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Artificial Intelligence and Economic Diplomacy in Developing Countries: A Scoping Review of Applications, Evidence, and Challenges

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Abstract: Artificial intelligence (AI) is increasingly being incorporated into activities relevant to economic diplomacy, including treaty analysis, trade facilitation, customs administration, and international trade analytics. However, evidence concerning its implications for developing countries remains fragmented across empirical studies, conceptual contributions, and institutional reports. This study maps the available evidence on AI and economic diplomacy in developing countries through a review of 22 documents published between 2016 and 2026, following the reporting principles of PRISMA 2020. The documents were identified through 18 web-based search queries conducted on 8 November 2026 and classified into six thematic areas. The findings reveal an uneven evidence base. Empirical research primarily addresses trade analytics, customs administration, and firm-level economic outcomes, whereas studies directly examining AI applications in diplomatic negotiations and bargaining processes remain largely conceptual or qualitative. Institutional reports highlight the importance of digital infrastructure, reliable data, institutional capacity, and technical skills in determining the extent to which developing countries can benefit from AI adoption. Reported estimates of occupational exposure to AI range from 26% of jobs in low-income countries to 60% in advanced economies; however, these figures indicate potential exposure rather than realized economic or diplomatic benefits. Similarly, the geographical concentration of computing infrastructure suggests potential inequalities in technological access and strategic capacity, although its direct effect on diplomatic bargaining power remains unestablished. Building on these findings, the study develops an exploratory conceptual framework connecting technological readiness, institutional capabilities, and structural constraints, alongside a policy matrix outlining potential priorities for ministries of trade and foreign affairs. Given its reliance on web-based sources, a heterogeneous document base, and single-reviewer screening and coding, this study should be interpreted as an exploratory evidence map rather than a definitive assessment of AI's impact on economic diplomacy. The findings identify evidence gaps and research priorities for future empirical investigations, particularly in developing-country contexts.

Keywords: Artificial intelligence; Developing countries; Digital divide; Economic diplomacy; Trade facilitation

Introduction

Economic diplomacy refers to the activities through which states manage and advance their international economic interests, particularly in trade, investment, finance, and economic cooperation. Its principal activities include negotiating trade and investment agreements, promoting exports, attracting foreign

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investment, managing economic disputes, and strengthening bilateral and multilateral economic relationships. Traditionally, these activities have relied heavily on diplomatic expertise, institutional knowledge, documentary analysis, and established communication channels. However, the increasing availability of artificial intelligence (AI) is creating new possibilities for processing economic information, supporting policy analysis, and improving the administrative processes associated with international economic relations. Machine learning models, natural language processing, and predictive analytics, for example, can assist in classifying treaty provisions, identifying unusual patterns in customs declarations, and analysing trade indicators across potential economic partners. Hrushchynska (2025) discusses these applications in relation to decision support, economic forecasting, and diplomatic analysis, while Justinek (2026) considers algorithmic mediation as a possible development in the evolution of economic diplomacy. Nevertheless, the application of AI to economic activities should not automatically be interpreted as evidence of improved diplomatic negotiations or bargaining outcomes.

It is important to distinguish economic diplomacy from related concepts that frequently appear in discussions of AI and international relations. Economic diplomacy concerns the management of states' external economic interests and relationships. Digital diplomacy, by contrast, refers more broadly to the use of digital technologies and communication platforms in diplomatic activities. Trade facilitation focuses on simplifying and improving the procedures associated with cross-border trade, including customs clearance, documentation, and border administration. Firm-level internationalization concerns the activities through which businesses enter and expand in foreign markets. Although these areas are interconnected, they represent different analytical levels and outcomes. AI applications in customs administration or international business may contribute to the broader environment in which economic diplomacy operates, but they do not necessarily demonstrate improvements in diplomatic negotiation or interstate bargaining. This distinction is particularly important when evaluating the strength and relevance of the available evidence.

The implications of AI adoption are especially significant for developing countries, where institutional capacity, technological infrastructure, and access to skilled professionals remain uneven. AI-based analytical tools may provide government institutions with additional opportunities to process trade information, monitor international markets, identify investment opportunities, and support the preparation of economic policy decisions. However, the ability to benefit from these technologies depends on more than the availability of software. Reliable datasets, affordable computing infrastructure, institutional expertise, regulatory arrangements, and adequate financial resources are also necessary. The World Trade Organization (WTO, 2025) presents a scenario in which AI could increase global trade by nearly 40% by 2040 under conditions that include reducing disparities in access to AI-related technologies. This figure represents a conditional projection rather than an observed increase or a guaranteed outcome. Similarly, the United Nations Conference on Trade and Development (UNCTAD, 2025) identifies infrastructure, data availability, and technical skills as important conditions for more inclusive AI adoption. Gehl Sampath (2021) further discusses the possibility that unequal control over data, digital technologies, and the economic value generated by AI could reinforce existing structural inequalities between developed and developing economies.

These challenges create a complex position for developing countries. On the one hand, AI may help government institutions address certain administrative and analytical limitations by improving access to information and supporting evidence-based decision-making. On the other hand, the concentration of advanced computing infrastructure, semiconductor production, cloud services, and AI development capabilities in a relatively small number of countries may create new forms of technological dependence. Such concentration could influence the policy choices and technological autonomy available to countries with limited domestic capacity. However, the relationship between computing infrastructure and diplomatic bargaining power remains insufficiently established. Technological access alone does not necessarily translate into stronger negotiating positions, as diplomatic outcomes are also influenced by economic resources, institutional credibility, regulatory capacity, geopolitical relationships, and the strategic interests of negotiating partners.

