scientific reports

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AI specialization for pathways of economic diversification

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The growth in AI is rapidly transforming the structure of economic production. However, very little is known about how within-AI specialization may relate to broad-based economic diversification. This paper provides a data-driven framework to integrate the interconnection between AI-based specialization with goods and services export specialization to help design future comparative advantage based on the inherent capabilities of nations. Using detailed data on private investment in AI and export specialization for more than 80 countries, we propose a systematic framework to help identify the connection from AI to goods and service sector specialization. The results are instructive for nations that aim to harness AI specialization to help guide sources of future competitive advantage. The operational framework could help inform the public and private sectors to uncover connections with nearby areas of specialization.

Artificial intelligence (AI) carries the promise of making industry more efficient and our lives easier. AI has been called the "new electricity"[1] reflecting an economic framing of AI as a "general purpose technology" (GPT)[2]. AI may be poised to join the steam engine, the electric motor, and the silicon wafer as a "technological prime mover",[3] but it may also be "disruptive" and cause structural changes (which then often generates resistance by some vested interests). With this promise, however, also comes the fear of job replacement, manufacturing stagnation, hollowing out of the middle class, and increased income inequality[4–7]. With the growing call for national AI strategies, governments around the world have a mandate to leverage AI for economic competitiveness and to help shape their industrial strategy. Rather than looking at AI as a potential threat, AI can be viewed as one factor in economic transformation. However, very little is known about sources of AI specialization, and how specialization in AI could be leveraged for strategic diversification opportunities based on existing endowments of a country. How might developing countries leverage AI to keep traditional industries competitive and discover new opportunities?

Take the example of a country like Bangladesh, an economy that is characterized by low diversification and a specialization in the garments industry. How could AI help Bangladesh achieve more prosperity for its citizens? This question can be viewed from different lenses. For example, which AI use cases are most closely related to the garment industry and may be deployed for competitive advantage? Identifying sub-sectors in AI could help the efficiency of Bangladesh's garment production chain and create an easier pathway to discovering new specializations most aligned with garment and related AI capabilities. Note that low-income or lower-middle-income countries like Bangladesh may not have the capability to produce a certain type of AI domestically. However, developing strategic AI sectors may help traditional industries become more competitive which in turn could help discover pathways for developing capabilities in other AI, goods, or services. Second, how might any existing capabilities in Bangladesh's AI ecosystem create opportunities for broad-based economic diversification i.e. discovery of specialization in nearby goods and services? Third, how could existing specializations in goods and services lead to developing new AI capabilities for Bangladesh's economy? Answers to these fundamental questions can offer pathways for developing countries to formulate data-driven industrial and growth strategies that promote diversification and long-term prosperity.

Some of the more popular AI models are large neural networks that run on state-of-the-art machines. In light of recent breakthroughs in AI, such as the emergence of powerful language models like ChatGPT that require millions of dollars in computing power for training AI models, pre-trained AI models could influence production and consumption patterns across industries. Further, it is important to acknowledge that AI research is being shaped by a few actors, mostly affiliated with large technology firms, "GenAI" unicorn start-ups or elite

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universities[8]. In fact, the OECD now recognizes the growing compute divide characterized by the limited number of countries that have the domestic capacity to train large-scale models within their borders[9]. Illustratively, as of 2023, 100% of the world's supercomputers reside in only 30 nations, so 85% of the world's 204 nations lack the domestic AI infrastructure to compete in the new AI economy[10]. More than a fear of missing out, emerging economies are, for now, dependent on foreign sources of AI production, which has potentially sweeping implications for the future distribution of economic prosperity. Progress in AI is being driven by the availability of a large volume of training data, algorithmic innovations, and computing capabilities. For example, the time to train object detection tasks like ImageNet to over 90% accuracy has been reduced from over 10 hours to a few seconds, and the cost has declined from over $2000 to significantly less than $10 within the span of the last three years. Similarly, there are dynamic technical and market changes emerging that are leading to huge reductions in the cost of training real-world large models in other domains such as language, vision, robotics, and others. Leveraging capabilities in AI will be pivotal for the competitiveness of traditional industries and the discovery of new industries, both for advanced and emerging markets (EM's).

This paper measures cross-country specialization in AI, to inform how current AI specializations could guide pathways for future diversification. The paper addresses three fundamental questions: (1) what is the optimal way to measure AI specialization inclusive of economic specialization patterns, not just in manufacturing and goods but also in service specialization? (2) where does AI specialization appear to fit into global production networks—are they central or peripheral, i.e., what are the backward and forward linkages and plausibility of knowledge spillovers between AI services and other sectors of the economy? and (3) might AI specialization provide pathways for new applications to integrate inherent capabilities of an economy's production pattern? These questions are important for advanced economies too but particularly for developing countries with younger industrial strategies. Developing countries are especially vulnerable to poorly constructed national AI plans. These often default towards "vanity" projects at the expense of more sophisticated investments that capitalize on AI specialization and promote diversification without accounting for core areas of economic specialization. It is also common to find discussions in military and defense circles on technology offsets i.e., combining various technologies to build a new source of specialization to drive growth and competitiveness.

Pathways for economic diversification have emerged as a central theme in economic growth and development literature. A nascent but growing body of literature provides insights into structural transformation, exports, and development. Economic diversification is known to follow a non-monotonic path over the stages of economic development[11–13] and there is a positive relationship between structural shifts and per capita income[14–18]. Diversification of exports (in terms of products and destinations) helps to stabilize export earnings in the longer run, with benefits analogous to the portfolio effect in finance[19, 20]. Recent work has accounted for combining goods and services specialization to offer a more comprehensive view of national diversification patterns[21–24]. However, in the economic and policy literature, AI has been missing from economic diversification discussions.

AI is a data-driven field but, paradoxically, detailed data about within-AI specialization at a cross-country level is limited[25]. Beyond data limitations, there are measurement challenges, especially those regarding consistent ways to quantify AI's technical progress, investment, or research and development output across countries. For example, national statistics agencies' methodologies do not measure public investments in AI R&D or private investment in AI in a similar manner to classical sectors[26]. Unlike data for economic statistics such as goods exports or services exports, that follow international classification standards, for example, SITC, HS, ISIC, etc., data on AI is not collected in standard format from statistical agencies. Data on corporate activity collected through digital channels is potentially a formidable opportunity for empirical researchers and has the potential to significantly improve our ability to track changes in firms' technological configurations[27]. Since several disparate inputs are required to put AI into production—human capital, software, data, computational power, and new management practices—none of these are easy to observe and statistical agencies do not regularly collect data on them.

As firms are still adjusting inputs to AI and experimenting with the technology, investment data tends to be a noisy indicator. For instance, rapid changes to AI technologies can change the value of investments in AI-related skills[28]. Illustratively, what was a hot skill may become a commodity-skill two years later. It is important to measure AI inputs, i.e., skills, software, data, and management practices as well as AI outputs, for example, user consumption patterns related to AI products and services. Both are difficult to measure, however, as they are often service-based, and their intangibility remains a measurement challenge[26]. All of these challenges are amplified when assessing developing countries. To address these challenges at the firm level, we use macro-data on private sector AI investments from credible and reliable sources, such as Crunchbase, CapIQ, Netbase Quid, to serve as proxies to measure detailed sub-sectors of private investment in AI at the national level.

To aid potential pathways for economic diversification in emerging markets (EM's), the field of economic complexity[29] has emerged as an important metric to measure nations' inherent capabilities embodied in the structure of economic production. Acquiring the knowledge to host these capabilities—physical and human capital, institutions, organizational abilities—are reflected in the ability to produce and export sophisticated products and services[22, 23, 30–32]; as a consequence, the co-occurrence of products in countries and firms can be used to reconstruct the relatedness of industrial, technological, and scientific sectors[33–37]. In a similar vein, the trends of investment in specific AI sub-sectors offer a proxy of capabilities to produce specific AI specializations that are present in the startup community and are attracting those investments. Accounting for AI specialization along with broader economic specialization remains pivotal for EM's that are unable to generate sufficiently high growth and could get stuck in a "middle-income" trap or a "resource-curse" with limited opportunities for diversification[38–40]. EM's can leverage specific AI specializations for transforming their production pattern to help make pre-existing industries more competitive or discover new sources of comparative advantage.

