   - Collect and analyze results
   - Assess the impact of different strategies
4. **Interpret results and make recommendations**
   - Review the outcomes of the simulations or analyses
   - Provide insights into optimal strategies and potential consequences
   - Offer recommendations for policymakers
5. **Update and refine the model as needed**
   - Adjust parameters and strategies based on new data or feedback
   - Iterate the process to improve accuracy and relevance

Fig. 7. Workflow for decision-making models in diplomacy.

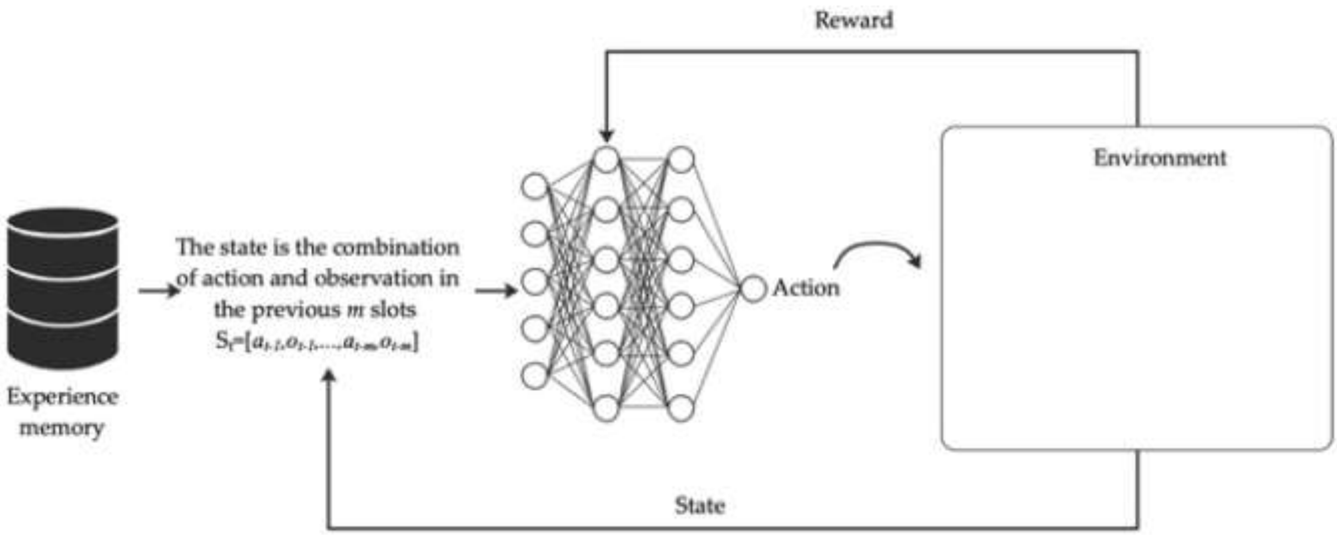

Fig. 8. An DQNs architecture from [20].

The training process involves initializing the Q-network and target network, collecting experiences by interacting with the environment, and updating the Q-network using mini-batches from the replay buffer. The network's weights are updated by minimizing the loss between the predicted and target Q-values:

$$Loss = \frac{1}{N}\sum_{i=1}^{N}(y_i - Q(s_i - a_i))^2 \tag{2}$$

where N denotes the number of experiences in the mini-batch. Periodic updates to the target network ensure that the estimates remain stable over time.

Deep Q-Networks have shown impressive performance in a range of complex environments, including Atari games, where they achieved human-level performance in several instances. They are also applied in robotics, autonomous vehicles, and other areas that require decision-making in high-dimensional spaces. In summary, DQNs represent a powerful fusion of reinforcement learning and deep learning, effectively addressing the challenges of approximating action-value functions in complex scenarios and achieving notable successes across various domains.

Proximal Policy Optimization (PPO). Proximal Policy Optimization (PPO) is a state-of-the-art algorithm in reinforcement learning that aims to improve the stability and efficiency of policy optimization. PPO addresses several limitations of previous reinforcement learning algorithms by providing a robust method for updating policies while balancing exploration and exploitation.

At its core, PPO is designed to optimize a policy directly rather than approximating a value function, as is done in methods like Q-learning. The algorithm operates on the principle of policy gradient methods, where the objective is to find the optimal policy that maximizes cumulative rewards. PPO introduces key innovations to enhance the policy optimization process, including the use of a clipped objective function and adaptive updates.

