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AI Ecosystem and Value Chain: A Multi-Layered Framework for Analyzing Supply, Value Creation, and Delivery Mechanisms

Robert Kerwin C. Billones [1,2,3,*], Dan Arris S. Lauresta [1,2], Jeffrey T. Dellosa [4], Yang Bong [3,5], Lampros K. Stergioulas [3,6] and Sharina Yunus [3,7]

1 Department of Manufacturing Engineering and Management, De La Salle University, 2401 Taft Avenue, Manila 0922, Philippines; dan_lauresta@dlsu.edu.ph
2 Center for Engineering and Sustainable Development Research, De La Salle University, 2401 Taft Avenue, Manila 0922, Philippines
3 Asia-Europe for Artificial Intelligence (AE4AI) Network, Asia-Europe Foundation, Singapore 119595, Singapore; yang.bong@nottingham.ac.uk (Y.B.); l.stergioulas@hhs.nl (L.K.S.)
4 Department of Electronics Engineering, Caraga State University, Butuan City 8600, Philippines; jtdellosa@carsu.edu.ph
5 N/Lab, University of Nottingham, Jubilee Campus, Nottingham NG8 1BB, UK
6 Faculty of IT and Design, The Hague University of Applied Sciences, 2501 EH The Hague, The Netherlands
7 Department of Electrical and Electronic Engineering, Universiti Teknologi Brunei, Bandar Seri Begawan BE1410, Brunei
* Correspondence: robert.billones@dlsu.edu.ph

Abstract

Despite the rapid adoption of artificial intelligence (AI) on a global scale, a comprehensive framework that maps its end-to-end value chain is missing. The presented study employed a multi-layered framework to analyze the value creation and delivery mechanism of the five core layers of an AI value chain, including (1) hardware, (2) data management, (3) foundational AI, (4) advanced AI capabilities, and (5) AI delivery. Using a qualitative–descriptive approach with a multi-faceted thematic analysis and a SWOT-based bottleneck analysis of each core layer, the study maps a sequential value flow from a globally dependent hardware foundation to the deployment of AI services. The analysis reveals that international knowledge flows shape the ecosystem, while the "last-mile" integration challenge is not merely a technical issue; instead, it highlights a significant socio-technical disconnect between technological advancements and the preparedness of the workforce. This study provides a holistic framework that frames the AI value chain as a socio-technical system, offering critical insights for stakeholders. The findings emphasize that unlocking AI's full potential requires strategic investment in the managerial competencies and digital skills that constitute human–capital readiness.

Keywords: AI as a service (AIaaS); AI governance; bottleneck analysis; data management; digital transformation; global value chain; supply chain management; socio-technical system; statist triple helix; SWOT

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1. Introduction

Rapid advancements in AI technology have already altered drastically the way many sectors operate. Several sectors are concentrating more on automation and technology for effective production and manpower optimization as the economy enters the fourth industrial revolution [1]. AI is especially changing the value chain and supply chain industries because it emerges as a key factor propelling creative and smart solutions across

supply chain management (SCM) and value chain operations as companies struggle with changing market demands and technology improvements [2]. Particularly, understanding how value is produced and distributed within the AI ecosystem is crucial as AI becomes increasingly integrated into infrastructure, services, and products. McKinsey [3] claims that generative AI is creating a whole ecosystem, ranging from hardware suppliers to application developers, that will help realize its commercial potential. As a result, a new value chain is emerging to enable the development and adoption of AI systems. However, despite the growth of AI [4], there is no comprehensive framework that maps the supply and value chain across AI's key functional layers.

A value chain refers to the sequence of activities involved in transforming a product from its initial concept to its final delivery to the consumer. It outlines each stage where value is added along the way, including sourcing of materials, manufacturing processes, and marketing efforts. It helps an organization pinpoint area of inefficiency within its operations, allowing it to implement strategies that enhance processes and improve overall productivity and profitability [5]. The study of Lee et al. [6] states that AI has been hailed as having enormous potential for value chain enhancements. Significant potential exists to enhance the design, manufacture, delivery, marketing, and usage of goods and services via the development of new technologies in vital fields, including natural language processing, sensors, robotics, edge computing, machine and deep learning, and image identification. However, numerous obstacles are reflected in the slow adoption rate throughout the value chain phases, including design, manufacture, transport, and usage. This may be due to a lack of expertise, financial resources, established technologies, and information technology infrastructure. Additionally, beyond these technical and structural challenges, a critical but often overlooked aspect is the socio-technical dimension, which includes the required workforce readiness to effectively adopt and embed AI technologies.

Furthermore, a value chain framework for AI contains three major components consisting of hardware devices, data infrastructure, and applications. Computing equipment primarily focused on central processing units (CPUs) and graphics processing units (GPUs) define the hardware layer, and AI requires substantial data infrastructure support to process the huge data volumes. AI workloads continue to grow; therefore, the infrastructure sector is predicted to grow at a significant rate. The application layer functions as the most market-focused and competitive field because AI technologies merge with products and services to build productivity gains and generate fresh innovations. When combined with abundant installed equipment and exclusive data access, companies become strong competitors for valuable market segments in this field [7]. According to Laurentys [8], the foundation for the AI value chain is divided into five components that guarantee the success of every AI operation or project. These include "AI Strategic Alignment," which refers to 'matching AI capabilities with business strategy'; "Data Enablement," which involves 'supplying trustworthy data at scale as input to AI models'; "AI Development," which involves 'producing AI at scale that resolves a problem based on data'; "AI Business Application," which 'deploys and assesses the impact of AI in the real world'; and "AI Foundations," which aims to 'provide efficiency, stability, and security for AI assets'. It is also added that the AI Value Chain offers organizations a 'detailed, step-by-step plan for developing, implementing, and growing AI solutions.' This paradigm guarantees that AI provides quantifiable value by concentrating on the full lifecycle, from data sources to business outcomes. By taking this systematic approach, businesses will be better positioned to harness the AI revolution, driving future innovation and growth.

The implementation of AI has transformed the idea of value chains throughout different industrial sectors. The pervasive integration of AI technologies into products, services, and organizational structures [9] underscores the urgent need for businesses to understand

the processes through which value is generated and how it is distributed within AI systems. From previous studies, there exists no complete framework that defines supply and value delivery across AI's major functional areas. Various research usually examines independent components like data, algorithms, and hardware without establishing a complete AI system examination [7,8]. Organizations that adopt the evaluation of AI value chain structures alongside their elements will better manage AI implementation and its useful outcomes. They can discover fresh growth potential in addition to AI-driven economy innovation by creating an integrated analysis framework for supply and value creation delivery systems [1,2,6]. Building this framework demands detailed knowledge about the AI ecosystem, including exploration of its essential stakeholders along with technologies and main difficulties [10,11]. The assessment would start with locating performance deficiencies while pinpointing optimization areas, together with the design of implementation and scaling strategies for AI solutions. Organizations can secure success in the quickly changing AI landscape by implementing a complete method to understand the AI value chain.

In that sense, the present study aims to conduct value chain mapping through the integration of a multi-layered framework focusing on the analysis of the supply, value creation, and delivery mechanisms. Its distinct contribution is its holistic methodological integration, combined with a new analytical perspective applied to the context of developing countries. The AI value chain is analyzed using a supply and value chain development framework in the areas of hardware devices, data management systems, foundational AI models and algorithms, advanced AI capabilities (software and systems), and modes of delivery [11]. To guide this analysis, the study is framed by the following research questions: (1) What are the key components, processes, and stakeholders that constitute each layer of the AI value chain? (2) What are the primary bottlenecks and critical challenges that constrain value creation within each layer? (3) How does the interplay between technical capacity and the broader socio-technical environment impact the overall AI ecosystem? By answering these questions, this study's distinct contribution is its holistic methodological integration, combined with a new analytical perspective applied to the context of developing countries.

This research investigation holds major importance because it develops an understanding of the AI value chain to help the economy and ecosystems deal with complex AI integration processes and extract maximum benefits. For this study, the AI value chain refers to the interconnected sequence of processes and activities, from data sourcing and foundational model development to AI product and service deployment, with value generation occurring throughout the progression. This chain includes the flow of information, algorithms and computing power, alongside the contributions of essential stakeholders involved in the creation and delivery of AI-driven solutions including hardware and data providers, AI developers, platform providers, end-users, and regulators. This research develops multiple layers of analysis to study supply systems alongside value creation and delivery procedures to fill the current gap in single-feature investigations of existing research. The study provides valuable information that stakeholders can use for policy-making and investment choices and strategies to propel AI ecosystem development. This study is important because it helps businesses find unproductive operational sections while offering them necessary process optimizers for maximum productivity and profit generation. The distribution and production of value inside the AI system allows organizations to formulate tactics that optimize their product and service design and delivery, and both marketing and utilization processes. The research outcomes of this study will create a systematic procedure that organizations can use to build, implement, and expand AI solutions while ensuring the generation of measurable AI value through complete life cycle assessment from data origins to business results. Lastly, the study's analysis and findings

can also uncover economic and policy areas that need attention to address AI adoption barriers, thus promoting innovative economic growth.

2. Review of Related Literature

2.1. Value Chain Theories and Models

As the Value Chain highlights the creation of value through a series of interconnected activities, Porter [12] provides the fundamental framework for understanding how a value chain operates within an organization. Porter's seminal model categorizes activities into primary activities and support activities which facilitate and enhance the overall value delivery process [12]. Extending this organization-level perspective, the Global Value Chain (GVC) theory further analyzes how value-adding activities are distributed across different geographical locations and among various industries, which considers the role of different stakeholders within the global production system [13].

While these established value chain theories offer a strong foundation and a good analytical view for traditional industries, the unique characteristic of AI requires the adaptation and advancement of these models. Several recent studies have sought to create a more complete model. For instance, Heeks and Spiesberger [14] concentrated on building an AI value chain model to drive national and organizational goals. Similarly, a systematic literature review mapped the current landscape of AI value chain research, identifying its core stages and actors [15]. While these studies provide essential foundational maps, our research builds upon them by proposing a framework that explicitly integrates a socio-technical 'Enabling Environment' to better analyze the human–capital dimensions and adoption challenges often overlooked in purely technical models. Table 1 provides a comparative summary of these key frameworks and highlights the specific gap addressed by this study.

Table 1. Comparison of AI value chain frameworks.

