Will Data Science and Artificial intelligence Significantly Impact Eliminating Energy Poverty?

BY KABIRAT NASIRU

Data science and artificial intelligence are crucial in tackling energy poverty by enabling precise identification of energy-vulnerable households, optimizing energy use, and fostering sustainable practices. This article explores how AI-driven insights can guide energy poverty alleviation, offering potential socio-economic benefits for both developed and developing nations.

The focus on ensuring universal access to modern energy is a global conversation on energy poverty, especially as international organizations like the IEA, UN, and World Bank present it. It is also generally agreed that to lessen the effects of climate change, the global energy system must be decarbonized (Samarakoon, 2019). Scientists and entrepreneurs are focusing on carbon markets and renewable fuel solutions, amongst other things. Beckmann et al. (2020) explained how it is imperative to discern multiple pathways of association, particularly in oil exporting nations, with exchange rates to oil prices, keeping in mind how ethanol blending may or may not influence the uniformity of oil prices. The necessity to develop only supporting mechanisms within the net zero energy transition defeats the fact that energy poverty is a severe challenge in many countries and that energy poverty is prevalent all contribute to our growing capacity to anticipate homes and countries that are energy susceptible.

The Adoption of Data Science Techniques and Artificial Intelligence for Socio-economic Benefits

Lately, Artificial intelligence has been the talk of many fields, businesses, and organizations; it makes it possible to employ different types of machine learning algorithms for data analysis and other day-to-day assistance. AI can carry out tasks including data classification, pattern recognition, and predictions; it is a valuable tool for many industries and, lately, energy and sustainability (Chamola et al., 2020; Thamik et al., 2022). Regardless of the application areas, it will be highly relevant in solving problems considering the current trend. According to Allam and Dhunny (2019), metro areas have begun to employ new technology more frequently to address problems such as big data via the Internet of Things.

Recent research has focused on improving energy poverty schemes by applying artificial intelligence and machine learning techniques. This will ensure the prediction of energy-vulnerable homes using various objectives and publicly accessible data. However, what do we do when we cannot easily access data? I revel at the thought of treating instances of energy not just as a whole but on a need basis.

It is general knowledge that some countries highly depend on fossil fuels, and some have diverse sources based on several socio-economic factors. Will our models be based on standard variables that affect both, or will there be some wiggle room? (Roberts et al. 2015, Spandagos et al. 2023) Explained that no widely acknowledged criterion exists for identifying whether a person or household is energy-poor. Energy poverty measurements are divided into primary, secondary, and relative or absolute categories (et al., 2022; Spandagos et al., 2023). While secondary measures use aggregated data from utilities and weighted scoring of specific indices, primary metrics directly use consumer-level data. Moreover, relative measures offer comparison data across several households, nations, or regions, whereas absolute metrics quantify energy poverty through rigid thresholds.

Kabirat Nasiru is 2 year + appointed ORISE fellow, she has an Msc in Agribusiness Management, Bioenergy focus '2022, Msc Data science '2025 at the University of the Cumberland's and can be reached at kabirat.nas@gmail.com

There are a few examples of using AI methods, such as machine learning methods, to precisely guide the reduction of energy poverty (López-Vargas et al., 2022). Some research endeavors focus on pinpointing the most significant energy poverty indicators in one or more nations. The study on energy poverty predictors in the Netherlands conducted by Dalla Longa et al. (2021) is a recent example of work focusing on developed countries. The study's authors used machine learning to divide Dutch families into four risk groups for energy poverty. They found that factors like home ownership, value, age, income, and household size were significant predictors.

The machine learning techniques explored by Spandagos et al. 2023 offer promising directions for a better understanding of alleviating energy poverty. They suggest expanding the research to include additional data that could reveal more profound insights into factors like household supplier changes, which takes us to our questions. Keeping in mind that the focus is mostly on global potential, improvements should be focused on where the impact varies significantly to achieve a positive impact.

Since a growing trend of research is being done in that area, this increasing interest should be embraced and instead used effectively to solve the problems at the top level and the root. We want to start thinking outside the box and consider other variables and dependencies, such as the occupation of a farmer with a renewable energy plant that caters to its running cost and rural communities. In essence, do poverty alleviation schemes in both developed and underdeveloped countries follow up with practices? What do they do with the data and the project's success? Is there a follow-up with the recipients, and how does that fit into the larger perspective? These are the questions we should be asking.

References

Allam Z., Dhunny Z.A., (2019). On big data, artificial intelligence, and smart cities. Cities 89:80–91. https://doi.org/10.1016/j.cities.2019.01.032.

Beckmann, J., Czudaj, R. L., & Arora, V. (2020). The relationship between oil prices and exchange rates: Revisiting theory and evidence. *Energy Economics*, *88*, 104772.

Chamola V, Hassija V, Gupta V, Guizani M (2020). A comprehensive review of the COVID-19 pandemic and the role of IoT, drones, AI, blockchain, and 5G in managing its impact. IEEE Access 8(April):90225–90265. https://doi.org/10.1109/ACCESS.2020.2992341.

Cong, S., Nock, D., Qiu, Y., Xing, B., 2022. Unveiling hidden energy poverty using the energy equity gap. Nat. Commun. 13, 2456. https://doi.org/10.1038/s41467-022- 30146-5.

Dalla Longa, F., Sweerts, B., van der Zwaan, B., 2021. Exploring the complex origins of energy poverty in the Netherlands with machine learning. Energy Policy 156, 112373. https://doi.org/10.1016/j.enpol.2021.112373.

IEA, (2017).” World Energy Outlook 2017”, [Online], Available at: http://www.iea.org/Textbase/npsum/weo2017SUM.pdf.

Rsa -Vargas, A., Ledezma-Espino, A., Sanchis-de-Miguel, A., 2022. Methods, data sources and applications of the Artificial Intelligence in the Energy Poverty context: a review. Energy Build. 268 https://doi.org/10.1016/j.enbuild.2022.112233.

López-Vargas, A., Ledezma-Espino, A., Sanchis-de-Miguel, A. (2024). The Role of the Artificial Intelligence of Things in Energy Poverty Alleviation. In: Misra, S., Siakas, K., Lampropoulos, G. (eds) Artificial Intelligence of Things for Achieving Sustainable Development Goals. Lecture Notes on Data Engineering and Communications Technologies, vol 192. Springer, Cham. https://doi.org/10.1007/978-3-031-53433-1_3.

Roberts, D., Vera-Toscano, E., Phimister, E., 2015. Fuel poverty in the UK: is there a difference between rural and urban areas? Energy Policy 87, 216–223. https://doi.org/10.1038/s41467-022-30146-5.

Samarakoon, S. (2019). A justice and wellbeing-centered framework for analyzing energy poverty in the Global South. Ecological Economics. 165. 10.1016/j.ecolecon.2019.106385.

Spandagos, C., Tovar Reaños, M. A., & Lynch, M. Á. (2023). Energy poverty prediction and effective targeting for just transitions with machine learning. *Energy Economics, 128*, 107131. https://doi.org/10.1016/j.eneco.2023.107131.

Thamik, Hanane & Wu, Jiang. (2022). The Impact of Artificial Intelligence on Sustainable Development in Electronic Markets. Sustainability. 14. 3568. 10.3390/su14063568.