One of the main challenges in policy optimization is ensuring that policy updates do not lead to drastic changes that can destabilize learning. PPO addresses this by employing a clipped objective function. This function limits the extent to which the policy can deviate from the previous policy during updates. Specifically, PPO modifies the policy objective to include a clipping mechanism that prevents the ratio of the new policy probability to the old policy probability from moving too far from one. The objective function is given by:

$$L(\theta) = \hat{E}_t\left[\min\frac{\pi_\theta(a_t|s_t)}{\pi_\theta old(a_t|s_t)}\hat{A}_t,\ Clip\left(\frac{\pi_\theta(a_t|s_t)}{\pi_\theta old(a_t|s_t)},\ 1-\epsilon,\ 1+\epsilon\ \hat{A}_t\right)\right] \tag{3}$$

where π_θ represents the new policy, $\pi_\theta old$ is the old policy, $\hat{A}_t$ is the advantage estimate at time t, and ϵ is a hyperparameter that controls the clipping range. By clipping the probability ratio, PPO maintains a balance between updating the policy effectively and avoiding excessive changes that could degrade performance.

PPO also incorporates adaptive learning rates and multiple epochs of optimization to further enhance the stability and efficiency of training. Instead of updating the policy after each batch of data, PPO performs multiple updates using the same batch, which helps in better utilizing the collected data and improving the convergence of the learning process. Fig. 9 illustrates PPO structure.

Actor-Critic Methods. Actor-Critic Methods represent a powerful class of algorithms in reinforcement learning that combine the advantages of both policy-based and value-based approaches. These methods aim to optimize the decision-making process by simultaneously learning a policy (the "actor") and a value function (the "critic"). The integration of these two components allows for more effective and efficient learning, particularly in complex environments with large state and action spaces.

In reinforcement learning, policy-based methods focus on directly learning the policy that maps states to actions, aiming to maximize cumulative rewards. Value-based methods, on the other hand, learn value functions that estimate the expected reward of being in a particular state or taking a specific action. Actor-Critic Methods unify these approaches by employing both a policy network (the actor) and a value network (the critic), leveraging their complementary strengths.

Fig. 10 illustrates Actor-Critic Methods structure. According to this figure, key components of this method is as follows:

1. **Actor:** The actor is responsible for learning and optimizing the policy. It determines the actions to be taken in various states based on a probability distribution. The policy is typically parameterized by a neural network, which outputs probabilities for each possible action given the current state. The actor aims to maximize the expected cumulative reward by improving the policy based on feedback from the critic.
2. **Critic:** The critic evaluates the actions taken by the actor by estimating the value function. It provides feedback on the quality of the actions by calculating the advantage function, which measures the difference between the expected return and the estimated value

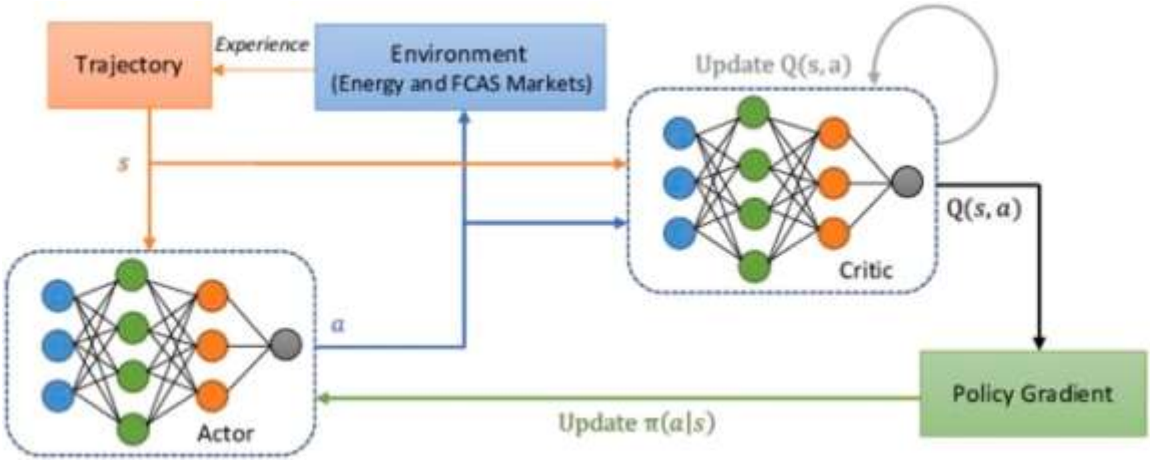

Fig. 9. An PPO architecture from [21].

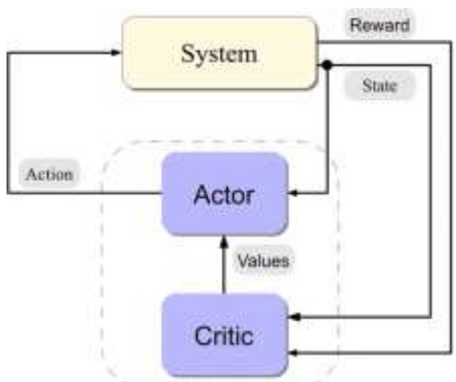

Fig. 10. An actor-critic methods architecture from [22].

of the current state. The critic is also parameterized by a neural network, which learns to predict the value function (or the state-action value function, Q(s,a))