Study	Focus	Layers Covered	Method	Gaps Addressed by This Study
McKinsey [3,4,9]	Generative AI opportunities and market structure	Hardware, cloud, data, foundation models, apps	Industry analysis	Lacks a holistic, end-to-end process view; limited focus on socio-technical factors.
Heeks & Spiesberger [14]	A foundational model for national/organizational goals	Infrastructure, data, MLOps, apps, services	Synthesis of existing models	Does not explicitly integrate a socio-technical enabling environment.
This Study	A holistic, multi-layered socio-technical framework	Hardware, data management, foundational AI, advanced AI, delivery	Qualitative mapping, thematic analysis, bottleneck (SWOT) analysis	Integrates a human–capital/socio-technical layer; focuses on challenges in developing countries.

Considering prior works—from existing literature-which aimed to synthesize and build a comprehensive AI value chain model, a simplified chain, shown in Figure 1, was developed based on the Mckinsey Configuration [3] and offers a simple and better representation of the informatics structure. Remodeling the complex AI chain presents a relevant contribution to this study, given its focus on developing and strengthening the AI value chain based on earlier findings and existing literature. This directly influences the "Mapping the AI Value Chain" study's structure and possible tiers, which encompass "Delivery Mechanisms" (Applications, Services), "Value Creation" (Data Preparation, Model Building, Machine Learning Operations/MLOps), and "Supply" (Infrastructure, Cloud, Data).

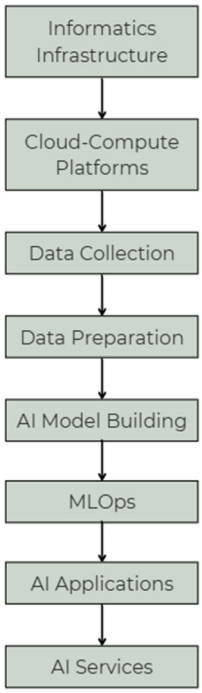


Figure 1. Simplified AI value chain [14].

McKinsey [3,4,9] provided diverse opportunities encompassing the generative AI value chain, highlighting the importance of differentiating it from the ideas of generative AI and conventional AI. It also accounted for the variations in the 'Value Creation' (model type) and 'Delivery Mechanism' (application/service type) layers.

Similarly, Gambacorta and Shreeti [16] emphasized understanding the effects of the intricate AI supply chain on innovation, risk, stability, and welfare is necessary. The AI value chain map describes the market structure and economic dynamics at each tier, offering vital background information for comprehending the power dynamics and interdependence along the chain.

Complementing this, Botero Arcila [17] examined AI liability across the entire value chain, emphasizing the necessity for policymakers to have mechanisms in place to allocate accountability and liability across the AI value chain. The study identified the challenges of accountability within the AI value chain, emphasizing the distinct and overlapping responsibilities of important players (such as providers and deployers) in the chain without offering a functional map.

Extending the discussion to economic impact, Sonjai et al. [18] assert that it is important to comprehend the economic implications of AI adoption due to the absence of empirical data and strategic direction, across the Association of Southeast Asian Nations (ASEAN) industries. The study utilized structural modeling methodologies and industry input to quantify both immediate and long-term economic effects of AI adoption, which offers practical insights to support the growth and strategic alignment of the AI value chain in other countries.

This present study shows that the AI value chain must be understood as a multi-layered system where technical, economic, and governance domains intersect. The integration of generative and conventional AI [3,4,9], the focus on the AI chain dynamics [16], the concern for accountability and liabilities [17], and the economic implications of adoption [18] demonstrate the distribution of value creation, risks, and responsibilities across the five interconnected layers. This holistic framework provides a foundation for

policy development and strategic alignment, specifically for developing countries like the Philippines where adoption of AI is still in its infancy.

2.2. AI Ecosystem Structure

Whang et al. [19] emphasized the need for data quality, quantity, and dependability to guarantee that the models function as intended. It outlines the responsibilities needed to make AI data-centric, highlighting the need for both automation and human involvement in data creation and maintenance. It reviews current research trends and offers a comprehensive perspective of technical advancements in data-centric AI, presenting activities, processes, standards through a goal-driven taxonomy designed to focus automation and cooperation.

Evangelista et al. [20] concentrated on creating laws and rules that are essential for controlling the use of AI to harness its benefits while reducing its drawbacks. Enabling natural language communication between humans and robots is the goal of their research, which might lower labor costs and enhance services. However, obstacles include a digital gap, ethical issues, privacy [21] problems, and employment displacement, which is circumvented by establishing rules and policies to control adoption and providing government incentives to organization for retraining and reskilling displaced workers, and development of training programs for outdated skills of workers. AI value chains explore the need for information and communications technology (ICT) infrastructure, supportive policy and regulation, and development of human capital through skilled workforce training, and curriculum advancement.

While infrastructure and policy are foundational, the successful adoption of AI is critically dependent on human capital. Neumeyer and Liu [22] highlights managerial competencies—such as digital literacy, adaptive leadership, and a strategic mindset—are important for addressing the complex nature of AI integration. Santos and Neumeyer [23] provide that evolution in human capabilities requires the 'technologization' of processes to avoid value destruction, particularly in environments with limited resources. These perspectives reinforce the idea that human dimension is not merely a support activity but a key component of value creation in the AI ecosystem.

In the adoption of AI use in the industry, specifically in the construction sector, Santos and Jocson [24] emphasize that an understanding of the present level of AI adoption is required to identify the obstacles and create solutions. Certain uses and difficulties in AI, and as well as its adoption and integration were discussed and analyzed in the construction sector, a particular and important business vertical. This draws attention to sector-specific requirements for human capital and infrastructures and discusses the moral implications of this sector. In this study, the lack of qualified AI specialists and the requirement for focused infrastructure and training expenditures are the identified obstacles, and it was addressed by emphasizing investments in technology and data infrastructure are required to overcome technological and data obstacles. Training and education investments are required to acquire the necessary abilities and deal with ethical dilemmas. The theoretical frameworks such as Technology-Organization-Environment (TOE) and Technology Readiness Index (TRI), and diffusion of innovation theory, are used to examine AI adoption in this environment.

A thorough framework for examining the creation, execution, and coordination of AI projects across government, industry, and academia is lacking, according to Billones et al. [25]. Furthermore, there is limited understanding of the collaborative interactions and interdependencies within the AI ecosystem. The research then suggests a modified Statist Triple Helix (STH) model that conceptualizes the AI ecosystem as an interplay between three core pillars: government, industry, and academia. This model

emphasizes the overlapping roles and collaborative relationships between these entities, all framed within a national vision, to map how AI development is advanced through policies, initiatives, and sectoral plans [25]. This study used the triple helix model to examine institutional linkages and innovation paths, in contrast to many studies that only concentrate on technological breakthroughs or single-sector policy assessments. In the development of AI, a strong emphasis is placed on governance, national policy (such as national AI roadmaps), and cooperative procedures [26]. The AI innovation ecosystem is mapped out, stakeholders and policy tools are identified, and value chain analysis at the institutional layer (government, industry, academia) is given contextual depth. Additionally, it supports the value chain framework's delivery methods and policy coordination components.

The structure of this ecosystem can also be understood through analogies with other complex systems. For instance, the digitalization of the agri-food supply chain highlights the importance of interoperability and trust in tracking value end-to-end [27], which parallels the challenges in the AI Delivery layer. Similarly, the concept of a multi-layered framework for orchestrating innovation ecosystems [28] reinforces our approach, emphasizing the systemic and dynamic governance required to manage the interconnected layers of the AI value chain.

2.3. Studies on AI Infrastructure and Market Trends

The International Monetary Fund (IMF) [29] claims that there are gaps in AI deployment, particularly related to digital infrastructure. In certain countries, significant disparities exist in the quality and availability of digital infrastructure between urban and rural areas. Strategies are required to handle this to optimize beneficial results, including increased productivity and the generation of new employment opportunities, while reducing negative impacts like job displacement. This report links scholarly research on occupational AI exposure and complementarity to the unique conditions of some countries. This is extremely relevant as it focuses on how AI is affecting the labor market, which is an important component of the result and human capital levels of the AI value chain. In line with the human capital development component, it highlights the necessity of worker preparation via education and training. Regulatory frameworks and digital infrastructure discussions are essential to the value chain's enabling environment layer.

Furthermore, Villarino [30] found limited research on college students' use and perceptions of AI technologies in non-urban higher education settings. Students worry that AI may provide inaccurate or skewed information. In that instance, the study centered on formulating clear institutional guidelines for AI implementation. Using a sequential explanatory mixed-method cross-sectional survey, it examines adoption, attitudes, difficulties, and ethical issues among college students in rural areas. This material is essential for comprehending the AI value chain's human capital development layer, particularly as it relates to the educational system that trains the next generation of workers, with an emphasis on the sometimes-neglected rural sector. It highlights the crucial importance of ethical standards and AI literacy in education [31], which forms the foundation for responsible AI development and utilization throughout the value chain.

Additionally, the United Kingdom (UK) Government [32] states that there are issues with uneven and disjointed AI policies, regulatory ambiguity, and new AI hazards that are not adequately covered by current legislation. It is critical to implement a framework that is principles-driven, context-based, and leverages current regulations. It is bolstered by central monitoring, risk assessment, and testbeds. This places more emphasis on flexibility, creativity, and non-statutory concepts that are adapted by sector-specific authorities than prescriptive frameworks (such as the European Union (EU) AI Act) [33]. It offers a legal and policy framework to facilitate the examination of the governance and delivery levels in

the AI value chain; it also fits in with the mapping of public–private duties and contextual applications of AI. Also, British academies published a joint statement [34] about AI safety to guide research and industries in the development and implementation of AI.

The European Commission [35] emphasized the need for global competition, diverse legal frameworks, and reliable, human-centric AI that is in line with EU principles. They put out a two-pronged approach in this regard: (1) an ecosystem of excellence to increase research and development (R&D) and adoption, and (2) an ecosystem of trust with risk-based regulation for high-risk AI. Because it integrates a regulatory and investment strategy and highlights the EU's principles and sovereignty in contrast to other economic blocs, it stands apart from previous studies. Additionally, it supports a thorough legislative and regulatory framework that ensures ethical AI development, deployment, and service delivery, which is in line with the value chain.

The United Nations (UN) [36] underscored several critical challenges, including the rapid pace of AI development outstripping governance mechanisms, the fragmentation of standards, persistent digital and data divides, the emergence of a widening AI gap, and the lack of coherence across international initiatives. They called for capacity building and inclusive frameworks, advocated for agile, anticipatory governance, suggested a toolbox approach, and emphasized the significance of utilizing the UN's current tools. It highlights sustainability, equity, and human rights in governance frameworks with a multi-agency, cross-sectoral focus. It highlights differences in responsibilities and advantages across AI supply and service chains, providing information to the global governance and institutional layer of the AI value chain. Additionally, this prompted organizations to work on AI governance initiatives [37] not only for industries, but also with other stakeholders such as academia [38] and civil society.

