Bibliometric Analysis of The Literature Review on The Use of Artificial Intelligence (AI) In Supporting Poverty Analysis

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Abstract. This article provides a thorough bibliometric study of the literature review on the utilization of Artificial Intelligence (AI) to assist in poverty analysis. The study utilizes quantitative and statistical methodologies to assess the scientific literature on the contribution of AI to poverty alleviation, with a specific emphasis on important topics, authors, and academic journals. The research examines a substantial dataset of articles to identify significant patterns and advancements in the utilization of artificial intelligence (AI) for poverty studies. This article provides a thorough bibliometric study of the literature review on the application of Artificial Intelligence (AI) in facilitating poverty analysis. This includes the application of machine learning algorithms and natural language processing techniques. The findings offer valuable insights into the present condition and prospects of AI in tackling poverty, emphasizing the potential of AI-powered solutions to improve data-based decision-making and policy interventions. The objective of the research is to enhance comprehension of the changing AI environment in poverty analysis, hence aiding the creation of more efficient approaches to alleviate global poverty.

Keywords: AI, Poverty, Google Scholar, Machine Learning, Algorithm.

1 Introduction

The fast developing field of artificial intelligence (AI) has the potential to completely transform a number of different sectors and businesses, including healthcare, banking, and transportation. Even while AI has a lot of potential advantages, there are worries about how it can affect the economy. This essay will examine the potential effects of artificial intelligence on the economy, namely on employment, productivity, and globalization [1]. The impact of AI on poverty will depend on factors such as government readiness, socio-economic policies, and wealth distribution. However, by employing meticulous planning and strategic thinking, artificial intelligence (AI) may significantly contribute to the reduction of poverty and the promotion of inclusive economic growth [2]. However, the increasing utilization of AI also raises concerns over the privacy and security of data, as well as the potential for monopolies to develop as a result of AI-powered technologies. Furthermore, it would pertain to the field of governance and regulation, since countries around the

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world are confronted with the task of creating regulatory structures to oversee the ethical and public-interest-oriented application of AI. These concerns include issues related to safeguarding data privacy, revealing algorithms, and attributing responsibility for faults resulting from AI technology. Effective collaboration between governments and regulatory organizations is essential to establish clear and unequivocal regulations for the use of AI, particularly in sensitive sectors such as healthcare and finance [3]. By implementing this method, we can ensure the appropriate and ethical utilization of AI, while simultaneously protecting the well-being of employees and customers [4]. Hereby the number of global total corporate artificial intelligence (AI) investment from 2015 to 2022(in billion U.S. dollars);

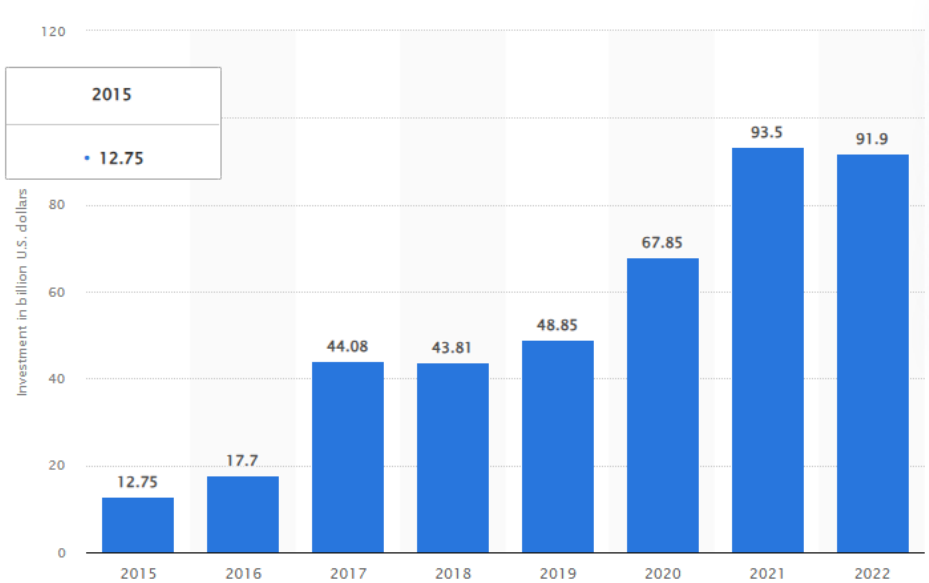

Fig. 1. Global total corporate artificial intelligence (AI) investment from 2015 to 2022
Source: Statista, 2024

