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The promise and perils of artificial intelligence: Overcoming the odds

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THE PROMISE AND PERILS OF ARTIFICIAL INTELLIGENCE:

OVERCOMING THE ODDS

Martha Garcia-Murillo and Ian MacInnes

1. Introduction

Artificial Intelligence has been received with both great enthusiasm and great concern. From a positive perspective, IBM's CEO, Ginni Rometty, stated, "It will be a partnership between a man and machine. It is a very symbiotic relationship that you are conversing with this technology. Our purpose is to augment and really be in service of what humans do" (N. Singh, 2017). In contrast, other tech executives have reacted like Bill Gates, who stated that "[h]umans should be worried about the threat posed by artificial Intelligence" (Rawlinson, 2015). Many academic researchers have voiced their concerns about the disappearance of jobs, with machines replacing workers (Brynjolfsson & McAfee, 2015). Yet beyond the enthusiasm and the concerns, there has been an increased interest in AI in all areas of human endeavor. In manufacturing, for example, the number of publications related to AI has grown from about 500 in 2010 to more than 2,000 in 2020 (Arinez et al., 2020), and this trend can also be seen in other areas where AI is being incorporated. A 2003 study from Filippi et al. found exponential growth in the number of papers focusing on AI.

Whether we use it or not, artificial Intelligence is already part of our lives. The capabilities of computing power and the vast amounts of data we generate from our digital interactions and transaction have enabled many industries to use this technology to enhance their operations, decisions, and services. With these developments, there are many promises, but also perils. To

take advantage of the benefits that this technology offers, we need to identify the ways in which AI can negatively affect society. With an awareness of potential risks, we will need to intervene to minimize negative effects without impairing positive developments. The interventions we devise to avoid the deleterious consequences of AI deployment we term *targeted interventions against impending negatives* (TIIN).

This paper begins with a general explanation of AI and associated technologies, which we term AI+. Then we examine AI's impact on two industries corresponding to the two traditional economic sectors: agriculture and manufacturing. We describe the capabilities of AI for invigorating these industries and explore whether its introduction will be beneficial or harmful.

The last part of the paper introduces the notion of *targeted interventions for impending negatives* (TIIN). A TIIN is an action or strategy aimed at addressing and mitigating potential adverse outcomes or consequences. In this case, the negative effects that we hope can be alleviated are effects that emerge when AI+ is introduced into sectors of the economy. These interventions are unlikely to be proactive; they are instead more likely to be reactions to early warning signs of adverse outcomes. The goal of a TIIN is thus to intervene to address a problem and alter the trajectory of an action towards a more favorable outcome.

2. Exploring the impacts: Contrasting broad and narrow contributions

Through a systematic analysis of the AI literature, Filippi et al. (2023) found that the main research gaps concerned macro-level impacts at a high level of analysis across geographical regions. Considering Filippi's review, we noticed an additional gap in the literature, based on the scope of the research. Most studies to date are narrowly defined; for this reason, this paper

broadens its scope to include impacts across countries, highlighting the differential effects between developed and less developed nations.

This paper also expands the scope to include not only the labor impacts of AI, which has been one of the most researched areas, but also other areas where its consequences can be felt.

Thus, when we look at how technology can be helpful/harmful to humans, we need to expand our scope beyond how it affects us both individually and collectively.

Identifying the benefits of AI is a complex task, as the stakeholders are not monolithic. While some events, technologies, interventions, policies, and so forth, will positively affect some, the same will not be true for others. A wider lens is needed to include ***the impacts on individuals' health and well-being*** and ***the impacts on the economy*** (whether it will increase productivity, job creation, innovation, or economic growth). Moreover, given the significant changes the earth is undergoing due to human activity, a broader focus should also consider ***the impact on the environment***. As we expand our scope to determine the effects of AI+ on two sectors of the economy, we recognize that we will not be able to explore the impacts on them in detail. However, we will allude to them, even if briefly, and, to whatever extent is possible, point to research that provides insights.

Academic researchers typically narrow the scope of their research. Much of the literature on research design starts with prompts about determining a study's focus (Creswell & Creswell, 2017). This is not uncommon because researchers need to conduct manageable studies in terms of time, resources, and data collection. However, when research is narrowly focused, it can fail to identify the complexity of problems that affect us today. We recognize that there are

trade-offs between narrow- and broad-scope research and that narrowing one's focus can generate details and nuanced findings that can lead to insights about a problem; however, these insights may be only one component of a more extensive system. Narrowly defined studies risk overlooking essential aspects of a problem we are trying to understand. As Yin observes, a narrow focus can lack comprehensiveness, limiting the range of possible conclusions (Yin, 2018).