Finally, according to the Department of Information and Communications Technology [39], some countries have several obstacles when it comes to using AI. Digital infrastructure, skill development, data availability, legal frameworks, and energy sufficiency are all major obstacles. To overcome obstacles and successfully use AI, it is crucial to choose the most critical course of action and policy orientations. It was recommended that countries should establish a single national AI policy and assign a lead agency to direct its plan and implementation to cut down inefficiencies and realize the full potential of AI technologies. This policy statement, which focuses on establishing policy directions and activities, was specially created by a government-affiliated entity. It offers a thorough summary of the difficulties based on national evaluations such as the AI Readiness Index. It covers the enabling environment, which includes infrastructure, human capital development, and policy and governance.

The literature review has provided a comprehensive summary of existing studies that concern AI value chains, ecosystem structures, infrastructure, and market trends. While the theories of Porter [12] and GVC [13] offer foundational frameworks for value creation and distribution, recent studies started to utilize these in the AI domain [3,4,9,14,17,18], our review identifies that these studies primarily highlight conceptual models focusing on specific segments such as data-centric AI [19], generative AI [3,4,9], AI liability [17], or analyze broad regional trends [16,18,29,32,35,36]. There remains a notable absence of integrated, multi-layered mapping of the complete AI value chain in developing countries, which continue to face challenges related to digital infrastructure, skills development, and policy coherence [39]. This study aims to address this gap with the development of a comprehensive and integrated mapping approach of the AI value chain, thereby offering an understanding of value creation where detailed insights are currently limited.

3. Methods

3.1. Research Design and Approach

This research employs a method that utilizes qualitative-descriptive and analytical research design to investigate and assess the AI value chain using a stratified supply and value chain development framework. This approach is particularly effective for conducting comprehensive mappings and detailed analyses of complex systems, as demonstrated by previous research in technology value chains [40,41] and industrial ecosystems [42]. This study aims to map the different, distinct segments of the AI value chain, which include hardware devices, data management systems, foundational AI models and algorithms, advanced AI capabilities, and delivery mechanisms, to analyze how value is created and transferred across each layer.

A multi-level value chain analysis is conducted to identify key components, stakeholders, interdependencies, and possible bottlenecks. The global value chain (GVC) theory is used to break down complex production systems into functional stages and utilize a layered flow diagram to visually represent how resource flow and value are created. Thematic analysis using qualitative coding is applied to extract insights from literature and industry reports for value-creating activities, while the Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis is employed to determine constraints and evaluate bottleneck points that slow down the chain and disrupt value creation. Moreover, a comparative analysis across countries and industries is used to check for distinctions between them in terms of their AI development and deployment. The methodological novelty of this study lies in the combination of different analyses to provide a qualitative, descriptive, and analytical view of the AI value chain, specifically addressing a gap in the literature by focusing on the challenges faced by developing countries. Figure 2 provides a visual representation of the overall research design and the logical flow of the study.

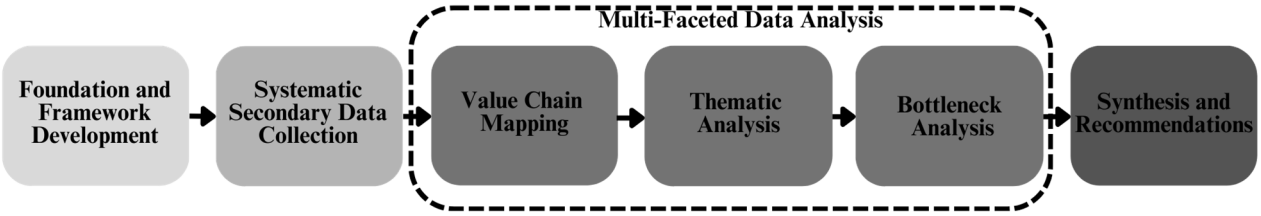


Figure 2. Research design and logical flow of the study.

3.2. Conceptual Framework

The conceptual framework represents the AI ecosystem as a multi-layered value chain wherein each layer—from hardware development to service delivery—contributes to its overall value creation. Crucially, this entire value chain is embedded within a broader socio-technical context where its effectiveness is moderated by enabling factors such as policy, governance, and, most importantly, human capital—including the digital competencies and adaptive mindset of managers and employees who drive adoption and value creation [22]. Synthesizing existing theories such as the global value chain theory [13], which examines how inter-organizational collaboration affects and benefits each global value layer, and Porter's value chain [12], which highlights the value added at every stage of production, this study employs a modified supply and value chain development framework. These theories are particularly suitable for the analysis of the AI ecosystem due to their capacity to systematically dissect complex, multi-actor production processes. GVC offers a strong foundation for understanding the globally distributed and interdependent nature of AI development [13], while Porter's framework provides a micro-level analytical tool to unpack and investigate the value-adding activities within each distinct layer of the AI value

chain from foundational infrastructure to end-user applications [12]. It aims to analyze the AI ecosystem across five critical areas [11]: hardware devices, data management systems, foundational AI models and algorithms, advanced AI capabilities, and AI delivery methods. Figure 3 shows the proposed AI supply and value chain development framework used in this study.

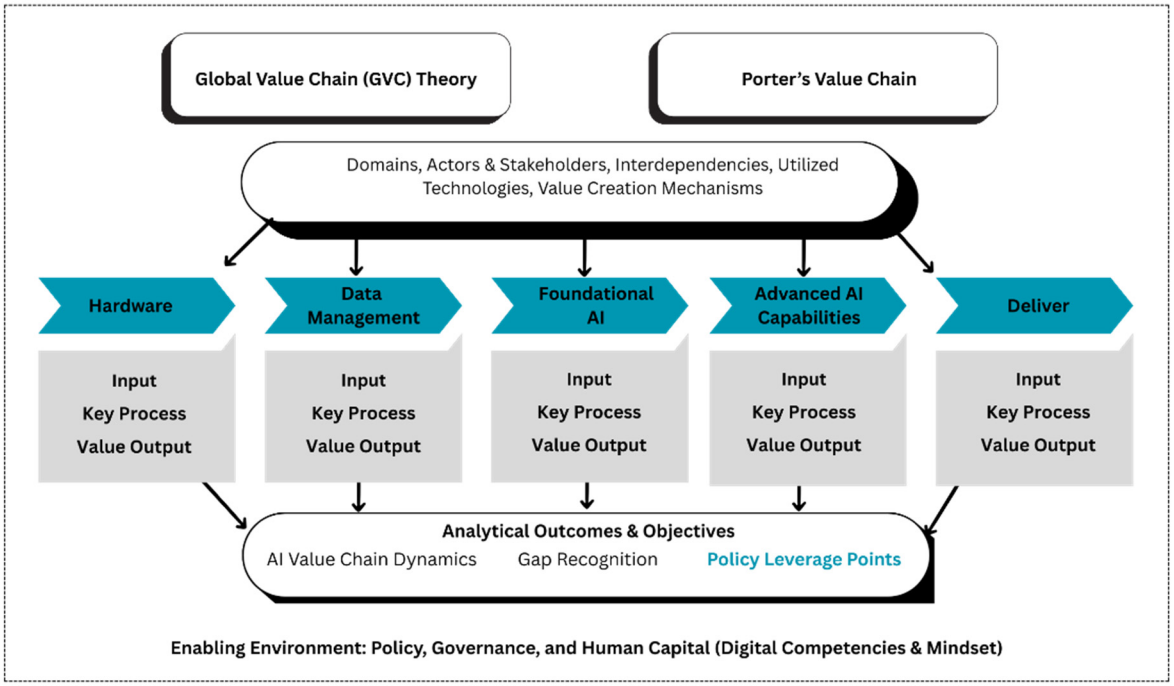


Figure 3. Proposed AI supply and value chain development framework.

The framework is organized into multiple interconnected layers, each driven by specific processes and featuring its input and output. This design generates value at each stage, serving as input for the subsequent layers. The hardware layer includes the production and deployment of physical infrastructure such as chips, processors, storage devices, GPUs, and edge devices that support AI computations and enable computation power for AI. Subsequently, the data management layer, which is critical for training AI systems and providing high-quality data for models, covers data sourcing, annotation, storage, pipeline design, and governance. Following the treatment of data for the training, the foundational AI layer presents the development of foundational models and frameworks such as PyTorch, TensorFlow, and large language models, which serve as a reusable platform for a variety of applications. Consequently, the fourth layer facilitates the creation of custom-designed AI systems, analytic tools, and other industry-specific platforms, while the fifth shows the ways in which AI capabilities are provided and utilized. Potential delivery methods include hardware appliance, licensed software, and Artificial Intelligence as a Service (AIaaS).

In addition, the framework identifies domains, actors, and interdependencies in the value chain. The inclusion of stakeholders such as chip manufacturers, data brokers, AI developers, and utilized technologies provides a clear view of their roles in the AI value chain development and the identification of bottlenecks. Furthermore, the incorporation of actor mapping and gap recognition presents insights into policy leverage points where intervention and improvement can be made.

3.3. Data Collection Method

The mapping of the AI value chain through a multi-layered framework employs a qualitative-descriptive and analytical approach that utilizes a mapping technique based on

the global value chain theory, qualitative coding, and bottleneck identification. This approach exclusively relies on secondary data sources to provide reliable and comprehensive insights about the AI value chain.

Secondary data is obtained from peer-reviewed journals, government reports, industry white papers, and academic studies to ensure credibility and relevance. To ensure transparency and systematic rigor, the comprehensive search and selection process for these secondary data sources is explicitly detailed below and illustrated in Figure 4.

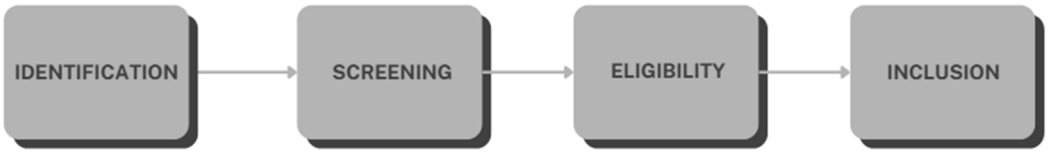


Figure 4. Secondary data selection process.

