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Human-Centered Artificial Intelligence: The Superlative Approach to Achieve Sustainable Development Goals in the Fourth Industrial Revolution

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Abstract: Artificial intelligence (AI) is currently being developed by large corporations, and governments all over the world are yearning for it. AI isn't a futuristic concept; it is already here, and it is being implemented in a range of industries. Finance, national security, health care, criminal justice, transportation, and smart cities are all examples of this. There are countless examples of AI having a substantial impact on the world and complementing human abilities. However, due to the immense societal ramifications of these technologies, AI is on the verge of disrupting a host of industries, so the technique by which AI systems are created must be better understood. The goal of the study was to look at what it meant to be human-centred, how to create human-centred AI, and what considerations should be made for human-centred AI to achieve sustainability and the SDGs. Using a systematic literature review technique, the study discovered that a human-centred AI strategy strives to create and implement AI systems in ways that benefit mankind and serve their interests. The study also found that a human-in-the-loop concept should be used to develop procedures for creating human-centred AI, as well as other initiatives, such as the promotion of AI accountability, encouraging businesses to use autonomy wisely, to motivate businesses to be aware of human and algorithmic biases, to ensure that businesses prioritize customers, and form multicultural teams to tackle AI research. The study concluded with policy recommendations for human-centred AI to help accomplish the SDGs, including expanding government AI investments, addressing data and algorithm biases, and resolving data access issues, among other things.

Keywords: Artificial Intelligence; Fourth Industrial Revolution; human-centred; sustainability

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1. Introduction

Artificial intelligence (AI) has progressed from a theoretical field to finding possible applications in various industries and everyday life in recent years [1]. Williams [1] went on to state that the development of sophisticated Machine Learning algorithms and models, with high predicted accuracy, has greatly contributed to the spread of AI. According to West and Allen [2], AI is a broad tool that allows people to reconsider how they integrate information, how they perform data analysis and apply the ensuing insights to make better decisions, and it is already revolutionizing every aspect of life. AI is, indeed, a technology that is revolutionizing every aspect of human life, even though people are not generally familiar with it. In the United States, for example, Davenport et al. [3] found that only 17% of 1500 senior corporate leaders were aware of AI. Many corporate leaders were unaware of what it was or how it might influence their firms, as West and Allen [2] put it. Many company leaders recognized that AI can significantly transform business processes, but they were unsure how AI might be used within their firms. AI isn't a far-fetched concept; it is already here, and it is being integrated and implemented across a wide range of industries [4]. West and Allen [2] indicated that the industries where AI is now being applied include "finance, national security, health care, criminal justice, transportation, and smart cities among many others".

One of the explanations for AI's growing importance is the enormous opportunity it provides for economic progress, as well as its ability to ensure that nations achieve sustainable development goals [4]. According to PriceWaterhouseCoopers [5], "AI has the potential to enhance global Gross Domestic Product (GDP) by $15.7 trillion, or 14%, by 2030. As articulated by West and Allen (2018) this can be outlined as advances of $7 trillion in China, $3.7 trillion in North America, $1.8 trillion in Northern Europe, $1.2 trillion in Africa and Oceania, $0.9 trillion in the rest of Asia outside of China, $0.7 trillion in Southern Europe, and $0.5 trillion in Latin America". China is making tremendous progress because it has established a national target of spending $150 billion on artificial intelligence by 2030, making it the world leader in this field. However, Linardatos et al. [6] pointed out that, despite increased AI and machine learning effectiveness, the models are becoming more complex, resulting in "black boxes" with which the processes are concealed from the user, making them difficult to comprehend.

Capone and Bertolaso [7] highlighted that the "black box" dilemma has sparked a great deal of debate, especially now that AI platforms are increasingly getting utilized to make vital decisions, such as aiding healthcare interventions, informing criminal justice, and assisting employment procedures, among other things. This emphasizes the importance of individuals realizing why Machine Learning methods make judgments to promote AI system knowledge, openness, confidence, and proper management [1]. Wang et al. [8] indicated that explaining capability is critical for reducing algorithm bias, strengthening human-machine collaboration, and boosting user confidence in systems. Vinuesa et al. [9] also claimed that the rise of AI, and its increasingly broad impact across various sectors, necessitates an examination of its impact on achieving the Sustainable Development Goals. In their research, Vinuesa et al. [9] discovered that AI can help achieve 134 targets throughout all goals, but it could also hinder the achievement of 59 targets. However, the fast growth of AI must be accompanied by the relevant regulatory foresight, monitoring, and supervision of AI-based technologies to facilitate long-term development. Without effective regulation, there may be inconsistencies in "transparency, safety, and ethical norms". Furthermore, research shows that AI systems are mostly oriented toward areas of the SDGs, which are important to the countries where most AI researchers live and work [9]. According to studies, there are limited examples of AI technology being used to address SDG-related concerns in countries with weak AI research. For instance, Vinuesa et al. [9] argued that AI systems used in agriculture to optimize harvesting timing are mainly located in wealthy countries.

There is a case to be made that, if AI technologies are created and developed for technologically advanced contexts, they will exacerbate food production challenges in less developed countries [9–11]. There is widespread worry that advances in AI technology could exacerbate inequality both between and within countries, undermining the SDG's overarching goal [9,12]. As a result, academics and funders must focus more on creating and developing AI solutions that address specific problems in less developed countries and areas. To boost the possibility of adoption and success, Vinuesa et al. [9] emphasized that projects doing this work should guarantee that solutions are not simply transplanted from technology-intensive nations but, rather, are designed based on a thorough appreciation of the local region and the culture.

Access to finance, according to How et al. [13], is a crucial factor in poverty alleviation, but financial institutions must know how to target the neglected effectively.

How et al. [13] went on to say that using artificial intelligence (AI) for data records can assist financial institutions in predicting how prospective clients will react when contacted. However, how et al. [13] suggested that implementing AI projects for financial service providers who are not computer programmers remains difficult. As a result, How et al. [13] developed a no-coding, human-centric AI-based methodology for simulating the probable dynamics between prospective customers' financial profiles, obtained from 45,211 contact experiences and predicting their intention toward the financial goods being sold. Awan et al., [14] suggested, in another study, that artificial intelligence (AI) becomes an increasingly effective digital domain that promises to promote instant accessibility to facts, as well as efficient decision-making, in ever-increasing business situations. Despite the growing use of big data analysis for decision-making, Awan et al. [14] noted that too little is understood, regarding whether information administration skills contribute to improved data insight, for sustainable supply chain management and circular economy.

According to Awan et al. [14], the widespread use of big data analytics and artificial intelligence, by businesses, is a vital and necessary instrument for designing the supply chain 4.0 industry's future. Explainability methods should be established to make sure that users can learn the models' behaviours and that interpretations provided to users can be enriched with greater insights that foster the users' curiosity, resulting in an exploratory dynamic toward artificial intelligence applications and domain-specific troubles, thus enabling the development of trust, according to Roanec et al. [15]. One strategy to attain this goal, according to Rožanec et al. [15], is to enrich explanations with information gathered from other sources to supplement users' knowledge and assist them in making responsible decisions.

According to Goralski et al. [10], AI is rapidly entering a fresh boundary in the sectors of "business, corporate practices, and government policy, and the intelligence of machines and robotics with deep learning capabilities has had profound disrupting and enabling impacts on business, governments, and society". Aside from that, Goralski et al. [10] feel that AI is having an impact on global sustainability trends. Goralski et al. [10] also stated that "as the AI revolution affects our world, it may announce a utopian future in which humans and machines coexist peacefully, or it may herald a nightmarish future filled with conflict, poverty, and pain". The dilemma is whether AI will help us achieve the Sustainable Development Goals (SDGs) of the United Nations (UN) or whether it will lead us down a path of more economic uncertainty, environmental collapse, and social unrest. The study's goal is to answer this question by highlighting the meaning of human-centred AI, as well as the importance of human-centred AI for sustainability, and by elucidating the implications of human-centred AI in achieving the SDGs.

2. Fourth Industrial Revolution, Artificial Intelligence, Sustainable Development, and the Global Goals

This section will help to give a background and definition of important terms in the study, such as the Fourth Industrial Revolution, artificial intelligence, sustainable development, as well as the global goals.

