Energy Poor No More

Intelligent Approaches to Realizing Energy Well-being

By Jacqueline Corbett and Bastin Tony Roy Savarimuthu

Access to clean, affordable and reliable energy services is a key requirement for global sustainability. The United Nations reports that 91% of the world's population had access to electricity in 2021, up from 87% in 2015. However, grid connection does not guarantee energy well-being, which New Zealand's Ministry of Business, Innovation and Employment defines as the situation "when individuals, households and whanau are able to obtain adequate energy services to support their wellbeing in their home or kainga." When a household is unable to meet its energy needs, either because it does not have access to a reliable energy supply or cannot afford the necessary energy services, it suffers from energy hardship, or in the extreme, energy poverty.

Energy well-being is a universal objective and energy poverty is universal challenge: although the forms, causes and magnitudes vary, energy poverty exists in all corners of the world. In the United States, 27% of households had difficulty meeting their energy needs in 2020. In New Zealand, the estimates for energy hardship range from 4.5% to 25%, depending on how it is measured while in Canada, an energy-rich country, between 6% and 19% of households experience energy poverty (see Riva et al. 2021).

The large variations in energy poverty estimates reflect the invisibility of the problem and the difficulty of measuring energy well-being and hardship (also referred to as energy insecurity). In urban settings, many people will not know if their neighbors live in a home that is uncomfortably cold or hot, whether they have sufficient energy to cook their meals, or to have a warm shower. Utilities and energy providers may see certain indications of energy hardship within their customer bases, for instance, when customers are unable to pay their bills, but these situations do not tell the whole story.

As with energy justice, to achieve universal energy well-being, we first need to understand where energy poverty occurs and who is affected, so that we can then design and implement appropriate solutions. Advances in digital technologies and big data mean that 'intelligent' digital technologies and information systems have an enormous potential for enhancing energy well-being by providing insights and tools for addressing the problem. As researchers, we are interested in the ongoing digital transitions associated with the smart grid and investigate how machine learning and artificial intelligence can contribute to the achievement of sustainability objectives. We draw on this body of work to propose EWISe — an integrated Energy Well-Being Information System platform that collects, analyzes and diffuses relevant information to support energy-poverty reduction at multiple levels. While technology solutions provide a number of promising avenues, truly 'intelligent' and sustainable solutions must also take into account human intelligence, agency and involvement.

1. Understanding Energy Well-being and Energy Poverty

Energy well-being is a fundamental tenant of energy justice, which aims to "achieve equity in both the social and economic participation in the energy system, while also remediating social, economic, and health burdens on those historically harmed by the energy system". Energy hardship adversely affects individuals' physical and mental health, contributing to problems such as cardiovascular and respiratory diseases and depression. Lack of access to sufficient energy services can also impact personal development in terms of learning because people in situations of energy poverty have less access to educational resources, spend less time in learning activities, and have fewer years of schooling. Often, these detrimental effects are compounded for young people, students, people with long-term illnesses and disabilities, and other vulnerable members of society who are more likely to find themselves in situations of energy hardship. For local communities and society more broadly, energy poverty can weaken social inclusion, increase inequalities, and create political and social instability (for further reading on health implications, see Filcak & Zivic 2017, Riva et al. 2023, Xiao et al. 2021).

Energy poverty is a multifaceted social challenge. It can arise from three main causes as shown in Figure 1. First, energy systems may not be available. This is situation of the approximately 9% of the global population that is not yet connected to electricity services. Addressing this cause of energy policy requires large-scale investments to build out energy services in geographically unserved areas.