Despite growing academic and institutional interest in AI and international economic relations, the available evidence remains fragmented across several research domains. Studies of economic diplomacy frequently examine institutional arrangements, international negotiations, and the changing nature of diplomatic practices, whereas technical research tends to concentrate on applications such as treaty text analysis, trade forecasting, customs monitoring, and firm-level economic performance. These research areas provide useful but different forms of evidence. For example, the ability of an algorithm to classify treaty provisions does not establish that it improves the effectiveness of a complete negotiation process. Similarly, improvements in customs monitoring or export performance cannot

automatically be interpreted as evidence of stronger economic diplomacy. Institutional reports also provide important comparative indicators and policy perspectives, but their findings may rely on different populations, measurement approaches, and analytical assumptions. Moreover, evidence from advanced economies and large multinational firms cannot necessarily be transferred directly to developing-country ministries, particularly where differences in institutional resources, infrastructure, and administrative capacity are substantial. The limited representation of some geographical regions, including Latin America and Central Asia, further restricts the extent to which existing findings can be generalized across developing countries.

Against this background, there is a need for a structured examination of the available literature to determine what is currently known about AI applications relevant to economic diplomacy, where the strongest evidence exists, and which issues remain insufficiently investigated. A consolidated evidence map can help distinguish directly examined diplomatic applications from related developments in trade administration, customs operations, and international business. It can also clarify the institutional and technological conditions that may influence the adoption of AI in developing countries without assuming that all reported applications produce measurable diplomatic benefits.

Accordingly, this study reviews 22 documents published between 2016 and 2026 and addresses three research questions:

RQ1: Which AI applications relevant to economic diplomacy in developing countries are reported in the existing literature, and what is the strength and nature of the available evidence?

RQ2: What technological, institutional, economic, and regulatory conditions enable or constrain the adoption of these applications?

RQ3: What implications do the available findings have for policy development and future empirical research on AI and economic diplomacy in developing countries?

The study makes three contributions. First, it provides a structured evidence base of 22 documents, distinguishing empirical research, conceptual contributions, and institutional or policy-oriented publications. Second, it develops a six-theme synthesis to organize the available evidence across diplomatic analysis, negotiation-related applications, customs and trade facilitation, technological inequality, institutional capacity, and broader economic outcomes. Third, it proposes an exploratory conceptual framework connecting technological readiness, institutional capabilities, and structural constraints to potential economic diplomacy applications. The framework is intended to guide future investigation rather than represent an empirically validated relationship. By clarifying the current state of evidence and its limitations, the study seeks to provide a more grounded basis for understanding the opportunities and challenges associated with AI adoption in the economic diplomacy of developing countries.

Method

Design and reporting

This study adopts a structured literature review to map the available evidence on artificial intelligence (AI) and its applications in economic diplomacy among developing countries. The review follows the reporting principles of the PRISMA 2020 statement (Page et al., 2021), with adaptations to accommodate the use of web-based search sources and institutional publications that were not retrieved through a single bibliographic database. The purpose of this approach is to identify relevant documents, assess their methodological and contextual characteristics, and synthesize the available findings across different research domains. Given the diversity of the included evidence, the study emphasizes evidence mapping and narrative thematic synthesis rather than statistical aggregation or estimation of a common effect.

Search strategy

The literature search was conducted on 8 November 2026. The search covered a general web search engine, RePEc, IDEAS, EconPapers, publisher and journal websites, and the official websites of selected international and regional institutions. These institutional sources included the World Trade Organization (WTO), United Nations Conference on Trade and Development (UNCTAD), International Monetary Fund (IMF), Asian Development Bank (ADB), United Nations Economic and Social Commission for Asia and the Pacific (ESCAP), and African Union (AU).

A total of 18 search queries were used. Ten queries were designed for document discovery by combining AI-related terms, including artificial intelligence and machine learning, with economic diplomacy, trade negotiations, customs administration, trade facilitation, foreign direct investment, and digital trade. Geographic terms such as developing countries, Global South, Africa, ASEAN, and Afghanistan were incorporated where relevant. The remaining eight queries followed a known-item search and citation-chasing approach to verify the bibliographic information and publication details of documents identified during the initial search.

The 18 queries returned 187 search results in total. These figures represent the reported results returned across the searches and should not be interpreted as 187

independent publications. After record consolidation and preliminary screening, 64 unique records were identified for eligibility assessment. The distinction between raw search results, duplicate entries, non-document web pages, and unique records is maintained in the screening procedure.

Table 1 presents the search-query topics, search type, and reported number of results. The complete executable search strings, platform-specific search details, and retrieval records are provided in the supplementary search log.

Table 1. Search queries and records returned

Query focus	Type	Records
AI and economic diplomacy	Discovery	10
AI, Global South, trade policy, and the digital divide	Discovery	10
WTO World Trade Report 2025 on trade and AI	Known item	17
UNCTAD Technology and Innovation Report 2025	Known item	10
AI and diplomacy in developing states	Discovery	10
Machine learning in customs and trade facilitation	Discovery	10
Unsupervised learning for ASEAN partner selection: author check	Known item	10
IMF note on generative AI and work	Known item	10
African Union AI strategy and AfCFTA digital trade	Discovery	10
AI chips, export controls, and the compute divide	Discovery	10
Geography of AI compute: publication data	Known item	10
Afghanistan, digital economy, AI readiness, and trade	Discovery	10
AI and international trade (trade economics)	Known item	10
AI and foreign direct investment in developing countries	Discovery	10
AI and outward investment: author check	Known item	10
AI, trade agreements, and negotiation text analysis	Discovery	10
AI in customs administration in Uganda: publication data	Known item	10
AI adoption and firm exports in emerging economies	Discovery	10
Total	10 discovery, 8 known item	187