The training process of Actor-Critic Methods involves the following steps:

1. **Policy Improvement:** The actor updates the policy parameters based on feedback from the critic. The policy is adjusted to increase the probability of actions that lead to higher rewards, as indicated by the critic's evaluation.
2. **Value Function Update:** The critic updates the value function parameters based on the observed rewards and the estimated values of the states or state-action pairs. The value function is refined to better predict the expected return, which helps the actor to make more informed decisions.
3. **Advantage Calculation:** The advantage function, A(s,a), is computed to measure the relative benefit of taking a specific action in a given state compared to the average expected return. This advantage estimate is used to guide the policy updates and improve learning efficiency.
4. **Policy Gradient Update:** The actor's policy is updated using the policy gradient theorem, which provides a way to adjust the policy parameters to maximize the expected return. The policy gradient is computed based on the advantage function and used to perform gradient ascent on the policy objective function.
5. **Value Function Loss:** The critic's value function is updated by minimizing the loss between the predicted value and the observed rewards. This loss function helps to improve the accuracy of the value estimates and provides better feedback to the actor.

Actor-Critic Methods are versatile and have been applied to a wide range of reinforcement learning problems, including robotics, game playing, and autonomous systems. They are particularly useful in continuous action spaces where traditional value-based methods may struggle. By combining the strengths of policy-based and value-based approaches, Actor-Critic Methods offer a robust framework for solving complex decision-making tasks.

3.3. *Data analytics in international trade*

Data analytics in international trade is essential for understanding and managing the complexities of global trade dynamics. By applying predictive, descriptive, prescriptive, and diagnostic analytics, stakeholders can gain deeper insights into trade patterns, forecast future trends, and make strategic decisions. The use of advanced models such as FCN [23], Autoencoders [24], Generative Adversarial Networks (GANs) [25], and Graph Neural Network (GNNs) [26] enhances the capability to analyze trade data, optimize operations, and improve decision-making processes. Data analytics not only supports effective trade management but also drives growth and competitiveness in the international marketplace. Fig. 11 outlines the general process of data analytics in international trade, from data collection and preprocessing to analysis, visualization, and decision-making.

FCN. FCN introduces a architecture where the traditional fully connected layer is substituted with an up-sampling layer and a deconvolutional layer, as depicted in Fig. 12. These particular layers are envisioned as the counterparts of pooling and convolutional layers but in reverse. The pivotal innovation of FCNs lies in their capacity to produce separate score maps for each class instead of a single probability score. Notably, these maps maintain the same dimensions as the input image, effectively enabling a pixel-wise classification approach.

The accuracy of FCNs is subsequently elevated through the utilization of upsampling and deconvolutional layers, a strategy known as a "skip connection." These additional layers have found application across various deep learning algorithms in a multitude of domains, augmenting the potential of FCNs in numerous applications. These networks have proven adept at segmenting medical images by providing dense pixel-wise predictions, making them well-suited for applications such as tissue delineation and organ segmentation.

Autoencoders. Autoencoders are a type of artificial neural network used for unsupervised learning, primarily aimed at learning efficient data representations, or encoding, by training the network to compress and then reconstruct input data. As depicted in Fig. 13, they consist of

1. Data Collection
Collect trade data(source) -> trade data
2. Data Cleaning and Preprocessing
Clean trade data (trade data) -> cleaned trade data
Preprocess data (cleaned trade data) -> preprocessed trade data
3. Data Analysis
Predictive, Descriptive, Prescriptive, and Diagnostic Analytics
Predictive model (preprocessed trade data, model type) -> trade predictions
Descriptive analysis (preprocessed trade data) -> trade summary
Prescriptive recommendations (preprocessed trade data, criteria) -> trade recommendations
Diagnostic analysis (preprocessed trade data) -> trade diagnostics
4. Data Visualization and Reporting
Generate visualizations (trade summary, trade predictions, trade recommendations, trade diagnostics) -> visual reports
Create final report (visual reports) -> final report
5. Decision Making
Derive actions (final report) -> trade decisions

Fig. 11. Workflow for data analytics in international trade.