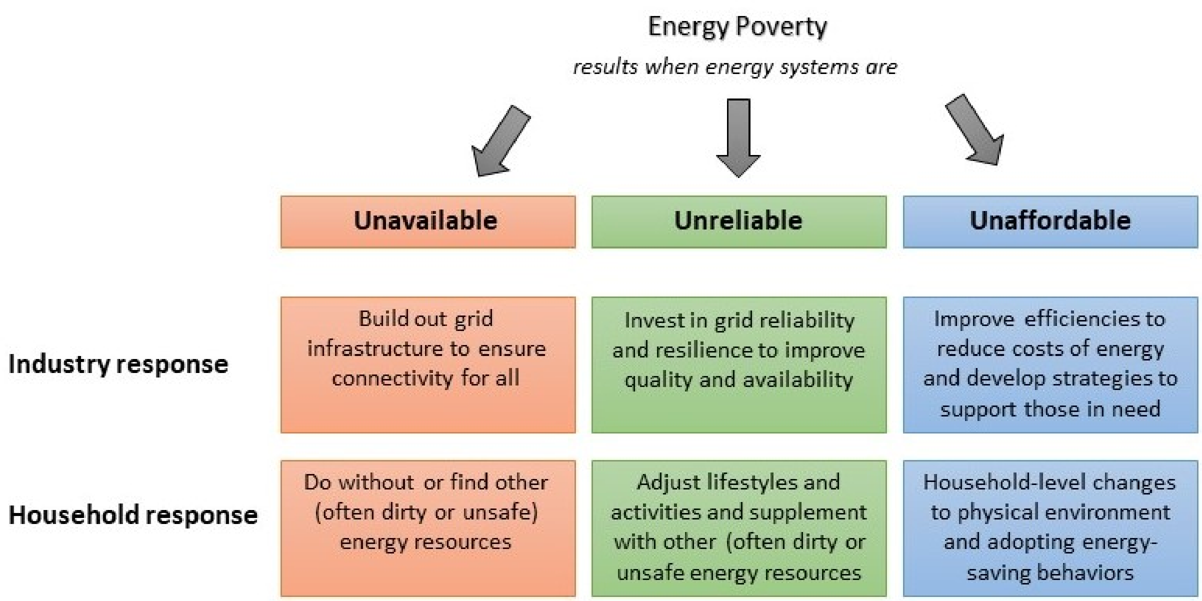

Figure 1 Causes and Responses to Energy Poverty

Second, energy poverty may result when households are connected to energy systems, but such systems are highly unreliable, with frequent outages and poor quality. In such cases, households experience important disruptions in carrying out their daily activities, or have to resort to unclean or unsafe energy sources to meet their basic needs. This is most common in lesser developed countries or rural areas where electricity grid infrastructure may be insufficient, outdated, or lacking resilience to recover quickly from extreme weather or other events. By one estimate, in 2019, approximately 3.5 billion people (45% of the world's population) lived without access to reasonably reliable electricity systems (see Ayaburi et al. 2020). To address energy poverty due to unreliability similarly requires large-scale investments.

While AI techniques can assist in improving energy reliability, this is not the focus of our work. Instead, we focus on the third situation — energy poverty that occurs when households have access to reliable energy systems, but are still unable meet their basic energy needs. This cause of energy poverty occurs around the world and is most common for those living in developed countries, who cannot afford the energy required to provide for their basic activities, such as heating, cooling, cooking, and working. In this situation, there is no single cause or pathway leading to a household's energy well-being or hardship and it can take many forms. Energy poverty is not simply an offshoot of financial poverty because the underlying causes are different, highly varied and complex. Raising a household's income is rarely enough on its own to eliminate energy hardship and poverty. Factors influencing a household's energy well-being includes its financial and other resources, characteristics of its dwelling and appliances, energy supply, environment (e.g., climate, temperature, weather), energy literacy, its size and composition (e.g., singles vs. multi-family), circumstances and practices, and energy prices and pricing structures.

1.1 Challenges to Addressing Energy Poverty

There are several important challenges that make it difficult to eliminate energy poverty (see O'Sullivan & Viggers 2021). The first is definitional. From a public-policy perspective, defining energy poverty is important because it sets the expectations and motivations for actions and interventions. However, this process is a negotiated process through which different stakeholders with conflicting interests must come to an agreement. It is also a delicate balancing act to ensure that thresholds are not set too low as to exclude those facing energy hardship, or too high such that interventions are too costly or unfairly benefit those who are not truly in need.