Table 2. Eligibility criteria

Criterion	Inclusion	Exclusion
Topic	AI, including machine learning and algorithmic systems, applied to or analysed for trade, investment, customs, negotiation, or diplomacy	AI work with no economic or external-relations dimension
Setting	Developing or emerging economies, or global analyses that report results for them	Analyses limited to advanced economies
Document type	Peer-reviewed articles, conference papers, scholarly books, working papers from recognised series, and official reports or official summaries from international organisations	News items, blogs, training notices, testimony, dashboards, commercial or advocacy press releases, unpublished preprints
Period	January 2016 to November 2026	Earlier documents
Language	English	Other languages
Verifiability	Authors, date, and at least the abstract retrievable and consistent across sources	Authorship or content not verifiable

The eligibility criteria were established to ensure that the selected documents addressed AI applications or their implications for international economic relations, with particular attention to developing and emerging economies. The review considered peer-reviewed journal articles, conference papers, scholarly books, recognized working-paper series, and substantive institutional reports. Institutional publications were considered eligible based on their institutional provenance, relevance, transparency, and availability of sufficient methodological or analytical information, rather than peer-review status alone.

Documents were included when they examined AI, machine learning, or related algorithmic systems in

connection with economic diplomacy, trade negotiations, international trade, customs administration, investment, or related economic policy activities. Global studies were also considered when they reported findings relevant to developing or emerging economies. The publication period was restricted to January 2016 through November 2026, and only English-language documents were considered.

Documents were excluded when they lacked a substantive connection to AI and international economic relations, focused exclusively on advanced economies without transferable findings, or consisted of news items, blogs, training announcements, commercial promotional materials, advocacy press releases, dashboards, or unpublished materials that did not meet the review's documentary and analytical requirements. Documents with unverifiable authorship, publication dates, or insufficient accessible information for eligibility assessment were also excluded.

Abstracts and executive summaries were used for preliminary screening. However, the presence of an abstract or summary alone was not treated as sufficient evidence of methodological quality. Where complete texts were unavailable, the accessible material was examined to determine whether the document's objectives, analytical approach, context, and principal claims could be established. Such documents were separately identified in the evidence extraction process, and conclusions based on limited-access material were interpreted cautiously.

Appraisal and synthesis

Synthesis was narrative. The documents were coded inductively and grouped into themes by following the steps of thematic analysis in Braun and Clarke (2006): reading, generating initial codes, searching for themes, reviewing them against the data, and naming them. Designs ranged from panel regressions to policy reports, so no effect size was pooled. No formal risk-of-bias tool fits such a mix. Documents were instead classified as empirical, qualitative or conceptual, or policy reports, and claims in the discussion are weighted by that classification. Most documents were read at the level of abstract, executive summary, or available excerpt. This limit is discussed at the end of the paper.

Screening and selection process

The selection process consisted of identification, record consolidation, preliminary screening, eligibility assessment, and final inclusion. The 187 returned search results were first examined to identify duplicate entries and non-document web pages. Following this preliminary cleaning process, 64 unique records remained. These records were screened according to their titles, abstracts, and available summaries. Documents meeting the preliminary relevance requirements proceeded to further eligibility assessment using the best available publication version.

Reasons for exclusion were recorded during the screening process, including insufficient topical relevance, unsuitable geographical coverage, ineligible document type, publication outside the specified period, unverifiable bibliographic information, and insufficient accessible content. The final evidence base comprised 22 documents.

The screening process is presented in Figure 1. Duplicate records and non-document web pages are reported as separate categories rather than being combined into a single exclusion figure. The numbers for these categories and the subsequent full-text assessment are reported separately in the PRISMA flow diagram, based on the record-level screening log.

Evidence quality appraisal

Because the included documents encompass different research designs, including quantitative studies, qualitative analyses, conceptual publications, working papers, and institutional reports, a single conventional risk-of-bias instrument was not considered appropriate for the entire evidence base. Nevertheless, methodological heterogeneity does not eliminate the need for critical appraisal. Therefore, a structured evidence-quality assessment was applied to examine the credibility, transparency, and limitations of each included document.The appraisal considered five dimensions: (1) source credibility and publication provenance; (2) methodological transparency and appropriateness of the research design; (3) data adequacy, including sample characteristics and representativeness where applicable; (4) analytical transparency and the validity of reported interpretations; and (5) acknowledgement of methodological limitations and potential sources of bias. Each applicable dimension was assessed using a three-level scale: 0 (not demonstrated or insufficient information), 1 (partially demonstrated), and 2 (adequately demonstrated). Where a criterion was not applicable to a conceptual or institutional document, it was marked as not applicable rather than automatically assigned a zero.

The resulting appraisal was used to characterize the relative credibility and limitations of the evidence, not to establish a universal ranking across fundamentally different document types. Particular attention was given to the distinction between empirical results, conceptual arguments, and institutional projections. Documents based primarily on abstracts, executive summaries, or limited excerpts were assigned an access limitation and

were not treated as equivalent to studies for which complete methodological information was available.

Data extraction and thematic coding

Data extraction was conducted using a structured evidence-extraction framework. For each included document, the following information was recorded where available: author and publication year, document title, publication source, geographical setting, document type, research design, data source and sample characteristics, AI application, principal findings, methodological limitations, and implications for economic diplomacy in developing countries.

The unit of analysis was the individual document. Coding was conducted through an iterative process informed by the thematic analysis approach of Braun and Clarke (2006). Initially, the included documents were read to identify relevant statements concerning AI applications, institutional conditions, economic outcomes, technological constraints, and diplomatic implications. These statements were assigned preliminary descriptive codes. Related codes were subsequently compared, grouped, and refined into broader analytical categories.