Initially, a total of 250 documents were identified across academic databases including Scopus, Web of Science, and Google Scholar, as well as industry and governmental reports, using primary search strings such as ("AI value chain"), ("AI ecosystem" AND "framework"), and ("foundation model" AND "supply chain"). After systematically removing 64 duplicates, 186 unique records were reviewed to verify the relevance and quality of the data collected. The selection criteria prioritized data validity and reliability, relevance to the five core AI chain segments, and date of publication, focusing on sources published between 2018 and 2025 to capture the most recent advancements. During the initial title and abstract screening, some documents were excluded due to their irrelevance to the AI value chain context, while 100 documents were excluded after full-text review, due to the lack of sufficient detailed information for mapping the core layers of AI value chain. After this systematic approach, 86 documents were included for an in-depth qualitative and coding analysis and were mapped based on the five cores of AI chain segments, namely hardware, data management, foundational AI, advanced AI capabilities, and delivery. The data collected and processed in this analysis are available in the Supplementary Materials.

3.4. Data Analysis Techniques

This study combines a value chain mapping framework and layered-flow diagrams to provide a comprehensive diagram that illustrates the flow of inputs and outputs across the five core layers and identify the value contribution at each stage. In addition, thematic analysis is employed to identify, examine, and interpret patterns within the data to understand key themes within the core layers and the roles of stakeholders, technologies, and gaps in the value creation. Moreover, a bottleneck analysis is performed to determine constraints and limitations that prevent the optimal performance of each layer and highlight where inefficiencies are introduced, and value is lost.

Ensuring that the data was ready for the thematic analysis, detailed coding using ATLAS.ti software (version 25, ATLAS.ti Scientific Software Development GmbH, Berlin, Germany) was employed. With the familiarization of the selected secondary data, initial coding was performed iteratively, which generated 156 open codes for each AI value chain core layer. These codes were iteratively grouped into 29 distinct sub-themes based on conceptual similarity. To ensure reliability, this process was conducted by two researchers, and any coding discrepancies were resolved through discussion to reach a consensus. Subsequently, these sub-themes were further abstracted into 6 overarching themes representing the most significant and recurring patterns across the entire AI value chain: input, processes, output, stakeholders, bottlenecks, and created value.

3.4.1. Value Chain Mapping and Layered-Flow Diagram

Through the creation of the value chain mapping and the layered-flow diagram creation identifies critical segments of the AI value chain were identified based on the contribution of each core layer and stakeholders. To effectively and comprehensively map its value and flow, Mohapatra and Ramadas [43] introduced a structured approach by first mapping the key stakeholders and defining their functions within the value chain. It is then followed by outlining the product flow and information exchange, which highlights the value, constraints, and bottlenecks in each stage. Lastly, these factors are analyzed to provide insights into possible strategies that promote dynamic progress of the chain. Unlike other static models, the study emphasizes chain-wide learning where feedback loops and iterative analysis are applied to foster an adaptable framework. Due to its support of layer-by-layer analysis, the application of this technique in mapping the core layers of the AI value chain helped discover useful observations to completely understand each layer's value and gaps, the stakeholders' roles, and policy impacts.

Zamora [44], highlighted the significance of Buyer-Driven versus Producer-Driven chains across various industries, as well as the crucial role of market mapping and policy support in enhancing global connections. While many studies focus solely on the formulation of the value chain and its economic impact, this study explores governance structure and actor-driven value creation of buyer- and producer-controlled industries such as cloud services and tech and semiconductor manufacturing, respectively. Furthermore, Knez et al. [45] consider the complexity of global and domestic fragmentation using input-output analysis to trace value creation across each layer. Their study also introduced the Value Chain Tree Concept (VCTC) to visualize end-to-end flows from raw materials to consumer delivery. By analyzing the inputs and outputs at each stage, divisions can be easily distinguished between global and domestic production, which offers a clearer perspective on inefficiencies and redundancies.

Considering the factors that were identified by the studies [43–45], this study employs a methodical procedure for the mapping of the AI value chain. The creation of an AI value chain framework starts by establishing boundaries for the analysis and determining primary value drivers for each core layer. This ensures that key objectives are identified, and relevant information is gathered. Following the recognition of value creation, transfer, and potential loss, core actors and activities are mapped. In this step, Input–Process–Output are also illustrated, together with the policy and regulatory influences. GVC analysis is performed, which distinguishes producer-driven and buyer-driven mechanisms and maps key enabling environments. Lastly, an input–output analysis is applied to highlight cross-border movement of raw materials, data, and AI solutions, and analyze participation rates and linkages.

3.4.2. Thematic Analysis

Employing a thematic analysis on the AI value chain can provide a clear perspective of the relationship between the core layers, which can uncover deeper linkages, recurring patterns, and stakeholders' views. For this section, a bibliometric analysis is applied using VOSViewer (version 1.6.20, Centre for Science and Technology Studies, Leiden University, Leiden, The Netherlands) to analyze the core themes and trends in the AI value chain using co-occurrence analysis and evaluating the intellectual network and knowledge flow through bibliographic coupling. Integrating these analyses creates a multifaceted thematic exploration that enables a qualitative approach in understanding complex relationships, key themes, and development gaps in the mapping of the AI value chain and explicitly addresses the gap in the literature by focusing on the challenges faced by developing countries, which are often underrepresented. The bibliographic coupling

case study of the Philippines, which represents a developing country, is presented as a practical application of the framework, showing how a developing nation's AI ecosystem is shaped by a strategic combination of foundational knowledge from global leaders and practical, regional collaborations.

To conduct the bibliometric analysis, a CSV file containing extracted data from Scopus and other peer-reviewed journals was uploaded to VOSviewer (version 1.6.20, Centre for Science and Technology Studies, Leiden University, Leiden, The Netherlands). The counting method was configured to full counting, requiring a minimum of 15 documents and citations for a country to be included. For the co-occurrence analysis, the analysis type was selected accordingly, with "All Keywords" specified as the unit of analysis. The counting method for this analysis was also full counting, and the minimum number of keyword occurrences was set to 30. These thresholds were chosen to ensure that the analysis focused on the most salient and well-established topics in the literature, thereby reducing noise from less frequent keywords and providing a clearer visualization of the field's core intellectual structure.

3.4.3. Bottleneck Analysis

It is important to identify key constraints and barriers that impede the efficient flow of value within the AI value chain to effectively focus on the critical stages, quantify impact on the created value, and propose possible intervention and improvement. Bottleneck analysis systematically identifies the components that limit the overall capacity or flow of the entire system [46], and applying it within a multi-layered framework like the AI value chain can identify constraints, resources, and areas where efforts can be better directed to promote efficiency, prevent disruption, and enhance the progression of value creation and delivery.

Following the mapping of the AI value chain and the identification of key themes and trends through a thematic approach, a bottleneck analysis is conducted through a SWOT analysis to identify existing gaps and areas for potential improvement. By breaking the analysis across the five core layers, identified strengths may be leveraged to support current inter-stage activities; recognized weaknesses may address developmental issues, presented opportunities may be capitalized for future advancement, and perceived threats may be mitigated. The result of the SWOT analysis is visualized through a matrix for easier reference and findings are mapped in the value chain.

4. Results

4.1. AI Ecosystem, Value Chain Mapping, and Layered-Flow Diagram

From the analysis of the literature sources, the AI ecosystem can be characterized by the different stakeholders and their interactions in the value chain. Table 2 outlines the key stakeholders involved in each of the five layers of the AI value chain, highlighting the complex, multi-actor ecosystem that drives AI development and deployment. The hardware layer relies on international suppliers, data center operators, and infrastructure providers, reflecting global dependencies in physical AI infrastructure. The data management layer involves roles focused on ensuring data quality, governance, and compliance—essential for reliable model training. In the foundational AI layer, nation-states, private firms, and research institutions work together to develop general-purpose models, emphasizing the strategic and high-investment nature of this stage. The advanced AI capabilities layer shifts toward practical use, involving developers, vendors, regulators, and user communities to ensure AI systems are ethically and effectively deployed. Finally, the AI delivery layer includes service providers, end users, and compliance organizations responsible for integrating AI into workflows and ensuring performance, usability, and trust. This stakeholder mapping shows how each layer has unique yet interconnected actors, and how the effective

operation of the entire AI value chain depends on strong coordination across technical, regulatory, and societal areas.

Table 2. AI value chain, ecosystem, and stakeholders.

AI Value Chain Layer	Stakeholders
Hardware	Hardware manufacturers/providers/component suppliers [9,11,14,16,17,36,47,48] Cloud computing providers/data center operators [11,14,16,36,47,49–54] AI system developers and providers [3,14,16,17,48,50,51,55–57] Deployers and end-users [16,17,50] Research institutions and academia [6,16,32,36,48,58] Policymakers and regulators [11,16,26,27,32,36,51,57,59] Benchmarking and standardization bodies [16,17,36,56,60]
Data Management	Data stewards [11,51,61–64] Information Technology (IT) operations/infrastructure teams [63–66] Metadata managers [11,61] Legal and governance officers [11,50,51,61,62,65] Analysts [11,61,64,65,67–69] Quality Assurance (QA) teams [19,51,57,61,62,70] Decision makers [1,60,62–65,68,71–73]
Foundational AI	Nation-states and companies/private entities [3,16,17,26,27,32,36,48,51,56,60,65,74,75] Policymakers and government entities [1,11,16,26,27,32,48,51,56,57,65,75] Researchers and academics [1,16,17,26,32,36,50–52,56,64,68,73,76] Providers of AI services [3,11,16,50,51,56,61,70] Organizations that adopt and implement AI [16,17,32,50,62,64,65,71,74,77,78] Federal agencies and nonprofits/foundations [11,16,27,32,36,38,56,67,79]
Advanced AI Capabilities	Service consumers/users [1,6,9,11,16,17,27,32,35,38,48,50–52,55,61–63,65,73–75,80,81] Service providers and infrastructure [1,6,11,14,16,27,32,35,36,50,55,60,61,64,66,70,71] Developers and designers [6,11,16,17,32,35,38,50,51,55,57,64,65,75,82] Vendors and third parties [6,11,17,32,51,64,71] Regulatory bodies [17,27,32,38,50,51,57,65,75] Experts and researchers [1,6,9,11,16,17,19,25,26,32,36,38,48–51,60,64,68,71,72,75,76,79,81,83] Affected communities [1,31,32,36,51,56,62,65,68,75,78]
AI Delivery	Service consumers [1,2,6,9,11,16,17,27,32,47,50,55–57,61,62,65,69,74,75,77,78,80,84,85] Providers and infrastructure [1,3,6,11,14,16,17,27,32,36,50,55–57,59,60,62–65,70–72,74,78,80,86,87] Regulatory and compliance bodies [2,11,16,27,29,32,36,38,49–51,56,57,59,65,66,75,88] Data owners and providers [1,3,6,14,16,17,36,50,51,55,56,61–65,71,72,77,78] Supply chain actors [1,2,4,6,9,11,16,17,21,32,40,43,49,51,55,57,63,64,69,71–73,76,78,80,81]

This section presents the result of mapping the AI Value Chain, utilizing a multi-layered Porter's framework to represent the development stages in each core layer. The analysis systematically traces the movement of resources and activities that generate value, from the foundational supply of physical infrastructure to the final delivery of AI solutions. This can be visualized in the layered-flow diagram which is the sequential and interconnected relationship among the five AI value chain layers: (1) hardware devices, (2) data management systems, (3) foundational AI models and algorithms, (4) advanced AI capabilities, and (5) AI delivery. This indicates that the value generated by each preceding layer serves as the foundation for the subsequent one. Figure 5 shows the AI value chain and its different layers used in this study.