We present an innovative, data-driven methodology for identifying connections between distinct AI sectors to strengthen a nation's overall industrial capabilities. This framework is applicable to all countries, irrespective of their economic development, as gaining insights into their areas of specialization allows for a more comprehensive understanding of industries that require further reinforcement or the exploration of new specializations. As of this publication, many nations (75+) have adopted a national AI strategy, while most developing countries have yet to do so. For this latter group, applying this framework earlier in their journey, such as cultivating linkages in novel areas of specialization in goods, services, or specific AI-related competitive advantages during strategy formulation, may accelerate economic gains. Moreover, this framework remains crucial for more advanced economies, as they shift deeper into the implementation of their national AI programs, augmenting the value of public investments and the associated competitive edge. Developing nations, in particular, can capitalize on this framework by concentrating their efforts on cultivating linkages to uncover novel areas of specialization in goods, services, or specific AI-related competitive advantages. Similarly, this framework is crucial for advanced economies to sustain and augment their competitive edge. We compute statistically validated normalized co-occurrences of trade and AI sectors in countries, taking into account time evolution in an explicit way and thus providing an arrow of development from AI sectors to trade sectors. This will allow us to build a recommendation framework to detect which AI investment better supports a specific target industry, i.e. the ability to export a specific good or service.

We acknowledge that data coverage and reliability for AI investments in emerging economies might not be as comprehensive as for advanced economies. The complex network learns from cross-country information, which helps to better inform developing countries' progression. While data uncertainty may be higher for developing countries, the usefulness of the approach might be more impactful for them. Meanwhile, this framework is invaluable for advanced economies, with more granular insights to help them maintain and expand their set of competitive advantages.

The rest of the paper is organized as follows: section "Data and methods" outlines the data and methods. Section "Global results" presents the results from the global network of AI to goods and services specialization. Section "Country case studies" discusses an operational framework to help guide country-specific diversification strategies. Section "Discussion and conclusions" concludes with applications of our framework and future work.

Data and methods

Data

This section presents the diverse sources of data and our proposed novel methodology to link AI specializations with sources of comparative advantage in goods and services. Traditionally, economic complexity analysis has been conducted with goods exports statistics[30, 32, 36], while integration with service database is relatively recent[21–24]. The trade data is from U.N. COMTRADE (https://comtrade.un.org) for physical goods and from the Balance of Payments database collected by the IMF (https://data.imf.org). These two databases both refer to export volumes, so they can be integrated giving rise to what we call the Universal database[22, 24]. In this paper, we use the export data regarding 35 different goods and 12 services; the number of countries fluctuates around 100 in the considered time span.

On the other hand, AI specialization is largely missing in complex network studies. To study comparative advantage in specific AI sectors, we use data from diverse sources including private investment in AI; in particular, we use data on AI investment from Crunchbase, CAPIQ, Netbase Quid that originally provides data for 49 AI sub-sectors that we manually curate to obtain 29 AI sub-sectors, reported in the Supplementary Information. The data covers 80 countries. Quid embeds organizational data from CapIQ and Crunchbase (more details on the AI investment data can be found in the Supplementary Information). The AI private investment is a comprehensive and accurate source that embeds investments from global organizations, including early-stage startups and funding events data providing a strong signal of AI-related investment activities. Quid then uses a boolean query to search for focus areas, and keywords within the companies database, and categorizes and visualizes these companies based on their business descriptions using Quid's proprietary NLP algorithm. More details on the proprietary algorithm can be found at Quid technologies. The Quid methodology is also available from the Stanford Institute for Human-Centered Artificial Intelligence AI Index Report Chapter 3 (page 31–32). We index 3.6M public and private company profiles from multiple data sources that are indexed to search across company descriptions while filtering and including metadata ranging from investment information to firmographic information such as year-founded, headquarters (HQ) location, and more. Company information is updated on a weekly basis. AI investment is concentrated in select countries, for example, graphs in the Supplementary Information show that between 2019-2020, North America accounted for 58% of global AI investment, followed by East Asia & Pacific (28%), Europe and Central Asia (10%), Middle-East and North Africa (2%), South Asia (1%), Latin America (0.5%), and Sub-Saharan Africa (0.2%). China alone accounts for approximately 20% of global AI investment in 2019–2020. Also, the country coverage of this data is heterogeneous in time, with only the developed countries reporting investments in all AI sectors. Details about the data, sources, and definitions for AI, goods, and services are available in the Supplementary Information. The universal AI dataset, represented as UAI incorporates the AI matrix denoted as (A), the goods matrix denoted as (G), and the services matrix denoted as (S). This is summarized in Table 1.

Methods

Detecting specialization dynamics

In order to detect whether we can say that a country specializes in a specific trade (G or S) or AI sector, we first compute the Revealed Comparative Advantage (RCA), independently for the three G, S, and AI sectors. The RCA index[41] informs whether a country's share of an item in its export (or investment) basket is larger (or smaller) than the items' share in the world export (or investment) basket, where an item can be an AI, an industrial, or a service sub-sector. Note that a country could have an RCA higher than 1 in an AI sub-sector if it invested even a

Sector	Nomenclature	Numerosity
Goods (or products)	G	35
Services	S	12
Artificial intelligence	AI	29
Universal artificial intelligence	UAI	76

Table 1. Nomenclature for AI (A), Goods (G), Services (S), and Universal (UAI) datasets.

small amount in the one AI sub-sector, and nothing at all in any of the other AI sub-sectors. The advantage is that RCA will provide a clear and properly normalized view of the relative specialization. This is the well-recognized method to obtain a natural threshold of relative specialization, not just in exports but also in scientific and patenting activities[22, 29, 32, 36, 37]. The RCAs are then converted to binary values (i.e., 0/1) based on whether they are above a threshold or below it, where the generally accepted threshold is 1. The binary matrices are then used to compute the Assist Matrix, which is then statistically validated. The RCA matrices are computed independently for AI (A), Goods (G), and Service (S) matrices to create a dataset for universal AI (UAI) that is used to build the global progression network from AI to broader trade networks.

In formula, RCA of country c in item x is computed as:

$$\mathrm{RCA}_{\mathrm{c,x}} = \frac{\mathrm{E}_{\mathrm{c,x}} / \sum_{\mathrm{x}} \mathrm{E}_{\mathrm{c,x}}}{\sum_{\mathrm{c}} \mathrm{E}_{\mathrm{c,x}} / \sum_{\mathrm{c,x}} \mathrm{E}_{\mathrm{c,x}}} \tag{1}$$

where x is either $\{a, g, s\}$, that is AI, goods (or products), or services sectors, and $E_{c,x}$ is the value of products g or services s, in US dollars, exported by country c; if instead the RCA is computed for the AI investment data, $E_{c,a}$ is the investment of country c in the AI sector a. We refer to items (or activities) as individual categories (or sub-sectors) within AI investment, goods exports, or services exports.

Then, the c, x element of the binary matrix $\mathbf{M}$ is defined to be 1 if $\mathrm{RCA}_{\mathrm{c,x}} > 1$ and zero otherwise. Note that all these quantities are time-dependent and that we have dropped the temporal variable t only to obtain a lighter notation. However, the key element of our analysis is actually to compare $\mathbf{M}(t)$ with $\mathbf{M}(t + \Delta t)$ in order to study how an AI investment of a country influences its products or services trade specialization.

Progression network

This section introduces our methodology—the Progression Network—to estimate the weight of the connections from AI sectors to trade sectors or other AI sectors. This technique has been introduced by[37], adopted for the universal database (goods and services) in[22, 24] and is inspired by the Assist Matrix introduced in[35] and the recommendation system discussed in[42].

Consider the schematic representation of Fig. 1. Each arrow represents a nonzero element of the export or investment matrix $\mathbf{M}$ discussed previously: for instance, the fluorescent arrows represent USA having a Revealed Comparative Advantage (RCA) higher than one in computer vision (AI) at time t and in the export of construction (Services) at time t plus a given time interval Δt, thus introducing a delay (in the following we will let this time delay vary). In this hypothetical example, a country at time t specializes in computer vision, and after three years it will specialize in construction—if this pattern is systematically present in many countries, then there appears to be a *connection*, a directed link, going from computer vision to construction which implies a time-delayed correlation between these two sectors (from computer vision in AI to construction in services). The network, nodes, and statistically validated links between those sectors, form the idea of the Progression Network (PN). More specifically, we will estimate the conditional probability that a bit of information starting from a

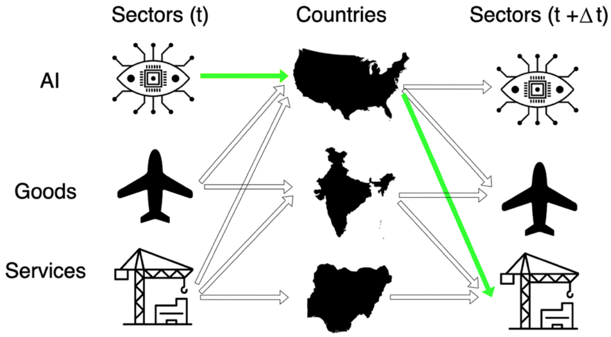

Figure 1. A schematic representation of the connections among sectors via the respective countries' specialization. This idea is at the basis of the algorithm to build the progression network, as explained in the main text. The bipartite networks connecting G, S, and AI with countries are projected to new bipartite or monopartite networks, connecting for instance AI with G and S.