The six themes were developed by examining similarities and differences across the extracted evidence and reviewing whether each proposed theme represented a coherent analytical area. The thematic structure was reviewed against the original documents to avoid assigning findings to categories that were not supported by their content. A document could contribute to more than one theme when it contained substantively relevant evidence for multiple analytical areas. However, each document was counted only once in the total number of included documents.

The coding process also distinguished three forms of evidence: empirical findings derived from observed data, conceptual or qualitative interpretations, and institutional or policy-oriented projections. This distinction was maintained throughout the results and discussion to prevent theoretical claims and conditional forecasts from being interpreted as demonstrated empirical outcomes.

Evidence synthesis and interpretation

A narrative synthesis was used to compare the findings across the six themes. Statistical pooling was not undertaken because the included documents differed considerably in their research objectives, units of analysis, data sources, methodological designs, and outcome measures. In particular, national economic growth, firm-level exports, customs performance, occupational AI exposure, and diplomatic negotiation outcomes were not treated as interchangeable indicators.

The synthesis therefore focused on identifying recurring findings, contrasting evidence, institutional and technological conditions, and gaps in the existing literature. Policy implications were developed by considering the relevance and strength of the available evidence alongside the institutional circumstances of developing countries. Recommendations that were not directly evaluated in the included documents were identified as analytical or normative proposals rather than established intervention effects.

Methodological limitations

Several limitations should be considered when interpreting the findings. First, the search relied on web-based sources and selected institutional and academic indexes rather than a comprehensive search of all major bibliographic databases. Second, the use of known-item searches and citation chasing may have influenced the composition of the final evidence base. Third, the review was conducted and coded by a single reviewer, without independent duplicate screening or inter-rater reliability testing. Fourth, access to some documents was restricted to abstracts, executive summaries, or available excerpts, limiting the depth of methodological verification. Finally, the geographical and methodological diversity of the included documents restricts the extent to which their findings can be generalized across developing countries.

Accordingly, the review is best interpreted as an exploratory evidence map of the relationship between AI and economic diplomacy rather than a definitive assessment of causal effects or demonstrated diplomatic performance.

Result and Discussion

Study selection and profile of the evidence

The 18 queries returned 187 records. After 123 duplicate records and non-document pages were removed, 64 records were screened. Twenty-one were excluded on title and abstract, and 43 reports were assessed for eligibility. Of these, 21 were excluded: 17 because authorship, full text, or peer-review status could not be verified, and 4 because they covered advanced economies only. Twenty-two documents remained (Figure 1). Table 3 lists them.

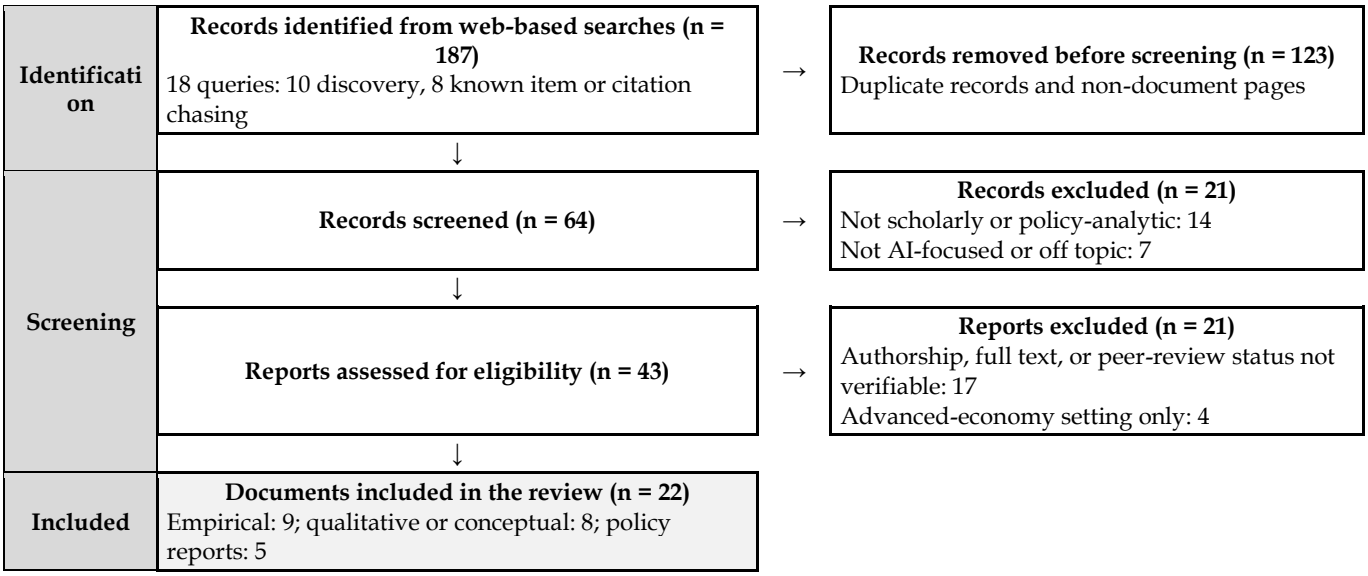


Figure 1. PRISMA 2020 flow diagram of the review. The diagram is a native Word table, so every box and number can be edited directly.