The graph illustrates the worldwide aggregate corporate expenditure on artificial intelligence (AI) from 2015 to 2022, measured in billions of U.S. dollars. During this decade, there has been a significant rise in investment, indicating the increasing significance and incorporation of AI technology in different industries. The data shows a strong and consistent increase in AI investment over the course of seven years, with small variations that represent periods of consolidation and strategic evaluation. The significant increase from 2015 to 2021 highlights the quick acceptance and expansion of AI in several sectors, propelled by breakthroughs in machine learning, data analytics, and computing capabilities. From 2015 to 2017, there was a significant rise in corporate investment in artificial intelligence during the initial boom period. Investments had a substantial increase from $12.75 billion in 2015 to $17.7 billion in 2016. The trend of increasing investments in AI continued in 2017, reaching a total of $44.08 billion. This represents a substantial and quick growth phase for AI investment. Subsequently, within a phase of stabilization and marginal variations between 2018 and 2019, there was a little decline in corporate investment in artificial intelligence, reaching a value of $43.81 billion in 2018. Subsequently, there was a resurgence in 2019, with investments escalating to $48.85 billion. During this decade, AI investment experienced a stable rise with few variations, indicating that corporations were focused on consolidating and evaluating their AI technology. They were refining their strategy and implementations following the rapid expansion in previous years. In addition, corporate investment in artificial intelligence experienced a significant spike during the period of accelerated growth and peak expenditure from 2020 to 2021. The investments in 2020 surged to $67.85 billion, most likely propelled by the heightened dependence on AI solutions as a reaction to the COVID-19 epidemic. The trend persisted in 2021, with investments reaching a record-breaking amount of $93.5 billion. The prominence of this peak highlights the crucial role that AI has played in tackling difficulties associated to the pandemic, such as improving healthcare systems and facilitating remote work solutions. It emphasizes the fundamental significance of this technology during a worldwide catastrophe. The investment witnessed a little decrease to $91.9 billion in 2022. Although there was a slight decrease, the investment level remained considerably high, demonstrating continued interest and confidence in AI technologies. The graph accurately depicts the continuous and rapid increase in global corporate investment in AI from 2015 to 2022. This trend demonstrates the disruptive capacity of AI and its growing incorporation into the fundamental strategy frameworks of organizations globally. Further investigation could focus on investments particular to different sectors and their influence on operational efficiencies and outcomes related to innovation.

The study of poverty within the context of government support and artificial intelligence (AI) has become increasingly crucial in recent years. As societies grapple with the complex challenges of income inequality and social welfare, qualitative research offers a unique lens through which to explore the lived experiences of individuals affected by poverty. By delving into the nuances of individuals interactions with government support programs and the potential impacts of AI on these systems, researchers can uncover valuable insights that may inform policy decisions and social interventions. Bibliometric ans qualitative research methods, such as in-depth interviews and observational studies, allow researchers to capture the multifaceted and dynamic nature of poverty, shedding light on the interplay of structural barriers, individual agency, and technological advancements. This research seeks to deepen our understanding of poverty in the modern age and contribute to the development of more effective and equitable social policies.

This present article look at the researches on the consequences of adopting artificial intelligence (AI) to analyze the poverty. The convergence of AI and poverty research represents a critical and burgeoning area of scholarly inquiry. This study employs bibliometric methods to systematically analyze the literature, providing insights into the publication patterns, citation dynamics, and thematic developments in this field. The analysis underscores the relevance of AI in addressing poverty-related challenges and highlights significant contributions and emerging trends.

2 Literature Review

2.1 Brief History and Definition of AI

To ascertain and forecast poverty, diverse data sets were employed to establish a more accurate delineation of poverty. Various models have been developed to identify a universal model that may be equally beneficial in all countries. However, models that have proven efficient in one country may not be useful in other countries due to economic, social, and cultural differences throughout nations [5]. Various econometric approaches have been utilized to gauge and forecast poverty rates, including correlation analysis, regression analysis, factor analysis, panel data analysis, and time series analysis. The incorporation of AI techniques into the poverty prediction sector began in 2016 [6]. Primarily, two prominent subcategories of artificial intelligence, namely machine learning and deep learning, have been utilized in poverty study. Early research studies conducted a comparison between AI models and econometric models to determine the feasibility of applying AI in poverty prediction [5], [7], . Following the acquisition of compelling results about the efficacy of AI models, the subsequent step involved comparing various AI models in order to determine the most optimal model [8]. AI models have several advantages over econometric models. They can handle the issue of multicollinearity, exhibit greater levels of accuracy, have faster computation speeds, can handle huge data, and require less human participation [9][10].

AI techniques are utilized in poverty prediction methods for both the prediction itself and the selection of relevant features. Feature selection is a crucial step in poverty prediction, involving the identification of factors that might effectively explain poverty [5]. When choosing variables, we analyze the significant level of a variable's impact on poverty. We select the factors that have a strong influence and use them to develop models [15]. Research has shown that models including a small number of significant variables can achieve better levels of accuracy [11]. Furthermore, constructing models that incorporate a limited number of variables will facilitate the collection of data for analysis and streamline the analysis process. Prior to the advent of AI applications, econometric approaches such as stepwise, LASSO, and PCA analyses were utilized for the purpose of feature selection [12].