We recognize that expanding the scope of a study to consider the more complex extent of a problem can result in a shallow understanding of the problem. Also, because the nature of science requires us to provide evidence about the hypothesis we put forward, a broader approach runs the risk of missing substantial evidence that could corroborate an initial hypothesis. When we chose an expansive scope for this study, we recognized that one of the weaknesses of this approach would be a lack of definitive evidence. To frame the current state of knowledge regarding the different sectors we address, this paper relies on prior literature. As we broadened our scope, we strove to provide what evidence we could to support our claims. The primary benefit of this approach is that it captures the complexity of the problem we seek to understand by drawing on additional contributing factors.

3. Balancing perspectives: Exploring the dualities of AI deployment

This paper also differs from other contributions in that we try to take a neutral perspective. There are differing perspectives on AI. Some scholars take an optimistic view that sees the applications and outcomes of AI as beneficial; others focus on negative consequences. We titled this paper "The Promise and Perils of Artificial Intelligence" because we recognize that

there are risks related to the broader deployment of AI in many aspects of our lives, but we also know that there are great benefits. It is unrealistic to focus only on the positive or negative consequences of technology. In fact, throughout most of our history, the introduction of new technology has led to both.

4. Artificial intelligence and associated technologies (AI+)

Advances in information technology are profoundly affecting our everyday lives, transforming how we learn, work, interact with companies and government, and entertain ourselves.

Broadband expansion, access to petabytes of data, increasing storage capabilities, and the faster processing power of machines have made the introduction of life-transforming innovations possible.

Artificial intelligence did not appear in a vacuum; it is the result of the evolution of many information technologies. The digital revolution that began quietly in the 1950s has gone through multiple phases. Greater computing power, more storage space, faster and more ubiquitous connectivity have led to advances whose impacts we could not have foreseen. One significant advance is the massive amount of data at our disposal. Data comes in multiple forms – text, audio, video, and images – that computers use to generate AI. For this study we use the term *AI plus* (AI+) to refer to the combination or integration of artificial intelligence with other technologies, approaches, or disciplines to enhance its capabilities or extend its application.

Artificial intelligence relies on connectivity, which should be conceived broadly. Communication networks are multi-pronged and rely upon many technologies, from satellites and fiber and copper broadband to wi-fi and Bluetooth. These modes of connection facilitate data collection

from devices that would be impossible to connect through conventional means. Connectivity is crucial for AI because its data comes from large equipment and many small devices that connect to the Internet through these various modes. In many applications of AI, the massive amount of data needed for a computer to make inferences depends on the scraping of information from websites; the aggregation of personal data from social media posts and purchases of products and services; and data from home appliances, personal activity trackers, and company sensors. AI thus relies not only on connectivity, but also on the many devices that connect to the Internet, called the Internet of Things (IoT). In addition to ubiquitous sensors in most buildings, artificial intelligence also takes advantage of sensors on mobile machines such as drones and of the countless robots that are now common in manufacturing, agriculture, and retail.

Thus, to make inferences, AI+ uses the algorithms that computer scientists have developed for computers and takes advantage of cloud computing (CC), IoT, and Big Data analytics (BDA).

In the past, there was a demarcation between artificial intelligence and robotics. Robots fall within the realm of hardware and are typically designed to perform specific tasks. They have been used in manufacturing since heavy-duty industrial robots were first introduced into production lines, where they increase productivity and relieve humans from routine, repetitive, and dangerous tasks (Liu et al., 2022). In contrast, AI has generally been conceived as a digital construction with broad applications such as speech recognition, computer vision, and natural language processing. Today, AI developers are aiming to create intelligent systems that exhibit independent intelligence without significant human intervention; however, at times, their work has ignored the importance of the physical (i.e. hardware) components of technology.

Now, these two technologies are beginning to converge and are evolving to the point where hardware, including robots, and software are being integrated and becoming capable of more complex functions. For instance, AI+ draws on all these technologies to generate the knowledge that a company or organization needs to make decisions. Their convergence in AI+ will transform how models, methods, and ecosystems are used to impact national economies, societal well-being, and national security.

4.1 Artificial intelligence: Building blocks and functionality

There are two types of artificial intelligence. One is *artificial general intelligence* (AGI), which mimics human behavior in all respects. The other is *specialized AI*, which takes advantage of one of AI's multiple capabilities to enhance or complement a human activity. Generalized AI is unlikely to emerge any time soon (Gillani, 2023), but specialized AI is already being used in many areas of our lives. While humans can learn and perform many complex jobs, human labor has constraints. Our minds and bodies are limited in strength, flexibility, speed, memory, complex analysis, and endurance. Table 1 presents a comparison of human capabilities and their AI equivalents.

Table 1. Comparison of human and AI capabilities

| Human function | Artificial intelligence function |
|-----------------------|---|
| Sight | Computer vision (object recognition) |
| Speech | Speech recognition |
| Body movement | Navigation, manipulation, and transportation of objects (untiring and stable) |
| Comprehension | Natural language processing |
| Conversation | Chatbots |
| Creation | The ability to develop compositions from existing compilations of different text types, images, and sound to create something new; the ability to integrate multiple forms of numerical and sensory data. |

Sources: Compiled by the authors from Frey and Osborne (2013) and Patel et al. (2017).