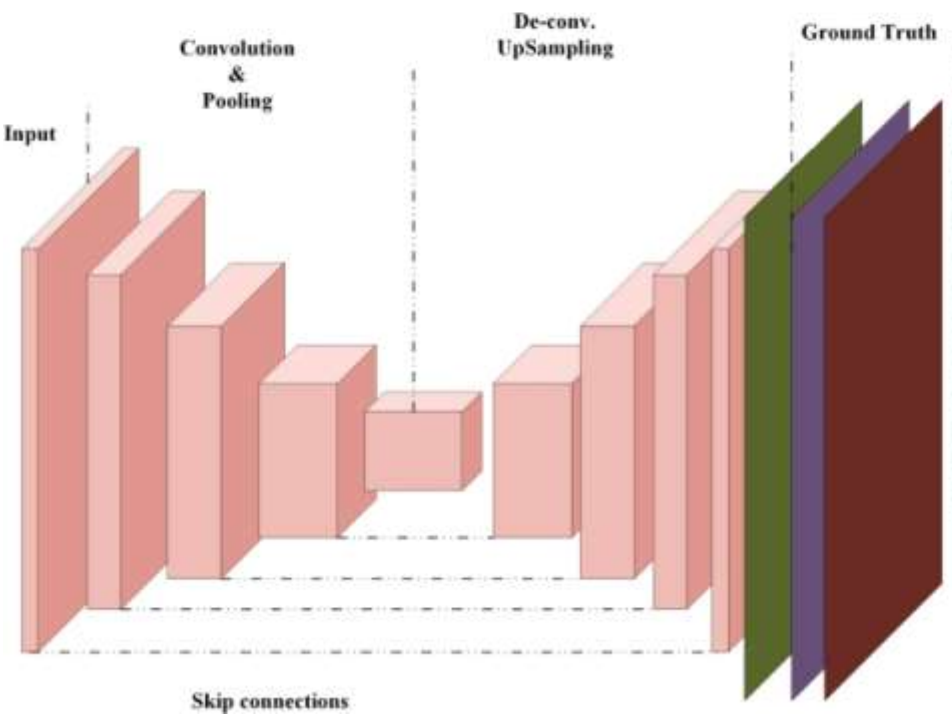

Fig. 12. Fully convolutional neural networks architecture from [27].

two main parts: an encoder and a decoder. The encoder compresses the input data into a lower-dimensional representation, often referred to as a "latent space" or "bottleneck." The decoder then reconstructs the original data from this compressed form.

The primary objective of an autoencoder is to minimize the reconstruction error, meaning it attempts to make the output as similar as possible to the input while passing through the compressed latent space. This makes autoencoders useful for tasks like dimensionality reduction, anomaly detection, and feature extraction.

Several variants of autoencoders have been developed to extend their functionality, including Denoising Autoencoders [28] (which reconstruct noisy data), Sparse Autoencoders [29] (which impose sparsity constraints on the latent representation), and Variational Autoencoders [30] (which generate new data samples by learning probability distributions).

Autoencoders have a wide range of applications, from image compression to data denoising and generative modeling, and they form a foundational component in many modern machine learning tasks, particularly in cases where understanding or generating complex data distributions is required.

Generative Adversarial Networks (GANs). GANs are a class of machine learning models designed for generative tasks, where the goal is to create new data instances that resemble a given dataset. According to the Fig. 14, GANs consist of two neural networks—the generator and the discriminator—that compete against each other in a zero-sum game framework. The generator creates fake data instances (e.g., images, text, or audio), attempting to mimic the real data, while the discriminator evaluates these instances to distinguish between real and generated data. The generator's objective is to produce data that the discriminator cannot differentiate from real data, whereas the discriminator's objective is to improve its ability to correctly identify real versus fake data. Mathematically, GANs are formulated as a minimax game between the generator G and the discriminator *D*. The discriminator tries to maximize its performance, represented by a loss function *V (D, G)* while the generator attempts to minimize this loss:

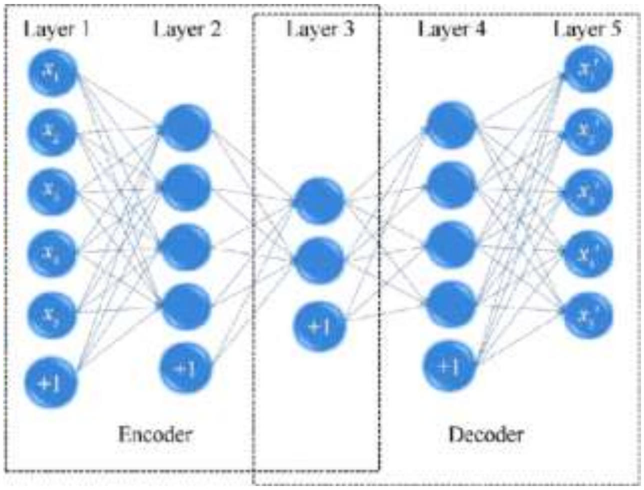

Fig. 13. Autoencoders architecture from [31].

$$\min_{G}\max_{D} V(D, G) = E_{Pdata(x)}[logD(x)] + E_{z\sim Pz(z)}[log(1 - D(G(z)))] \quad (4)$$

Here, $Pdata(x)$ represents the distribution of real data, and $Pz(z)$ represents the distribution of the random input to the generator (often called latent space). The generator G transforms the input noise z into synthetic data, while the discriminator D evaluates whether a given data point is real or generated.