The evidence is recent. Sixteen of the 22 documents appeared in 2024 or later, and the earliest dates from 2016 (Figure 2). Nine are empirical studies, eight are qualitative or conceptual, and five are policy reports (Figure 3). Empirical work clusters in two places: trade analytics, where four of five documents are empirical, and growth, investment, and exports, where all three are. Studies of diplomacy itself, in contrast, are conceptual or qualitative, and none measures a negotiation outcome. Settings are uneven. Africa appears through Uganda, Togo, Zimbabwe, and the African Union strategy, and Asia through ASEAN, the Asia-Pacific region, and Chinese listed firms. The remaining documents are global, multi-country, or do not name a single country.

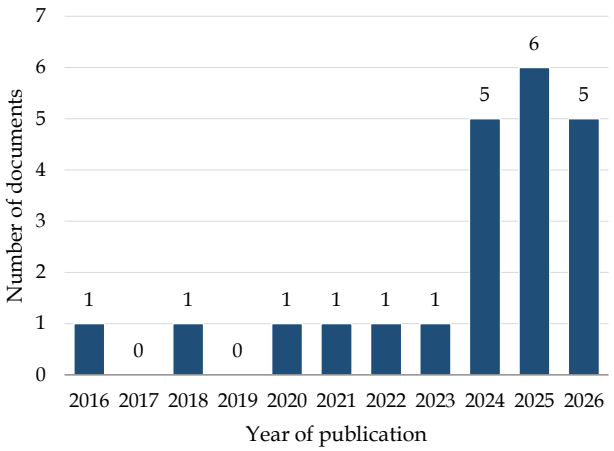


Figure 2. Included documents by year of publication (n = 22). The chart is a native Word chart; use Edit Data to change values.

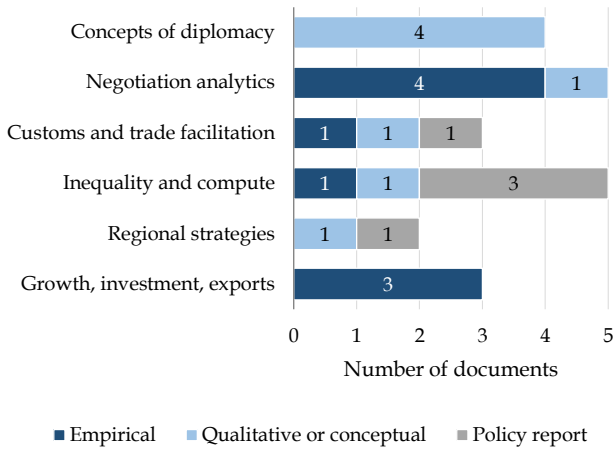


Figure 3. Document design within each theme (n = 22).

Table 3. Characteristics of the 22 included documents

No.	Source	Type	Setting	Design or method	Theme
S1	Alschner & Skougarevskiy, 2016	Conference paper	International investment treaties	Recurrent neural network trained to draft treaty articles	T2
S2	Goldfarb & Trefler, 2018	Working paper	Global	Conceptual trade analysis of AI, with policy discussion	T2
S3	Kugonza & Mugalula, 2020	Journal article	Uganda and East African transit corridor	Case study of electronic cargo tracking in customs	T3

No.	Source	Type	Setting	Design or method	Theme
S4	Gehl Sampath, 2021	Journal article	Global South	Field interviews and policy review	T4
S5	Damoc, 2022	Journal article	ASEAN, ten member states	k-means clustering of economic and governance indicators	T2
S6	Sun & Trefler, 2023	Working paper	Global, mobile app services	Empirical analysis of AI and cross-border data rules	T2
S7	African Union, 2024	Policy strategy	Africa	Continental strategy with a five-year implementation plan	T5
S8	Cazzaniga et al., 2024	Staff discussion note	Advanced, emerging, and low-income economies	Cross-country measures of AI exposure and complementarity	T4
S9	Lehdonvirta et al., 2024	Conference paper	Global	Census of public cloud GPU regions and expert interviews	T4
S10	Mayer et al., 2024	Working paper	Free trade agreements, global	Machine learning and text analysis to code agreement provisions	T2
S11	Rossidis, 2024	Journal article	Global	Conceptual analysis of public diplomacy and AI	T1
S12	Akıllı, 2025	Book	Global South cases	Conceptual framework of cognitive diplomacy	T1
S13	Hrushchynska, 2025	Journal article	United States, China, European Union	Comparative analysis	T1
S14	Maaboudi et al., 2025	Journal article	Multi-country panel	Dynamic panel GMM	T6
S15	Tchila et al., 2025	Journal article	Togo	Machine learning with mirror analysis on customs and COMTRADE data	T3
S16	UNCTAD, 2025	Policy report	Developing countries	Policy analysis	T4
S17	WTO, 2025	Policy report	Global, by income group	Scenario modelling and policy analysis	T4
S18	Aghazadeh & Rahmani Gohar, 2026	Journal article	Exporting firms, developing-country context	Mediation and moderation analysis	T6
S19	ESCAP & ADB, 2026	Policy report (official summary)	Asia and the Pacific	Survey of AI use in trade facilitation	T3
S20	Justinek, 2026	Journal article	Global	Theory-building	T1
S21	Kazizi et al., 2026	Journal article	Zimbabwe, foreign ministry	Qualitative case study with 15 stakeholder interviews	T5
S22	Wu et al., 2026	Conference paper	China, listed firms, 2009 to 2023	Two-way fixed effects panel	T6

Themes: T1 concepts of economic diplomacy; T2 analytics for negotiation and partner choice; T3 customs and trade facilitation; T4 inequality, compute, and exposure; T5 regional and national strategies; T6 growth, investment, and exports.

Thematic synthesis

Six themes emerged from the coding (Table 4). They are described in turn below.