AI capabilities can enhance, complement, or potentially substitute for labor. AI can automate processes, relieving workers from simple, repetitive, and mundane tasks and freeing them up to engage in other more complex and creative activities. AI can perform complex repetitive tasks autonomously and more efficiently than humans and can achieve higher quality results. Some examples include managing vehicles and manufacturing goods, but AI-enhanced automation can also support activities like fraud detection, customer service, and human resource management (Shekhar, 2019). AI-enabled systems can enhance decision-making by providing a variety of possible outcomes and letting humans make final decisions based on their recommendations (Duan et al., 2019). AI can also formulate predictions to support human decision makers and enable them to take proactive measures when anticipating negative outcomes. This application of AI is often called *predictive analytics* and can help businesses optimize their operations. It can also help doctors to prescribe medications or other medical interventions before the onset of a detrimental medical condition (Keijzer et al., 2021). At the individual level, we can use our watches to answer phone calls or analyze sleep patterns, health conditions, and exercise habits.

Artificial intelligence and robotics advances are no longer in the realm of science fiction.

Machines can now perform tasks that were once exclusive to humans, using cognitive functions and automated programming.

4.2 The synthetic revolution

The term *synthetics*, in a general sense, refers to things that are artificially created or manufactured. Technology has reached a point where humans are no longer the only entities that can develop tools that support human activity.

The availability of massive amounts of data and more sophisticated programming enable computers to learn on their own, “the synthetic” part of development. These systems are now capable of developing unique and quite different outputs that were not possible before. They are also capable of doing things that are not achievable by humans. A recent example was a competition between an F-16 AI agent and an experienced Air Force F-16 pilot in a simulator; the AI agent won five out of five aerial combat matches, what are known as “dog fights” The AI agent was able to engage in more aggressive and accurate maneuvers than its human counterpart (*AlphaDogfight Trials Foreshadow Future of Human-Machine Symbiosis*, n.d.).

In the next two sections, we discuss the impacts of AI+ on agriculture and manufacturing. As stated above, we adopted a comprehensive approach that not only emphasizes economic advantages, but also takes into account impacts on labor and the environment.

5. AI+ in agriculture

AI+ in agriculture encompasses a whole slew of interconnected systems that allow large-scale farmers not only to reduce costs and increase productivity, but also to reduce the harmful effects of waste and chemical use. The use of AI+ in agriculture is giving rise to many terms,

from “smart farming” to “AgTech,” “digital agriculture,” and “Agriculture 5.0”¹ Because agriculture relies on physical labor, the use of AI+ in this sector of the economy is transitioning from humans to robots; thus, Agriculture 5.0 is characterized by the introduction of robots that rely on AI.

AI+ in agriculture involves connectivity; the collection of data from multiple sources, which can include sensors (IoT) on soil and agricultural equipment; drones; satellites; and market and distribution data. Implementing IoT in agriculture involves building sensors into a variety of agricultural equipment. These sensors collect data, analyze it, and make informed decisions based on environmental conditions, crop states, plant health, soil composition, and moisture levels, and they can identify diseases that affect crops.

The data generated by these devices is also beneficial because it helps farmers make decisions. The volume, speed, veracity, and variety of data enable farmers to solve problems faster and on a greater scale (Saiz-Rubio & Rovira-Más, 2020).

Combining and consistently utilizing these technologies can generate a feedback loop, leading to significant improvements in decision making over time. The introduction of these technologies has been calculated to expand agricultural productivity by 70% by 2050 (Mariani & Kaji, 2019).

5.1 AI tools for minimizing the environmental impact of agriculture

¹ The initial wave of precision agriculture involved mechanization, followed by a second wave, the “green revolution,” which introduced genetic modification; the third wave is evolving through the integration of farm knowledge systems, facilitated by an abundance of data resources, which characterizes the fourth wave (Saiz-Rubio & Rovira-Más, 2020).

From an environmental perspective, agriculture causes significant adverse impacts on the environment. AI and related technologies can address many of these negative factors, effectively alleviating their impact. One example is reducing water usage in crop production, thereby mitigating excessive consumption. According to the UN's Food and Agriculture Organization (FAO, 2016), agriculture accounts for 70% of global freshwater use.

The California Central Valley has made significant strides in introducing technology to reduce water use in the production of almonds and pistachios. Moreover, high salt levels in the soil are a challenge faced in common by growers in the Central Valley and worldwide, negatively impacting sensitive crops. High salt levels lead to stunted crop growth, leaf damage, and reduced yields. Technology developed by AQUA4D® reduces soil salinity by treating water without relying on water-intensive leaching or chemicals. This company also has a product that uses real-time data about the condition of plants to optimize irrigation duration and quantity (AQUA4D, 2020). It has been used in Switzerland, where two vineyard plots were outfitted with a modern drip irrigation system and equipment for monitoring soil moisture and plant health in real time. One of the plots was equipped with resonance-based water treatment technology, also developed by AQUA4D. Compared to traditional watering methods, the drip irrigation system reduced water usage by 20%, and the AQUA4D technology achieved an additional 20% reduction in water use (AQUA4D, 2023).