GANs have gained widespread recognition for their ability to produce highly realistic outputs, particularly in areas such as image generation, video synthesis, and text-to-image translation. However, training GANs is challenging due to issues like mode collapse and unstable gradients, which researchers have been addressing through various improved architectures like Wasserstein GAN (WGAN) [32] and Progressive GAN [33].GANs are now fundamental tools in applications ranging from computer vision to creative arts, offering immense potential for innovation in generating synthetic data, improving data augmentation, and addressing privacy concerns through techniques like differential privacy.

Graph Neural Networks (GNNs). GNNs are a class of deep learning models specifically designed to operate on graph-structured data. Graphs consist of nodes (or vertices) and edges, which represent entities and their relationships, making them highly suitable for tasks involving social networks, molecular structures, recommendation systems, and many other applications where data points are interconnected.

GNNs aim to leverage the graph's structure by learning node representations that incorporate both the feature information of the nodes and the topology of the graph. This is achieved through iterative message-passing mechanisms, where nodes aggregate information from their neighbors to update their own representations. Mathematically, a GNN layer can be expressed as:

$$h_v^{(k)} = \sigma\left(W^k \cdot AGGREGATE\left(\left\{h_u^{(k-1)} : u \in N(v)\right\}\right)\right) \quad (5)$$

Here, $h_v^{(k)}$ represents the embedding of node v at the k-th layer, $N(v$ is the set of neighbors of node v, W^k is the weight matrix of the layer, and σ is an activation function such as ReLU. The AGGREGATE function can vary (e.g., mean, sum, max) depending on the GNN variant and determines how neighboring node information is combined. The network iterates through multiple layers, enabling each node to gather information from progressively larger local neighborhoods.

Popular GNN architectures include Graph Convolutional Networks (GCNs) [35], Graph Attention Networks (GATs) [36], and GraphSAGE [37], each offering different mechanisms for aggregating information from neighboring nodes and updating node representations.

GNNs have been successfully applied to a wide range of problems, such as node classification, link prediction, and graph classification. They have also become critical in modeling relational data and have advanced research in fields like drug discovery, recommendation systems, and knowledge graphs.

Despite their success, GNNs face challenges such as scalability to large graphs, over-smoothing when stacking too many layers, and difficulties in dealing with dynamic graphs. Nonetheless, their versatility and effectiveness in handling complex data structures have made them a crucial tool in modern machine learning research.

3.4. Dataset

Table 1 provides an overview of the key datasets required for applying artificial intelligence in global diplomacy and economic analysis. It categorizes these datasets into three main domains which reviewed previously. For Predictive Models for Economic Growth, datasets include historical macroeconomic data, financial and trade statistics, and socio-political features, enabling accurate forecasting of trends, market dynamics, and policy impacts. In the domain of Decision-Making Models in Diplomacy, datasets encompass behavioral data of governments and organizations, network-based representations of international relations, and global environmental variables, which are vital for simulating diplomatic scenarios and evaluating strategies. Lastly, for Data Analytics in International Trade, the required datasets consist of trade statistics, policy details, and time-series data to identify patterns, optimize agreements, and support strategic decisions in economic diplomacy. This table highlights how domain-specific datasets

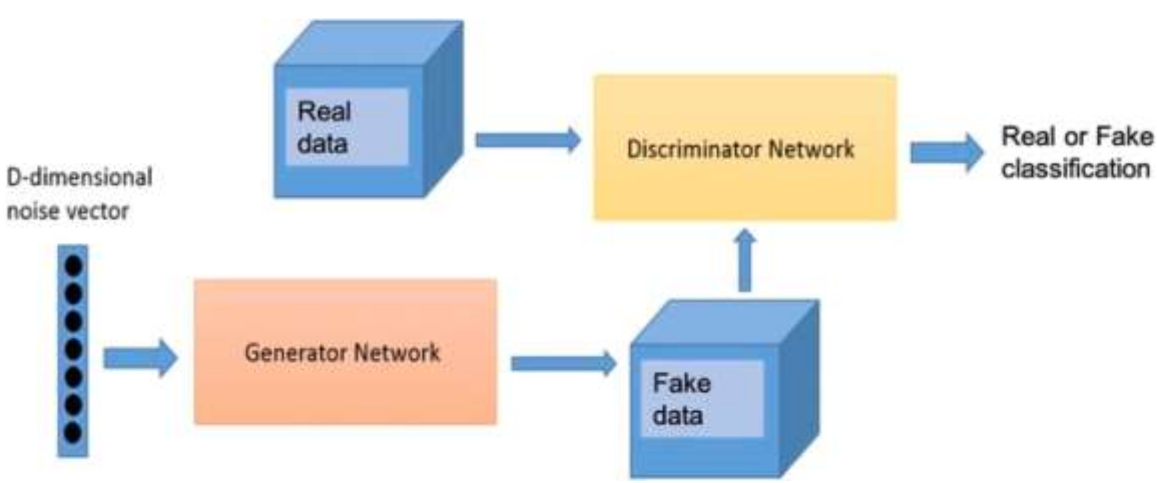

Fig. 14. Autoencoders architecture from [34].