2.1. The Fourth Industrial Revolution (4IR)

The 4IR, also known as Industry 4.0, is defined as a "fusion of technology that blurs the barriers between the physical, digital, and biological spheres" [16,17]. The 4IR is not a continuation of the third industrial revolution, but rather, it is a new and distinct revolution. The 4IR is one-of-a-kind because of the breadth, speed, and systemic significance of the innovations, which have never been seen before. The industrial 4.0 revolution is bringing massive changes to every area of the economy; nevertheless, the potential to connect billions of people through mobile devices, with unparalleled power, storage capacity, and access to knowledge, distinguishes this revolution. Industry 4.0 is defined by emerging technology breakthroughs in artificial intelligence, robots, the internet of things, internet services, autonomous cars, 3-D printing, nanotechnology, materials science, energy storage, and quantum computing, according to Mhlanga [17].

2.2. The Background and Definition of Artificial Intelligence

The exact definition and interpretation of the term intelligence and, more specifically, artificial intelligence (AI), has sparked significant debate and uncertainty. For instance, one dictionary provides four interpretations of AI [18]. The following definitions were given by Kok et al. [18]. Firstly, in the realm of computer science, this is a field of research. Artificial intelligence is devoted to the development of computers capable of learning, reasoning, and self-correction in the same way that humans do. It can also be viewed as the idea that machines can be upgraded to have some of the same skills as humans, such as learning, adapting, self-correction, and so on. It can also be viewed as a scenario where human intelligence has been extended via the use of computers, just as physical power has been stretched using mechanized equipment in the past. Lastly, in a limited sense, artificial intelligence can be viewed as the study of methods for more successfully using computers through enhanced programming approaches. Ramesh et al., [19] also defined AI as a branch of engineering and science focused on the computational study of what is generally referred to as intelligent behaviour, as well as the construction of objects that display it.

Ramesh et al., [19] stated that "the British mathematician Alan Turing (1950) was one of the founders of modern computer science and AI. He defined intelligent behaviour in a computer as the ability to achieve human-level performance in cognitive tasks, this later became popular as the 'Turing test'". As put clearly by Kok et al. [18] rather than looking at a broad definition of artificial intelligence, one could focus on the notion of artificially intelligent systems. There are numerous definitions available, but most of them fall into one of four groups, which include human-like computer systems that can act and think rationally. This will help us describe the general qualities of AI in Figure 1 below.

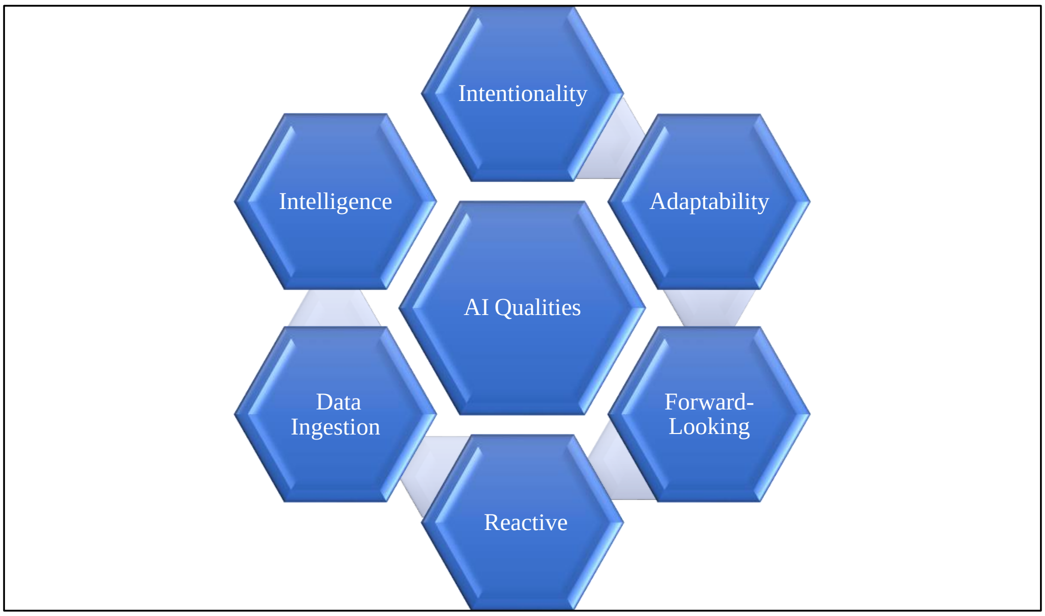

Figure 1. Qualities of AI Source: The Analysis by Author.

In Figure 1, above, the general qualities of AI are given, which include: data ingestion, which is described as AI systems with a capacity to cope with massive volumes of data, in billions of records, generated at a high rate. Intentionality means AI-powered algorithms that can make judgments based on data that is often updated in real-time, and they are different from passive machines, which are limited to mechanical or pre-set responses. Due to the increase in storage capacity, the ability to process data at high speeds, and deep analytical capacity, AI is changing how we live and posing questions for society, such as what it means to be a human being, how the economy is managed, and what systems of governance are better. Intelligence implies that AI systems can make informed decisions in conjunction with machine learning and data analytics. Here, the quality of data forms the most important part of the system: for algorithms to be able to recognize patterns that are useful for decision-making. Adaptability implies that, as computers make decisions, AI programs can learn and adapt. For instance, we have autonomous vehicles that can inform drivers and vehicles and are aware of the construction of roads along the highway, traffic obstructions, and potholes, among many other issues. Being reactive means that AI systems respond to changes in their environment. Forward-looking AI systems don't merely react;

they frequently search through a space of possible scenarios to find a successful outcome. They achieve this by projecting several steps into the future.

2.3. The Three Main Groups of AI

AI is divided into three groups, which are artificial narrow intelligence, artificial general intelligence, and artificial superintelligence.

Artificial narrow intelligence—This generally refers to AI machines' specialization, which indicates that they can use machine learning and deep-learning tools to perform a specific activity. This technique has beaten chess and Go masters, and it has won Jeopardy, an American game show [20,21]. Artificial narrow intelligence systems have been here for a long period and are used in a range of systems today, including Google's search engine. One of the limitations of artificial narrow intelligence is that it can quickly respond to factual queries that people would find difficult to explain, such as the depth of the Atlantic Ocean, what global warming is, and what causes global warming, but artificial narrow intelligence cannot answer simple questions, i.e., it is unable to respond to a question about whether a cow can ride a bicycle, which is easy for humans to answer, even as toddlers.

Artificial general intelligence—Artificial general intelligence (AGI) refers to an AI computer that is as smart as a human across the board, capable of performing any intellectual work that we can, with the ability to comprehend, and reason with, its surroundings, as well as employ understanding to any challenge, instead of just one [22–24]. Strong AI and deep AI are two terms for AGI. According to Ranjitha [25], some of the characteristics of AGI are common sense, background knowledge, transfer learning, abstraction, and causality.

Artificial Superintelligence—This relates to a machine which is substantially smarter than the smartest humans in almost every subject, including scientific inventiveness, general knowledge, and social skills [26,27]. Artificial superintelligence is a far-fetched concept that AI will one day be able to outperform human intelligence, and computation algorithms must outperform human intellect in all dimensions and settings for artificial superintelligence to emerge and then, become a reality [17,27].

2.4. Applications of AI in Real Life Situations

AI is being used in a variety of areas of human existence and in numerous sectors of the global economy. Figure 2 gives a summary of the sectors where AI is being applied the world over.