Agriculture also suffers from waste; in developed countries such as the United States, between 20% and 40% of food doesn't make it to market for aesthetic reasons, while in less developed countries (LDCs), waste results from inadequate harvesting techniques and a lack of proper

transportation packing and storage infrastructure (Food and Agriculture Organization, 2011). AI and computer vision can help farmers better predict the optimal time to harvest crops. Faculty at the University of Lincoln in the UK used visual AI technologies from the company V7 to indicate the readiness of strawberries for harvesting (Turnstill, 2023).

Agricultural waste can also be minimized by using AI and market data to adjust production based on supply and demand data from retailers and food-service providers. An example is Gro Intelligence, a company that collects agriculture-related data from nearly 200 sources, including satellite image and granular price data from all over the world, to develop models that take advantage of AI to forecast demand and weather factors relating to agricultural products (Gro Intelligence, 2023).

5.2 Precision farming and its potential to improve human health

Modern agriculture has brought increases in land productivity and output but relies on pesticides, fungicides, and herbicides, with significant costs to human health (Pathak et al., 2022) and other species; these substances poison animals, destroy beneficial natural predators and parasites, strengthen the resistance of pests to crop treatments, and diminish pollination by reducing the bee population (Pimentel et al., 1992). Runoff from fertilizers and pesticides contaminates food and drinking water (Tilman et al., 2002). Precision farming assisted by AI+ enables farmers to apply irrigation and chemical treatments with greater precision and to address the needs of individual plants. This approach contrasts with previous practices, where treatments were uniformly deployed across entire fields, regardless of the needs of individual areas. AI+ “allows precise applications of phytosanitary products, resulting in a reduced used of

herbicides and pesticides, improved water use efficiency, and increased crop yield and quality” (Saiz-Rubio & Rovira-Más, 2020, p. 4). An example is Bilberry, a French company that uses AI+ and related technologies to scan and detect problems and to spray individual plants instead of at the level of the field, with the exact amount of herbicide that corn and wheat need at a given time (Bilberry, 2023).

The combined use of these technologies will reduce harmful effects on humans and lower costs to farmers by helping them to optimize their use of fertilizers, pesticides, and other chemicals. Another example is CropX, an Israeli company that uses AI+ technologies to minimize the use of resources while expanding yields. The AI app the company developed uses soil maps, topographic maps, weather data, weather forecasts, satellite imagery, hydraulic models, and crop models, and data from irrigation systems, controllers, and agricultural equipment which is then analyzed to inform farmers as to where and how much to irrigate, fertilize, or spray (Amazon, 2023).

5.3 Differential impacts of AI in agriculture: Developed countries versus LDCs

The introduction of AI+ to the agricultural sector will lead to differences in challenges and benefits to countries, depending on whether they are more or less economically developed. Technologically advanced and rich economies are more likely to experience the most considerable benefits. Access to technology, technical literacy, widespread connectivity, access to finances, and well-established infrastructure will allow already highly mechanized farmers to continue to increase their productivity and decrease costs, while reducing the harmful impacts of agricultural chemicals.

For LDCs to take advantage of AI they will have to overcome limitations related to connectivity, digital and data literacy, , infrastructure, and wastage due to poor transportation, storage, and general logistics.

Furthermore, the agricultural sector remains a crucial part of the economy in LDCs. It represents 3% of the world's gross domestic product (GDP) and employs 30% of global labor (The World Bank, 2023). However, while in developed economies it represents only 1% of GDP, in poorer regions such as Africa and Asia it accounts for 50%, a much larger share of the economy. In terms of labor, only 1.36% of the U.S. labor force is in agriculture, compared to 51% in Africa (AfDB, ADB, EBRD, IDB, 2018).

The perils of AI+ in agriculture are many, particularly if we expand it to a global scope, where three billion people live on 475 million farms smaller than two hectares (Duffy 2009). The challenges to small farmers worldwide can have significant consequences on labor because there are great benefits to farming on a large scale, which is evident in the sector's concentration into more prominent players (Renda, 2023, in Garcia-Murillo [in production]).

Despite the challenges, there are signs of technological evolution that can help small farmers in less developed economies. In Zambia, for example, farmers are using AgriPredict, an AI-powered app that can detect crop diseases. The farmers can use the camera on their mobile phone, and even if they do not have connectivity in the field, they can connect to public wi-fi elsewhere to access information about a problem they are detecting ("How AI Is Helping Rural African Farmers," 2020).