Table 1
Overview of datasets required for AI applications in global diplomacy and economic analysis.

Category	Required Dataset
Predictive Models for Economic Growth	– Historical macroeconomic data (e.g., GDP, inflation rates, market indices). – Financial and trade data (e.g., exports, imports, trade balance, exchange rates). – Socio-political features related to economic policies.
Decision-Making Models in Diplomacy	– Behavioral data of governments and organizations (e.g., negotiation records, foreign policy actions). – Network-based datasets (e.g., international relations represented as graphs). – Global environmental and contextual variables (e. g., climate change, economic crises).
Data Analytics in International Trade	– International trade statistics (e.g., import/export volumes, trade balances). – Data on trade policies and tariffs. – Time-series data for trend and pattern analysis.

contribute to the effective implementation of AI-driven solutions in diplomacy and international economic analysis.

4. State-of-the-art studies

In this section, we will review and analyze recent state-of-the-art studies that explore the intersection of Artificial Intelligence with international relations and economics. We will categorize the research based on key themes that have emerged, providing insights into how AI is influencing global dynamics and decision-making processes. By organizing our review around these themes, we aim to illustrate the major trends and challenges in this interdisciplinary field. The literature review has identified several core themes, which will be discussed in detail in this section.

Digital Diplomacy: This theme is the most prominent, highlighting the significant impact of digital tools and online platforms on international relations and statecraft. Digital diplomacy involves utilizing digital technologies and social media to achieve foreign policy objectives, allowing for more direct and effective communication with international and public audiences. Insights from the literature suggest that AI can greatly enhance digital diplomacy by analyzing extensive data sets, predicting trends, and generating human-like content. These capabilities can provide diplomats with advanced tools for scenario planning, create sophisticated communication materials, and offer deeper insights into public sentiment, potentially revolutionizing traditional approaches to international relations and negotiation [38–43].

Public Diplomacy: The literature extensively addresses the evolving role of AI and digital platforms in transforming how states interact and communicate with the public in foreign countries. AI holds the potential to revolutionize public diplomacy by offering advanced tools for developing targeted and impactful messaging, analyzing real-time public sentiment, and customizing engagement strategies across various cultural contexts. These advancements can significantly enhance the reach and effectiveness of diplomatic efforts [44–48].

Foreign Policy: The literature explores how AI can be leveraged to improve foreign policy through advanced predictive analytics and tailored communication strategies for international audiences. AI has the potential to greatly impact foreign policy by offering detailed data analysis, predictive insights into global trends, and customized diplomatic communication. These capabilities can enhance decision-making processes and enable more responsive and informed strategies in addressing international developments [49–53].

Economic Diplomacy: While there is less emphasis on the economic aspects of AI in diplomacy, its impact on trade and international economic policy is notable. AI has the potential to transform economic diplomacy by offering advanced predictive analytics for market trends, automating the evaluation of economic agreements, and modeling trade scenarios. This allows diplomats to approach negotiations with a data-driven advantage, which can lead to more favorable outcomes. However, it is crucial to ensure that AI's predictive tools are unbiased to avoid misleading economic policies or creating inequities, thus preserving the fairness of economic diplomacy [54–57].

Negotiation: Examining how AI might transform diplomatic negotiations by offering simulations and predictive models to guide strategy development. Tools like ChatGPT's Negotiator can enhance this process by simulating negotiations, predicting counterpart positions, and drafting diplomatic communications. While AI tools can improve efficiency and provide data-driven strategies, they also present risks such as over-reliance on technology and potential misalignment with nuanced human judgment. Therefore, a balanced approach that integrates AI assistance with skilled human diplomacy is essential [58–63].

Table 2 provides a comprehensive classification of reviewed studies of this section based on geographic region, AI application, and methodology, highlighting the diversity and breadth of research in AI-driven diplomacy. Geographically, the studies cover a wide range, including

Table 2
Classification of studies based on geographic region, AI application, and methodology.