Besides the political challenges associated with understanding energy poverty, there are important measurement challenges, which contribute to limited visibility of the problem. Not only is it difficult to observe physically energy poverty in households, we lack appropriate indicators for measuring energy poverty. As the statistics in the opening section reflect, the prevalence of energy hardship depends on how one approaches its definition and measurement, whether through income-based, spending-based, or needs-based assessments and thresholds. The current plethora of different indicators is a barrier to achieving a consolidated view and agreement on the size of the problem and it effects. Moreover, even with reliable numbers, there is the problem that energy hardship is an 'experienced' phenomenon that is highly subjective. Households with the same level of income for example may experience different levels of energy poverty depending on a variety of internal and external factors, many of which are often beyond the household's control. Thus, we cannot objectively determine an absolute point at which energy well-being ends and energy hardship begins; it must be thought of more as a dynamic continuum that ebbs and flows through different seasons and phases of a household's life.

A third challenge relates to the information asymmetry that exists between households, their energy providers, landlords, policy-makers, and other key actors in the energy sector. On the one hand, households know best their living conditions and their own degree of energy hardship, but may not be willing or able to share this information with others who are in a position to assist (e.g., government, energy providers, and landlords). Revealing such sensitive, personal information requires a degree of trust that may not exist between the parties and assurance regarding the protection of personal privacy. On the other hand, electricity utilities, governments, and landlords possess other information that is not easily accessible to households. For instance, landlords typically know more about the energy-efficiency performance of their buildings (one of the key factors contributing to energy poverty), but may not share this information with potential tenants. Households may not discover until it is too late that their accommodation is poorly insulated or that appliances consume high levels of energy.

Central to resolving all of these issues is good quality, timely, and relevant information from which informed decisions can be made. It calls for 'intelligent' solutions that leverage the best of human and artificial intelligence, and places people at the center. Mindful development and implementation of digital technologies, such as we propose with EWISe, offer an important path forward for ensuring energy well-being.

2. Digital Transformation in the Electricity Sector

Digital transformation in the electricity sector continues to gain momentum, with analysts predicting significant information technology (IT) spending over the coming years. Since being deployed, smart meters and other sensors deployed on the grid have facilitated the capture of large streams of data more quickly and cost effectively. These data can be coupled with other streams of open and big data and advanced analytics to support strategic and operational decision making. New digital and increasingly 'intelligent' technologies are enabling industry participants to develop innovative solutions, such as distributed energy resources, to deal with challenges of energy security, resiliency, and sustainability. Furthermore, as the digital transformation takes hold, expectations of energy consumers and customers, many of which are digital natives, have increased and they expect to be able to interact with companies through mobile applications and have greater control over their choices and services.

When talking about digital technologies, we include traditional information systems, such as outage management systems (OMS), customer information systems (CIS), and geographic information systems (GIS), as well as emerging technologies such as artificial intelligence (AI), blockchain, and the metaverse. Research and development related to the use of intelligent digital systems underpinned by AI continues to grow in the energy domain (see Ahmad et al. 2021). Such intelligent information systems can manage power generation schedules and handle supply and demand management leading to efficient energy generation and effective management of demand-side response, lowering both the cost of energy production and consumption and reducing overall carbon emissions. The umbrella of digital technologies also includes platforms, big data, analytics and other digital services that are becoming ubiquitous in business operations. Despite the different forms and applications of digital technologies, they afford the same fundamental capabilities in terms of being able to collect, store, organize and process data, and diffuse the resulting information. The power of AI means that digital technology solutions can continue to learn and adapt based on data inflows and take action partially or completely autonomously on the basis of that data and its programmed objectives.

2.1 Intelligent Approaches to Reduce Energy Poverty

Most electricity utilities and energy providers, mandated by public policies, have implemented programs to assist consumers in reducing their energy costs through improved energy efficiency. While these strategies are relevant, they are not sufficient for eradicating energy poverty. Breaking away from a traditional, incremental improvement trajectory requires rethinking and reframing the problem and devising a comprehensive digital strategy. While such an approach has been advocated for overall digital transformation, we argue that the same principles and approaches can be effectively applied to combatting energy poverty.