In Kenya, the insurance company Kilimo Salama, which means safe agriculture in Kiswahili extends coverage to small-scale farmers with plots as small as one acre. The insurance protects them from the perils of drought and excessive rain. The program is a collaboration among the Syngenta Foundation for Sustainable Agriculture, UAP Insurance, and Safaricom. By mitigating the financial risks associated with weather-related crop failures, Kilimo Salama offers crucial protection to farmers. The project also provides farmers with access to precision agriculture technologies such as soil moisture sensors and mobile weather stations. With these technologies, farmers can optimize their water and fertilizer use and improve their crop yields. The project has been successful in helping farmers adopt precision agriculture despite financial constraints (International Finance Corporation, 2015; Technology exchange lab, 2023).

In Uganda, a group of farmers has adopted precision agriculture using a mobile platform called EzyAgric, which provides access to precision agriculture tools such as soil testing kits and mapping with real-time weather information. Farmers can optimize their use of inputs through the platform and improve their crop yields. It also provides farmers with access to credit and insurance, which helps to remove the financial barriers to adopting these technologies (Wudonig, 2019).

In LDCs, lack of access to credit is a significant challenge that can limit farmers' ability to take advantage of new AI+ technologies. In sub-Saharan Africa, 90% of its 48 million small farmers lack access to credit (Engineers without borders, 2023). Similarly, in this region of the world, agriculture employs 35% of the population and accounts for 32% of GDP, but it receives less than 6% of the credit. This lack of access to credit is a significant hurdle that prevents farmers from acquiring the resources they need to enhance their crop yields. However, farmers are

afraid of taking out a loan because they fear losing their land if they have a poor crop season and are unable to pay it back. On the other side, the challenge for financial institutions is that they do not have enough information to assess a farmer's financial viability.

However, there is progress being made in this area as well. Since 2014, the FarmDrive mobile app in Kenya has used data analytics to connect small farmers with financial institutions to obtain credit using a mobile phone. FarmDrive aggregates data from satellite images and weather forecasts and produces market data to track the productivity of a farm, its expenses, and revenue. The app generates performance patterns from this data that financial institutions can use to approve a loan. Because lack of digital literacy can also impede these communities, a local university provides mobile training sessions they call Apps4Ag Learning Opportunities", which not only help farmers track their farming activities, but also provide agronomic recommendations (Engineers without borders, 2023).

These examples show that African farmers, with the proper support and tools, can overcome problems with digital literacy and financial challenges and adopt precision agricultural techniques.

There are also larger-scale projects involving multiple governments, private sector entities, and philanthropic entities such as the Commercial Agriculture for Smallholders Agribusiness (CASA) project that work in a number of countries to address the challenges faced by farmers in respect to climate change. The project aims to provide support services to improve investments in intelligent agricultural technologies that are resilient in their response to climate change. The positive impact this can have on the environment is unmistakable. These technologies can help

reduce waste, water use, and the application of chemicals that can harm the environment and humans.

The effects on labor could be significant but might vary in LDCs. It will largely depend on the pace of technology adoption and the ability of small, less advanced farmers in less developed nations to withstand the impact of large agricultural farms that can dominate the international commodities market and potentially displace them.

6. Industry 4.0: intelligent manufacturing

The incorporation of technology into manufacturing is not new. It resulted from a long incremental process that started with the First Industrial Revolution. AI+ will transform the manufacturing sector, influencing various aspects of the production process, such as design, production, management, testing, and integration. These areas constitute the entire manufacturing lifecycle, highlighting AI's extensive reach in this economic sector (Li et al., 2017)

The integration of cloud computing (CC), Big Data analytics (BDA), AI, and IoT makes up systems called *cyber-physical systems* (CPS)² (Gupta et al., 2022). The combination of these technologies is often referred to as the Fourth Industrial Revolution,³ also known as Industry 4.0. UNCTAD (2022) defines Industry 4.0 as industry equipped with smart and connected production systems driven by automation, data exchanges, and AI. It integrates sensors and digitally networked

² The term was first introduced by the National Science Foundation (NSF) in the United States in 2006 as part of its Cyber-Physical Systems Program. Since then, CPS has become a widely used term to describe systems that combine sensing, computing, communication, and actuation capabilities to interact with and control physical processes in various domains, such as manufacturing, transportation, healthcare, and infrastructure.

³ The First Industrial Revolution was made possible by the steam engine. The Second was made possible by electricity, which powered engines and turbines. The Third took advantage of digital communication. The Fourth Industrial Revolution is occurring with the integration of CC, IoT, BDA, and AI (Gupta et al., 2022).

equipment to facilitate novel interactions between humans and machines, and it optimizes efficiency and productivity by leveraging advanced technologies and data-driven insights.

Manufacturing entails many complex processes and manufacturing AI+ can include connectivity (to the industrial IoT), hardware (including robots, collaborative robots, and 3D printers), and software (AI, data analytics). These components work together to create a networked system capable of real-time sensing, prediction, and decision-making in production processes.