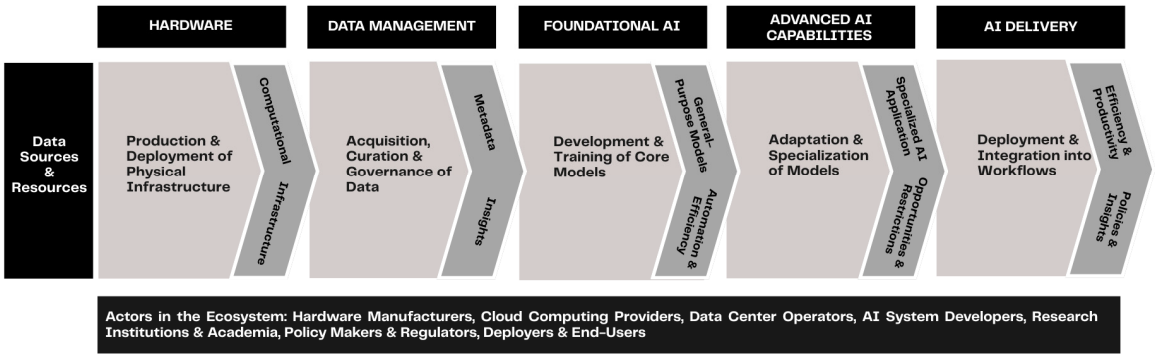


Figure 5. AI value chain layers.

4.1.1. Hardware Layer

The Hardware layer establishes the physical foundation of the AI value chain by converting inputs like raw materials and data specifications into essential computing power. This stage is characterized by a dependency on global supply chains for components like GPUs and servers. Value is created through core and operational computation to ensure powerful, energy-efficient processing, culminating in a robust and scalable computational infrastructure. However, this layer is constrained by high costs and significant integration challenges. Table 3 shows the input, key process, and value output in the hardware layer.

Table 3. Input, key process, and value output in the hardware layer.

Input/ Key Process/ Value Output	Category	Description
Input	Data type and sources	Raw, real-time, historical, simulation, structured/unstructured, and contextual [1,9,11,14,35,42].
	Model and algorithm inputs	Pretrained models, neural networks (NN), parameters, synthetic AI for benchmarking, governance libraries, and training data [11,16,56,60].
	Operational configurations	Frameworks, application programming interfaces (APIs), workload parameters, execution frequencies, cluster settings, and control commands [16,28,32,54,60,75].
	Physical resources	Power, materials, chip design data, and feedstock for additive manufacturing [11,16,27,56,69].
Key Process	Core computation	Parallel processing, tensor ops, matrix ops, and nonlinear activation [11,28,53,89,90].
	Data management	Memory hierarchy such as Static Random Access Memory (SRAM) and Dynamic Random Access Memory (DRAM), data transfer, storage, vectorization, and text extraction [11,56,67].
	Optimization techniques	Model compression (quantization, pruning), hardware-embedded NN, conditional computation, and adaptation strategies [11,62,70,80,81].
	Orchestration and control	AI-software-hardware orchestration, infrastructure control, and system monitoring [51,64,65,72,75].
	Edge/specialized processing	Edge AI, photonic tensor cores, embedded AI engines, spiking dynamics, and motion/orientation sensing [11,51,72,80,87].
	Benchmarking	Frequency calculations, workload clustering, and synthetic model execution [19,52,64,65,90].
Value Output	AI outputs	Predictions, decisions, classifications, content (text/graphics), and recognition results [11,80,81].
	Performance metrics	Latency, throughput, energy/time efficiency, memory reduction, bandwidth savings, and improved accuracy [56,62,90].
	System capabilities	Functional AI systems (vision, natural language processing (NLP), gesture), digital twin functionality, and updated model parameters [26,80,91].
	Value creation	Foundational AI enabler, efficiency boost, support for edge computing, and innovative architectures [14,62,63,65].

4.1.2. Data Management Layer

Acting as the value chain's quality control checkpoint, the Data Management layer transforms raw data into high-quality, organized datasets vital for model training. The process involves acquiring, cleaning, and structuring data, followed by creating metadata and insights through tagging and documentation. Effective governance and automation are key factors in producing trustworthy AI, but this layer is constrained by significant challenges in scalability and metadata handling. Table 4 shows the input, key process, and value output in the data management layer.

Table 4. Input, key process, and value output in the data management layer.

Input/ Key Process/ Value Output	Category	Description
Input	Raw data	Data from systems, users, sensors, and legacy datasets [1,11,49,56,61,71,72,92].
	Annotated data	Human-labeled or crowdsourced data for supervised learning [11,16,19,27,56,67,71,72,76,93].
	Model info	Training protocols, performance metrics, lineage, and model facts [3,11,19,27,35,46,58,61,66,70,74,76,87,90].
Key Process	Acquisition and collection	Gathering relevant datasets from structured and unstructured sources [9,11,61,68,71,80].
	Preparation and processing	Removing noise, handling missing values, preprocessing, and feature engineering (extracting, selecting, transforming features) [14,19,56,61,71,72,82,92].
	Organization and management	Storage, retrieval, structuring, and versioning [11,19,42,46,61,71,91].
	Governance and quality	Policies, roles, access, compliance, standards, accuracy, completeness, timeliness, and profiling [19,32,36,46,58,61,67,72,74,87].
	Metadata and documentation	Cataloging, tagging, tracking, and glossary [6,11,46,61,68,74].
	Understanding and exploration	Summarization, visualization, and valuation [9,11,19,42,68,91].
	Storage and retrieval	Efficient access, capacity planning, and optimization [11,19,46,61,72,74,84].
	Integration and interoperability	Merging structured/unstructured data from multiple sources [3,14,16,61,82].
	Labeling	Supervised labeling, semantic tagging via humans or machine [11,16,19,27,56,67,71,72,76,93].
	Reduction and augmentation	Dimensionality reduction, feature selection, and synthetic data generation for diversity/robustness [16,19,51,61,71,72,82,87].
	Prompt design	Designing inputs for large language models (LLMs) or foundational models [3,9,11,16,19,55,61].
	Entity matching	Linking/merging duplicate or related records [11,19,56].
Value Output	Clean and labeled data	Refined, labeled, and reduced data ready for modeling [2,6,14,16,19,51,56,58,61,64,84,87,92–95].
	Metadata and documentation	Factsheets, lineage, and auto-generated documentation [9,56,61,74,91].
	Insights and visualization	Dashboards, summaries, and insights from structured exploration [6,9,11,19,56,61,66,68,84,91,95].

4.1.3. Foundational AI Layer

Following the curation of data, the Foundational AI layer transforms curated datasets into versatile, large-scale AI models that can understand broad patterns and serve as a baseline for specialized solutions. The process begins with model design and architecture selection, followed by training on large datasets to recognize patterns. The resulting models are then refined through fine-tuning and optimization before undergoing rigorous testing and evaluation to ensure robustness. While this layer supports scalable intelligence, it is constrained by high costs, significant resource requirements, and ethical concerns such

as bias and explainability. Table 5 shows the input, key process, and value output in the foundational AI layer.

Table 5. Input, key process, and value output in the foundational AI layer.

Input/ Key Process/ Value Output	Category	Description
Input	Data	Diverse datasets, broad data, supervised data, curated datasets, large data amounts, enterprise data, system/tool integrations, real-world data, digitally encoded images, audio, sensor readings, linguistic inputs, multiple languages, computer code, database files, metadata, spatial coordinates, climate information, task-specific labeled data, structured data, invariant data, temporal data, time series, image data, text data, speech data, tabular data, protein sequences, organic molecules, reinforcement learning data, motion data, pointing gestures, point clouds, spoken instructions, offline data, historical training data, and interaction data [2,9,11,19,51,56,65,71].
	Resources	Compute resources, computational power, computing scale, and hardware accelerators [11,16,51,63–65,71].
	Existing models/knowledge	Previous AI models, pre-trained parameters, human knowledge (general, domain), qualitative knowledge (plain language, logic rules, invariance, equations, knowledge graphs), expert knowledge, mathematical websites, textbooks, radio archives, podcasts, digital archives, prompting, and metadata [3,11,56,70,76,80].
Key Process	Training	Pre-training, self-learning, training on diverse/broad datasets, self-supervision at scale, general methods leveraging computation, learning from historical data, learning from interaction, learning co-occurrence patterns, goal-directed training, multitask learning, multiagent learning, multimodal training, and metadata as targets [11,14,16,50,51,56,60,70,71,87].
	Model development and architecture	Transformer-based sequence modeling approaches and the self-attention mechanism, focusing on integrating different modalities into a universal feature space and learning compositional representations [1,11,14,55,60,92].
	Refinement and adaptation	Fine-tuned for specific applications, where an adaptation loss on task-specific data is minimized; this includes model compression techniques and adapting using methods like prompting [3,11,55,76].
	Processing data and performing tasks	Ingesting and mapping whole organization data, processing raw perceptual information, reasoning with formal symbolic language, active learning, and processing diverse data types using various NLP techniques [9,22,35,56,64].
	Evaluation	Effective and consistent testing and evaluation protocols to identify which adaptation methods make best use of resources and to control the behavior of very capable models [42,52,56,60].
Value Output	Models and capabilities	Large-parameter models, foundation models or general-purpose AI models, which are highly adaptable models capable of performing a wide variety of tasks [9,11,16,55,56,70].
	Derived tools and applications	ChatGPT, Gemini, and Microsoft, which can perform tasks including text generation, question answering, and image creation, and can serve as a 'building block' of hundreds of single-purpose AI systems [4,11,16,26,55,56].
	Industry-related outputs	Prediction outputs, content outputs, recommendation outputs, decision outputs, and even inference or test-time computation that shows reasoning processes [9,26,49,56,76].
	Restrictions	Use of output may be restricted, for instance, not being permitted to develop competing models [32,55,56,59,75].