The use of AI to reduce energy poverty is in the nascent stages. Broadly speaking, AI is the ability of computers to perform tasks that, in the past, were associated with human intelligence. Narrow AI techniques that focus on solving specific problems (as opposed to generic problems) are widely used. Often, these employ a subset of algorithms called machine learning (ML), which are used to create prediction models that are trained based on data. To develop ML models, features within the data should be identified. However, there exist a sub-set of algorithms called deep learning (DL) that can infer these features automatically based on the dataset provided. Both ML and DL algorithms have been used to try to predict energy poverty in households. For example, these models have identified household income, the floor area of the house, and household size as some of the key factors that influence energy poverty in a household. Other ML models have been successful in addressing specific energy-poverty related issues by helping to identify low-income households, estimating energy pricing, and detecting poor energy efficiencies of houses. In addition, more advanced DL techniques have been employed to detect energy billing irregularities and unpaid energy bills.

3. A Holistic EWISe Solution

While there has been 'pockets' of work focusing on specific issues of energy poverty (e.g., detecting who is likely to default on energy bills), a more integrated approach is needed to tackle energy poverty holistically considering different stakeholders. We suggest this may be realized in the form of an Energy Well-Being Information System (EWISe) that can be operationalized in three levels – household level, community/utility level, and the regional/national level. Figure 2 shows the capabilities of such a system. The row headers show the three levels. The first column shows the three operational phases to tackle energy poverty at each level – collect and store, process and communicate. First, the system *collects and stores* energy-related information at an appropriate level of granularity required for the level. Second, it *processes* the stored information using a four staged approach called DARE (Detect-Analyse-Reduce-Eliminate). Third, it *communicates* the results to the stakeholders. We describe the operational details of each of these levels next.