Industry 4.0 is driven by smart and intelligent manufacturing (IM). According to Zhou et al., IM has evolved through three stages: digital manufacturing before 2000, smart manufacturing after 2000, and next-generation IM (NGIM) after 2020. In stage one, digital manufacturing involved the use of computers to support machine and system operations with limited expert systems. In stage two, smart manufacturing leveraged networking and developed digital models to adapt to dynamic environments and customer needs. In the third stage, NGIM connects machine learning, Big Data, and IoT to integrate human and machine systems (Wang et al., 2021). Thoben et al. (2017) noted that the terms *smart manufacturing* and *intelligent manufacturing* are often used interchangeably but that IM focuses more on technological aspects, while SM emphasizes analytics and control.

IM takes advantage of ubiquitous sensors to collect large amounts of data that can improve manufacturing operations. The sensors communicate with each other to perform autonomous actions that can become increasingly more accurate (Gupta et al., 2022). Furthermore, this technology offers improvements in many manufacturing capabilities, in areas such as design, demonstration, simulation, experimentation, production, maintenance, integration of the

manufacturing process, and interconnection with other products. Introducing AI+ into manufacturing is likely to result in new manufacturing models that are more flexible, collaborative, customizable, and cost-effective than current ones.

The sensors in an IM ecosystem support remote monitoring, diagnosis, and planned maintenance. With remote capabilities like these, manufacturing can be extended beyond a single plant. Widespread connectivity and the vast accumulation of data from numerous devices and machines enable remote resources to be integrated, leading to what Li et al. (2017) referred to as an *ecosystem of intelligent manufacturing*.

A highly connected manufacturing operation will be integrated with other company's systems, such as in enterprise resource planning (ERP), supply chain management (SCM), and manufacturing execution systems (MESs). A MES allows workers to connect to machines to access real-time data that will help improve efficiency, reduce scrap, and improve quality.

6.1 Intelligent manufacturing for improved quality management

An interconnected IM plant is guided by autonomous decisions and is able to identify problems that can affect the quality of a product and, over time, improve it. Statistical process control (SPC) monitors machines and supports the analysis of data. When quality control relies on the visual inspection of equipment, there is a high probability that a problem will be discovered only when defective parts have already been produced. SPC enables technicians to immediately adjust machines that violate spec limits.

The visual inspection of parts can support the machine manipulation of those parts and help to improve throughput (Alexopoulos et al., 2020). Advanced MES systems send automated

notifications to the appropriate operators and enable engineers to respond immediately to any disruptions at the plant, and if a person in the command line is not responding, the system can automatically notify the next in line. All the data collected from machines and systems, such as data from help calls, down-time events, machine failures, idle times in production, and so forth is put into the system to continually improve the AI engine that powers it.

6.2 Intelligent manufacturing and benefits to human well-being

AI in manufacturing, as in agriculture, will significantly impact many types of work. As technology advances, new tools will lead to IM systems that seamlessly integrate the work of humans and machines. Wearable devices that communicate with machinery will enhance collaboration and interaction between humans and automated systems. Intelligent factories working along with human labor will produce more and better products.

An MES, for example, can gather and present information about machines that are not available to prevent people from scheduling jobs on the wrong machine, thereby avoiding conflicts that can delay production. Workers with access to real-time data can see what is running, including non-production tasks such as scheduled maintenance; can detect scheduling problems and delays; and can identify the capacity of other machines to take on more work.

In addition to the increased profits that these expanded capabilities and this increased productivity will generate, the use of wearables will benefit workers in this sector. Integrated sensors will be able to monitor workers' health and safety when operating machinery. They can also alert workers to any safety risks, such as leaks of toxic chemicals or other substances that can endanger workers or equipment. These technologies can also send text messages and

emails and make loudspeaker announcements supported by flashing lights and alarms to alert people that something or someone needs immediate attention.

The world has recently experienced one of the most significant pandemic events in a century. In response, AI technologies in manufacturing can help support the trend toward working remotely.

6.3 Smart waste management in manufacturing using AI

Producing goods and services involves complex processes that waste resources at each stage. Materials used in manufacturing often aren't recovered or reused, so there is substantial amount of waste, which may include electronics/electrical items, manufacturing scrap, discarded construction materials, and polymers, and proper disposal and management of this waste are falling behind (S. Singh et al., 2017).

Waste disposal is a common challenge across industries. Consequently, the planet is grappling with problems related to waste accumulation. IM uses AI+ to model, design, simulate, and analyze machines, tools, and materials that can use resources more efficiently. *Resource efficiency* is the optimal utilization of materials, energy, and water in manufacturing, reducing pollution and resulting in cost savings (S. Singh et al., 2017).