4.1.4. Advanced AI Capabilities Layer

The Advanced AI Capabilities layer bridges general intelligence and actionable solutions by adapting foundational models to perform specific, high-value business tasks. This stage involves acquiring human-centric data, followed by training and optimizing the models for tasks like classification or anomaly detection. By integrating these fine-tuned capabilities into products and services, this layer creates real-world value through increased productivity and innovation. However, it faces significant risks from inheriting bias from foundational models, alongside other ethical and regulatory challenges. Table 6 shows the input, key process, and value output in the advanced AI capabilities layer.

Table 6. Input, key process, and value output in the advanced AI capabilities layer.

Input/ Key Process/ Value Output	Category	Description
Input	Data sources	Raw/pre-processed data, integrated information, task information, positional encoding, sensor data, and diverse data [60,64,74,88].
	Human-centric data	Patient data, patient values and preferences, and user feedback [56,58,73,74].
	Model-related data (from foundational AI)	Training data, input data for inferencing, test, evaluation, verification, and validation data [11,56,80].
Key Process	Algorithmic processing	Algorithm execution, data preparation, model training and optimization, transformer architecture processing, and model aggregation [51,56,70,72,73,76].
	Knowledge creation and decision-making	Knowledge creation (classification, segmentation, anomaly detection), decision support/making, planning and policy [51,72,77].
	AI applications	Applying AI capabilities (NLP, speech recognition, computer vision) and integrating AI into products/services [3,16,26,58].
	Human-AI interaction	Generating explanations, human-AI synergy, schema activation, and incorporating patient values [6,11,56,80].
Value Output	Insights and analytics	Derived insights, contextual summaries, predictions, and enhanced decision-making [9,62,63,72,77,91].
	Operational decisions	Automated tasks, offloading decisions, and AI-infused product enhancements [10,14,56,65,71,86].
	Human support	Decision support (recommendations, data summaries) and explanation types (local, global, counterfactual) [4,11,14,51,68,69].
	Content and innovations	Generated content (text, images), innovative outcomes, and enhanced efficiency [3,11,51,56,62,68].

4.1.5. AI Delivery Layer

As the final "last-mile" of the value chain, the AI Delivery layer focuses on deploying specialized models by integrating them into business workflows, platforms, and consumer-facing applications. The process begins with the integration and orchestration of systems and resources, emphasizing usability, automation, and user experience to ensure the potential created in preceding layers translates into real-world impact. Despite its high potential to democratize AI through AIaaS, this layer faces significant challenges with system complexity, user trust, and barriers to adoption. Table 7 shows the input, key process, and value output in the AI delivery layer.

Table 7. Input, key process, and value output in the AI delivery layer.

Input/ Key Process/ Value Output	Category	Description
Input	Data for processing/inference	Historical and real-time data, diverse data sources (structured/unstructured), application-specific data, telemetry data, metadata, and labeled datasets [11,14,60,66,80].
	User/system queries	Prompts, queries, or functions triggering AI processes, including data-specific requests and transformations [9,16,56,80,91].
	Models and algorithms	Pre-built or trained models for analysis, prediction, classification, association, or optimization [9,35,51,55,56,64].
	Infrastructure and resources	Hardware, cloud platforms, GPU systems, storage, networking, and fog/edge devices [52,53,80].
	Configuration and parameters	Execution parameters, caching indications, and model configurations [50,55,77,87].
	Organizational context	Timelines, organizational maturity, available expertise, and performance goals [16,26,69,78].
Key Process	Pipeline execution	Running artificial intelligence/machine learning (AI/ML) pipelines on required infrastructure [11,14,59,70,87].
	Capability application	Applying AI for predictions, detection, clustering, optimization, text analysis, and vision tasks [62,64,75].
	Data processing and transformation	Converting unstructured data to structured formats, tagging, and processing [11,75,88,91].
	System integration	Embedding AI into applications, workflows, and external systems [66,70,71,80].
	Storage and access management	Retrieving, processing, and caching data efficiently using metadata and indexing [11,19,51,64].
	Resource orchestration	Coordinating computing resources for pipeline execution and load management [3,65,68,74].
	Content generation	Producing text, audio, video, imagery, code, and simulations [9,51,75].
	Decision support and recommendations	Enhancing decision-making with predictive intelligence and smart insights [26,64,72,75].
	Trust and compliance assurance	Ensuring AI operates ethically, adheres to regulations, and meets privacy standards [1,29,38,50,65,71,74,76].
Value Output	Insights and analytics	Actionable insights, sentiment analysis, pattern identification, predictive analytics, decision support, and automation [26,49,64,66,71,72,77,80].
	Content creation	Generated text, multimedia, code, and simulations [11,56,66,77,80].
	Enhanced capabilities	Improved operations, streamlined workflows, and faster processing [9,78]
	Information and knowledge	Knowledge extraction, trend analysis, and job completion estimates [60,80].
	Structured data outputs	Transformed and structured data for further processing [68,77,91].
	Automated responses	Intelligent agent responses, notifications, and event-based actions [26,73,80].

4.2. Thematic Analysis

The study conducted a thematic analysis of the AI Value Chain and Ecosystem using two complementary methods. First, co-occurrence analysis identified which keywords appear together most often in AI publications, revealing the field's core topics and how they interconnect. This is followed by bibliographic coupling, which traced clusters of shared references across papers to show how different countries' AI research traditions have evolved and influenced one another.

4.2.1. Co-Occurrence Analysis

The mapping of frequently appearing keywords in the dataset and their connections is shown in Figure 6. The analysis can help stakeholders (universities, private sectors, and the government) to pinpoint areas that play a significant role in advancing AI development

and the regions that need improvement and greater interdisciplinary collaboration. As presented by the network, "Artificial Intelligence" was mapped at the center of the visualization, which represents its centrality in the value chain and research landscape. Placed as the central hub signifying a foundational role, AI is closely linked to "Machine Learning" and "AI Design," which represent core technical competencies required to design and develop AI solutions within the value chain. Additionally, "AI Ethics" and "AI Fairness" highlight the significance of developing and deploying AI in a responsible manner. In an AI value chain, this translates to integrating ethical considerations throughout all stages, ranging from data collection and model development to deployment and post-monitoring, impacting all core layers of the AI chain. "Big Techs," on the other hand, was linked closely to the central hub due to the influence large technology companies have in shaping ethical discussions and potentially setting standards.

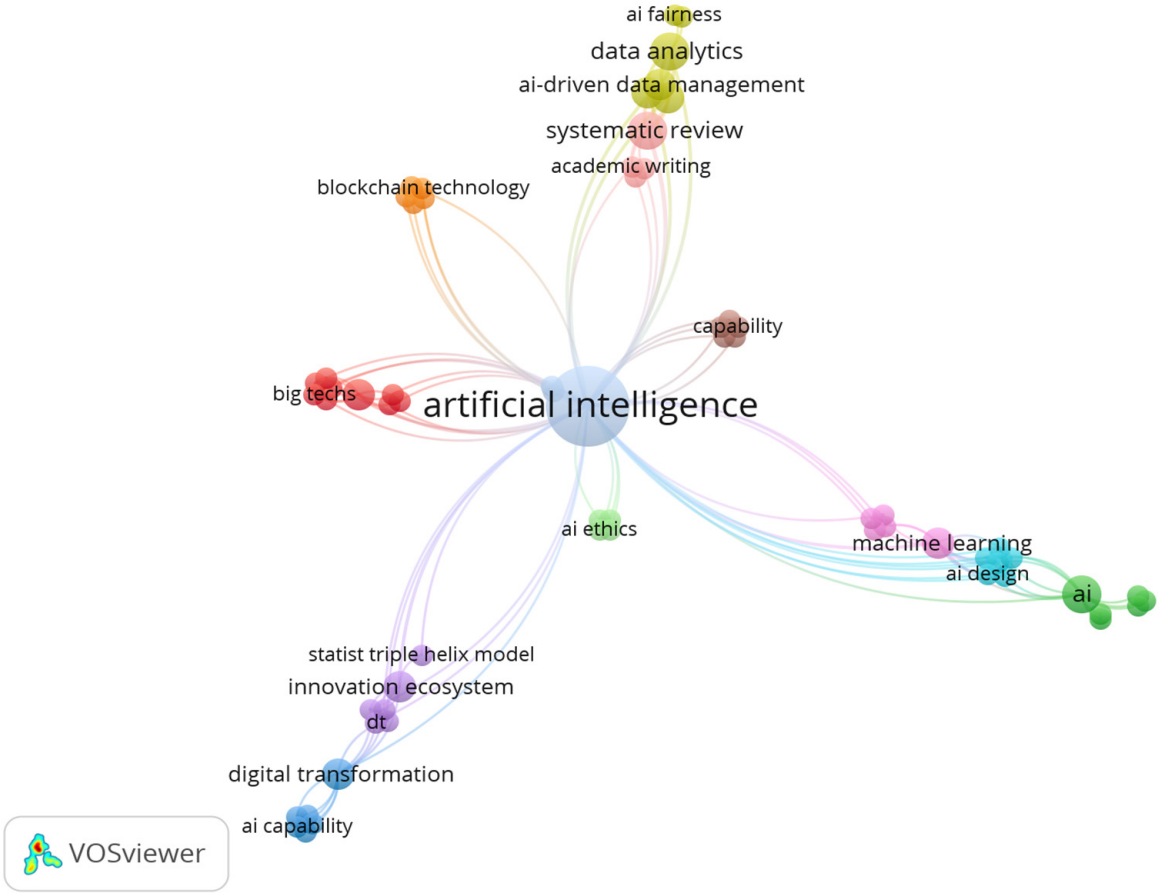


Figure 6. Network visualization of the five core layers of the AI value chain map.

Moreover, "Data Analytics" and "AI-driven Data Management" were strongly connected to "Artificial Intelligence", which emphasizes the role of efficient acquisition, storage, processing, and governance of data. This clearly strengthens the inclusion of data preparation/sourcing and data management in the core layer of the AI value chain. Also, "Systematic Review" and "Academic Writing" being linked to this cluster might indicate the research-intensive nature of understanding and managing data for AI, and the dissemination of best practices. Furthermore, the presence of "Blockchain Technology," "Digital Transformation" or "DT," and "Innovation Ecosystem" suggests future AI integrations, applying its advanced capabilities and efficient delivery. It also features the relevance of external partnerships, knowledge transfer, and robust policy implementation to support

the development and advancement of the value chain. Table 8 lists the identified nodes in the co-occurrence analysis of the AI value chain.