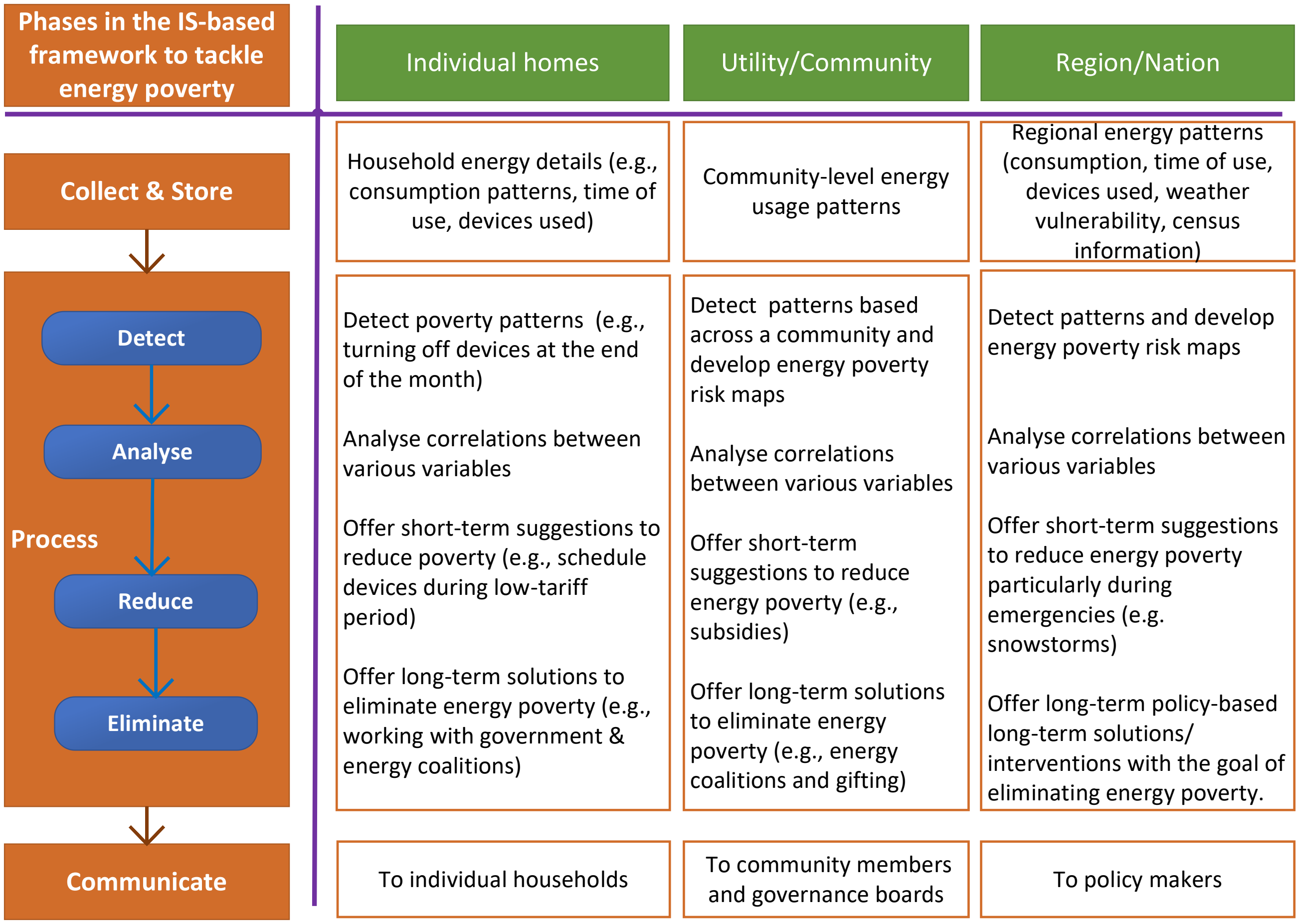

Figure 2 Capabilities of the EWISe Solution

3.1 Household Level

At the household level, the system collects and stores information about households' energy usage (e.g., time-of-use and patterns of device use) and weather details. Next, during the first stage of DARE, the *Detect* stage, it identifies (within a certain confidence interval) where a household places on the energy wellness-hardship continuum (Figure 3). For example, based on data collected, it could detect patterns of turning off appliances (heating and cooking) towards the end of the month to save energy costs. This can be achieved by training machine learning models (e.g., classification algorithms) that can predict whether a monthly usage pattern has an energy poverty signature. For example, time series data for the overall power usage that has marked differences say at the last week of the month compared to the other weeks of the month, or the variations in specific appliance usage patterns (e.g., heaters) can be used for this purpose. From these analyses, the EWISe system could classify households into different groups, such as those experiencing energy well-being, energy hardship, and, in the extreme, energy poverty.

Figure 3 Energy Well-being Continuum

Upon detecting potential cases of energy hardship and energy poverty, the *Analyze* stage involves analyzing different variables, selecting the prominent ones (e.g., through feature selection), and building machine learning models that can help achieve the goals provided by the household (e.g., energy budget and time of non-negotiable use of appliances). For example, given a weekly/monthly budget, models can be built that offer optimized solutions that maximize energy use of a household while minimizing thermal discomfort. The model would also consider external factors such as weather information and utility's variable time-of-use pricing to make predictions of energy usage. As a concrete output, the system would generate an energy use schedule where time-of-use for specific devices/appliances are recommended (e.g., cloth dryers to be used when the tariff is low, or the air conditioners to be turned on at certain times when the outside temperature reaches a threshold). If the time-of-use prices of multiple providers are available, the system can also compute energy costs under different schemes offered with the goal of improving energy well-being.

In the *Reduce* stage, a set of preferred solutions from the second stage are presented to the user. Thus, the aim of the third stage is to find the optimal short-term solution for the user. This could take different forms, such as a recommended device-use schedule, moving to a different plan and switching providers. The *Eliminate* stage has a long-term horizon to design and develop approaches to eradicate energy poverty considering results from stage 3 in conjunction with other avenues such as the support from government, NGOs, local communities. These could be in the form of improving energy infrastructure within a household through smart investments (e.g., solar roof-top installation) and integrating energy donation/gifting features operationalized through local community groups and utility providers. Upon the completion of the processing phase, the results/solutions are disseminated to the user in the *communicate* phase. The users can decide which of the presented options they would like to pursue. This final point is essential as the goal of the EWISe approach is not to take agency away from individual households but to allow them to make more informed choices given their specific context and values. As we will discuss below, the human cannot be taken out of the loop.