An advantage of AI techniques is the ability to utilize various datasets for poverty prediction. The conventional datasets used for poverty analysis consist of survey and census data. However, these factors alone are insufficient for fully understanding poverty from different perspectives. As a result, remote sensing data, call detail records, and e-commerce data are now being utilized in poverty prediction. This is because AI applications have the ability to extract the essential variables needed for analysis [13].

AI technologies have been extensively utilized for poverty prediction globally within a relatively brief timeframe. While surveys have been conducted on explainable AI [14], the impact of AI on sustainability [15] [16], and health systems in resource-poor settings [17], there is currently no comprehensive survey that encompasses the existing literature on the uses of AI in poverty prediction, to the best of our knowledge. Our objective is to address this deficiency by offering a comprehensive review of the advancements in AI technology for predicting poverty. Additionally, we seek to acquaint you with the AI models developed for poverty prediction and their corresponding results.

2.2 The Theoretical Definitions of Poverty and AI

Poverty is a phenomenon that lacks a single, definitive description. There are multiple methods for defining and quantifying poverty, but they can generally be categorized into two main groups: monetary and non-monetary techniques. The primary and most used method of measuring poverty is through a monetary approach: Individuals are classified as impoverished when they lack sufficient financial resources to sustain their basic needs and well-being. Put simply, poverty is quantified in terms of monetary factors, such as income and expenditure. Monetary measures are commonly used to measure poverty in various nations and international agencies [18]. Nevertheless, the assertion that poverty can be only attributed to financial factors has raised doubts among some experts, prompting them to subsequently devise alternative methods for defining poverty. According to their assertion, poverty encompasses a deficiency in opportunities, education, healthcare, and other related factors [19]. Currently, an increasing number of academics concur that poverty is a multifaceted problem that cannot be solely elucidated by financial factors.

In the realm of qualitative research on poverty, a deeper understanding emerges when examining the multifaceted implications of artificial intelligence (AI) applications. As [20] underscores, while AI holds great potential in enhancing governmental operations and addressing societal challenges, concerns regarding equity, ethics, and accountability remain paramount. The dichotomy between AI advancement and responsible implementation necessitates a nuanced approach to poverty alleviation strategies. Moreover, [20] emphasizes the importance of AI adoption and expertise in national strategies, such as Thailands AI initiatives, to bridge the gap between technological innovation and socioeconomic development. By incorporating qualitative analyses of AI research landscapes in poverty studies, policymakers can glean valuable insights into leveraging AI for poverty reduction effectively and ethically. This comprehensive approach underscores the critical role of qualitative perspectives in navigating the complexities of poverty dynamics in an AI-driven era.

2.3. Poverty Statistics in The World

According to the World Bank, there are around 736 million individuals residing in severe poverty globally, with half of them concentrated in five specific countries: India, Nigeria, Democratic Republic of Congo, Ethiopia, and Bangladesh. The World Bank and the United Nations depend significantly on research and data to assess the advancement made in their efforts to combat poverty [21].The Decentralized AI Alliance (DAIA) stated that the inability to gather data is a direct result of poverty [22]. According to [22], geography plays a crucial role in the effort to eradicate poverty in all its manifestations worldwide. There is a belief that governments are not sufficiently gathering data and expanding traditional household surveys to accurately determine the number of impoverished individuals and the specific regions in which they reside. This issue is further exacerbated by the high cost of conducting traditional household surveys in many countries.

Nevertheless, AI has the potential to facilitate this transformation. A recent study conducted by a team at Stanford University utilizes satellite photos as a substitute for mapping poverty [23]. A study conducted in five Africana countries - Nigeria, Tanzania, Uganda, Malawi, and Rwanda - involved social scientists and computer experts who proposed the use of high-power satellites to identify poverty by analyzing satellite photos. To validate the predictions made in the study, the researchers utilized precise survey data [23]. To accurately delineate poverty, artificial intelligence can integrate high-resolution satellite information with sophisticated machine learning algorithms to forecast the economic status of specific global places. Artificial intelligence (AI) can efficiently give information on various critical variables used in evaluating poverty, such as the distance to the nearest water supplies, urban markets, and agricultural areas [21].

3 Research Methodology

The study employed secondary research methods to examine the influence of artificial intelligence on poverty during the fourth industrial revolution. The study employed content analysis, a method that involves examining and interpreting recorded information found in texts, media, or physical objects. One benefit of content analysis is its non-intrusive approach when examining a social phenomenon refers to a certain occurrence or event that is related to human society. This term was used by Colorado State University in 1997 [22]. Content analysis is employed for distinct purposes. There are three distinct approaches: conventional, guided, and summative. Elo et al [24] assert that the three approaches facilitate the extraction of meaning from textual data, enabling them to align with the naturalistic paradigm. The present study primarily focused on doing a summative content analysis, which entails quantifying and comparing keywords and interpreting their contextual meaning. This is followed by an evaluation of the underlying context.