specific AI sector will arrive at a specific AI (A), goods (G), or services (S) sector. Depending on which of the three activities are selected to be sources and/or targets, the final PN will vary. In general, the above-mentioned probability is given by the Assist Matrix $\mathbf{B}(t, t+\Delta t)$, whose elements are

$$B^{i,f}_{x,x'}(t, t+\Delta t) = \frac{1}{u_x(t)} \sum_c \frac{M^i_{c,x}(t) M^f_{c,x'}(t+\Delta t)}{d_c(t+\Delta t)} \tag{2}$$

where x is the specific starting or source sector (in our case, an AI sector), while x' is the final or target sector, in our case, from the trade or AI activities (that is, $x = a$ and $x' = a', g, s$). Depending on the specific choices of the i and f activities, the resulting progression network B will be different; for instance, the matrix $\mathbf{B}^{AI \rightarrow G,S}$ will have rows corresponding to AI sectors and columns referring to the export G and S sectors. Note that the two normalizations, the first using the ubiquity of the source sector $u_x(t) = \sum_c M_{c,x}(t)$ and the second using the diversification of the countries in the middle layer $d_c(t+\Delta t) = \sum_x M_{c,x}(t+\Delta t)$, take into account the number of possible paths this bit of information may take[42]. The economic interpretation is that if a country is very diversified, like the USA, the information coming from this country is less, and the same is valid for those goods, services, or AI sectors that are more ubiquitous.

The general matrix **B** can be seen as the adjacency matrix of the network defined by the collection of nodes (the UAI sectors) and the directed links, or arrows (since, in general, **B** is not symmetrical), among them. This network is almost completely connected, in the sense that practically all the possible links are present. However, we need to discriminate the real inter-dependencies from the random co-occurrences coming simply from the fact that a product is very common, or a country is highly diversified. To do so we *statistically validate* each link by comparing its weight with an ensemble of matrices generated using a null model, the Bipartite Configuration Model[43,44]. The idea, borrowing concepts and methods from statistical physics, is to fix some constraints (in this case, we fix the average ubiquity and diversification) and to randomize everything else[45], generating in such a way an ensemble of null matrices $\tilde{\mathbf{B}}$ whose elements will produce a probability density distribution for each link x, x'. Each element of the empirical matrix **B** will be compared with the respective distribution generated using the null model; if the weight is larger than a given percentile then the link from x to x' will be statistically validated.

This procedure is repeated for all the couples of years $(t, t+\Delta t)$ in the database; from each of the resulting networks we selected only those links that have been statistically validated with p-value 0.05, leading to as many filtered networks, where the same link could have been validated several times. In order to obtain a single view of the global connections among the sectors (that is a unique, time-independent matrix **B**), we consider the links that are validated at least once; in other words, the set of links in the time-aggregated network is the union of the set of links belonging to the single networks. As weights, we consider the average weights of the corresponding validated links (with the exception of Fig. 6, where the weights are given by the number of validations).

To make the connection between varied sectors within AI, goods, or services more practical, Fig. 2 presents an operational abstraction. Take for example an economy like Bulgaria or Jordan. The data shows that there is growing investment and specialization in these countries in Robotic Process Automation (AI) and offshore oil rigs (Goods). Given the specialization in these co-occurring sectors, there may be opportunities to connect them where robotic capabilities can be applied to offshore oil drilling for making the oil industry more productive and competitive, with applications such as teleoperation robotics, underwater inspection, or robotic surveillance. Another line of reasoning could be a reverse linkage, where there is specialization in offshore oil rigs but not in Robotic Automation. Given the learning from the global network that informs the strong linkage between these two sectors, either the country could import Robotic Automation capabilities or through connection with other AI and broader economic specializations help create a pathway to develop specialization internally in Robotic Automation.

Density computation

Once the connections **B** from AI sectors to trade are known, we can perform a country-specific analysis, and in particular compute how *close* a country c is to a given item x given its AI investments. This will be given by the normalized sum of the influence of the active AI sectors that are connected to the target x. In formula, this corresponds to compute the density[36] of country c's AI investments around the target item x

$$D_{c,x} = \frac{\sum_{x'} M_{c,x'} B_{x',x}}{\sum_{x'} B_{x',x}} \tag{3}$$

where we removed the time dependency since we computed this quantity only for the last year of the database. The density values inform about the feasibility of a new trade sector, or the possibility to maintain an already present comparative advantage, given the country's present investments in AI. The more a country invests in sectors a which are strongly connected with the target x, the more its AI specialization supports economic development in that sector.

The choice of the threshold

The density of the filtered network is given by the number of validated links, which in turn depends on the threshold p-value α. In this work, we arbitrarily choose to use $\alpha = 0.05$. In principle, our statistical validation procedure may produce some spurious links, i.e. false positive connections. This is a well-known problem in the vast literature about statistically validated networks[44–48]; however, as far as we know, no agreed solution exists. For instance, Cimini et al.[49] showed that the density of the filtered network critically depends on the type of null model, even if belonging to the same class. In this work, we choose to avoid false negatives, at the price of

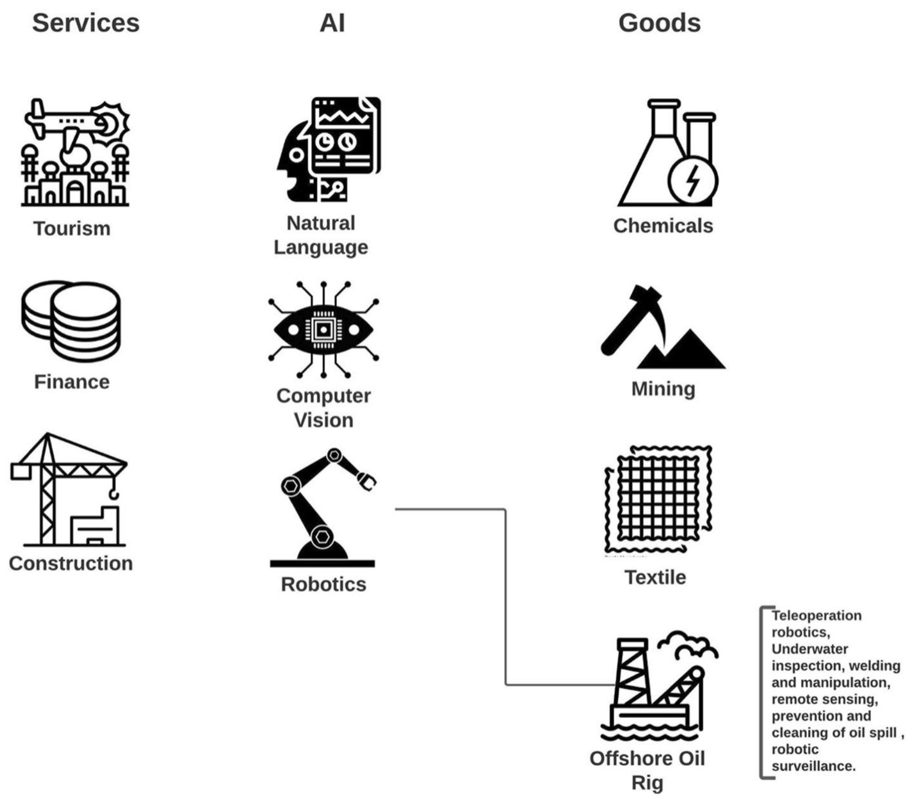

Figure 2. Sample abstraction for possible linkages in a country's specialization pattern. This figure represents a stylized example of a possible result of our investigations. We consider three sets of activities: export of services, investments in AI, and export of physical goods. Our database permits the identification of specific sectors within these activities, and to know which countries specialize in which sectors. If the number of countries active in two sectors, with a possible time delay, is high enough, then we put a link between those sectors. In the example above, many countries (with respect to our null model) are investing in robotics at time t and exporting oil from oil rigs at $t + \Delta t$. Concrete examples are also reported.

accepting the possibility of having false positives (but note that, since the links are ordered and validated according to their p-values, the results are robust with respect to the choice of different statistical thresholds, and the α parameter only controls the density of the filtered network). Let us suppose that we take the opposite attitude and we adopt a very strict methodology, such as the Bonferroni correction[50] or the False Discovery Rate[44, 51]. In practice, this is roughly equivalent to decreasing the α threshold. This would lead to a high number of false negatives, that is links that should be validated and are not. This would mean leaving out meaningful links. Moreover, even if a stricter threshold may lead to a more readable network, a piece of general information would be lost: the total number of statistically validated links, or the average connectivity between AI and trade sectors. In our work we found that many sectors are connected; this is interesting because it stresses the high and heterogeneous influence of AI on trade. Lowering the threshold only to find a readable figure may have led to a sparse network, but its sparsity would have been due to an arbitrary choice and not to an economic reason.