3.2 Community Level

In the context of the EWISe solution, we define a community as a geographical area or neighborhood, or households that are subscribed to a specific utility provider within a given area. Column 3 of Figure 2 shows the operationalization details at the community level. Within the processing phase, the *Detect* stage identifies patterns that are specific to a community. In the *Analyze* stage, appropriate variables and their correlations are investigated at the community-level (e.g., the role of geo-graphical features impacting weather which impacts energy needs) and models are built that can help reduce these needs. In the *Reduce* stage, appropriate community-based poverty reduction mechanisms obtained based on the analyze stage are operationalized through the system which can reduce energy poverty at the individual household level (thus, lowering poverty across the community level). For example, surplus renewable energy sharing and energy gifting when integrated, can reduce overall energy poverty levels in the community. Models for energy sharing and gifting energy can be developed during the analysis phase, and specific recommendations can be made to community and utility leaders at the reduce stage which are then considered for implementation at the individual household level. The long-term outlook for the eliminate stage will involve the modelling of coalitions across different communities (e.g., microgrids) and presenting the outcomes to the community and utility leaders for feedback and operationalization.

3.3 Regional/national Level

At a regional (or national) level, information regarding energy hardship at household level are collected, stored and aggregated based on jurisdictional levels such as districts and provinces. To keep data anonymous, representative synthetic and obfuscated datasets of real-world data can be used. The aggregated data can then be analyzed considering specific factors, such as seasonality and extreme weather events (e.g., heat wave, cyclone and hurricane), that may impact an entire region of interest. Models can be developed to identify energy poverty zones within the region with severe impacts, and these, when communicated to jurisdictional authorities, can help them make policy decisions about how best to support affected households (e.g., one-off energy subsidies) in the short-term. Data modeling can also provide greater visibility and understanding of microclimate patterns in different areas, highlighting areas more at risk of extreme weather that would benefit from targeted investments in dwellings. As key stakeholders of EWISe at this level, government agencies, responsible ministries or public health and safety organizations, and policy makers could receive results from the system and enact appropriate measures to remedy the short-term issues (e.g., subsidize power costs during heatwave). The EWISe system could also be used to model long-term solutions, such as building energy generation and storage infrastructures at scale, and forming energy coalitions across states/regions to mitigate the effects of such events.

4. Implementation of EWISe

4.1 Technical Operationalization of EWISe

To operationalize the EWISe system, a service-oriented architecture (SOA) is recommended as it offers discrete services using a modular approach. The user-facing parts of the system can be developed as a web-based system and a mobile app that use the offered services to respond to the needs of households, community and utility leaders, governments and other agencies. The services can be hosted on a suitable cloud platform, including the computationally-intensive parts (e.g., AI models) of the system. In this way, the EWISe system will have a device-flexible front-end (e.g., loaded on a browser or as an app), that will be used by different stakeholders, and a cloud-based server as the back-end which then stores data in appropriate databases (see Figure 4). The stored data can then made available in data warehouses using open data formats after ensuring privacy of stakeholders (e.g., using synthetic data or data obfuscation techniques). This open data can then be used by researchers and practitioners to design and develop other applications to perform various 'what-if' analysis of different scenarios using traditional simulations or digital twins approaches. Also, these scenarios can be visualized using 3D virtual platforms such as metaverse to better understand households' energy behavior and to unearth additional insights. Such approaches can facilitate stakeholder educational programs, delivered through the client interfaces. For example, recorded 3D simulations can be shown to households, landlords, utility leaders, and policy makers to show how energy hardship conditions change under different scenarios.