AI+ manufacturing can also have a positive impact on the environment, as it may promote the reuse or recycling of products, the reduction of scrap from the better monitoring of machines, and the use of processes that are less environmentally damaging (Gupta et al., 2022) IM offers benefits by aiming towards zero-waste manufacturing, using two approaches. The first involves redesigning products with materials that can be reused. This entails considering the entire

product lifecycle and ensuring that a product's components are designed for repurposing or recycling once they have served their initial purpose. The second approach focuses on conservation and recovery. It involves extracting valuable resources from used products and incorporating them into new ones. Adopting these approaches can enhance sustainability, reduce waste, and establish a circular economy that promotes resource reuse and regeneration (S. Singh et al., 2017).

Much progress is still needed in waste reduction, and companies and researchers are experimenting with AI+. In the manufacture of semiconductors, for example, AI+ is used for three aspects of production: (1) anomaly detection, (2) smart and predictive maintenance, and (3) defect-aware production optimization. Improvements in these three areas will enable engineers to identify and prevent anomalies, which can enhance semiconductor manufacturing performance and contribute to more sustainable practices (Sidahmed Alamin et al., 2022).

IM can also reduce negative environmental impacts by using energy better. An MES monitors and manages energy consumption through connected sensors.

6.4 Intelligent manufacturing: Divergent implications for developed countries and LDCs

Manufacturing plays a significant role in national economies, contributing 15% to 25% of GDP, and accounts for a quarter of the global workforce (S. Singh et al., 2017).

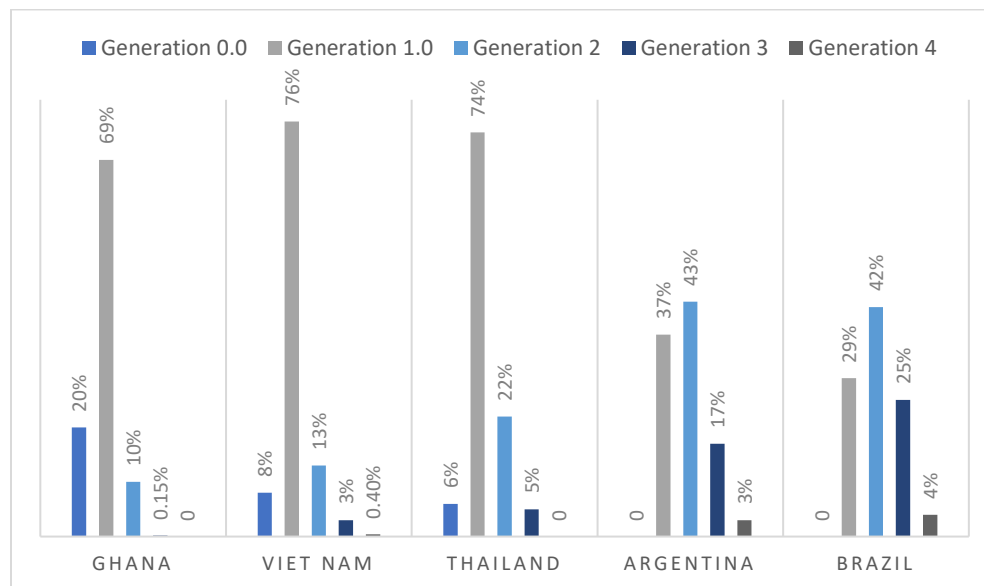
One of the most common fears about IM relates to job loss. This concern is somewhat warranted, as the increasing automation of tasks previously performed by humans may lead to job displacement. However, even for LDCs, one of the significant advantages of AI+ is its ability to lower, to an extent, the skills that people need to be able to perform certain tasks. This

means that a person without a higher education degree can, with some basic training, use sophisticated tools. In this way, AI+ can reduce entry barriers, enabling individuals who lack higher order qualifications to enter technically advanced industries.

Moreover, one important factor can make job less of an immediate concern. As Garcia-Murillo and MacInnes (2019) have reported, the process of integrating emerging technologies into organizations is slow. Large companies typically face the challenge of managing thousands of records stored in legacy computing systems, which makes upgrading or incorporating new technologies difficult. High switching costs also pose a challenge when it comes to integrating new technology, as companies often find themselves shackled to their existing systems. The problem is such that, in the 2020s, there are companies that still use computers that were programmed in COBOL (Paulson, 2001).

Because the integration of new technology is slow, companies, sectors, and countries should have time to adjust. The integration of AI+ into manufacturing will be especially slow in LDCs, which may not have the resources or technical capabilities to adopt these technologies. Figure 1 presents the adoption of automatic data processing (ADP) technologies in a sample of countries.

Fig. 1. Adoption of technologies in LDCs, by generation



(Source: Created with data from UNCTAD (2022)).

The employment and wage differential between developed countries and LDCs stems from differences in skills, education, and social and personal characteristics such as gender, age, and ethnicity (UNCTAD, 2022). The average income difference between developed countries and LDCs is \$40,000 (UNCTAD, 2022). One of the significant challenges to implementing AI+ in manufacturing within LDCs is the substantial presence (93%) of informal employment, which remains prevalent in these countries (ILO, 2018). In countries with high levels of unemployment and underemployment, companies are likely to have lower incentives to adopt Industry 4.0 technologies.