Global results

Pathways for discovering specialization in goods and services from AI specialization

The methodology discussed in the previous section allows us to obtain useful qualitative and quantitative insights into the complex dynamics of AI and broad-based economic specialization. By linking together AI and trade specializations which are related at a given level of statistical significance, we can build the whole network space in which AI, goods, and services are embedded (Fig. 3). The network shows the linkages from AI investment specialization to goods and service export specialization. The results imply that when countries invest in AI they subsequently develop capabilities in other sectors (both in other AI sectors and broader economic sectors). The bipartite network presented in Fig. 3 shows the most likely connections leading from specialization in AI subsectors to goods and services. Here the width of the links is proportional to the number of times they have been statistically validated. The complex network graph is presented in tabular format (see Fig. 4) to help discern the single connections in a simpler visualization.

As detailed in the "Methods" section, two sectors are connected if they are shared by many countries that are specialized in these two sectors and so follow similar time-based progress in common specialization patterns. From the fact that two sectors are concurrently invested in, or specialization is evident across many countries, we

Figure 3. The bipartite network connecting AI (on the left) to Goods and Service (on the right) specialization. Each link has been statistically validated using the Bipartite Configuration Model. For clarity purposes we have highlighted some links and the respective nodes, which we isolate and show in the subsequent figures.

can infer that there is a set of capabilities in common to develop and/or countries develop in similar specializations. After computing the normalized co-occurrences of the Assist Matrix, we statistically validate the links using our null model in order to obtain a relatively sparse network. In the instance of a fully connected network, where

Advertising	Insurance and pension Personal service
AgTech	Agrochemicals Aircraft Chemicals and health related products Electronics Food Processing Fruit Inorganic salts and acids Other Chemicals Petrochemicals ···
AR_VR	Aircraft Chemicals and health related products Processed minerals Pulp and paper Intellectual property Maintenance
AuthenticationTechnology	Chemicals and health related products Inorganic salts and acids Mining Other Chemicals Insurance and pension Maintenance Personal service
AutonomousVehicle	Electronics Leather Misc Agriculture Processed minerals Personal service Travel
BusinessManagement	Processed minerals
ComputingTechnology	Chemicals and health related products
DataAnalytics	Other Chemicals Finance Insurance and pension Transport
Drone_Satellite	Chemicals and health related products Coal Oil Tobacco Intellectual property
Education_Children	Aircraft Chemicals and health related products Inorganic salts and acids Other Chemicals Insurance and pension
Fitness_Wellness	Chemicals and health related products Other Chemicals
Gaming_E_Sports	Chemicals and health related products Fish & Seafood Insurance and pension
Hospitality	Government
ImageRecognition_VisualSe..	Chemicals and health related products Machinery Metal products Insurance and pension Maintenance
Insuretech	Aircraft Chemicals and health related products Oil Construction Insurance and pension Intellectual property Personal service
LegalTech	Chemicals and health related products Machinery Finance Maintenance
MediaContent	Chemicals and health related products Garments Inorganic salts and acids
MedicalSciences	Machinery
Money_PersonalFinance	Fish & Seafood Processed minerals Intellectual property Travel
RealEstate	Agrochemicals Aircraft Chemicals and health related products Garments Home and office products Inorganic salts and acids Machinery Mining Oil ···
Restaurants_FoodAndBever..	Chemicals and health related products Meat and eggs
RetailTech_E_Commerce	Chemicals and health related products Electronics Garments Home and office products Inorganic salts and acids Ships Textile & Fabrics Business service ···
RoboticAutomation	Machinery Metal products Other Chemicals
VentureCapital	Agrochemicals Aircraft Chemicals and health related products Electronics Food Processing Fruit Inorganic salts and acids Other Chemicals Petrochemicals ···
Wifi_HomeTech	Chemicals and health related products Machinery Pulp and paper Finance Maintenance Personal service

Figure 4. Global co-occurrence from AI investment to goods and service specialization. Column 1 is AI investment, column 2 is associated goods (blue) and services (orange) specialization that are closely linked to the given AI sub-sector of investment. The interpretation is specific and depends on each link. Some links are intuitive to interpret, for example, when countries invest in robotic automation, they subsequently develop a specialization in Machinery or Metal products. Interpreting other links could be more subtle, but provides a statistically valid data-driven linkage that requires domain knowledge in a country-specific context.

all items are connected to each other and time evolution is not explicitly taken into account[36], a fully connected network could hinder the understanding of which sector is close to which sector to offer pathways for development. Thanks to the use of the Bipartite Configuration Model, we can use the p-value thresholding to make the network less dense. Finally, our network is also visually interpretable with a p-value threshold that turns out to be perfectly reasonable (95% confidence level). This method offers the advantage to use conditional probabilities that are statistically valid to reliably infer connections such as, on average countries that invest in AgTech, subsequently gain specialization in Agrochemicals, Chemical and health products, Food processing, Fruit, Inorganic salts and acids, Petrochemicals (Goods); Finance, ICT, or Insurance services (Services). Similarly, countries that invest in Drone and Satellite related AI investment subsequently also gain specialization in Chemical and health products, Coal, Oil (Goods), or Intellectual Property (Services). The interpretability of our approach provides a key tool for policymakers, as we can validate if and how strongly linked each sector is to the other sectors.

Within AI specialization pathways

This sub-section presents a more focused analysis to show the inter-relation within AI specializations i.e. investment within a specific AI sector leads to gaining specialization in other nearby AI sectors. Figure 5 shows that many AI sectors are connected to each other. This implies that when a country specializes (or starts investing) in a given AI sub-field, it subsequently also develops a specialization in nearby AI capabilities (Fig. 5). Figure 5 provides a dynamic progression network that informs the sequence of capabilities learned by studying the pattern of specialization over time. Note the network has directed arcs, that imply sequential progress, since we are considering here all possible $\Delta t \geq 0$. For example, specialization in media content-related AI subsequently leads to AI-related investment in Internet security, or countries that initially invested in Wi-Fi home tech-related AI, subsequently started investments in Image Recognition and Visual Search. The directional arrow provides a taste of causal links and can be more clearly interpreted when we look at adjacent nodes, for example, Computing Technology related AI investment can subsequently lead to Medical Science, Data Analytics to Energy related AI investments, or Image recognition to Wi-Fi home tech, Recruiting to Business Management, Hospitality related AI investment leads to Restaurant, Food, and Beverage related AI investments. Here all possible time delays Δt are equally considered and the resulting network is rather dense, showing that investing in one AI sector may lead

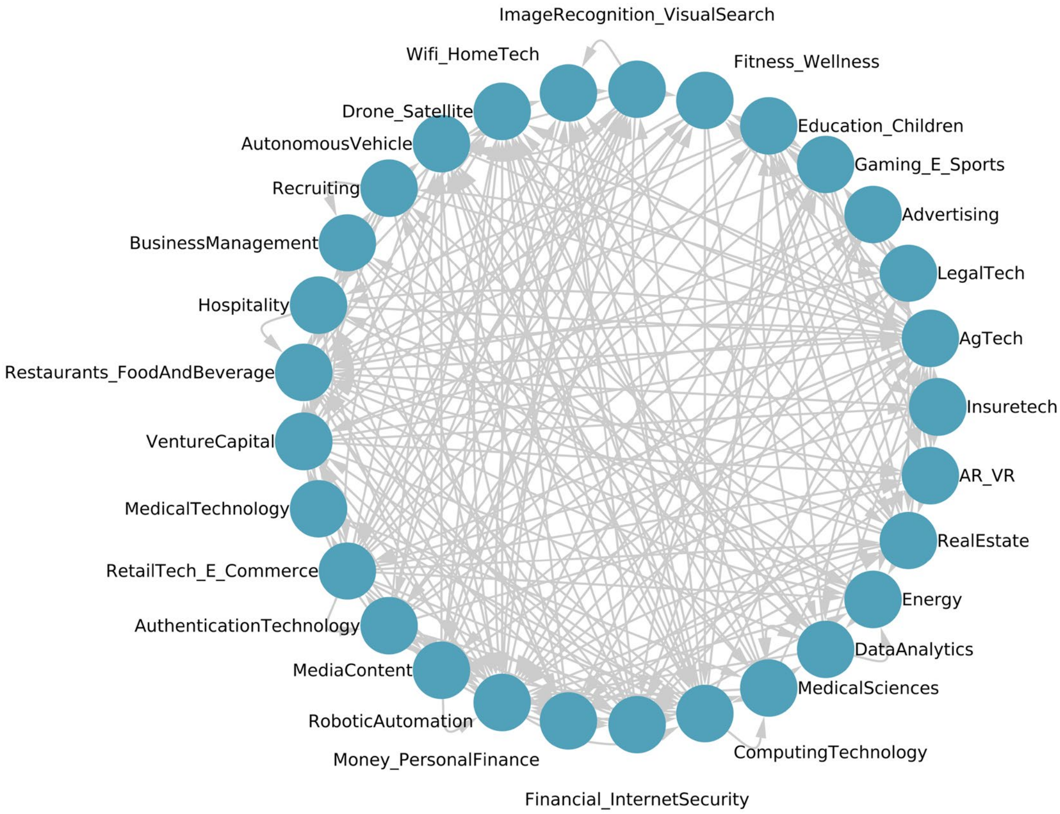

Figure 5. AI-based progression network (with time delay). The high number of validated links implies that strong connections exist among most AI sectors i.e., investing in one AI sub-sector usually leads to a subsequent specialization in other AI sub-sectors.