Concepts of economic diplomacy. Four documents treat AI as a change in how economic diplomacy works, but none tests that claim with data. Justinek (2026) separates three stages: modern public economic diplomacy, digital economic diplomacy, and an algorithmic stage in which economic knowledge and diplomatic agency are shaped by algorithmic infrastructure. He does not assume that every state reaches the third stage at the same time. Hrushchynska (2025) compares the United States, China, and the European Union, and links AI to faster decisions, forecasting, and negotiation support while pointing to bias, privacy risks, and unequal access among states. Rossidis (2024) places public diplomacy in the same picture, and Akıllı (2025) proposes cognitive diplomacy, built on presence, practice, and resilience, as a way to think about digital autonomy, with cases from the Global South. These sources agree on the direction of change. They say little about the position of a ministry in a low-income country, which is the gap this review targets.

Analytics for negotiation and partner choice. Here the evidence is most concrete. Alschner and

Skougarevskiy (2016) trained a character-level recurrent neural network on investment treaties. It produced article-level text of lawyer-like quality but failed to assemble a legally sensible treaty. Mayer, Rapoport, and Umana-Dajud (2024) built an algorithm that combines machine learning and text analysis to code the provisions of trade agreements automatically, which is faster and cheaper than hand coding by experts. Both tools lower the cost of reading treaty text, which matters for delegations with small legal teams. Damoc (2022) used k-means clustering to group the ten ASEAN states by economic size, business environment, and government effectiveness. He found three clusters and read them as a hierarchy of geoeconomic power that the European Union should address with differentiated policy. The study is written from the side of a large partner, yet the same method could help a smaller state choose among partners. Goldfarb and Trefler (2018) add the structural side: scale, competition, and knowledge diffusion shape comparative advantage in AI, and rules on privacy, data localisation, and standards affect how much scale a country can reach. Sun and Trefler (2023) ask how AI algorithms and cross-border data restrictions interact in digital service trade.

Table 4. Thematic synthesis of the 22 documents

Theme	Documents	Main finding	Strength of evidence
T1 Concepts of economic diplomacy	S11, S12, S13, S20	AI is described as changing how economic knowledge is produced and how states negotiate; adoption is not assumed to be uniform	Conceptual; no outcome data
T2 Analytics for negotiation and partner choice	S1, S2, S5, S6, S10	Tools can read treaty text and group partners at low cost; drafting tools still need legal review	Tool demonstrations and one clustering study
T3 Customs and trade facilitation	S3, S15, S19	Working applications exist at borders, but adoption is low and depends on data integration	Single-country cases and one regional survey
T4 Inequality, compute, and exposure	S4, S8, S9, S16, S17	Exposure is lower in poorer economies, but so is readiness; compute is concentrated in a few countries	Cross-country and policy evidence
T5 Regional and national strategies	S7, S21	Strategies exist; interviewed officials stress infrastructure, skills, and accountability	Early; policy text and interviews
T6 Growth, investment, and exports	S14, S18, S22	AI is linked to growth and export performance, and to lower outward investment in one study	Panel and firm-level data; contexts differ

Customs and trade facilitation. Three documents report applications at the border. Kugonza and Mugalula (2020) describe the Regional Electronic Cargo Tracking System on the Northern Corridor through Uganda, Kenya, Rwanda, and the Democratic Republic of Congo, where electronic seals let command centres detect off-route movement and seal tampering. They recommend public-private partnerships, integration with other customs systems, change management, and a pool of AI specialists in customs. Tchila, Agbanho, and Bouwe (2025) combined records of the Togolese Revenue Authority with COMTRADE mirror data and found that machine learning with mirror analysis improved the detection of customs fraud while keeping revenue mobilisation as the objective. At regional scale, the United Nations Economic and Social Commission for Asia and the Pacific [ESCAP] and the Asian Development Bank [ADB] (2026) report that AI use in trade facilitation stands below 15% among surveyed economies, with levels from 1% to 40% across subregions, and they point to gaps in data integration, interoperability, and operational readiness. Working applications exist, then, but adoption is low.

Inequality, compute, and exposure. Gehl Sampath (2021) argues that AI exemplifies structural inequality in the global South, and she describes digital cannibalisation by large firms from the North. Lehdonvirta, Wú, and Hawkins (2024) mapped public cloud GPU regions and divided countries into Compute North (compute used for training), Compute South (compute used mainly for deployment), and Compute Desert groups that host no public cloud AI compute at all. They argue that states hosting compute are better placed to impose their rules on AI systems. Cazzaniga et al. (2024) estimate that AI exposure covers about 60% of jobs in advanced economies, 40% in emerging markets, and 26% in low-income countries (Figure 4). Lower exposure looks like protection, but the same note finds that poorer economies are also less prepared to capture the gains. UNCTAD (2025) reaches a similar view from the development side, and WTO (2025) from the trade side: in its scenario with better infrastructure and broad adoption, the GDP gain for low-income economies reaches 15%, while access to AI remains highly unequal.

Regional and national strategies. The African Union Continental AI Strategy (African Union, 2024) was

adopted in July 2024 and runs on a five-year implementation plan from 2025 to 2030. Kazizi, Manyevere, Mhandara, and Manhibi (2026) interviewed 15 stakeholders linked to Zimbabwe's foreign ministry. They expect gains in data analysis and predictive modelling, and they name limited infrastructure, a skills gap, and the risk of biased or unaccountable algorithms as obstacles. These two documents are the only ones that speak at the level of a national or continental strategy, and neither reports measured results yet.

Growth, investment, and exports. Maaboudi, Nademi, and Khochiany (2025) used a dynamic panel model with private AI investment as the AI proxy and report a positive and significant effect on economic growth, stronger where productivity is higher. Aghazadeh and Rahmani Gohar (2026) find that AI adoption raises export performance mainly through innovation capability, with effects that vary by competitive intensity. Wu, Liang, Lian, and Zheng (2026) study Chinese listed firms from 2009 to 2023 and report that AI application significantly reduces outward foreign direct investment. The mechanism is not settled in the material reviewed, and the result is a reminder that effects on investment need not run in the expected direction.