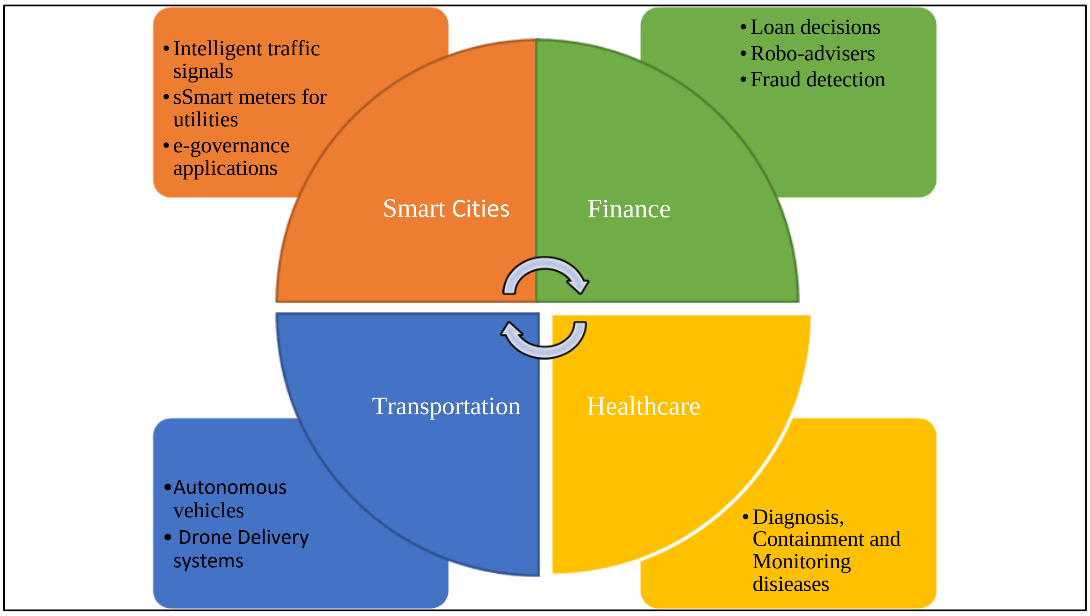

Figure 2. Applications of AI in Real Life Situations.

As shown in Figure 2, above, AI is being applied in various sectors of the economy, which include the financial sector, the healthcare sector, and the transport sector, in smart cities. Other sectors not included in Figure 2, where AI is being applied, including national security and the criminal justice system.

2.5. Research in Artificial Intelligence

AI research is progressing quickly, and the scientific debates surrounding this topic are dwindling with each passing decade. AI research output keeps rising steeply, as expenditures and profits rise year after year, and countries compete for dominance in this area [28,29]. Crew [29] stated that considerable ethical and technical difficulties remain to be overcome. Due to increased processing power, huge data sets, and unparalleled, algorithmic sophistication, the number of journal and conference publications referring to AI in the Dimensions from Digital Science database surged by more than 600% between 2000 and 2019 [29]. The "Nature Index provided the top 100 AI academic institutions", dominating AI research in the world. For purposes of this study, the top 10 and lowest 10 institutions will be presented to assist in understanding how AI research is spread. The top ten artificial intelligence academic institutes are listed in Table 1.

Table 1. The top ten AI academic institutes.

Number	Institution	Location	Share 2015–2019	Count 2015-2019	International Articles (%)
1	Harvard University	United States of America (USA)	331.08	937	57.0%
2	Stanford University	United States of America (USA)	257.90	629	54.4%
3	Massachusetts Institute of Technology (MIT)	United States of America (USA)	209.04	620	59.4%
4	Max Planck Society	Germany	167.98	628	83.0%
5	University of Oxford	United Kingdom (UK)	132.34	495	85.3%
6	University of Cambridge	United Kingdom (UK)	130.68	485	84.9%
7	Chinese Academy of Sciences (CAS)	China	130.00	492	73.2%
8	UCL	United Kingdom (UK)	129.70	415	77.1%
9	Columbia University in the City of New York (CU)	United States of America (USA)	127.56	386	61.9%
10	National Institutes of Health (NIH)	United States of America (USA)	122.69	302	52.0%

Source: The Author's computation Nature Index data [28].

According to the Nature Index [28], most institutions in the top ten dominants in AI research are all in America (Table 1). Only one German institution, three from the United Kingdom, and one from China made it into the top ten. The lowest ten of the top 100 artificial intelligence academic institutions, according to the Nature index of 2020, are listed in Table 2.

As shown in Table 2, most institutions leading the bottom 100 in AI research are in America, with only two from China, one from Italy, one from Singapore, and one from the Netherlands. This data is only showing that AI research is more common in America when compared to the whole world. According to Savage [30], over the last two decades, the United States has consistently been the global champion in AI-related research output, with the greatest number of articles. However, Savage [30] noted that China's output has risen in recent times. According to Dimensions, China produced more AI-related papers than any other country from 2016 to 2019. China's AI-related research production surged by a little over 120%, while the US output increased by over 70%. China published 102,161 AI-related articles in 2019, whereas the United States published 74,386. India finished third with 23,398 publications [30]. This was different from the information presented by the Nature Index 2020 where, AI-related publications, across all fields in the Dimensions database, China as the clear leader, in contrast to the Nature Index, where Western universities dominated in the application of AI in the natural sciences.

Table 2. The bottom 10 in the top 100 artificial intelligence academic institutions from the Nature index of 2020.

Number	Institution	Location	Share 2015–2019	Count 2015–2019	International Articles (%)
90	Cold Spring Harbor Laboratory (CSHL)	United States of America (USA)	23.15	54	44.4%
91	Dartmouth College	United States of America (USA)	22.89	53	45.3%
92	Purdue University	United States of America (USA)	22.78	98	74.5%
93	Carnegie Mellon University (CMU)	United States of America (USA)	22.77	99	58.6%
94	Utrecht University (UU)	Netherlands	22.61	87	83.9%
95	Mount Sinai Health System (MSHS)	United States of America (USA)	22.38	108	63.9%
96	Fudan University	China	22.14	77	72.7%
97	National Institute for Nuclear Physics (INFN)	Italy	22.14	233	97.0%
98	Tel Aviv University (TAU)	Israel	22.05	137	86.9%
99	National University of Singapore (NUS)	Singapore	21.81	84	85.7%
100	University of Science and Technology of China (USTC)	China	21.50	119	78.2%

Source: The Author's computation Nature Index data [28].

2.6. Sustainable Development and the Global Goals

Sustainable development is defined "as development that meets the current generation's needs without jeopardizing future generations' ability to meet their own" [4]. The notion of sustainable development "incorporates two major concepts: the requirements of the poor, particularly their basic needs, which should be prioritized, and the restrictions imposed on the environment's ability to supply existing and future demands by the state of technology and social organization" [4]. "Sustainable development" is described by Duran et al., [31] as "the juxtaposition of two major aspects". According to Duran et al. [31], "the first phrase, durable, refers to long-term viability and sustainability, whereas development refers to the process of extending or constructing one's potential; progressively bringing one's potential to a fuller, larger, or better condition". The term "sustainability" refers to a multifaceted strategy that is being discussed at a time when environmental concerns, caused by numerous human activities and, at the same time, the unavoidable changes caused by the Fourth Industrial Revolution, demand urgent action and remedies.

According to Dasgupta [32], the term "sustainability" became popular after the World Commission on Environment and Development published the Brundtland Commission Report, which defined sustainable development as "development that meets current needs without jeopardizing future generations' ability to meet their own needs", as defined by Mhlanga [4]. Dasgupta [32] went on to state that "the concept of sustainability is that each generation should leave its successor at least as large a productive foundation as it inherited from its predecessor in terms of their respective demographic bases". If that happens, "the successor's economic prospects would be no worse than those it had when inheriting productive assets from its predecessor" [32]. The country's productive basis includes capital assistance and institutions, as well as cultural coordinates. However, in the current revolution, the country's productive capabilities have been extended to incorporate big data, which is a post-industrial possibility, sometimes referred to as the new oil, in the twenty-first century, fuelling AI for development. The point we make in this article is that, as new drivers of development and as part of the productive basis, data and AI must be deployed with humans in mind. Since the productive foundation of the country is the source of its well-being, there is a need for the deployment of these resources to be at the centre of the people to attain sustainable development.