However, over the span of four decades, LDCs have become more integrated into global value chains, resulting in a significant rise in their value-added share of international trade, from 20% to 40% between 1990 and 2013 (UNCTAD, 2022). Their increased integration has largely been

caused by relatively low wages. Industrialization in LDCs has been slow, in part because they have been mostly limited to lower skill assembly processes.

Nevertheless, while LDCs face challenges, some of these countries are experimenting with IM. In Mexico, for example, the power tool manufacturer Black & Decker tagged nearly every material used in its factory with Cisco Wi-Fi radio-frequency identification tags, which were connected to a programmable logic controller that monitored quality control; this enabled the floor managers to see the entire production process and speed it up or slow it down. The introduction of this technology increased labor efficiency by 10% and improved quality by 16% (Tomás, 2018)

Similarly, in Thailand, the Thai Summit Group has introduced a fully automated assembly line that takes advantage of robots, automated guided vehicles for loading/unloading, computational vision that checks for part quality, and data that enables engineers to make corrections and reduce scrap (Thai Summit Group, 2023).

Also in Thailand, the government implemented a Thailand 4.0 initiative to move the country beyond agriculture (Thailand 1.0), light industry (Thailand 2.0), and advanced industry (Thailand 3.0), which the government believes have resulted in inequalities (Royal Thai Embassy, 2023). The objective adopts a holistic approach towards attaining economic prosperity, social well-being, uplifting human values, and environmental protection. To achieve these objectives, Thailand wants to focus on clusters of innovation and start-ups that will move its manufacturing sector from buying to making technologies. It is targeting several areas of technology and

industry including agriculture, health, smart devices, robotics, digital, IoT, and high-value services.

7. Targeted interventions over impending negatives (TIIN)

We indicated in the introduction to this paper that we would take a neutral approach to the broad assessment of AI+ in two different sectors. In doing so, we recognized that the challenges that countries face because they lack the resources, education, and technology to implement AI+ successfully will continue to be the case, but we also recognize that despite those obstacles, many entities have developed solutions to these challenges. However, it appears that we humans have not been able to anticipate or intervene proactively to address the adverse effects that technology may bring; instead, we tend to react once a problem has emerged. This is why we conceived of the notion of targeted interventions over impending negatives (TIINs). When we start to observe the negative effects of a technology before they precipitate a catastrophe, we need to seek solutions. Thus, TIINs are specific actions or strategies designed to address and mitigate potential adverse outcomes or consequences. As the name indicates, the interventions target a particular issue or challenge before it fully manifests or escalates to produce significant adverse effects.

A TIIN should be put into action upon observing evidence or early warning signs of an adverse effect, in order to prevent, minimize, or mitigate the effect. A TIIN aims to disrupt or alter the trajectory of a development towards a more favorable outcome. This paper presented examples from LDCs of the use of AI+ in agriculture and manufacturing TIIN will be needed to avert disasters.

8. Conclusion

In this paper, we describe some positive and negative consequences of introducing AI+ into agriculture and manufacturing. The paper contributes to the literature by filling a gap associated with a lack of studies at the regional level of analysis. An additional contribution is the broader scope we take to address not only labor issues, but also the well-being of workers in those sectors and the environmental effects of deploying AI+.

This paper describes the benefits of two traditional sectors, agriculture, and manufacturing. Intelligent agriculture has the potential to revolutionize food production, but it can have both positive and negative effects. It will reduce wasted resources and the costs of food production. Our review of the research indicates that AI+ can carefully monitor crops, help to reduce water usage, and minimize the use of fertilizer and pesticides, while optimizing harvest times and production (Eli-Chukwu, 2019). In contrast, adverse effects are associated with challenges in LDCs, namely, lack of credit, limited connectivity, and poor digital and data literacy. Introducing AI+ into developed countries could negatively affect small-family farmers, making them less able to compete. However, we found cases of TIINs that were able to address some of these challenges.

AI+ in manufacturing involves complex and interdependent processes that can optimize production. It can, for example, detect errors early before they propagate to later stages of production and can improve product quality. In detecting errors, AI+ can help identify the source of an error and support corrective actions. Using superior sensors, AI can improve throughput by identifying bottlenecks. Thus, AI can increase product quality and the efficiency

of manufacturing processes, and it can benefit workers through wearable technologies that provide data regarding their health conditions or alert them to the presence of pollutants and toxic chemicals.

We found that even though lower wages and education make the introduction of AI+ in LDCs difficult, the slower integration of modern technologies will give these nations some time to adjust as they catch up.

For the two sectors of agriculture and manufacturing, we have provided examples of TIINs used by companies and countries that are beginning to experiment with IM to improve their processes.

In general, we will see differential adverse effects of AI+ in agriculture and manufacturing between rich and poor regions. While TIINs offer a glimmer of hope for addressing disparities, the outcomes will be contingent upon the swiftness with which these interventions can be implemented.

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