to activity in many other sectors. Figure 6 shows the network of statistically validated co-occurrences without the time delay; as a consequence, the links are not directed and the network is quite sparse. Here we consider only simultaneous investment in both AI sectors, i.e. a link is present only if it is statistically validated in one year t with $\Delta t = 0$; this permits an immediate visualization of the general structure of the investments in the different AI sectors. This figure provides insights about the capabilities connection or nearby AI sub-sectors that require similar capabilities and can be viewed as the backbone of the interactions described above. The width of the links is proportional to the number of times the corresponding element of the adjacency matrix has been statistically validated. One can notice that some nodes, such as Hospitality and Recruiting, are more peripheral, meaning that these sectors have a lower degree of interaction with the other sectors, while other nodes, like Money and Personal Finance and Image Recognition and Visual Search, are more central, implying that investing in these sectors allows an easier subsequent diversification in many other AI sectors. To gain a diverse portfolio of AI specializations for small-developing countries, the results would imply beginning by investing in one of these central nodes presented in Fig. 6.

Sector specific pathways

This section presents how the global approach can be broken down into sector-specific analyses. Figure 7 provides a zoomed-in view of the sequence of specializations across all sectors learned from the global network of specialization patterns. In particular, we extract three subgraphs of Fig. 3 by selecting three nodes and the respective nearest neighbors. The subgraphs are highlighted in Fig. 3. The top figure shows how specialization in Wifi and Hometech related AI investment subsequently leads to specialization in various sets of goods and services, including Construction, Machinery, Pulp and paper, Chemical and health-related products (G) as well as Maintenance, Finance, or Travel related services (S). The middle graph shows the subsequent set of specializations that stem from specialization in Energy related AI investments. Energy-related AI investments could lead to gaining specialization in Ships, Petrochemicals, Electronics, Finance, Business, or Maintenance services. Finally, the bottom figure presents an alternative view i.e., that the connection of AI specializations such as Computing Technology, AR/VR, Real Estate, Autonomous Vehicles, Authentication Technology, etc. subsequently leads to specialization in home and office product-related manufacturing. Here the width of the link is proportional to the corresponding value of the matrix **B**.

By learning how strongly interconnected sectors are to each other, we find that once a country starts investing in one sector, the strategy is not to only invest in one sector but to develop capabilities in many other sectors. Moreover, the knowledge and know-how that a country learns by specializing in one sector can be applied to

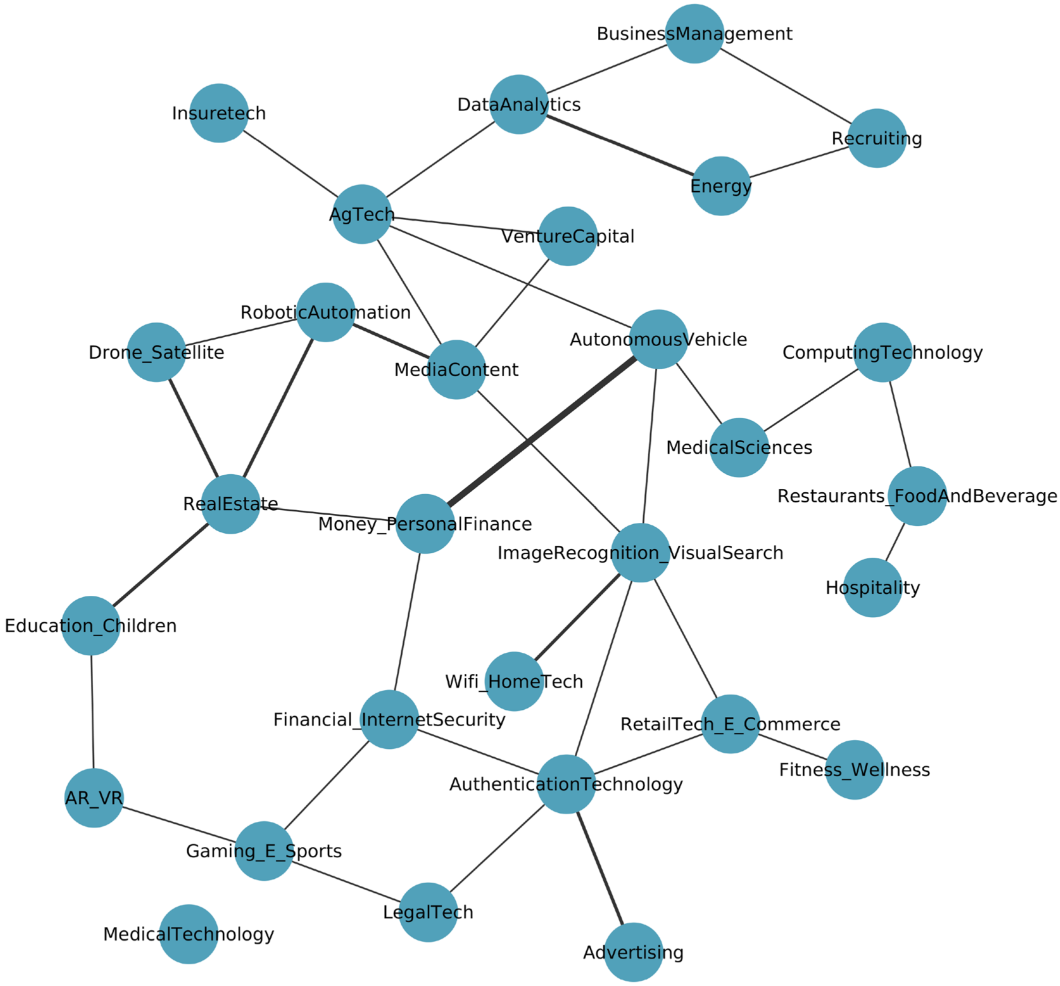

Figure 6. Network of statistically validated co-occurrences in AI specializations, without time delay ($\Delta t = 0$), so no arrow is present. Selecting only one value of Δt makes the network less dense than the one in Fig. 5. In this way, we can extract the simultaneous co-occurrences and better visualize the central nodes, which could represent a starting point for diversification within AI activities.

other sectors. These capabilities become the backbone that offers a unique pathway for countries to develop a portfolio of specializations. Based on the sequence of specialization over time, new links appear, and the consequences of specializing in one sector spread across other sectors of the economy.

Country case studies

This section provides an operational framework with country-specific case studies to help design diversification strategies. The cases are presented by stages of economic development. Beginning with an advanced economy, we show the case of Italy, followed by an upper-middle-income country—Mexico, and two lower-middle-income countries—India and Nigeria.