Rees [33] posits that "Sustainable development is the positive socio-economic change that does not undermine the ecological and social systems upon which communities and society are dependent. Its successful implementation requires integrated policy, planning and social learning processes, its political viability depends on the full support of the people it affects through their governments, their social institutions, and their private activities". As a result, it is equally clear that the issue of human-centred application of AI is prioritised because, in its absence, sustainable development will have some challenges before it can be achieved. Tomislav [34] argued that, since its inception, the notion of "sustainable development" has gone through several stages of development. The concept has evolved to meet the current needs of a complicated global ecosystem, but the core concepts and aspirations, as well as the challenges of execution, have remained largely unchanged [34]. This is the primary reason why topics such as human-centred AI should begin to be discussed. According to Redclift [35], the concept of sustainability is frequently muddled. Some academics are worried about the natural resources base's sustainability, while others are concerned about current or future levels of output and consumption [35]. Redclift [35] asserts that there are significant variations in thought about how to attain environmental sustainability and sustainable development. Therefore, it's crucial to study the many aspects of sustainability independently, as well as the kind of global regulations that will be necessary to attain sustainable development.

2.7. The Global Goals

According to UNICEF [36] "the Sustainable Development Goals (SDGs) were adopted by all United Nations Member States in 2015 to end poverty, reduce inequality and build more peaceful, prosperous societies by 2030". The Sustainable Development Goals (SDGs), often known as the Global Goals, are a call to action to achieve a world where no one is left behind [36]. Figure 3, below, outlines all the 17 global goals.

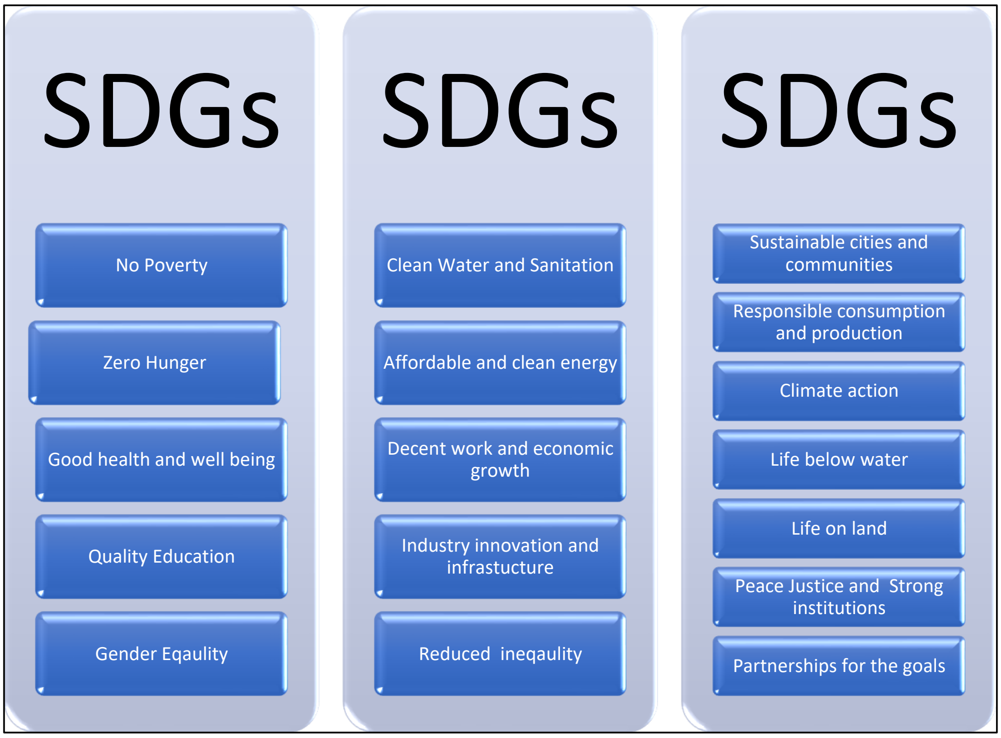

Figure 3. The 17 SDGs. Source: Author's Analysis.

Figure 3 outlines the 17 SDGs, which include "no poverty, zero hunger, good health and well-being, quality education, gender equality, clean water and sanitation, affordable and clean energy, decent work and economic growth, industry, innovation and infrastructure, reduced inequality, sustainable cities and communities, responsible consumption and production, climate action, life below water, life on land, peace, justice, and strong institutions, partnerships for the goals".

3. Empirical Literature Review

AI is influencing a growing number of industries, including global productivity, equality and inclusion, environmental results, and a variety of other domains [9]. The reported possible consequences of AI reveal both good and negative impacts on sustainable development [9]. As a result, several studies investigating the impact of AI on sustainable development are emerging in recent years. Di Vaio et al., [11] looked at the literature on the function of AI in the development of long-term business models. The findings of Di Vaio et al., [11] show that the innovation challenge has ethical, social, economic, and legal dimensions, and the findings also outline the framework of existing literature on AI and SDGs, particularly SDG12, which includes AI's link to cultural drift (CD) in the development of sustainable business models. Truby [12] has warned that big tech's unchecked roll-out of experimental AI poses a risk to the SDGs, with impoverished countries being particularly vulnerable. Truby [12] also said that the objective of inclusive growth is jeopardized by the flawed and unregulated formulation and construction of artificial decision-making software that affects consumers' economic choices. Computerized decision algorithms are biased, lack ethical accountability, and restrict openness in the rationale for their conclusions, resulting in unfair outcomes and exacerbating uneven access to money [12].

Truby [12] further argued that Big Tech's anticipated manipulation of underdeveloped countries, using AI to capture data and money, endangers poverty alleviation and sustainable development. The possible misuse of AI could jeopardize stakeholder gains in avoiding financial crime and corruption. Considering these dangers, Truby [12] stated that Big Tech's shady past implies it can't be trusted to operate without oversight and recommended viable pre-emptive legislative alternatives to reduce the possibility of AI harming the SDGs. Finally, Truby [12] claims that, by anticipating such issues in advance, well-designed rules, based on international standards, can permit continuing AI innovation. Again, Truby [12] emphasizes the dangers of unregulated AI endangering human values, where public and regulatory reactions could lead to overregulation, jeopardizing AI's otherwise beneficial growth.

Although there is a rising commitment toward AI for sustainability, such as towards the Sustainable Development Goals, van Wynsberghe [37] argues that it is necessary to go further and tackle the sustainable growth of building and using AI systems. Sustainable AI, according to van Wynsberghe [37], is a strategy to promote change throughout the whole lifespan of AI products, including idea development, education, re-tuning, deployment, and administration, to achieve higher environmental balance and social fairness. Sustainable AI, according to van Wynsberghe [37], is concerned with much more than machine learning and artificial intelligence; rather, it is concerned with the entire engineering design process of AI, and it is concerned with developing AI that is coherent with preserving environmental assets for existing generations and generations to come, economic structures for societies, and social norms that are foundational to a large community. Another key issue raised by van Wynsberghe [37] was that sustainable AI should be divided into two branches: AI for sustainability and the sustainability of AI. Sustainable AI should include three tensions: "AI innovation and equitable resource allocation; intergenerational and intragenerational justice; and the environment, society, and economy" [37].

According to Williams [1], the rising sophistication of AI processes that results in the black-box dilemma has prompted the subject of Explainable AI to emerge in response to user demand for transparency. Unexplainable AI research, according to Williams (2021), has leaned, primarily, more toward a technical, machine-centred approach, with little focus on the humans, as well as on how to make machine learning conclusions more comprehensible for them. According to Williams [1], the major purpose of explainable AI is to increase user trust in AI systems, and the most popular ways to human explainable AI are context-awareness and personalisation.

Astobiza, et al. [38] suggested that we live in a golden age, whereby global issues such as climate change exist, and responses to such issues must be organized at the global scale. Astobiza, et al. [38] believe that, as AI progresses, many academics are investigating the prospect of using it to solve societal problems, which is a concept known as AI for social good. AI for social good refers to the use of AI-powered technologies and capabilities to promote public welfare. The primary goal of any AI for social good application is to address social issues. One of the key goals of explainable AI, according to Jentzsch et al., [39], is to increase confidence in technologies by allowing users to explicitly request facts and explanations from an intelligent agent. van Berkel et al. [40] also argued that the resurgence of big data, combined with technological advances in AI, has opened new possibilities for independent and consistent decision-making. While preliminary research has started to study how human morality can impact the decision-making of future Artificial Intelligence systems, van Berkel et al., [40] contend that these approaches often treat human morals as static and immovable. Pisoni et al. [41] also conducted a research review on using technologies in museums and cultural attractions to develop and deliver accessible experiences. Pisoni et al. [41] emphasized the significance of delivering AI that is suitable for everyone from various fields of knowledge and experience, such as interaction design, pedagogical design, and participatory design, and it shows how recent and future AI advancements can be used to improve and broaden online and in-person accessibility. De Cremer et al. [42] also argued that the increasing usage of advanced systems has led us to a fork in the path. De Cremer et al. [42] went on to state that intelligent technology producers are gaining the ability to introduce a plethora of things that are significant to human end-users. The very same smart technology, according to De Cremer et al. [42], is also utilized, deliberately, to degrade and, sometimes, even intentionally hurt the interests of those same end-users. Consequently, in the lack of a re-calibration, technological solutions will, almost surely, represent the interests of technology developers and owners rather than the interests of humanity.