Table 8. List of identified nodes in the co-occurrence analysis of the AI value chain.

Co-Occurrence Analysis in the AI Value Chain	
Main Node	artificial intelligence
	machine learning
	ai design
	ai
	big techs
	ai ethics
	capability
	blockchain technology
	digital transformation
Other Cluster Nodes	dt
	ai capability
	innovation ecosystem
	statist triple helix model
	ai fairness
	data analytics
	ai-driven data management
	systematic review
	academic writing

4.2.2. Bibliographic Coupling

The AI value chain framework was tested in a case study in the Philippines. The illustration shown in Figure 7 depicts the "bibliographic DNA" of the Philippines' AI value chain development. As the central node, the chart reveals the different global knowledge clusters where the Philippines strategically anchor the construction of its value chain. The Philippines' AI evolution is shown to have been built upon two main pillars of influence, the green cluster representing Europe and Americas, and the red cluster for Asia and the Middle East. Known for its cutting-edge research and innovations, the strong links to Germany, Italy, Canada, and Brazil indicates a strong influence on the foundational and theoretical aspects of the Philippines' AI work such as core algorithms, machine learning models, and established AI frameworks, which strengthens the base of the local AI value chain. Moreover, the Philippines' interconnection between the red cluster suggests that the application and delivery layers of the Philippine AI value chain are shaped by its regional peers, which focuses on the identification and resolution of common problems and challenges, possibly on logistics, finance, agriculture, and disaster management. Furthermore, the bibliographic map shows that the Philippines is not developing its local value chain in isolation, but in collaboration with the global leaders in the west and its neighboring countries in Asia. The links between different countries provide a strong rationale for the country's strategy to absorb foundational AI knowledge that are useful in addressing relevant issues within regional neighbors. This approach can also be used by other countries to check their AI value chain influence.

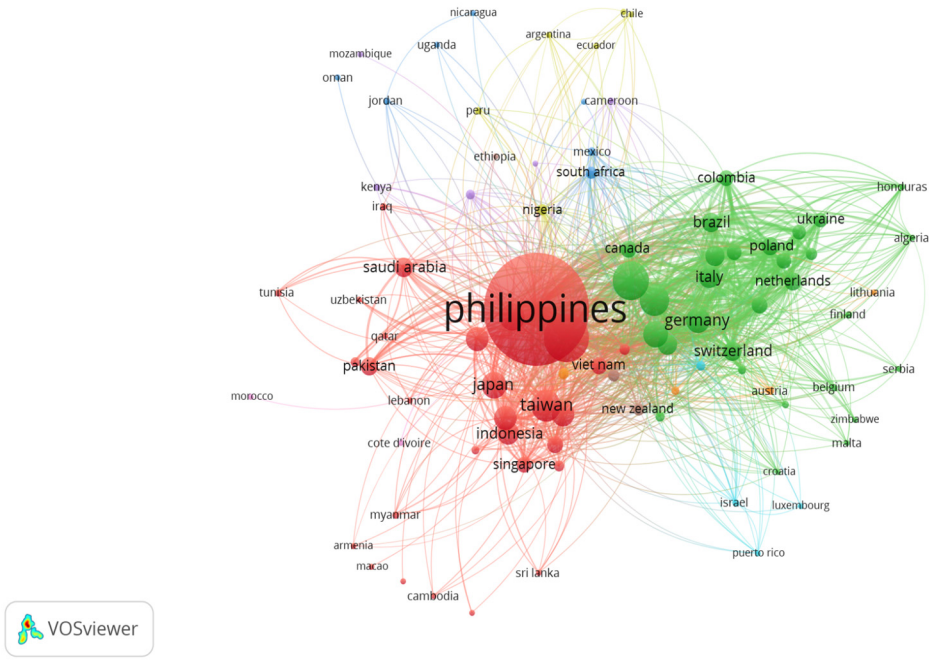


Figure 7. Bibliographic coupling: A case study on the Philippines' AI value chain influence.

4.3. Bottleneck Analysis

The AI value chain shows a dynamic and evolving ecosystem shaped and improved by its stakeholders. Each layer, reliant on the others, is constructed upon the preceding one, with the common goal of enhancing the chain while addressing the increasing demands for governance and security. To aid the advancement of the AI value chain, a comprehensive SWOT analysis was conducted, anchored and presented sequentially according to its five core layers: (1) hardware, (2) data management, (3) foundational AI, (4) advanced AI capabilities, and (5) AI delivery.

4.3.1. Bottleneck Analysis: Hardware

This Hardware layer provides the essential computing power that forms the physical foundation for the entire value chain, with key strengths in handling diverse data sources and offering flexibility for different operational configurations [14,59,71,76,86,89–91]. Its primary bottleneck is the high cost and dependency on a concentrated global supply chain for specialized components like GPUs, which requires significant resources and specialized expertise for efficient management [55,80,89]. While these significant challenges in managing integration complexity exist, they also create opportunities for improved governance and the development of more robust AI hardware infrastructures [16,80,81]. Table 9 shows the bottleneck and value creation in the hardware layer.

Table 9. Bottleneck and value creation in the hardware layer.

Bottleneck/ Value Creation	Category	Description
Bottleneck	Resource and cost barriers	Expensive infrastructure, and limited memory/power on edge.
	Integration complexity	Compatibility issues with legacy systems and new hardware.
	Hardware mismatch	Difficulties aligning AI workloads with emerging hardware (e.g., photonic, neuromorphic).
	Standardization gaps	Need for common frameworks and interoperable architectures.

Table 9. *Cont.*

Bottleneck/ Value Creation	Category	Description
Value Creation	Computational infrastructure	Provides high-performance computing resources (CPUs, GPUs, Tensor Processing Units (TPUs), and Application Specific Integrated Circuits (ASICs)) necessary for large-scale data ingestion, transformation, and storage operations. Supports real-time and batch processing needed for structured, semi-structured, and unstructured data.
	Data flow enablement	Ensures high-bandwidth, low-latency pipelines for efficient data transmission, essential for seamless Extract-Transform-Load (ETL) processes and data lake/warehouse integration.
	Scalable storage systems	Enables distributed, scalable storage architectures (Non-Volatile Memory Express (NVMe), Solid State Drive (SSD), Hard Disk Drive (HDD), memory hierarchy) to handle the variety and volume of data required by upstream AI components.
	Reliable access and uptime	Guarantees operational reliability, fault tolerance, and system availability to maintain data integrity and support 24/7 AI workloads.
	Edge and cloud interoperability	Facilitates hybrid and federated data systems by supporting both edge computing (e.g., for local data processing) and cloud infrastructure (e.g., for central data governance).
	Security and isolation support	Provides hardware-level support for encryption, secure enclaves, and data isolation, which are critical for sensitive data handling and compliance in the data management layer.
	Acceleration of preprocessing	Speeds up data preprocessing (compression, tokenization, format conversion) using hardware-accelerated vector operations, beneficial for downstream data wrangling tasks.

4.3.2. Bottleneck Analysis: Data Management

Acting as the value chain's quality control checkpoint, the Data Management layer transforms raw data into reliable assets for model training, utilizing high-quality data handling techniques supported by robust data governance and security frameworks [49,58,67,72,74,82]. The central challenge is the trade-off between data quality and scalability, where ensuring proper data ingestion and lineage for trust and compliance through manual annotation is often slow, expensive, and difficult to scale when integrating disparate data sources [49,67,68,72,74]. These weaknesses create significant opportunities for pipeline automation to overcome data scarcity, though the layer remains vulnerable to poor data quality and security breaches without proper validation [19,49,58,61,67,68,72,82]. Table 10 shows the bottleneck and value creation in the data management layer.

Table 10. Bottleneck and value creation in the data management layer.

Bottleneck/ Value Creation	Category	Description
Bottleneck	Scalability and standardization	Issues in scaling data systems; lack of standards in storage and structuring.
	Ownership and policy enforcement	Ambiguity in data ownership and difficulty in enforcing governance policies.
	Data quality and automation	Inconsistent quality metrics; limited tools for automated data profiling.
	Metadata documentation	Reliance on manual documentation; fragmented or disconnected metadata tools.
	Storage performance	Latency, high storage costs, and suboptimal access and capacity management.
	Visualization tooling	Limited capabilities of tools for data exploration and visualization.

Table 10. *Cont.*

Bottleneck/ Value Creation	Category	Description
Value Creation	Reliable data foundation	Enables consistent, trusted data pipelines for AI/analytics.
	Governance and compliance support	Ensures traceability, ownership, and adherence to data regulations.
	Improved data quality	Enhances data accuracy, completeness, and readiness for modeling.
	Operational efficiency	Streamlines data workflows, reduces duplication, and improves turnaround times.
	Metadata-driven insights	Promotes reuse, understanding, and discovery through structured documentation.

4.3.3. Bottleneck Analysis: Foundational AI

Subsequently, this layer transforms curated data into large-scale, general-purpose AI models, leveraging access to diverse data and resources to build powerful systems [56]. A primary tension exists between the power of these models and their immense computational and financial cost, which concentrates capabilities among a few major players who can afford the expensive solutions [75,83,92]. Key bottlenecks include the "black box" problem, which hinders explainability, and the critical risk of inheriting and amplifying biases from the training data [84,93]. Nonetheless, these challenges expose opportunities in "self-supervision" to reduce data dependencies and in advanced knowledge integration to develop more complex models [50,79,85]. Table 11 shows the bottleneck and value creation in the foundational AI layer.

Table 11. Bottleneck and value creation in the foundational AI layer.

Bottleneck/ Value Creation	Category	Description
Bottleneck	Implementation/integration complexities	Implementation/integration complexities
	Insufficient testing/evaluation	Insufficient testing/evaluation
	Black box problem	Resource intensity (data, compute, investment, talent)
	Lack of holistic systemic risk understanding	Lack of holistic systemic risk understanding
	Ethical/social implication challenges, and complex ethical/legal/technical navigation	Ethical/social implication challenges, and complex ethical/legal/technical navigation.
	AI system integrity	Security threats, cyberattacks, adversarial attacks, and safety concerns (misuse, inherent risks, and advanced AI risks).
Value Creation	General-purpose models	Foundation models (FMs) can perform a wide variety of tasks across different domains with minimal adaptation. Models like ChatGPT, Gemini, and Microsoft CoPilot enhance productivity and innovation.
	Complex reasoning and decision-making	Achieves state-of-the-art (SOTA) performance in tasks like image classification, natural language processing, and robotics.
	Knowledge transfer	Transferring knowledge across domains through fine-tuning and few-shot learning.
	Adaptive learning	Adapts quickly to new tasks and domains, allowing for continuous model improvement.
	Automation and efficiency	Reduces manual effort in data analysis and decision-making processes.