Reading across the themes

Three patterns recur. The applications with the firmest evidence sit close to documents and records: treaty text, customs declarations, and trade statistics. Data already exist for these tasks, the output can be checked, and a small team can start. The applications closest to the diplomat's judgment, such as forecasting partner behaviour or advising during a negotiation, are discussed far more than they are tested. Finally, every document that addresses adoption in a developing setting names the same conditions: infrastructure, data, and skills (UNCTAD, 2025; Kazizi et al., 2026; ESCAP & ADB, 2026).

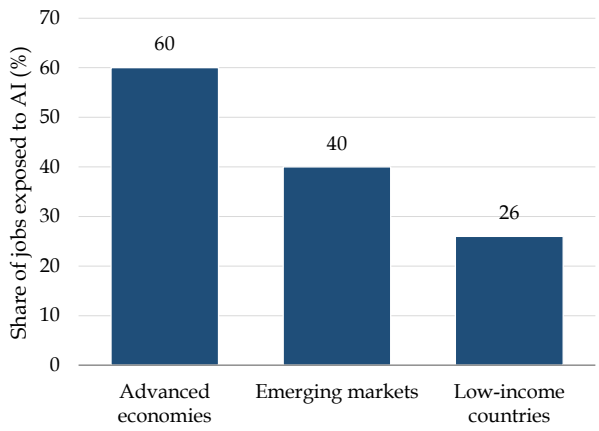


Figure 4. Share of jobs exposed to AI by country group. Data from Cazzaniga et al., 2024.

The exposure figures show why the conditions matter. A country with low exposure and low readiness gains little from the technology and may fall further behind those that adopt it early. Table 5 collects the main indicators reported across the documents.

Table 5. Indicators reported in the included documents

Indicator	Value	Source
Rise in global trade by 2040 if access gaps close	Nearly 40%	WTO, 2025
GDP gain for low-income economies with better infrastructure and broad adoption	15%	WTO, 2025
Jobs exposed to AI: advanced, emerging, low-income	60%, 40%, 26%	Cazzaniga et al., 2024
AI use in trade facilitation, surveyed Asia-Pacific economies	Below 15%	ESCAP & ADB, 2026
Range of AI use across subregions	1% to 40%	ESCAP & ADB, 2026
Clusters among ASEAN states	3	Damoc, 2022
AU Continental AI Strategy implementation period	2025 to 2030	African Union, 2024

Compute capacity adds a bargaining dimension that the diplomacy literature has barely touched. Lehdonvirta et al. (2024) report that states hosting AI compute within their territory are better placed to impose rules on AI systems than states that do not. A delegation from a Compute Desert country that negotiates over data flows or AI standards does so without that leverage. Goldfarb and Trefler (2018) note that data localisation rules restrict the scale of AI development, so the same rule can protect policy space for one country and shrink the market for another.

Figure 5 organises these findings. Readiness conditions (infrastructure and compute access, data governance and interoperability, and skills) determine which capabilities a ministry can build. The capabilities feed three outcomes that the documents report or imply: lower transaction costs, a stronger bargaining position, and a wider choice of partners. Constraints act on all three stages. They include the concentration of compute, regulatory asymmetry in digital trade rules, algorithmic bias with weak accountability, and fragmented data across agencies. The framework is a synthesis of the reviewed documents and has not been tested.

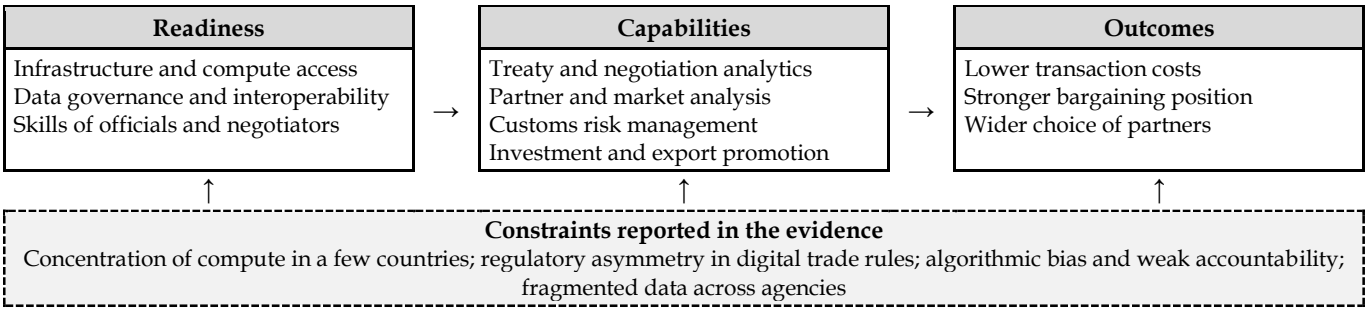


Figure 5. Readiness, capabilities, and constraints in AI-enabled economic diplomacy. The figure is a native Word table and can be edited directly.