4. Research Methodology

To address an articulated question, a systematic literature review through content analysis, which seeks, chooses, and then, critically assesses information, is used. First, before a thorough analysis is undertaken, the objectives must be explicitly outlined in a strictly delineated methodology or plan. It is an open, thorough search that spans several datasets and publications, and it can be duplicated by other academics [43,44]. A systematic literature review, according to Kitchenham et al. [44], entails devising a well-thought-out research strategy that focuses on a certain topic or addresses a particular question. Within established timelines, the review indicates the piece of data that is retrieved, criticized, and submitted. The evaluation should include the search words, search tactics, encompassing database identities, systems, searching periods, and limitations [45] (Fisch and Block 2018). Several principles are driving the systematic literature review [46]. Figure 4, below, outlines these principles.

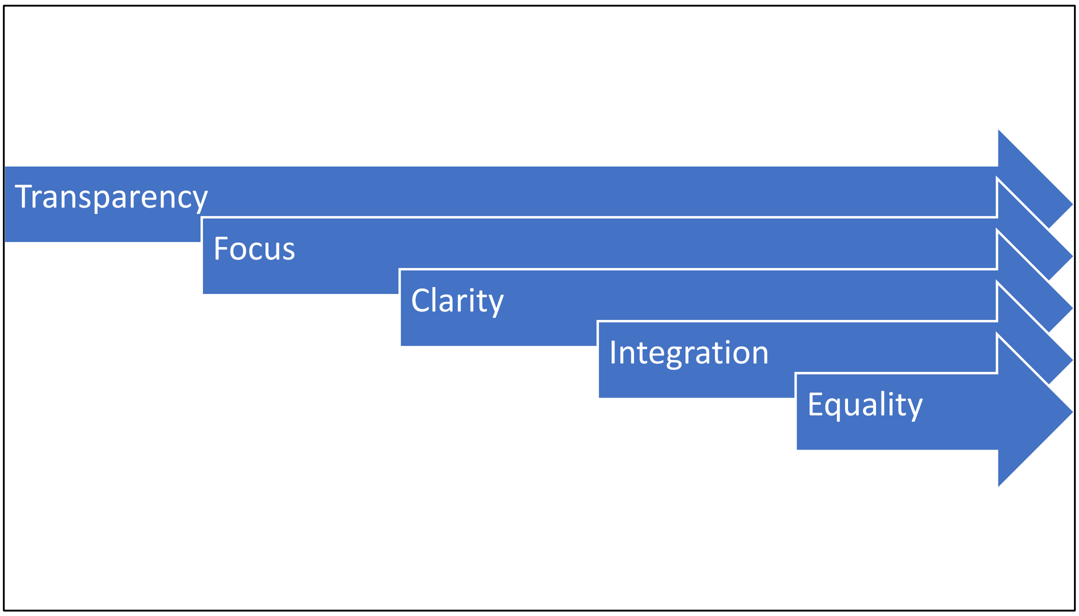

Figure 4. The principles behind the systematic literature review. Source: Author's Analysis.

Figure 4, above, is outlining the principles behind the systematic literature review, which include the following: transparency, clarity, integration, focus, equality, accessibility, and coverage.

A great literature review must have a strong focus and must concentrate on information that has already been published on a particular topic or set of questions. However, according to Linnenluecke et al. [43], although systematic reviews can be done by a single researcher, there is a risk that critical factors, such as the determination of criteria for study integration, aren't subjected to any assessment, which could create bias. A research group that includes a critical appraisal specialist, a subject matter/content expert, and, maybe, a technique specialist could help counter such restrictions [43]. The first scoping exercise must be carried out to get a basic understanding of the current situation of research, and it may even be advantageous for specialists, in their respective fields, to design a structure for a systematic review. The documents utilized in the systematic literature review are listed in Figure 5.

Figure 5. Documents used in the systematic literature review.

The papers and materials utilized for systematic evaluation in the systematic literature review are listed in Figure 5. Some of the documents include press releases, grey literature, conference proceedings, books, and journal articles, among others. The keywords that were searched in the research were Artificial Intelligence, Fourth Industrial Revolution, human-centered, Sustainability, and the sustainable development goals. In Table 3, important sources for the study were outlined, and the inclusion and exclusion criteria were also outlined.

Table 3. Important sources for the study.

Journal Articles	**Reports**	**Media Articles**	**Others**
55	25	30	20
Journals articles used were those published in 2000 upwards. Work from previous years was also considered but the focus was mainly 2000 upwards. Publishers-Springer Nature, Multidisciplinary Publishing, Es, Elsevier Institute of Electrical and Electronics Engineers, etc.	Reports from United Nations, The World Bank, The World Economic Forum, and Development (OECD) among others were also considered in the study.	Media articles were also considered mainly from countries such as the United State of America, South Africa, and the United Kingdom among other nations.	Various other documents were consulted to come up with the ideas that shaped the trajectory of the study.

Source: Author's Analysis.

The number of documents that aided in shaping the study's direction is listed in Table 1. Documents from peer-reviewed journals were used in the research. Journals published from the year 2000 onwards were considered, while work from previous years was also considered. Among the publishers chosen were Springer Nature, Multidisciplinary Publishing, Es, and the Elsevier Institute of Electrical and Electronics Engineers. Various reports and news items were also considered. The next section will directly deal with the research questions and objectives of the study.

5. Results and Discussion

As previously stated, according to Goralski et al. [10], "as the AI revolution touches our world, it may herald a utopian future in which humans and machines coexist happily, or it may herald a nightmare future filled with violence, poverty, and agony". The question is whether AI will assist us in achieving the SDGs or whether it will lead us down a path of increased economic uncertainty, environmental collapse, and social upheaval. This section will highlight the purpose of the study in greater detail. The section will begin by outlining the meaning of human-centred AI, and the considerations to be followed for human-centred AI, to attain sustainability and SDGs, are then discussed.

5.1. The Meaning of Human-Centred AI

A human-centred AI strategy aims to establish and implement AI systems in manners that enhance humanity and suit their interests. To achieve this goal, we acknowledge that a human-centred AI strategy should promote and strengthen people's feelings of competency, participation, authority, and well-being [42,47]. The question, now, is what is human-centred AI? According to IBM [47], human-centred AI is a new field aimed at developing AI systems that complement, rather than replace, human capabilities. The main idea is that AI aims to maintain human influence in a manner that guarantees artificial intelligence fits our requirements, whilst also being transparent, equitable, and respectful of privacy. Cognizant [48] human-centred AI focuses on algorithms that reside within a wider, human-based system, learning through human inputs and collaborations. Human-centred AI refers to technologies that improve over time, because of human involvement, while also offering a positive human–robot interaction. Again, human-centred AI refers to technologies that improve over time because of human involvement, while also offering a positive human–robot interaction. Figure 6, below, outlines the benefits of human-centred AI to various stakeholders.