Figure 8 shows an abstraction of a country's specialization pattern. The AI investment specialization for varied sub-sectors is presented on the top row where the green dot highlights an active AI specialization i.e. the RCA of private investment in a given AI sub-sector is greater than 1. Examples of various goods and service export specializations are presented in the bottom row. Here, the color codes signify classic, emerging, disappearing, or absent specialization (for goods and services). The links between AI and goods/services signify the normalized co-occurrence that has been statistically validated based on the global specialization network. The density metric is used to aggregate our findings into country-specific recommendations to highlight the top goods and services, as they relate to the portfolio of AI investment in that country. For example, if there is a strong linkage from fintech to garments and if garment is a classic specialization then these two sectors have strong synergies and this linkage could benefit pre-existing specialization in that country. Similarly, there may be a linkage from fintech to construction services, however, as denoted by the pink dot, the construction industry is an emerging specialization. In this instance, the linkage from fintech to construction may enhance this emerging specialization. The link from robotic process automation to home and office products is valid. However, home and office products are either an absent or disappearing specialization in this hypothetical example. Therefore, the country

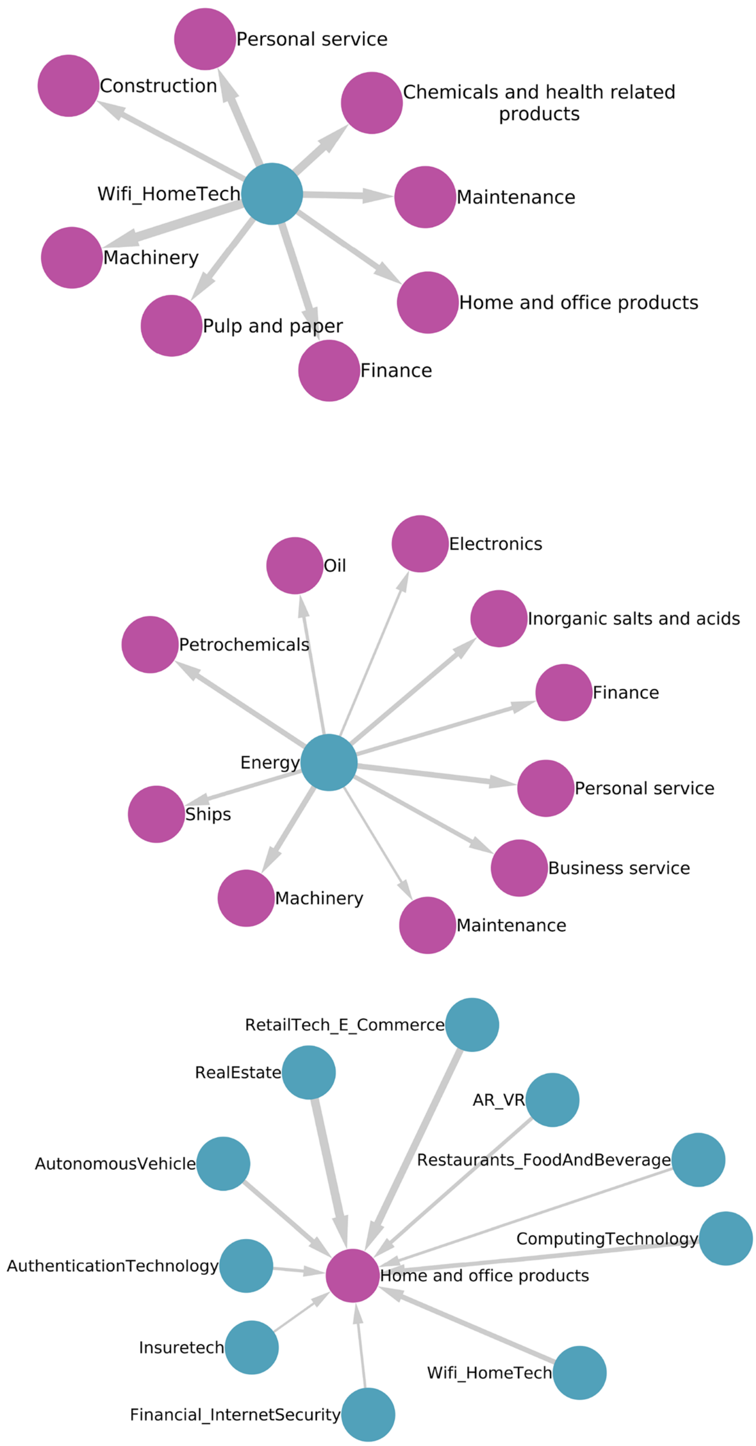

Figure 7. Three subgraphs extracted from Fig. 3, all with time delay. The linkages from Wi-Fi Home tech-related AI investments to Goods and Services specialization (top). The linkages from Energy-related AI investments to Goods and Services specialization (middle). The linkages from AI investments leading to Home and office products specialization (bottom).

can leverage its specialization in robotic process automation (RPA) to discover a new specialization in home and office products given it's already specialized in RPA and there exists a link from RPA to home and office products. The density metric is a country-item-specific measure. We can rank the top products and services most closely linked to AI specialization to help answer which sub-AI field can help either (a) enhance pre-existing specialization, or (b) discover a new specialization.

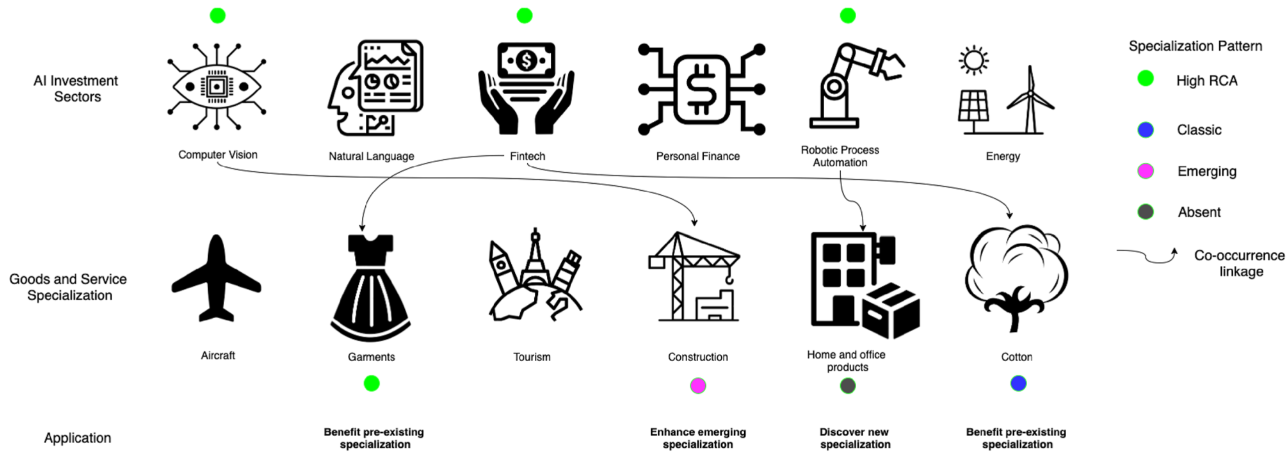

Figure 8. Operational framework to leverage co-occurrence between specialization in AI, Goods, and Services. The first row shows examples of AI investment (or AI specialization) sectors. The second row shows examples of Goods and/or Service specialization sectors. The color codes on the right denote the specialization patterns. By connecting AI specializations, for example Computer Vision to Construction services (which is an emerging area of specialization) for a given country context, the abstraction shows which AI sector could lead to enhancing an emerging specialization.

The country results are presented in two standardized tables. The first country table presents a high-level view of top specializations in a country by ranking the RCA of items (or activities) within AI, Goods, and Services. The RCA measure is based on Ricardian trade theory to reveal the relative difference in productivity. The RCA measure is a first approximation of competitiveness or export (or investment) strength. The RCA helps to avoid the trivial bias that pure export value (or volume) metrics may display, for example, over-representativeness captured by country size or size of the sector. For example, the market share or export value/volume of a country like the USA or China is very large because of their country size, or in many resource-rich countries, the dominance of the oil sector could overshadow other sectors. The RCA measure is an accepted, tried, and tested trade measure, backed by economic theory with practical implications about relative specialization and avoids the bias caused by the sheer size of a given sector. The second table provides a filtered ranking of co-occurrence in goods and services, as they relate to the AI portfolio of the country accounting for the nature of specialization (i.e., Classic, Absent, Emerging, Disappearing).

In order to examine the evolution of AI (A), Goods (G), and Services (S), we analyze the specialization dynamics of countries to segment traditional items versus engaging in completely new economic activities. To this end, specialization patterns are classified into four categories: "Classic", "Absent", "Disappearing", and "Emerging". A "classic" specialization is defined as an item in which a country had, on average, a Revealed Comparative Advantage (RCA) in both the 2010-14 and 2017-19 sub-periods[52]. In other words, the average relative specialization of an item (whether in AI, goods, or services) remained above 1 in the earlier and later sample periods. "Absent" specializations are those in which the country never had an average RCA>1. "Disappearing" specializations are those in which a country had an average RCA>1 during the initial period, but not during the final period. Conversely, "Emerging" specializations are those in which a country only developed RCA>1 at the end of the sample period.

Italy

Figure 9 shows the top specialization across sectors in Italy. Italy has developed AI-related investment specialization in Image, Recognition, and Visual search, followed by Advertising, Retail tech, e-commerce, and Wifi Hometech related AI investments. In goods, exports of leather, garments, chemicals, office products, and agricultural production of fruit, food processing, milk, and cheese have high RCA. In services, business services, followed by travel, and insurance services are the top areas of specialization.