Ref.	Region	AI Application	Methodology
[38]	European Union	Digital diplomacy	Critical discourse analysis
[39]	Global	Public engagement on Twitter	Social media analytics framework
[40]	General/global	Foreign policy in digital diplomacy	Theoretical analysis
[41]	Global	Success factors in digital diplomacy	Case study
[42]	Africa (Cameroon, Nigeria)	Response to online propaganda	Case study
[43]	Europe	Emotional labor in diplomacy	Qualitative interviews
[44]	Turkey (Bishkek)	Social media use by embassies	Content analysis
[45]	China	Digital strategies of EU, US, Japan	Comparative analysis
[46]	Global	Artificial diplomacy and AI use	Guide for officials
[47]	Global	Public engagement in social media	Cross-national comparison
[48]	Global	Impact of COVID-19 on diplomacy	Analytical overview
[49]	Russia	Social media and digital innovation	Case studies
[50]	Sweden	Feminist foreign policy storytelling	Narrative analysis
[51]	United States	Digital diplomacy in US foreign policy	Theoretical reflection
[52]	Portugal	AI-powered tool for event evaluation	Tool development
[53]	General/global	Digital foreign policy trends	Policy analysis
[54]	Indonesia	Digital economic diplomacy	Case study
[55]	General/global	Science diplomacy in the digital age	Mixed-method analysis
[56]	Indonesia	Innovation diplomacy	Theoretical analysis
[57]	Russia	Digital technologies in agribusiness	Application-oriented research
[58]	General/global	AI in diplomatic negotiations	Practical reflections
[59]	General/global	Negotiation in diplomacy games	Simulation and modeling
[60]	General/global	AI for honesty in board games	Experimental study
[61]	General/global	Trust and negotiation strategies	Strategic modeling
[62]	Russia	Digital-age negotiations	Analytical review
[63]	General/global	AI usefulness in diplomacy	Case studies

global perspectives and region-specific analyses in Europe, Russia, Africa, and countries such as Indonesia and the United States, showcasing AI's impact in both localized and international contexts. In terms of applications, AI is utilized for various diplomatic functions, such as digital diplomacy, public engagement, innovation in foreign policy, and negotiation strategies, demonstrating its versatility in addressing contemporary diplomatic challenges. Methodologically, the studies employ a mix of theoretical analyses, case studies, content and narrative analyses, and experimental approaches, reflecting a balance between qualitative insights and quantitative rigor. This classification underscores the interdisciplinary nature of the field and highlights how diverse methodologies and regional focuses contribute to a holistic understanding of AI's transformative role in global diplomacy.

5. Case studies

This section includes examples which highlight how AI can enhance the efficiency and effectiveness of diplomatic services, along with potential risks that require careful management. Table 3 includes examples of specific AI models or technologies applicable to each case, providing a clearer picture of how AI can be utilized in various diplomatic contexts. The integration of AI technologies into diplomatic practices and international relations presents transformative opportunities and challenges. The table highlights various AI applications across different diplomatic functions, emphasizing the diverse ways in which these technologies can enhance operational efficiency and decision-making.

AI models, such as predictive analytics and machine learning algorithms, offer substantial benefits by optimizing processes and improving responses in areas like consular services, crisis management, public diplomacy, and diplomatic negotiations. For instance, predictive models can streamline consular operations by forecasting demand and managing high volumes of requests, thereby increasing efficiency and reducing wait times. In crisis management, AI's ability to analyze real-time data allows for timely and informed responses, enhancing the effectiveness of interventions.

However, the application of AI is not without its challenges. The accuracy of AI predictions and the management of sensitive information are critical considerations. Inconsistencies in AI outputs or misinterpretations can lead to operational inefficiencies and reduced public trust. Additionally, ensuring that AI tools are used responsibly, with proper attention to ethical concerns and contextual factors, is essential for their successful integration into diplomatic practices.

Overall, the potential of AI to revolutionize diplomacy is significant, but it necessitates a balanced approach that leverages technology while maintaining human oversight. By addressing the risks and maximizing the benefits, AI can play a pivotal role in enhancing the effectiveness and reach of diplomatic efforts on a global scale.

6. Challenges and opportunities

The integration of AI into diplomatic practices offers a range of transformative opportunities. Contemporary research highlights how AI is reshaping global diplomacy by enhancing international collaboration and influencing new global governance actors. For instance, Roumate [64] emphasizes AI's potential in fostering international regulation and integrating with cyber diplomacy, utilizing social media as a tool for digital diplomacy while addressing cybersecurity and data sovereignty issues. Grincheva [65] discusses the acceleration of digital cultural production and how digital initiatives can complement official cultural diplomacy. Additionally, Bansal, Kunaprayoon, and Zhang [66] explore the role of robotic telesurgery in global health diplomacy, while Konovalova [67] underscores AI's capacity to stabilize cyberspace and enhance diplomatic effectiveness.

AI's role extends to improving international cooperation, refining diplomatic training, predicting political crises, and anticipating humanitarian challenges. Advances in technology, particularly AI, contribute to the development of virtual embassies, automated communication tools, and digital ambassadors, thereby modernizing diplomatic practices. Notably, a Hungarian innovation in blockchain-based digital applications for cyber diplomacy exemplifies AI's impact on communication security and diplomatic functions [68]. AI's ability to monitor, analyze, and respond during crises such as conflicts, migrations, and pandemics demonstrates its potential in peacebuilding and strategic planning. However, the integration of AI in diplomacy also highlights the need for responsible data management, transparent AI models, and enhanced training for crisis response personnel.