The bibliometric analysis was conducted using data sourced from Google Scholar databases. Key terms such as "artificial intelligence," "poverty," "machine learning," "inequality," and "social impact" were employed to retrieve relevant publications. The dataset was then subjected to various bibliometric techniques, including citation analysis, co-citation analysis, and keyword co-occurrence analysis, to elucidate the structural and thematic dimensions of the research landscape.

4 Discussion

4.1 Literature Review of AI and Poverty by Vos Viewer Bibliometric

4.1.1. Description on AI and Poverty Analysis

Citation metrics	Help
Publication years:	2018-2024
Citation years:	6 (2018-2024)
Papers:	311
Citations:	3216
Cites/year:	536.00
Cites/paper:	10.34
Authors/paper:	1.80
h-index:	21
g-index:	55
hI,norm:	16
hI,annual:	2.67
hA-index:	13
Papers with ACC >= 1,2,5,10,20:	76,53,29,17,9

Fig. 2. Citation Metrics of AI and Poverty from Google Scholars

The image displays a set of citation metrics, providing a comprehensive overview of academic performance over a defined period, specifically from 2018 to 2024. These metrics are essential in evaluating the impact and productivity of research within this timeframe. Below is a detailed analysis of the citation metrics is presented below;

1) Publication and Citation Years: The research outputs span from 2018 to 2024, indicating an ongoing and active period of scholarly contributions. Citations are accounted for within the same timeframe, covering a six-year citation window from 2018 to 2024.
2) Research Output and Impact: A total of 311 papers have been published during this period, signifying a substantial body of work. The cumulative number of citations received is 3,216, reflecting the recognition and influence of these publications within the academic community. On average, there are 536 citations per year, demonstrating consistent engagement with the research.
3) Per-Paper Metrics: Each paper, on average, has garnered 10.34 citations, indicating a moderate to high level of impact per publication. The average number of authors per paper is 1.80, suggesting a balance between solo and collaborative research efforts.
4) Hirsch Indexes: The h-index is 21, indicating that 21 papers have each been cited at least 21 times, highlighting both productivity and impact. The g-index is 55, which gives more weight to highly cited papers, showcasing the substantial impact of the most influential publications. The normalized h-index (hI,norm) is 16, adjusting for variations in co-authorship and providing a more individual-centric measure of impact. The annualized h-index (hI,annual) is 2.67, reflecting the steady accrual of citations relative to the number of years active.
5) Additional Metrics: The hA-index, which stands at 13, represents a variation of the traditional h-index, incorporating the age of citations to provide a nuanced perspective on the enduring significance of the research. This metric offers a more dynamic evaluation by accounting for how the impact of scholarly work evolves over time, thereby distinguishing research that maintains its influence from that which may experience a decline in relevance.

6) Papers with ACC (Adjusted Citation Count): The categorization of papers based on their adjusted citation counts reveals varying levels of citation impact. Specifically, there are 76 papers with at least one citation, 53 papers with at least two citations, 29 papers with at least five citations, 17 papers with at least ten citations, and 9 papers with at least twenty citations. This stratification highlights the distribution of citation impact across the body of work, offering a detailed understanding of how frequently each paper is referenced within the academic community.

In conclusion, the citation metrics indicate a prolific and impactful research output in the domain of artificial intelligence and poverty. The consistent number of citations per year, coupled with a substantial h-index and g-index, underscores the significant influence and recognition of the research contributions. The average citations per paper further reinforce the relevance and engagement of the scholarly community with this body of work. The detailed breakdown of papers with varying levels of citation counts provides additional granularity, highlighting both widely recognized and exceptionally influential publications. Overall, these citation metrics provide a robust framework for evaluating the research impact within the specified period. The data reflects both the quantity and quality of the academic output, demonstrating sustained engagement and influence in the field of artificial intelligence and its applications to poverty-related issues.

4.1.2. Network Visualization

The network visualization generated by VOS Viewer illustrates the interconnectedness of various terms related to "artificial intelligence" and "poverty." The visualization employs nodes and edges to represent terms and their co-occurrences within a given dataset, likely extracted from academic literature or research articles. The figure shows how the network is organized into distinct clusters, each differentiated by unique colors and representing groups of terms that exhibit closer interrelations compared to terms in other clusters. The green cluster is centered around "poverty" and connects terms such as "country," "person," and "world," indicating a focus on socioeconomic issues. The red cluster, centered on "artificial intelligence," links to terms like "impact," "challenge," and "work," highlighting themes related to technological advancements and their implications. The blue cluster includes terms like "study," "research," and "paper," reflecting an emphasis on academic and empirical investigation. This clustering offers a structured overview of the thematic interconnections within the dataset.