Figure 10 presents the strongest linkages from Italy's AI investment portfolio to goods and services. Many links highlight how AI sectors could help Italy retain a competitive edge in sectors of pre-existing specialization. For example, retail and e-commerce can aid business services, and the textile and fabric industry to retain global competitiveness. The deep specialization in image recognition could help metal products, boilers industry, and Venture Capital and fin-tech-related AI specialization could aid the food processing industries to maintain a global competitive edge. Given Italy's strong historic ties to the textile, leather, and food processing industries, the findings suggest an opportunity for Italy to strategically leverage its AI advancements in image recognition and fintech to further solidify its position in the global market. It underscores the importance of integrating AI specializations with traditional sectors to optimize policy initiatives for economic growth.

Mexico

The right mix of industrial policies could help countries like Mexico break out of a potential "middle-income trap" (MIT)[39, 53, 54]. MIT is a development stage that characterizes countries that are squeezed between low-wage

AI	RCA
Image Recognition and Visual Search	52.1
Advertising	2.1
RetailTech and E-Commerce	2.0
Wifi HomeTech	2.0
Venture Capital	1.7
LegalTech	1.6
Insuretech	1.4

Goods	RCA
Leather	4.7
Animal Fibers	2.7
Garments	2.5
Fruit	1.9
Food Processing	1.8
Other Chemicals	1.7
Milk & cheese	1.6
Tobacco	1.6
Home and office products	1.6
Construction materials and equip	1.6
Machinery	1.4
Metal products	1.4
Ships	1.3
Textile & Fabrics	1.1
Boilers	1.1
Processed minerals	1.0

Services	RCA
Business service	3.2
Travel	1.8
Insurance and pension	1.0
Transport	0.8

Figure 9. Top areas of specialization in AI, Goods, and Services for Italy, 2019.

Top Sectors	Density	Related AI Sectors	Specialization	Application
Business service	0.66	Retail Tech and E-Commerce	Classic	Benfit pre-existing specialization
Textile & Fabrics	0.65	Retail Tech and E-Commerce	Classic	Benfit pre-existing specialization
Metal products	0.58	Image Recognition and Visual Search	Classic	Benfit pre-existing specialization
Boilers	0.56	Image Recognition and Visual Search, LegalTech, Retail Tech and E-Commerce	Classic	Benfit pre-existing specialization
Food Processing	0.51	Venture Capital	Classic	Benfit pre-existing specialization

Figure 10. Strongest linkages from the portfolio of AI specialization to Goods and Services in Italy. Top sectors (column 1) presents the goods and services most related to the portfolio of AI specializations in Italy based on the density measure (column 2) i.e. the feasibility (or likelihood of specialization) given the basket of AI specialization. Related AI sectors (column 3) are the adjacent AI sub-sectors related to the top sectors presented in column 1. Specialization (column 4) is the current specialization trend of top goods and services sectors presented in column 1; Application (Column 5) is the recommendation based on the linkage between AI, Top Sectors, and Specialization status.

producers and highly skilled and fast-moving innovators. Caught between these two groups, many middle-income countries are without a viable high-growth strategy, and transition becomes difficult[40]. Figure 11 shows the top areas of specialization across sectors in Mexico. Mexico has high RCA in many AI sectors, including Money and Personal Finance, Financial and Internet Security, Insure-tech, and Medical Technology. In goods, sectors such as Beer, Spirits, and cigarettes, followed by Machinery, Food processing, and Construction material. Oil is the largest classic export in Mexico. In the early 1980s, products within the oil community accounted for more than 30 percent of Mexico's merchandise trade. In a more recent period, from 2015 to 2019, the oil

AI	RCA
Money and Personal Finance	7.2
Financial and Internet Security	5.9
Insuretech	4.6
Medical Technology	4.4
Business Management	3.2
Robotic Automation	2.5
Energy	2.1

Goods	RCA
Beer, Spirits and cigarettes	3.1
Machinery	2.1
Food Processing	2.1
Construction materials and equipment	1.8
Electronics	1.8
Misc Agriculture	1.6
Ships	1.2
Fruit	1.1

Services	RCA
Government	4.0
Travel	3.4
Transport	0.6

Figure 11. Top areas of specialization in AI, Goods, and Services for Mexico, 2019.

community of products represents only 4.9% of total merchandise exports. Many AI-related activities could help the oil sector become more competitive. In services, traditional services such as travel and transport are the most dynamic sectors.

Figure 12 presents the linkage of Mexico's unique AI portfolio that could help classic industries become more competitive and discover new niches. Mexico's unique AI capabilities including in fin-tech, insure-tech, internet security, medical technology, energy, etc. could help the travel services and ecosystem related to the oil industry remain competitive, whereas, robotic automation-related investment specialization could aid to discover new (or disappearing) specializations such as in metals, or fin-tech related specialization help re-gain specialization in fish and seafood industry. The number of fin-tech and insure-tech startups has been booming in Mexico. Fin-tech startups include sub-sectors of Payments and Remittances, Lending, Enterprise Financial Management, Personal Financial Management, Crowdfunding, etc. Garnering the diversity of AI investments in Mexico could help avoid the "middle-income trap" by formulating pathways for broad-based economic diversification. Mexico's distinct AI capabilities, especially in fintech and insure-tech, provide a strategic advantage that could revitalize traditional industries, like oil and travel, while offering avenues for diversification into emerging sectors. By aligning AI specializations with both existing and potential economic sectors, Mexico has a significant opportunity to navigate the challenges posed by the "middle-income trap" and carve a more sustainable and diversified economic future.

India

India has been progressively diversifying its goods and service exports[52]. Peculiar to India's specialization pattern is the size and sophistication of its service exports[55]. Figure 13 shows the top specializations for India across sectors. Robotic Automation, Restaurants, Food, and Beverage, Business Management, and AgTech-related AI investments are the most prominent. In goods, primary resource-based and low-medium tech manufacturing sectors are eminent, including precious stones for jewelry, cotton-based products, textile and fabrics, agrochemicals, etc. Services remain a relatively large portion of exports but are concentrated in manufacturing, computer service, insurance, and tourism[23, 52, 55].

Figure 14 presents examples of how India's unique AI capabilities could potentially help diversify and make manufacturing and services specialization more competitive. India's capabilities in Robotic Process Automation related AI investments could help benefit high-tech and medium-tech manufacturing in pre-existing specializations, such as metal, agro-related industries including cotton, or manufactured tobacco. Specialization in AgTech could help the agriculture and informal sector by discovering new niches in Food processing, Milk and cheese, and related agro and chemical products. India's AI capabilities in Robotic Process Automation and AgTech not only offer the potential to enhance competitiveness in its already established manufacturing sectors but also present an opportunity to revolutionize its agricultural landscape, enabling a fusion of traditional industries with modern tech. The fusion, in turn, can potentially drive economic growth and further diversify India's export portfolio, positioning the country as a leader in both services and tech-driven agriculture.

Nigeria

Resource-rich countries like Nigeria (or Mexico) face unique structural transformation challenges[56]. Structural transformation is broadly defined as the reallocation of resources from low to high-value-added tasks or sectors. For recent discussions of the importance of structural transformation and development, see[38, 57–59]. Resource sectors tend to be highly capital intensive and offer limited employment opportunities to accommodate workers exiting sectors with lower average productivity, such as agriculture and informal services leading to significant "Dutch disease" effects, stemming from a shift in demand following a resource discovery[38]. Figure 15 shows the

Top Sectors	Density	Related AI Sectors	Specialization	Application
Travel	0.49	Money and Personal Finance	Classic	Benfit pre-existing specialization
Tobacco	0.47	Robotic Automation	Absent	Discover new specialization
Metal products	0.42	Robotic Automation	Absent	Discover new specialization
Oil	0.39	Insuretech, Medical Technology, Financial and Internet Security, Business Management, Money and Personal Finance, Energy	Classic	Benfit pre-existing specialization
Fish & Seafood	0.38	Money and Persona Finance	Absent	Discover new specialization

Figure 12. Strongest linkages from the portfolio of AI specialization to Goods and Services in Mexico. Top sectors (column 1) presents the goods and services most related to the portfolio of AI specializations in Mexico based on density measure (column 2) i.e. the feasibility (or likelihood of specialization) given the basket of AI specialization. Related AI sectors (column 3) are the adjacent AI sub-sectors related to the top sectors presented in column 1. Specialization (column 4) is the current specialization trend of top goods and services sectors presented in column 1; Application (column 5) is the recommendation based on the linkage between AI, Top Sectors, and Specialization status.