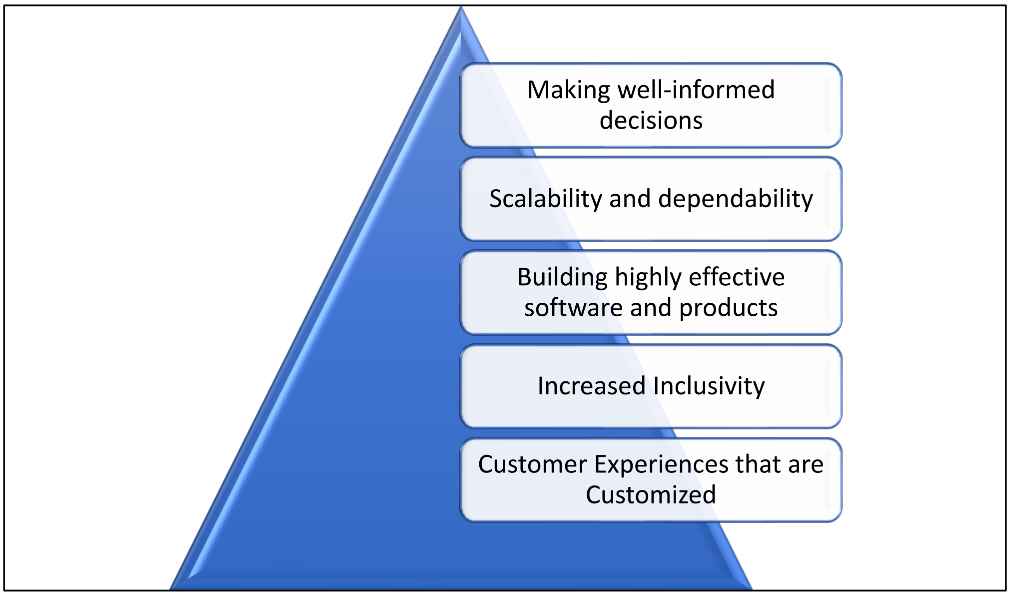

Figure 6. Benefits of human-centered AI to various stakeholders. Source: Author's Analysis.

In Figure 6, above, the various benefits of human-centred AI are outlined, which include making well-informed decisions, dependability, scalability, building highly effective software and products, increased inclusivity, and customised customer experiences. In terms of enhanced inclusivity, a human-centred strategy puts humans in the loop while developing AI, allowing them to check for prejudice in algorithm decisions [49]. Computer algorithms are not always the answer to the problems of human bias. With feedback loops, computer algorithms can aggravate and magnify biases [48–50]. Completely unchecked, a biased algorithm will not give objective, unbiased decisions, according to Appen [49], which is especially problematic if the algorithm is determining critical society decisions, such as parole, loans, and job seekers. Human-centred AI architects, according to Shneiderman [50], acknowledge that humans are gladly, and effectively, intertwined in social networking sites; for example, at the workplace, we are entrenched in social systems of superiors, colleagues, and employees whom we wish to impress, motivate, and appreciate. As a result, Shneiderman [50] advocated that those computers should serve a supporting role in human-centred AI, enhancing people's ability to work in skilful or remarkable ways. Although an increasing number of individuals are requesting that AI computers include a "human in the loop," Shneiderman [50] claimed that this phrase frequently indicates hesitant adoption of human control panels. Those who want a perfect solution, on the other hand, are averse to the idea that human interference, inspection, and control are necessary, but the "Human-Centered AI bumper sticker would be Humans in the group; computers in the loop" [51]. The method creates a system of checks and balances in which neither the person nor the computer is autonomous, making it easier to uncover methods to improve outcomes [48,49].

To make well-informed decisions, AI is also required [52]. The human-centred approach uses a combination of human and machine capabilities to counteract each other's shortcomings, resulting in more reliable algorithms centred on human values [53]. It was also argued that the goal of human-centred AI is to supplement human talents with smart, human-informed technologies, rather than to entirely replace humans. Furthermore, by combining the precision of machine learning with human guidance and values, human-centred AI assists firms, particularly their employees, in making more informed decisions and establishing clearer plans and responses to problems [54]. Companies profit because of being able to make well-informed decisions, which have the potential to provide the greatest results, thanks to the use of predictive modelling in mission-critical use cases, such as cloud operations [54].

Again, human-centered AI plays an important role in ensuring that our abilities, as human thinkers, and ideas are scaled to meet far greater data requirements [55]. AI's goal is to assist humans, yet sometimes, it can only do so much without human input and understanding. Taking a human-centric AI strategy, it is thought, puts some of the computational heavy liftings on technology's shoulders, while still leveraging emotional and cognitive input from humans. While it may appear that depending solely on algorithms is a better, more predictable option, a human-centred approach to AI is a more dependable alternative [55,56]. Designers and product developers can tap into "user behaviour and conscious and unconscious trends to build items/solutions that apply more fulfilment, informed, enriching, and, in the case of entities like Instagram or games, addictively rewarding user experiences by applying behavioural science principles to technology through human-centred AI" [56]. One of the advantages of human-centred AI is personalized customer experiences [57]. When we interact with technology, whether it is a chatbot, a personalized email, a social network geared to our wants, or a flawless search bar, we feel more content if the contact was tuned to us and our needs. Personalization such as this, according to Cognizant [48], can only happen if our goals, requirements, and behaviours are considered throughout the development of the technology. Human science informs AI research, resulting in solutions that provide a more enriching and rewarding user experience [57].

5.2. How to Create AI That Is Human-Centred

Following a discussion of the concept of human-centred AI and some of its benefits, it is equally necessary to define how to put this approach into practice. This study outlines a few measures that can be performed to help achieve the necessary balance for human-centred AI, as suggested by various scholars, including Lepri et al., [58], Shneiderman [51], Shneiderman [59], and Shneiderman [56].

In Figure 7, below, the procedure for creating human-centred AI is presented, which includes making use of the human-in-the-loop concept, promoting accountability for AI, considering how autonomy should be used wisely by businesses, being conscious of human and algorithmic biases, noting that customers should be a priority for businesses, and advocating that multicultural teams should be formed by organizations.

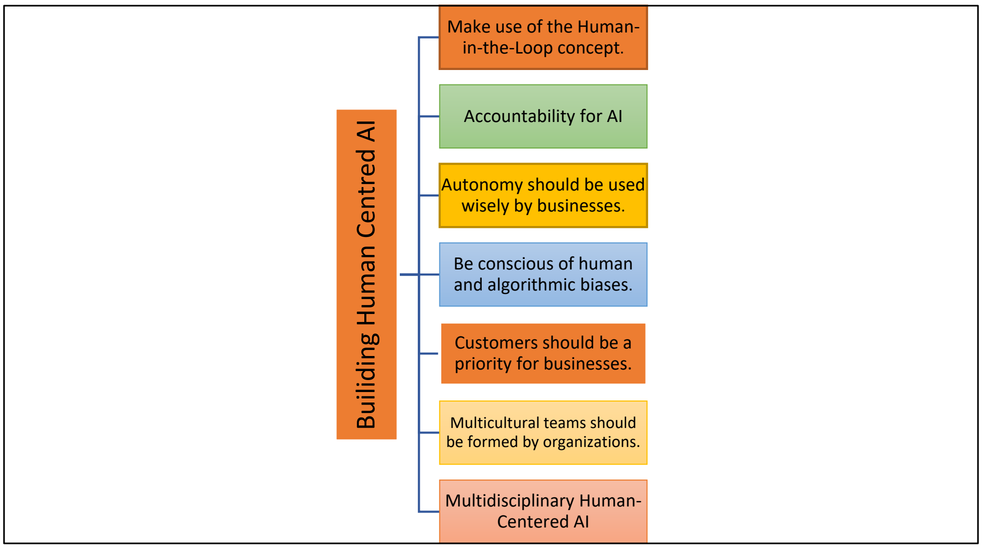

Figure 7. How to Create AI That is Human-Centered.

Make Use of the Human-in-the-Loop Concept—The human-in-the-loop approach is synonymous with human-centred AI, and it is defined as the process of involving humans in the intensive training, testing, and tuning of machine learning models. Humans can categorize the training data to help the model understand which characteristics to identify, for example. People may, again, evaluate the quality of the model's prediction, as well as provide input to the algorithm when it gets something wrong, implying that people are a component of the model's continuous feedback loop [60–62].