The figures show that the centrality of "poverty" and "artificial intelligence" nodes suggests that the dataset primarily explores the intersection of these two domains. The strong connection between "artificial intelligence" and terms like "impact" and "challenge" indicates a significant focus on evaluating the effects and difficulties of implementing AI in poverty alleviation efforts. The presence of the "country" node connected to "poverty" highlights the geographical aspect of the research, suggesting that studies may be exploring poverty within specific national contexts. Similarly, connections to "person" and "world" emphasize both individual and global perspectives on poverty. The blue cluster’s terms, such as "study," "research," and "paper," suggest that the network includes a substantial amount of academic literature. This implies that the visualization might be derived from a bibliometric analysis of scholarly articles focusing on AI and poverty.

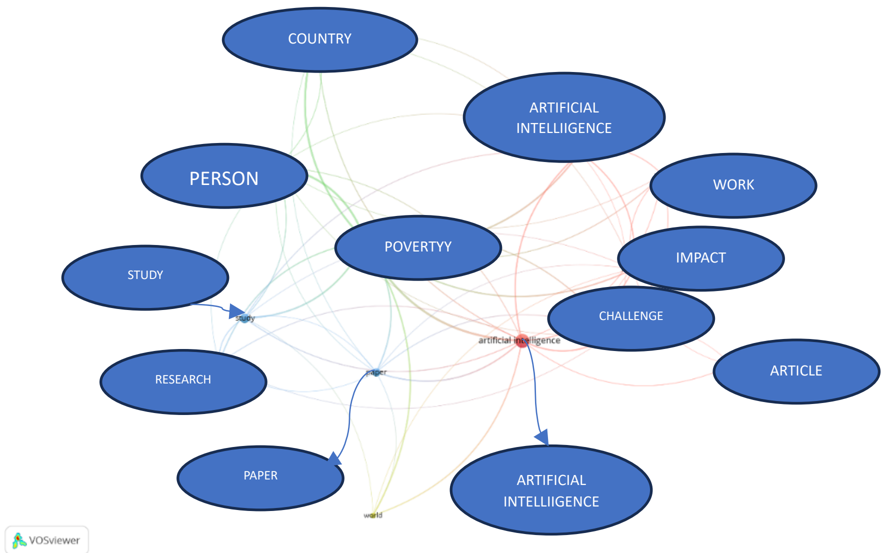

Fig. 3. Description on Network Visualization

In conclusion, the network visualization from VOS Viewer provides a comprehensive overview of the research landscape at the intersection of artificial intelligence and poverty. By illustrating the relationships and co-occurrences of key terms, the visualization highlights the main themes and focal points of academic inquiry in this field. The clustering of related terms further elucidates specific areas of interest and suggests potential directions for future research.

4.1.3. Description Overlay Visualization

The overlay visualization generated using VOSviewer depicts the temporal evolution and interrelationships of key terms within the academic literature focusing on the intersection of artificial intelligence (AI) and poverty. Central to this map is the term "poverty," which serves as the primary node, interconnected with various other significant terms through a network of links. The thickness of these links represents the strength of co-occurrence, with "artificial intelligence" prominently linked, indicating a robust research interest in the application of AI to poverty-related issues.

Color-coding on this overlay map denotes the average publication year, with a gradient from blue to yellow representing the timeline from 2019.5 to 2021.0. Terms shaded in blue, such as "research," "study," and "world," indicate earlier scholarly focus, while those in yellow, including "artificial intelligence," "challenge," and "impact," signify more recent academic attention. This temporal gradient suggests an evolving research landscape, with increasing emphasis on contemporary challenges and opportunities presented by AI in addressing poverty.