4.3.4. Bottleneck Analysis: Advanced AI Capabilities

Developing upon the outputs and values from the Foundational layer, the Advanced AI Capabilities tier specializes in fitting and recreating the general-purpose models into specific, user-centric applications. Its key strength is the refinement process, which uses targeted data to create flexible and adept systems with complex reasoning and planning [47,62,63,65,73,77]. This, however, due to its dependency in the pre-trained models, introduces a critical weakness in inheriting the possible bias or limitations created in the foundational layer [51,52,64,88]. Furthermore, handling sensitive and personal data produces significant integration challenges due to technical and ethical risks [48,57,62,66,87,88]. These organizational factors are often rooted in a managerial competency gap, where leaders and managers may lack specific digital-age skills needed to adopt and guide AI driven strategies and integration effectively [22]. These vulnerabilities provide opportunities to generate more specialized solutions with the addition of multi-objective optimization capabilities [62,69] and simulations anchored in traditional methods, while facing the ethical and privacy risks of managing human data and minimizing adoption impediment [53]. Table 12 shows the bottleneck and value creation in the advanced AI capabilities layer.

Table 12. Bottleneck and value creation in the advanced AI capabilities layer.

Bottleneck/ Value Creation	Category	Description
Bottleneck	Data and technology issues	Data quality, bias, integration complexities, technological support, bias, integration complexities, and technological support.
	Human and organizational factors	Cognitive load, automation bias, lack of understanding (black box models), and workflow integration.
	AI-specific challenges	Fairness, ethics, privacy, risk management, and explainability.
	Security and compliance	Adversarial attacks, property inference, data leakage, and legal/regulatory barriers.
	Operational environments	Real-time constraints, and complex adaptive systems.
Value Creation	Business and competitive edge	Business value, competitive advantage, improved market perception, and strategic potential realization.
	Operational efficiency	Enhanced efficiency, optimized resource allocation, and improved productivity.
	Innovation and product development	Innovation, enhanced products/services, and new value from data.

4.3.5. Bottleneck Analysis: AI Delivery

Lastly, the AI Delivery layer highlights a strong infrastructure and flexible model integration, which enables effective delivery of AI services and user-friendly AI interactions [54,94]. However, its complexities arise from managing delivery systems and numerous configurations [70,95–98]. Its dependency on pre-built models that possibly passes inherent data bias and ethical risk hinders full adoption of AI solutions [99–101]. Moreover, significant opportunities lie in leveraging different management systems such as MLOps to streamline processes and expand edge computing for real-time applications [102,103]. Conversely, while a scalable infrastructure exists for deploying AI, the final "last-mile" integration into business applications remains complex and is a primary hurdle to widespread adoption [60,78,104]. This significant "last-mile" barrier is a classic manifestation of a socio-technical gap, where the advancement of technology outpaces the users' capability to absorb it. The challenge lies more in the organizational mindset and digital competencies required for successful adoption, as highlighted in studies on

the technologization of business processes [23]. Table 13 shows the bottleneck and value creation in the AI delivery layer.

Table 13. Bottleneck and value creation in the AI delivery layer.

Bottleneck/ Value Creation	Category	Description
Bottleneck	Data issues	Data quality, heterogeneity, silos, inconsistency, and privacy/security concerns.
	Technical challenges	Latency, device heterogeneity, scaling issues, and interoperability.
	Expertise and integration	Need for expertise, seamless integration challenges, and IT alignment.
	Trust, ethics and explainability	Addressing AI biases, ethical concerns, and "black box" skepticism.
	Adoption and management	Organizational change, process redesign, and digital asset protection.
	User-centric limitations	Lack of customer-focused design in AIaaS and understanding user needs.
Value Creation	Accessibility and democratization	Seamless AI integration with AIaaS, enabling broader access.
	Efficiency and productivity	Task automation, enhanced productivity, and streamlined workflows.
	Innovation and optimization	Enabling product innovation and operational optimization.
	Cost efficiency	Lower implementation and operational costs through AIaaS.
	User experience enhancement	Improved service quality, personalization, and user satisfaction.
	Competitive edge	Boosted market positioning and strategic advantage.
	Sustainability and monetization	Supporting sustainable practices and data monetization.
	Faster feedback loops	Quick model iteration and practical application without heavy engineering.

Table 14 shows a summary of the bottleneck analysis performed to effectively understand the strengths, weaknesses, opportunities, and threats for each of the AI value chain layers.

Table 14. Summary of the SWOT analysis for the AI value chain.

AI Value Chain Layer	Strengths	Weaknesses	Opportunities	Threats
Hardware	Data versatility	Resource-intensive	Infrastructure development	Talent shortage
Data Management	Secure handling	Manual annotation	Pipeline automation	Data breaches
Foundational AI	Model generalization	High cost	Self-supervision	Data bias
Advanced AI Capabilities	Application refinement	Bias inheritance	Specialization	Ethical risks
AI Delivery	Scalable deployment	System complexity; lack of managerial/digital competencies	MLOps integration; workforce upskilling programs	Adoption barriers; skills gap and resistance to change

4.4. Generalizability of the Framework

While the analysis in this study is anchored in the case study of a developing nation, the proposed five-layer framework is designed for broad generalizability. The primary bottlenecks in advanced Organization for Economic Cooperation and Development (OECD) markets may shift from foundational infrastructure to the ethical and governance challenges found in the Advanced AI and Delivery layers. Furthermore, the framework can be used to formulate global supply chain strategies for large enterprises and helps identify niche opportunities and strategic partnerships to overcome resource-intensive bottlenecks like the Foundational AI layer for Small and Medium-sized Enterprises (SMEs). The core structure is intended as a robust tool for analyzing any AI ecosystem, irrespective of market maturity or organizational scale.

5. Conclusions

This study reveals that the AI value chain is not merely a technical pipeline but a complex socio-technical system where value creation is ultimately constrained by the "last-mile" integration hurdle. The multi-layered framework demonstrates that the critical bottleneck stems from a gap between technological advancement and human–capital readiness, particularly in managerial competencies and workforce skills. The analysis identified critical tensions within each layer, from dependency on global hardware supply chains to the immense computational expense and risk of inherited bias in foundational models. Furthermore, thematic analysis revealed the core themes shaping the field and uncovered the "bibliographic DNA" of a developing nation's AI development through a representative case study.

A key contribution of this study is the framework itself, which can be used as a practical diagnostic and strategic tool. Its impact could be measured through key performance indicators (KPIs) such as a reduction in the average time-to-deployment for AI projects, an increase in stakeholder collaboration across layers, or a quantifiable mitigation of identified bottlenecks. For policymakers, this framework provides empirical support for a national AI strategy that addresses not only weaknesses in digital infrastructure and data governance but also the critical need for human–capital development, fostering the digital competencies and adaptive leadership essential for the AI era. It emphasizes the need for policies that foster local innovation while managing dependencies on foreign technology. For industry leaders, it serves as a blueprint for competitor analysis and strategic planning, which allows them to assess their position within the value chain and identify where to invest in automation, MLOps, or stronger academic collaborations to overcome specific bottlenecks. For academics, the framework can guide the development of interdisciplinary curricula that directly address the skill gaps identified in the advanced and delivery layers of the value chain. Furthermore, the framework can be translated into operational tools, such as checklists for risk assessment, maturity index scorecards for each layer, or policy-impact dashboards, to guide practical implementation.

Based on the findings, the central recommendation is for the stakeholders to adopt a dual-investment strategy where socio-technical issues can be addressed. It is imperative for policymakers to formulate comprehensive national AI strategies that extend beyond mere financial support for digital infrastructure. These strategies must allocate equivalent resources to the development of human capital, thereby cultivating the digital competencies and adaptive leadership qualities that are indispensable in the AI-driven landscape. For the industrial sector, this signifies a pivotal transition from a technology-centric approach to a socio-technical framework. In this context, investments in organizational change management and workforce upskilling should be acknowledged as equally vital as the AI technologies themselves. Meanwhile, academia is urged to prioritize interdisciplinary

research that addresses the multifaceted practical, ethical, and societal challenges associated with AI integration. This shift in focus should transcend traditional technical analyses to encompass a broader understanding of AI's implications in real-world applications.

While this study provides a comprehensive qualitative map, it is based on secondary data in a rapidly evolving field. Future research should build upon this framework by quantifying the economic impact of the identified bottlenecks, conducting primary research with key stakeholders to validate these findings, and performing longitudinal analyses to track the evolution of the AI value chain as new policies and technologies are introduced. Such efforts are crucial in guiding any country or organization toward maximizing the benefits of the AI revolution and securing a competitive position in the global digital economy.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AI/ML	Artificial Intelligence/Machine Learning
AIaaS	AI as a Service
API	Application Programming Interface
ASEAN	Association of Southeast Asian Nations
ASIC	Application Specific Integrated Circuit
CDO	Chief Data Officer
CPU	Central Processing Unit
DRAM	Dynamin Random Access Memory
DT	Digital Transformation
ETL	Extract-Transform-Load
EU	European Union

FM	Foundation Model
GPU	Graphics Processing Unit
GVC	Global Value Chain
HDD	Hard Disk Drive
ICT	Information and Communications Technology
IT	Information Technology
IMF	International Monetary Fund
IP	Intellectual Property
KPIs	Key Performance Indicators
LLM	Large Language Model
MLOps	Machine Learning Operations
NLP	Natural Language Processing
NN	Neural Networks
NVMe	Non-Volatile Memory Express
OECD	Organization for Economic Cooperation and Development
QA	Quality Assurance
R&D	Research and Development
SCM	Supply Chain Management
SMEs	Small and Medium-sized Enterprises
SOTA	State-of-the-Art
SRAM	Static Random Access Memory
SSD	Solid State Drive
STH	Statist Triple Helix
SWOT	Strengths, Weaknesses, Opportunities, Threats
TOE	Technology-Organization-Environment
TPU	Tensor Processing Unit
TRI	Technology Readiness Index
UK	United Kingdom
UN	United Nations
UX	User Experience
VCTC	Value Chain Tree Concept

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