Promoting Accountability for AI—Accountable AI is a human-centred, empiricist-driven strategy which should apply in all spheres of life. Shneiderman [51] argued that "accountable AI should be strong in military applications where responsibility within a chain of command is a core value and even when the case for autonomy in defensive systems is strong, no weapons systems should be fully autonomous". Shneiderman [51] also stated that the "Human-Centred AI approach also applies to the popular notion of autonomous vehicles or self-driving cars, where attaining adequate levels of safety will require an empiricist's outlook and design of effective user interfaces to enable meaningful human control, even as the levels of automation increase". Self-driving cars should become safety-first cars in which proven methods, such as collision avoidance, are improved by better user interfaces [51,58]. Then, further, "improvements will come from vehicle-to-vehicle communication, improved highway construction, and advanced highway management centres that build on the strategies of air traffic control centres. Moreover, many types of AI systems should include logging activity to support a transparent and retrospective review of failures and aggregate patterns of usage" [51].

Autonomy Should Be Used Wisely by Businesses Organisations—Various academics think it is crucial to recognize that machine autonomy has a role in AI at selected critical times, but the autonomy must be utilized carefully and with greater caution [49,63]. Some believe that there may be few situations where computers should have complete authority over how to make a choice, particularly when human safety is at stake. Automated automobiles, according to some, are one example where autonomy is desirable. Human drivers are often susceptible to accidents, and most of these accidents are typically a result of poor judgment by drivers behind the wheel. According to Fan [64], human behaviour is one of the common sources of catastrophes on many highways where motorists fail to prevent or escape car collisions with automobiles that are about to clash. Aljaban [65] agreed with this, concluding that human behaviour is the primary cause of accidents. According to the findings by Aljaban [65], the two most important factors influencing car accident rates are traffic induced by work morning rush hours and urban density. Self-driving cars, according to Appen [49], offer the potential of generating efficient and safe judgments on behalf of human-driven cars, and that might be a good scenario wherein autonomy must be prioritized. However, Appen [49], concluded that autonomy should be used judiciously for more delicate use cases, and an effective combination of human and machine intelligence may be a viable option for making roads safer for all of us.

Be Conscious of Human and Algorithmic Biases—Bias awareness is critical in the AI development process to ensure that users do not depend too heavily on humans or computer judgments [49,66]. With the extensive usage of AI applications and systems in our daily lives, accounting for fairness has become increasingly critical in the development and engineering of these systems, according to Mehrabi et al. [66]. AI systems are increasingly often utilized in many sensitive contexts to make significant and life-changing decisions, so it is critical to guarantee that all such judgements do not exhibit discriminatory practices toward specific individuals and communities [66]. Organizations should consider the prejudices that their employees might unwittingly incorporate into their algorithms and formulate appropriate mitigation strategies to avoid this [49]. Algorithms can help compensate for human blind spots, but humans must make sure to check the model's outputs for biases regularly; machines can sometimes exaggerate human prejudices [49]. Biased algorithms, according to Panch et al. [67], might lead to a lack of a defined norm of fairness. Panch et al. [67] claimed that "a consumer study of an image search on a popular search engine indicated that 11 percent of results for the phrase CEO were female, even though 20 percent of CEOs in the United States were women at the time". The question is whether the algorithms in question were biased or if they reflected the available data. Algorithms are educated on data from the real world, which necessitates extra stewardship. This is exacerbated by the fact that there is no universally acknowledged quantifiable summary criterion for fairness. Therefore, assessment is essentially subjective and sensitive to the evaluators' latent biases [67].

Customers Should be a Priority for Businesses—The human-centred approach relies on keeping human experiences at the centre of all activities. When creating an AI product, companies should ensure that the result improves and enriches the lives of their customers [49,56]. Organizations should know who these consumers are and consider their demographic, background, interests, and location, among other factors. It is also important to think about how they will use AI technology. One of the best ways to get consumer input is to involve a section of the consumers who will use the product in the verification and validation process. People may believe that a product is only utilized for one purpose, whereas end users may use it for multiple purposes. The only approach is to include them in the testing and validation process [56].

Multicultural Teams Should be Formed by Organizations—Recalling the importance of being aware of human and algorithmic biases, AI is less prejudiced when created by multicultural groups [68,69]. Identical blind spots, prejudices, as well as other gaps, exist in more homogeneous teams, which might be captured in the actual models [49]. The individuals who analyse data in an organization, as well as those who develop the algorithms, must have at least some demographic varieties to have a wider range of viewpoints in the process, resulting in even more inclusive AI [68,69].

Human-centred AI should be Multidisciplinary—Another significant consideration is to tackle AI research from a multidisciplinary standpoint where "engineers, psychologists, designers, anthropologists, sociologists, and experts from other fields should all be included in the human-centred approach" [68,69]. According to Appen [49], developing a successful human-centred AI requires collaboration from several fields to create the hardware or software and analyse user behaviour when dealing with AI in various social circumstances, as well as domain knowledge for applications. Due to the disparity in discipline vocabulary and methods, collaboration can be challenging. Scholars have claimed that this wide range of participants' shared interest in human-centred AI is a powerful motivation for familiarizing oneself with and valuing the various ways of obtaining knowledge [68,69].

6. The Policy Recommendations for Human-Centred AI to Assist in the Attainment of the SDGs

This section will discuss the various policy implications of human-centred AI in achieving the SDGs. Some of the proposals for human-centred AI that can help with the SDGs are outlined in Figure 8.

Some policy ideas for human-centred AI, to aid in the achievement of the SDGs, are shown in Figure 8. Increasing government AI investments, addressing data and algorithm biases, and resolving data access challenges are just a few of the policies that will be presented and explained in the next paragraphs.

6.1. Increase Governments Investment in AI

The socioeconomic benefits of AI are significant and difficult to notice across the globe. As a result, there is an increased need for government investment in AI around the world. Governments should not transfer AI investment to the private sector because the duty of supervising AI and ensuring that any new technology is human-centred demands significant resources on its own. Therefore, governments must be the leaders in AI investment. As previously stated, Truby [12] warned that big tech's unfettered deployment of experimental AI constituted a threat to the SDGs, with developing countries being particularly vulnerable. Truby [12] has stated that the incorrect and unregulated formulation and construction of artificial decision-making software that influences consumers' economic decisions jeopardize the goal of equitable growth. To guarantee that AI deployment is human-centred and does not jeopardize the achievement of the SDGs, it must be included in a larger percentage of government spending. According to Williams, the increasing sophistication of AI processes, which leads to the black-box conundrum, has spurred the issue of explainable AI to emerge in response to user demands for transparency. Unexplainable AI research, according to Williams [1], has largely focused on a technical, machine-centric approach, with little regard for humans or how to make machine learning outcomes more intelligible for them. The major purpose of explainable AI, according to Williams [1], is to increase user trust in AI systems, with context-awareness and personalisation being the most popular techniques. The conclusion reached, in this article, is that governments should invest more in AI to ensure that it is more understandable and does not jeopardize the achievement of the SDGs.

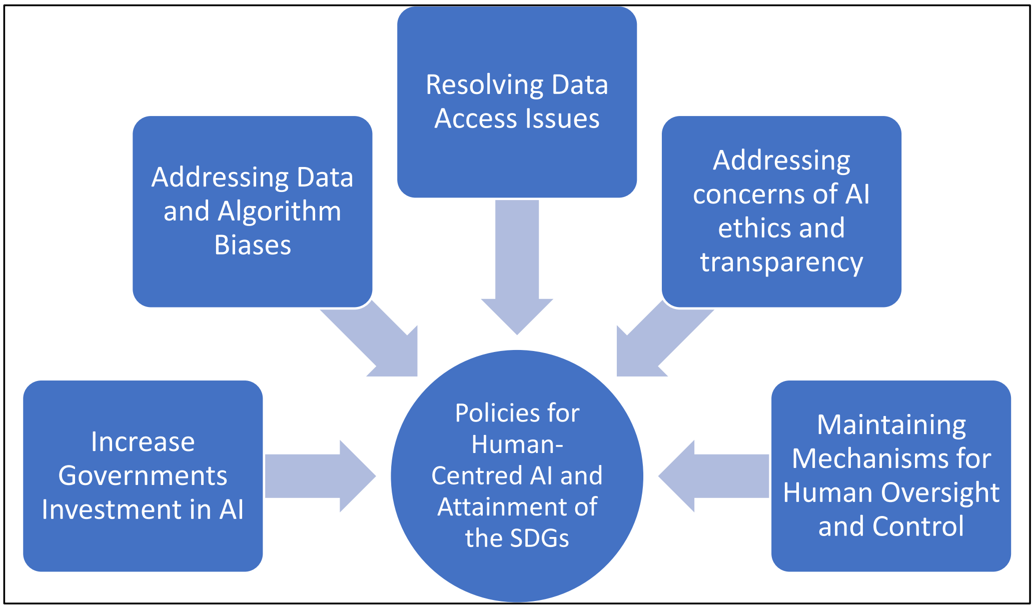

Figure 8. The Policy Recommendations for Human-Centred AI to Assist in the Attainment of the SDGs. Source: Author's Analysis.