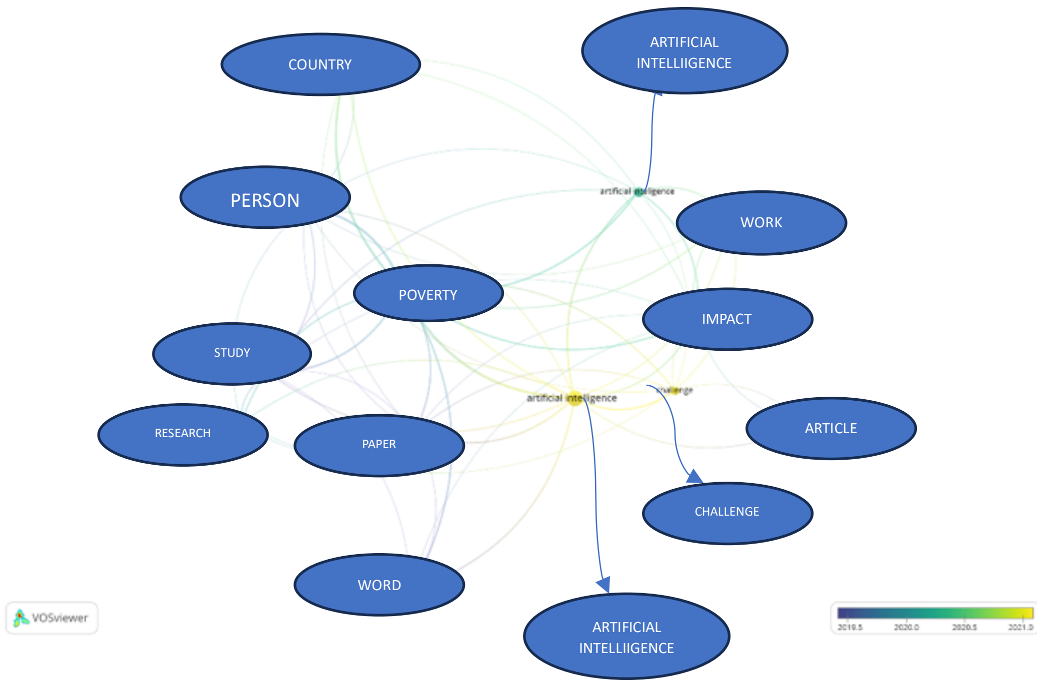

Fig. 4 The Overlay Visualization

The map also highlights other critical terms such as "country," "person," "work," and "article," each forming significant nodes within the network. These nodes represent various dimensions and stakeholders involved in the discourse. The interconnecting lines suggest a multi-faceted approach to the research, encompassing geographic, individual, and systemic perspectives.

In summary, this overlay visualization offers a dynamic and temporally nuanced view of the scholarly landscape, illustrating the growing convergence of AI and poverty research. It underscores the pivotal role of recent studies in advancing our understanding of how AI can address socio-economic challenges, while also mapping out the evolving priorities and focal points within this interdisciplinary field.

4.1.4. Description of Density Visualization

The visual representation provided is a density visualization map generated using VOS viewer, which showcases the co-occurrence of keywords within a scholarly dataset. The primary focal point of this map is the keyword "poverty," indicated by the highest density area marked in bright yellow. This suggests that "poverty" is the most frequently occurring term within the dataset, indicating its central role in the research context being analyzed. Surrounding "poverty," we observe clusters of other keywords, each varying in density and proximity. Notably, "artificial intelligence" appears prominently in two separate clusters, underscoring its significant association with poverty-related research. This dual presence might indicate distinct thematic areas within the broader AI and poverty discourse, such as applications of AI in poverty alleviation or ethical considerations of AI in socio-economic contexts.

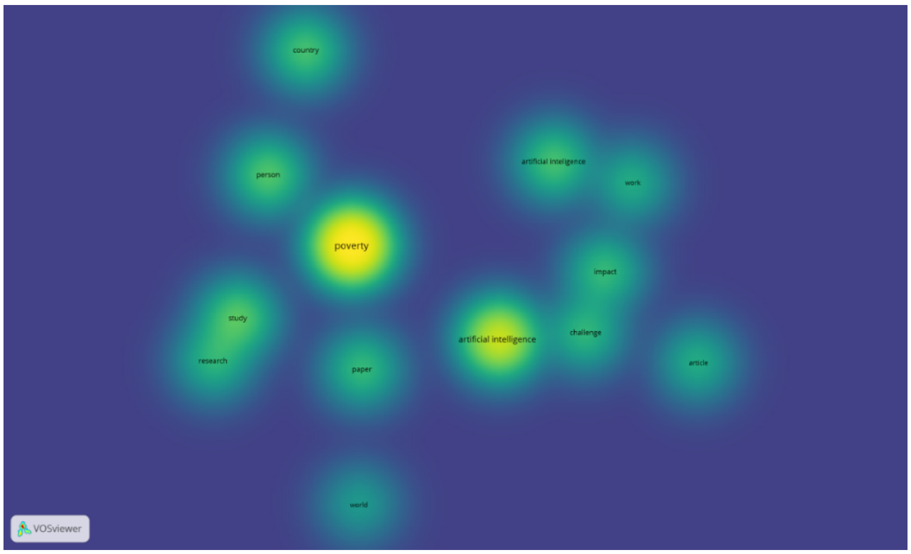

Fig. 5. Density Visualization

Other notable terms include "research," "study," "country," "person," and "world," each forming their respective clusters, albeit with lesser density. These terms reflect the multifaceted nature of research, encompassing geographical, individual, and global perspectives. Keywords such as "impact," "challenge," and "work" further highlight the diverse angles from which poverty and its intersection with artificial intelligence are being examined. The map also features terms like "paper" and "article," suggesting a significant volume of academic literature contributing to this field. The dispersed arrangement and varying densities of these terms offer insights into the breadth and depth of scholarly engagement with the themes of poverty and artificial intelligence.