Table 6. AI applications in economic diplomacy, the evidence for each, and the binding constraint

Function	Example in the evidence	Binding constraint
Treaty text analysis	Automated coding of agreement provisions (Mayer et al., 2024); recurrent neural network drafting of investment treaty articles (Alschner & Skougarevskiy, 2016)	Output needs legal review; the drafting model failed to compose a legally sensible treaty
Partner and market analysis	k-means grouping of ASEAN states (Damoc, 2022)	Indicator quality; the study is written from the side of a large partner
Customs risk and fraud detection	Machine learning with mirror analysis in Togo (Tchila et al., 2025); electronic cargo tracking on the Northern Corridor (Kugonza & Mugalula, 2020)	Data quality, integration with other systems, and a pool of AI specialists in customs
Regional trade facilitation	AI use below 15% among surveyed Asia-Pacific economies (ESCAP & ADB, 2026)	Data integration, interoperability, and operational readiness
Diplomatic analysis and reporting	Officials in Zimbabwe's foreign ministry expect gains in data analysis and predictive modelling (Kazizi et al., 2026)	Infrastructure, skills, and accountability for algorithmic advice
Investment and export promotion	AI adoption linked to export performance through innovation capability (Aghazadeh & Rahmani Gohar, 2026); AI application linked to lower outward investment (Wu et al., 2026)	Effects vary with competition and firm characteristics

Policy implications

Table 7 turns the synthesis into policy steps. The steps are the author's reading of the evidence, and each is tied to the documents that support it.

Table 7. Policy matrix for ministries of trade and foreign affairs

Action	Lead actor	Supporting evidence	Horizon
Start with document-based tools: build a small negotiation analytics unit using open text-analysis methods	Ministry of trade	Alschner & Skougarevskiy, 2016; Mayer et al., 2024	Short term
Pilot AI-assisted risk management at customs with human review, and use mirror trade data where records are thin	Customs authority	Tchila et al., 2025; Kugonza & Mugalula, 2020	Short to medium term
Fix data governance and interoperability before scaling pilots	National ICT and data agencies	ESCAP & ADB, 2026; UNCTAD, 2025	Medium term
Train diplomats and negotiators in data and AI literacy	Foreign ministries with universities	Kazizi et al., 2026; UNCTAD, 2025	Short to medium term
Pool bargaining power and compute access through regional bodies	African Union, ASEAN, and similar bodies	Lehdonvirta et al., 2024; African Union, 2024	Medium to long term
Set accountability rules for algorithmic advice used in foreign and trade policy	Cabinet offices and parliaments	Hrushchynska, 2025; Kazizi et al., 2026; Justinek, 2026	Medium term

Limitations

Several limits apply. One reviewer screened and coded the records, so no inter-rater check was possible. The search relied on web sources and did not use Scopus or Web of Science, and the counts in Figure 1 reflect this search and not a database export. Only English documents were included. Most documents were assessed from abstracts, executive summaries, and available excerpts, not from full chapters, so details of method and measurement may be missed. The five policy documents report figures from their own models and surveys. Several of the 2026 documents are very recent and have not yet been cited or replicated. No appraisal score was assigned, so the weight given to each claim rests on design type alone. A replication in licensed databases with two independent reviewers would test whether the themes hold.

Conclusion

The evidence reviewed in this study indicates that artificial intelligence is becoming increasingly relevant to activities associated with economic diplomacy in developing countries; however, the available evidence remains uneven in both scope and strength. The most substantial evidence concerns treaty-text analysis, trade analytics, and machine-learning applications in customs administration. Nevertheless, these applications should not be interpreted as proof that AI has already transformed diplomatic negotiations or improved countries' bargaining positions. None of the 22 documents examined directly measures AI's effect on negotiation outcomes. Most claims concerning its influence on diplomatic decision-making therefore remain conceptual, exploratory, or based on indirect evidence.

The findings also suggest that the benefits of AI adoption depend on more than the availability of technological tools. Reliable digital infrastructure, accessible computing resources, high-quality data, institutional coordination, and relevant technical skills are essential conditions for effective implementation. Developing countries that lack these capabilities may encounter difficulties in adopting AI and could become more dependent on external technology providers. Although the concentration of computing infrastructure raises concerns about technological inequality, its direct effect on diplomatic bargaining power has not yet been empirically established.

For ministries of trade and foreign affairs, a gradual and evidence-based approach is therefore advisable. Initial initiatives could include carefully designed pilot projects for treaty-document analysis, trade-information processing, and customs risk assessment, provided that the use of AI is technically verified and its outputs remain subject to human review. Such initiatives should be accompanied by clear data-governance arrangements, institutional capacity-building, transparency requirements, and safeguards against algorithmic bias. Regional cooperation may also provide opportunities to share technical expertise, strengthen computing capacity, and develop common principles for responsible AI adoption.

Several priorities emerge for future research. First, longitudinal and country-level studies are needed to examine how AI adoption affects the actual work of ministries responsible for trade and foreign affairs. Second, empirical evaluations should measure specific outcomes, including the accuracy and efficiency of treaty analysis, customs fraud detection, clearance times, trade costs, and, where measurable, negotiation performance. These evaluations should use clearly defined indicators and appropriate baseline comparisons. Third, further studies should examine contexts that are not represented in the present sample, particularly Latin America and Central Asia, to improve the geographical coverage and comparative understanding of AI adoption in developing countries.

Overall, this review provides an exploratory evidence map rather than a definitive assessment of AI's impact on economic diplomacy. Its principal contribution is to distinguish documented technological applications from conceptual expectations and to identify the institutional conditions and research gaps that require further investigation. Whether AI strengthens the economic diplomatic capacity of developing countries will ultimately depend not simply on access to advanced technologies, but on their ability to govern, evaluate, and apply these technologies within their own institutional and strategic contexts.

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Author Contributions

Conceptualization, M.H.; methodology, M.H.; investigation, M.H.; formal analysis, M.H.; writing—original draft preparation, M.H.; writing—review and editing, M.H.; visualization, M.H. The author has read and agreed to the published version of the manuscript.

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Conflicts of Interest

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