6.2. Addressing Data and Algorithm Biases

In many situations, AI systems have enabled discriminatory or biased practices [70,71]. One example that was given is Airbnb, which was accused of discriminatory practices, by some homeowners on its platform, against racial minorities. According to Edelman et al., [72], applications from visitors with distinctly African American names were 16% less likely to be approved as compared to visitors with exclusively white names. Edelman et al. pointed out that discrimination happens among landlords of all sizes: both small landlords sharing a single property and bigger landlords with many properties. While rental markets have seen considerable decreases in discrimination in the past few decades, Edelman et al., found that Airbnb's current design raises the prospect of reversing some of these civil rights gains. It was also mentioned that facial recognition technologies can cause racial issues. Most of these systems work by matching a person's face to a big database of faces. The difficulty is that if one's facial recognition data is primarily Caucasian, that is what the software will learn to recognize unless the databases have varied data. These programs struggle to acknowledge African, African American, or Asian-American traits. Several historic large datasets reflect conventional ideals, which might, or might not, reflect contemporary system choices. Due to the inevitable advent of automation and the greater dependence on an algorithm for high-stakes determinations, including whether people get insurance, the probability of defaulting on a loan, or the probability of readmission, algorithm bias is an issue that requires confrontation. Even admissions choices are becoming more computerized, including the schools our children attend and the options available to them. Efforts should be applied in such a way that we do not bring the past's structural injustices into the future we are creating. These prejudices must be addressed if AI is to be human-centred and not jeopardize the achievement of the SDGs.

6.3. Resolving Data Access Issues

Scholars feel that establishing a data-friendly ecosystem, with clear standards and cross-platform collaboration, is critical to getting the most out of AI. AI relies on real-time data that may be studied and applied to specific challenges. A necessity for successful AI development is having data that can be explored by the academic community. According to a 2020 McKinsey survey, countries that promote open data sources and data sharing are the ones most likely to experience AI advancements [73]. This paper contends that overcoming data access difficulties will allow AI to have a significant impact on economic development and, as a result, accelerate the achievement of the SDGs. Governments across the globe should have coherent national data strategies making it possible for people to access data with minimal restrictions [73]. There needs to be a clear understanding of who owns data and how much of it is in the public domain for everyone to access. There should not be a situation where there are uncertainties that impede economic innovation and occasionally negatively impact academic research. Various academics believe that AI requires data to test and improve its learning ability since gaining the full benefits of artificial intelligence will be difficult without structured and unstructured data sets [72,73]. However, it is vital to stress that there should be checks and balances in place to prevent the misuse of commercial and government data, as was the case with Cambridge Analytica's use of Facebook data. Data can be shared in a variety of ways, including voluntary agreements with firms, government infrastructure that facilitates collaboration, and public–private data partnerships that integrate government and industry data sets to improve system efficiency.

6.4. Addressing Concerns of AI Ethics and Transparency

Education and awareness of AI should be the beginning step. Externally and internally, there must be clear information about what AI can achieve and its challenges. It is possible to misuse AI, so businesses must determine the appropriate uses for AI and how to keep inside set ethical boundaries. Everyone in the company needs to know what artificial intelligence is, how it can be used, and what the ethical issues are. As previously said, organizations should be cognisant of bias in AI development to ensure that they are not relying too heavily on human or machine judgment [49,66]. As several researchers have pointed out, "algorithms embed ethical issues and value choices into program decisions, raising questions about the criteria utilized in automated decision-making. Some folks are interested in learning more about how algorithms work and what decisions are made. Many urban schools in the United States, for example, utilize algorithms to make enrolment selections based on factors such as parent preferences, neighbourhood characteristics, economic level, and demographic background". The algorithms must be transparent while making these decisions so that users can understand what is going on.

The "black box" dilemma has sparked a lot of debate, according to Capone and Bertolaso [7], especially now that AI platforms are increasingly being used to make important decisions such as assisting healthcare interventions, informing criminal justice, and assisting employment procedures, among other things. This highlights the significance of people understanding why machine learning methods make decisions to enhance AI system knowledge, openness, confidence, and good management [1]. Explaining capability, according to Wang et al. [52], is crucial for lowering algorithm bias, strengthening human–machine collaboration, and increasing user confidence in systems.

Another challenge is that AI should be "used in such a way that organizations welcome value pluralism and cultural differences while advancing ethical AI. Conversations concerning ethical AI should include people from all walks of life, including those from the West, East, Global North, and Global South. We must be sensitive to how values and interests are displayed differently across diverse cultural and social contexts, and how these differences may impact our thinking about and assessment of fairness, trustworthy, and ethical intelligent technologies, for human-centred AI to serve the needs of all rather than just a few humans". Another issue is that we need to make AI more inclusive; the situation where more males are working on AI and more white individuals are working on AI should not be the case; those developing future AI systems should be diverse to ensure that the AI-generated represents our culture.

6.5. Maintaining Mechanisms for Human Oversight and Control

Scholars believe that individuals need channels for monitoring and controlling machine learning systems. According to the Stevens Institute of Technology [74], these systems should be governed by rules. All existing laws governing human behaviour must be applied to AI, including those governing cyberbullying, stock manipulation, and terrorist threats, as well as enticing individuals to conduct crimes. Another issue is that AI systems should reveal that they are automated systems rather than human beings, and finally, an A.I. system cannot store or divulge confidential information without the source's explicit agreement. According to the data supplied by the Stevens Institute of Technology [74], these products keep so much data that consumers must be aware of the privacy issues that AI poses. According to the IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems [75], AI models should be programmed with consideration for widely accepted human norms and rules for behaviour, and AI algorithms should consider the importance of these norms, how norms conflict can be resolved, and how these systems can be transparent about norm resolution. Another concern, according to ethical experts, is that software designs should be coded for non-deception and honesty. There must be systems in place to cope with the consequences of failures. This would ensure that whatever progress is recorded is sensitive to human hopes and desires, ensuring that the global concerns confronting the world now are addressed in the end.

7. Conclusions and Policy Recommendations

Artificial intelligence isn't a distant concept; it is currently here and being implemented in a range of industries, and governments all over the world are looking for artificial intelligence (AI), which is being developed by large corporations. Finance, national security, health care, criminal justice, transportation, and smart cities are all examples of this trend. There are countless examples of artificial intelligence (AI) having a substantial impact on the world and complementing human abilities. However, because of the immense societal ramifications of these technologies, AI is on the verge of disrupting a host of industries, and the technique by which AI systems are created must be better understood. Therefore, the current study sought to investigate the meaning of human-centred, how to create human-centred AI, and the considerations to be followed for human-centred AI to attain sustainability and SDGs. Through the application of a systematic literature review approach, the study discovered that a human-centred AI strategy aims to establish and implement AI systems in manners that enhance humanity and suit their interests. The study also highlighted that, to build procedures for creating human-centred AI, a human-in-the-loop concept should be followed, among other initiatives, such as promoting accountability for AI, autonomy being used wisely by businesses, being conscious of human and algorithmic biases, customers being a priority for businesses, and organizations forming multicultural teams. The study concluded by proposing some policy ideas for human-centred AI to aid in the achievement of the SDGs, which include increasing government AI investments, addressing data and algorithm biases, and resolving data access challenges, among others. Other researchers can use data and statistical analysis in the future to investigate the influence of human-centred AI in achieving the SDGs.

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