Despite its potential, the application of AI in diplomacy faces significant challenges. AI technologies come with inherent limitations, including issues related to data quality, biases, and transparency [69]. One of the most pressing concerns is the rise of deepfake technology, which poses a unique threat to diplomacy. Deepfakes can be used to create highly realistic and deceptive media, potentially undermining trust between nations, spreading misinformation, and inciting diplomatic conflicts. Addressing this challenge requires robust detection tools, international regulations, and increased awareness among diplomatic actors [70].

For instance, during crises, AI tools must handle incomplete information and data obfuscation effectively. The stakes involved necessitate AI outputs that are explainable, secure, and integrated with domain knowledge. Additionally, the multi-layered nature of diplomatic interests can lead to mistrust and misuse of information, particularly with social media data prone to misinformation.

The rapid advancement of AI may disrupt traditional diplomatic roles, potentially overshadowing human judgment with automated data processing. This shift necessitates a re-evaluation of diplomatic operations, especially concerning the autonomy of diplomatic missions and their engagement with social media. While AI can optimize resource allocation and strategic planning, it also raises concerns about misinformation, erosion of diplomatic empathy, and the loss of nuanced human judgment in complex decisions. Addressing these issues requires a balanced approach that preserves essential human skills while leveraging AI capabilities.

Table 3
Overview of AI applications in diplomatic contexts.

Case Study	Description	AI Models	Risks
Case1: AI in Consular Services	AI can streamline consular services by managing high demand for passports, visas, and certifications. Predictive models can optimize demand and reduce wait times.	Machine Learning (e.g., Regression Models, Time Series Forecasting), Natural Language Processing (NLP)	Inaccurate predictions could worsen backlogs and reduce public trust.
Case2: AI in Crisis Management	AI systems analyze real-time data to understand and manage crises effectively, helping diplomats respond to evolving situations.	Predictive Analytics, Real-Time Data Processing, Machine Learning Algorithms	AI models may exacerbate crises if not carefully managed due to limitations in handling unanticipated situations.
Case3: AI in Public Diplomacy	AI can analyze social media data to gauge public sentiment and reception, optimize campaign strategies, and create engaging content.	Sentiment Analysis, NLP, Social Media Analytics, Generative Models	Misinterpretation of sentiment or cultural sensitivity may lead to ineffective campaigns and wasted resources.
Case4: AI in Diplomatic Negotiations	AI can support diplomatic negotiations by providing and analyzing critical information, simulating scenarios, and informing strategy.	Decision Support Systems, Simulation Models, AI-Based Strategy Tools	Risk of compromising confidentiality and sensitive positions during negotiations.

7. Conclusion and future work

This paper has examined the intersection of AI and global diplomacy through several key areas. Firstly, we explored practical AI models applicable to diplomatic contexts, including predictive models for economic growth, decision-making tools, and data analytics for international trade. These models offer transformative potential for enhancing diplomatic functions and addressing complex global issues. Secondly, we provided a comprehensive review of recent research and innovations in AI diplomacy. Thirdly, our paper illustrated practical applications through detailed case studies, demonstrating how AI technologies can be effectively utilized in consular services, crisis management, public diplomacy, and diplomatic negotiations. These examples underscore the benefits and effectiveness of AI, while also identifying potential risks and challenges. Finally, we explored the challenges and opportunities associated with integrating AI into global diplomacy. This analysis offered a balanced perspective, emphasizing the need for careful consideration of both the advantages and potential pitfalls of AI adoption.

Looking ahead, there are several promising avenues for future research. Firstly, it is essential to conduct empirical studies to validate and enhance the frameworks and models discussed. Real-world testing in diplomatic environments will offer valuable insights into the practical implications and effectiveness of AI technologies. Additionally, pilot projects and collaborations with diplomatic institutions can provide practical feedback and help refine these technologies. Moreover, future work should include a broad interdisciplinary approach, integrating perspectives from AI ethics, international law, and diplomatic theory. This approach will be instrumental in creating robust guidelines and ethical standards for the use of AI in diplomacy. Ensuring that AI technologies are aligned with the fundamental principles of diplomacy—such as trust, respect, and conflict resolution—is crucial for their successful integration into diplomatic practices. By addressing these areas, future research can contribute to a more nuanced understanding of AI's role in diplomacy, fostering advancements that support global cooperation and effective international engagement.

CRediT authorship contribution statement

Hamidreza Mostafaei: Writing – review & editing, Writing – original draft, Supervision, Software, Investigation, Formal analysis, Conceptualization. **Shirin Kordnoori:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Mohammadmohsen Ostadrahimi:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Conceptualization. **Saeed Seyed Agha Banihashemi:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Conceptualization.

Declaration of competing interest

The authors report there are no competing interests to declare.

Funding statement

No funding was received for conducting this study.

Data availability

No data was used for the research described in the article.

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