In sum, this density visualization effectively encapsulates the complex interplay of key themes within the academic discourse on poverty and artificial intelligence, highlighting areas of concentrated research interest and potential avenues for future exploration.

4.2. AI's Potential in Widening the Poverty Analysis

Rapid technical advancements have led to an astounding number of singularities in human history. Numerous facets of information's openness to data development have been demonstrated in the big data era. "Machine substitution" has taken hold, with high-paying occupations in production being replaced by low-cost, highly efficient artificial intelligence. Naturally, all of this has had a detrimental effect on employees' jobs. A 1% increase in robot size will result in the replacement of 4.6% of workers. Seventy-six percent of workers could potentially be replaced by new jobs in the next twenty years. Artificial Intelligence's Effect on Poverty [21]

A major issue regarding AI is its possible influence on jobs. As automation and AI-powered robots and machines become more prevalent, there is a rising concern that numerous jobs may be replaced by machines. Although it is true that certain occupations may become outdated, it is crucial to acknowledge that the overall effect of AI on employment is expected to be more complex. AI has the potential to automate monotonous and repetitive jobs, so allowing human workers to dedicate their time and energy to more intricate and innovative work. This has the potential to result in a rise in production and an elevated quality of life for numerous workers. Nevertheless, it is conceivable that certain occupations could become completely outdated, especially in sectors like manufacturing and transportation. To alleviate the adverse effects of job displacement, it is imperative for governments and businesses to collaborate in offering training and education programs to enable people to effectively transition into developing industries like as data analysis, cybersecurity, and AI development.

Based on the research findings and the potential impact on future studies, a thorough and interdisciplinary strategy is required to tackle the difficulties presented by poverty, economy, and artificial intelligence. It is crucial to have the cooperation of legislators, social scientists, engineers, and community members to create morally upright and fair methods for using AI in social welfare programs. Through promoting open communication and collaboration among different sectors, individuals with a vested interest can collaborate to develop policies and technology that give priority to fairness, openness, and the welfare of marginalized communities. Incorporating qualitative research into the policymaking process allows governments to ethically harness AI to promote social justice and alleviate poverty for all members of society.

4.3. AI to Predict Poverty

4.3.1. Satellite Imagery and Machine Learning Algorithms to Predict Poverty

The research examines the precision and efficiency of Artificial Intelligence models in comparison to conventional econometric methodologies. As a result, academic efforts have allocated significant resources to laying the foundation and creating instruments for precise prediction. Artificial intelligence techniques, such as machine learning algorithms, have been increasingly used for predicting inflation [19]. [25] offer significant perspectives on the significance of predicting inflation and the possible advantages of employing machine learning methods in this specific environment, especially in Nigeria. The study emphasizes the notable deficiency in research on the use of machine learning techniques for predicting inflation in the country, indicating a necessity for additional investigation in this field. The study showcases the effectiveness of many machines learning techniques, including ridge regression, LASSO, elastic net, partial least squares regression analysis, and Artificial Neural Network (ANN), in predicting inflation in Nigeria. The results indicate that ridge regression outperforms the other machine learning approaches that were examined. This study makes a significant contribution to the existing body of knowledge on inflation predicting techniques. Other researches such as [7] demonstrates the efficacy of utilizing very high spatial resolution (VHR) images to collect socioeconomic data in metropolitan areas. We utilize land cover, spectral, structure, and texture information derived from a Google Earth image of Liverpool (UK) to assess their capability in predicting Living Environment Deprivation at a fine-grained statistical area level. In addition, we enhance the methodological literature on estimating socioeconomic indices using remote-sensing data by incorporating components from contemporary machine learning techniques. We investigate the effectiveness of the Gradient Boost Regressor and Random Forests, in addition to traditional methods like Ordinary Least Squares (OLS) regression and a spatial lag model, in enhancing predictive performance and accuracy. Furthermore, we present tools for model interpretation and evaluation with our innovative predictive techniques.

4.3.2. Random Forest as A Machine Learning Algorithms to Predict Poverty

Another different research which used machine learning is called random forest methodology. This study aims to enhance the current body of knowledge on poverty indicators by exploring a different approach to selecting and predicting poverty status. Currently, the prevailing method for determining the pattern of poverty involves utilizing various forms of linear regressions. The Random Forest algorithm has proven to be an effective data-driven prediction approach in various study domains. This study demonstrates that Random Forest is an effective predictor of poverty, and in certain instances, it outperforms previously used approaches. While Random Forest may not always be the most accurate method, it is generally more robust and has smaller prediction errors at rural/urban levels compared to commonly used linear regression models. This aligns perfectly with the RF literature, which highlights that using several models enhances the robustness of RF as a predictor. The use of numerous models is an essential component of the RF approach. While it is possible to use iterative approaches and resilience testing using multiple models to linear regression methods, this is rarely done in a systematic manner. The absence of an established industry standard and the unavailability of publicly accessible programs for implementing iterative approaches inside a linear regression framework are likely obstacles that hinder the broad and systematic use of such methods. RF is a user-friendly and automated tool that can be utilized as an alternative to or in conjunction with other existing approaches [5].