AI	RCA
Robotic Automation	8.7
Restaurants, Food And Beverage	6.8
Business Management	1.9
AgTech	1.5
Education	1.3
Image Recognition and Visual Search	1.1
Medical Technology	1.0
Gaming and Sports	1.0

Goods	RCA
Precious Stones	12.1
Cotton, rice, soy beans and others	7.0
Textile & Fabrics	4.2
Ships	2.5
Fish & Seafood	2.4
Agrochemicals	2.3
Misc Agriculture	2.2
Boilers	2.1
Processed minerals	2.0
Metal products	1.7
Garments	1.6
Other Chemicals	1.4
Tobacco	1.4
Leather	1.3
Chemicals and health related prod	1.3
Mining	1.3
Meat and eggs	1.1

Services	RCA
Manufacturing service	3.8
ICT	1.0
Insurance and pension	0.9
Travel	0.7

Figure 13. Top areas of specializations in AI, Goods, and Services for India, 2019.

Top Sectors	Density	Related AI Sectors	Specialization	Application
Metal products	1	Image Recognition and Visual Search, Robotic Automation	Classic	Benfit pre-existing specialization
Cotton, rice, soy beans and others	0.50	AgTech, Restaurants, Food And Beverage	Classic	Benfit pre-existing specialization
Food Processing	0.49	AgTech	Absent	Discover new specialization
Tobacco	0.47	Robotic Automation	Classic	Benfit pre-existing specialization
Milk & cheese	0.41	AgTech, Business Management	Absent	Discover new specialization

Figure 14. Strongest linkages from the portfolio of AI specialization to Goods and Services in India. Top sectors (column 1) presents the goods and services most related to the portfolio of AI specializations in India based on density measure (column 2) i.e. the feasibility (or likelihood of specialization) given the basket of AI specialization. Related AI sectors (column 3) are the adjacent AI sub-sectors related to the top sectors presented in column 1. Specialization (column 4) is the current specialization trend of top goods and services sectors presented in column 1; Application (column 5) is the recommendation based on the linkage between AI, Top Sectors, and Specialization status.

top specializations in Nigeria. Nigeria shows strong AI investment-related specialization in Money and Personal Finance, and Business Management related AI clusters that could help guide pathways for diversification. Sectors such as Oil, Cotton, rice, tropical tree crops, and leather exhibit high RCA in goods; Finance, Transportation, and Construction in services.

Leveraging capabilities in the oil, agriculture, and infrastructure-related sectors, AI could be a strategically important asset to aid the competitiveness of pre-existing sectors and discover new ones. Figure 16 shows the

AI	RCA
Money and Personal Finance	18.1
Business Management	11.7

Goods	RCA
Oil	18.5
Cotton, rice, soy beans and others	2.6
Tropical treecrops and flowers	2.5
Leather	1.7
Processed minerals	0.9
Agrochemicals	0.7

Services	RCA
Finance	7.4
Transport	2.5
Construction	1.5
Travel	1.3
Government	1.0

Figure 15. Top areas of specializations in AI, Goods, and Services for Nigeria, 2019.

strongest linkages to Nigeria's AI investment portfolio. Travel and tourism-related services are emerging specializations where investment in Money and Personal finance could help make tourism-related specialization more resilient. Personal finance and business management-related AI investment could also aid the discovery of new capabilities. For example, fish and seafood, processed minerals, or animal fibers are linked to initial investment in fin-tech-related AI capabilities. Current AI specializations could help plan physical infrastructure investments, and help discover pathways to other AI sectors that in turn could aid broader diversification strategies. Leveraging its AI specialization in financial sectors, Nigeria can address the "Dutch disease" effects by diversifying beyond its traditional oil and agricultural sectors. The intertwining of AI in personal finance and business management can propel sectors like tourism and minerals processing, fostering sustainable growth and facilitating a more balanced structural transformation essential for its long-term economic resilience.

Discussion and conclusions

The paper provided a first-of-a-kind novel integration of data and methodology to examine the relationship of AI-based specialization to broad-based economic specialization. The results have practical implications for potential strategic resource allocation and policy decisions. Technological changes are driving up the demand for AI-based services. AI services can be developed in one location but consumed in many other places. Historically buyers and sellers needed to be face-to-face. However, AI services between buyers and sellers can be traded globally across and within borders almost instantly. Increasingly, AI services are embedded in various manufacturing and service-based products that are digitally traded. Our study offers hope for developing countries to leverage AI specialization as an opportunity to diversify the sources of comparative advantage. The paper documented how sector-specific AI investments not only lead to subsequent specialization in other AI investments but could also lead to developing capabilities in goods and services. The paper also offered an operational framework with country case studies to present how inherent AI capabilities could help pre-existing industries become more competitive and/or discover new areas of specialization. The systematic framework can directly aid growth and competitiveness strategies for nations across all stages of development.

In Silicon Valley, there is a truism that "70 percent of hardware is software"—this was the early recognition of the tight link between sales of computers and software services. The life cycle and adoption of AI at a national level or in enterprises rely on an ecosystem of services to translate into broad-based economic transformation. AI services are becoming the glue that binds many manufacturing supply chains and are critical to their reliable operations. The future wealth of nations could very well depend on an underpinning of AI components, from research and development at the inception of the product to automated distribution and repair at completion. Our paper combines a traditional view of industrial strategies and the growing wave of national AI strategies to offer a complete data-driven view that may be critical to shaping the future growth patterns of nations. This research also has implications for the Venture Capital community to help design more macro-focused investment strategies accounting for current AI capabilities and broader economic capabilities to aid strategic diversification and value creation opportunities.

This work has helped open many areas of future research. This paper focused on links among AI sectors and from AI to broader economic specialization linkages even if, in principle, one could compute also the links in the opposite direction (from goods and services to AI). We made these choices for two reasons: i) the AI data is new and never used in this framework and ii) at both company and country level, the economic activity is the final aim of the AI activity. It is then more natural to check whether an R&D activity leads to a successful export than vice versa. Moreover, already this analysis led to a number of applications and case studies. However, future

Top Sectors	Density	Related AI Sectors	Specialization	Application
Travel	0.49	Money and Personal Finance	Emerging	Enhance emerging specialization
Fish & Seafood	0.38	Money and Personal Finance	Absent	Discover new specialization
Processed minerals	0.36	Business Management, Money and Personal Finance	Absent	Discover new specialization
Milk & cheese	0.22	Business Management	Absent	Discover new specialization
Animal Fibers	0.22	Money and Personal Finance	Absent	Discover new specialization

Figure 16. Strongest linkages from the portfolio of AI specialization to Goods and Services in Nigeria. Top sectors (column 1) presents the goods and services most related to the portfolio of AI specializations in Nigeria based on density measure (column 2) i.e. the feasibility (or likelihood of specialization) given the basket of AI specialization. Related AI sectors (column 3) are the adjacent AI sub-sectors related to the top sectors presented in column 1. Specialization (column 4) is the current specialization trend of top goods and services sectors presented in column 1; Application (column 5) is the recommendation based on the linkage between AI, Top Sectors, and Specialization status.

research could indeed explore how goods and services-based capabilities can lead to the discovery of new AI-based specializations. This research focused on AI investment as a proxy for AI specialization but future studies could also incorporate scientific discoveries, i.e., specialization in AI stemming from patents, journal publications, and conference papers. Nevertheless, investment data is more robust and relevant as it provides a stronger signal of economic activity that is sensitive to domestic companies (or startups) that are fuelling the wave of AI diffusion within and across countries. Future research could also provide deeper country-specific case strategies that will help validate the specific linkages presented in this paper based on industry-specific domain knowledge and national context. There are unanswered technical challenges. For example, given different data sources and units for AI investment (versus export data) pose a constraint to combining all the data in a unified matrix. There are also open questions about the implications of this study, such as the trade-offs involved for developing countries to import AI capabilities versus producing their own AI domestically. The real-world application areas based on the identified linkages between AI and broader economic sectors are also worthy of future research.

Data availability

The data about AI investment contains sensitive information and so cannot be publicly shared; however, it could be available from the corresponding author (A.Z.) upon reasonable request. The data about the export of goods and services are available in Ref.[24].

Received: 14 December 2022; Accepted: 23 October 2023
Published online: 09 November 2023

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Acknowledgements
The initial work for this article was conducted when some of the co-authors were with different institutions. Saurabh Mishra was with Stanford University, Institute for Human-Centered Artificial Intelligence (HAI); Robert Koopman was with the World Trade Organization (WTO); Anand Rao was with PricewaterhouseCoopers (PwC); Julie Kim was with Netbase-Quid. Andrea Zaccaria acknowledges the PRIN project number 20223W2JKJ WECARE. All the authors acknowledge the Heinz College of Information Systems and Public Policy, Carnegie Mellon University.

Author contributions
S.M. and A.Z. designed the work and analyzed the data. S.M. and A.Z. wrote the manuscript. All authors discussed the results. All authors reviewed and approved the manuscript.

Competing interests
The authors declare no competing interests.

Additional information
Supplementary Information The online version contains supplementary material available at https://doi.org/10.1038/s41598-023-45723-x.

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