4.3.3. LASSO as Another Machine Learning Algorithm to Predict Poverty

The LASSO (Least Absolute Shrinkage and Selection Operator) is employed to identify the subset of variables that may effectively forecast monthly per capita consumption expenditure. The LASSO model is trained using k-folds cross-validation. Performing 10-fold cross-validation using the "cv.glmnet" function. Subsequently, various lambda values were generated by selecting different numbers of variables. Variables that possess. Non-zero coefficients are identified as selected variables in this step [26].

4.3.4. Explainable Artificial Intelligence Methods on Poverty

Explainable Artificial Intelligence (XAI) has been a crucial focus of study and advancement in the realm of artificial intelligence. This abstract presents a comprehensive summary of Explainable Artificial Intelligence (XAI), encompassing its techniques, uses, and obstacles. Explanation: XAI approaches strive to improve the clarity and comprehensibility of intricate machine learning models. Model-agnostic techniques like LIME and model-specific methods like SHAP have become increasingly important in offering explanations for AI predictions. The field also investigates interpretable deep learning architectures and methodologies to enhance the transparency of neural networks. Applications of Explainable Artificial Intelligence (XAI) can be found in several disciplines. Within the healthcare field, Explainable Artificial Intelligence (XAI) plays a crucial role in the interpretation of medical diagnosis and the formulation of treatment recommendations. Finance employs it to facilitate risk evaluation and ensure adherence to regulations. Explainable Artificial Intelligence (XAI) plays a vital role in autonomous cars by providing clear explanations of the decision-making processes, hence enhancing safety, and fostering trust. Customer service is enhanced by ensuring that chatbot interactions yield responses that are clear and comprehensible. Furthermore, XAI is pertinent in several industries such as agriculture, manufacturing, energy efficiency, education, content recommendation, and others. Explainable Artificial Intelligence (XAI) encounters several hurdles despite its importance. Striking a balance between the complexity of a model and its interpretability is an essential trade-off. Identifying and reducing bias in AI systems is of utmost importance, particularly in domains that require careful handling. Prioritizing ethical considerations, safeguarding data privacy, and obtaining user consent are of utmost importance. Challenges encompass the task of establishing justifications for significant judgments, dealing with the requirement for human supervision, and adjusting to global and cultural standards. Ultimately, Explainable Artificial Intelligence (XAI) is crucial in enhancing the transparency, equity, and responsibility of AI systems. As it progresses, it is positioned to influence the future of AI by allowing users to comprehend and have confidence in AI systems, promoting responsible AI advancement, and tackling ethical and practical obstacles in many applications [14].

5 Conclusion

After some searching, it is discovered that most academics' studies on the poverty at present brought about by AI concentrate. This study examines the replacement and complementing effects of artificial intelligence on poverty in detail." This paper argues that the development of AI has improved science by widening the tools by using AI.

Furthermore, this paper reviews the effects of AI on poverty analysis, emphasizes the value of AI, and offers resources to support the definition pf poverty to embrace the advancement of society. Despite significant advancements in the theoretical and empirical studies on the impact of artificial intelligence on poverty, a review of the literature reveals numerous gaps in the current body of work.

Moreover, the findings of this qualitative research highlight the complex and multifaceted relationship between poverty, economy, and artificial intelligence (AI). The data gathered from literature reviews represented the relationship between AI advancement with the economics perspective on poverty. Moreover, the study revealed the potential benefits and drawbacks of using AI technologies in administering social welfare programs. While AI has the capacity to streamline processes and improve service delivery, concerns were raised regarding privacy, accountability, and the potential for algorithmic bias. Moving forward, it is essential for policymakers to carefully consider these findings and take a holistic approach when implementing AI in social welfare systems. By addressing these issues proactively, governments can ensure that technology serves as a tool for enhancing equity and reducing poverty while safeguarding the rights and dignity of all citizens.

In conclusion, this bibliometric analysis provides a detailed overview of the research landscape at the intersection of AI and poverty. The findings underscore the dynamic and interdisciplinary nature of this field, highlighting key trends, influential contributors, and emerging themes. By mapping the intellectual terrain, this study offers valuable insights for researchers, policymakers, and practitioners aiming to leverage AI technologies to address poverty and inequality.

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