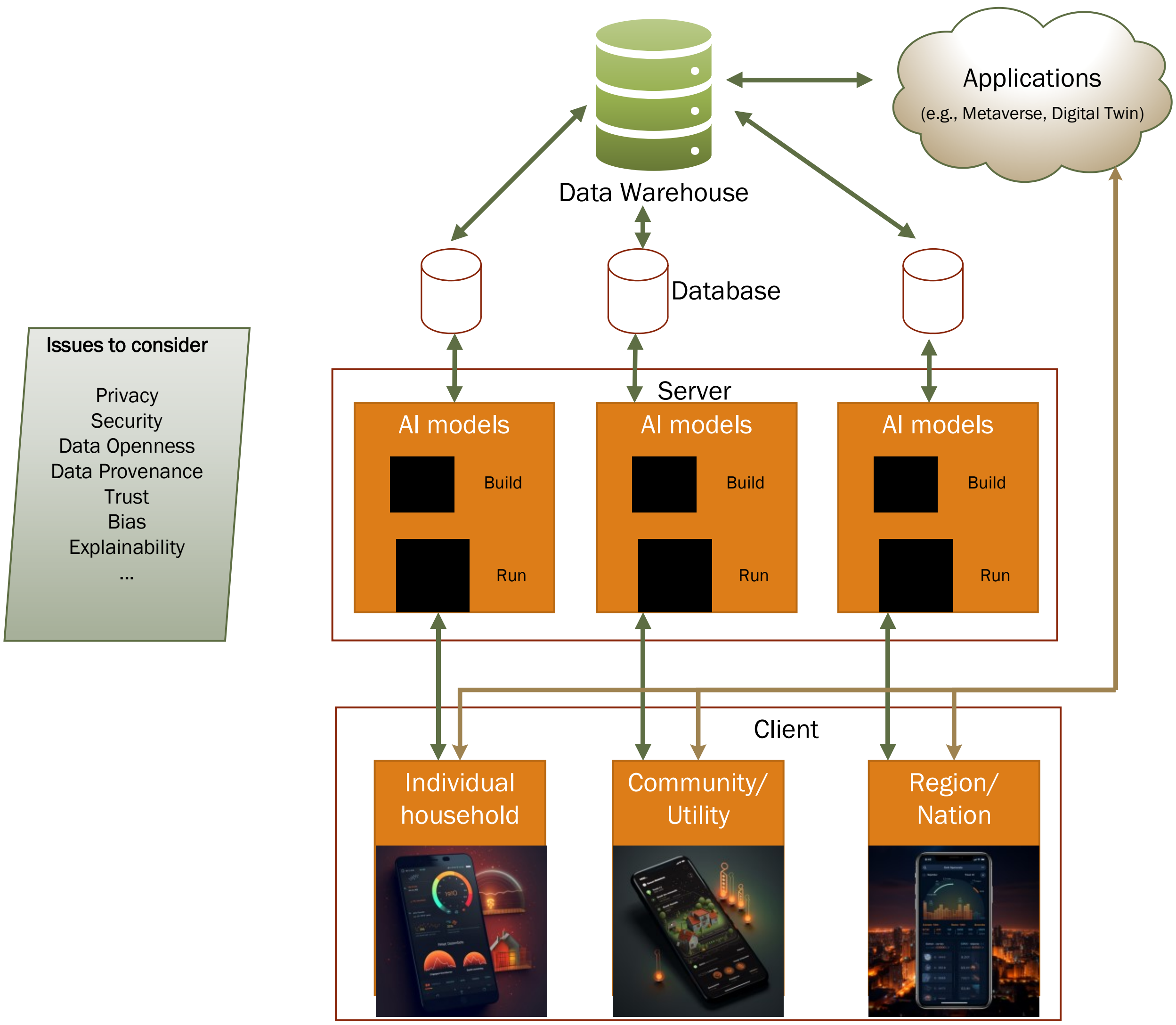

Figure 4 High-level architecture of EWISe

4.2 Advantages of EWISe Solution

The EWISe solution approach offers operational solutions to the three challenges outlined earlier in the paper. First, the system overcomes the definitional challenge by offering the ability to detect energy hardship across the entire spectrum – from well-being to poverty. By unearthing 'signatures' of the different categories (i.e., discrepancies in power-usage data across different weeks of a month), EWISe can offer an evidence-based approach for defining energy poverty at the household level. This also contributes towards the second challenge, the measurement challenge, as it identifies the metrics used in the quantification of hardship. This quantification makes the problem more visible. At the household level, making energy use more visible will help to improve energy literacy and empower households to make more informed decisions about how best to manage their energy health (although, literacy does not resolve the fundamental issues that give rise to energy poverty). It can provide more flexible or personalized appliance scheduling options based on weekly billing or matching billing to income cycle. Third, it also contributes to resolving the information asymmetry challenge by recording household hardship and in this process revealing information about energy-efficiency performance of a household (i.e., high demands to heat the household will mean reduced energy-efficiency performance). Through the recording of this information in a public space, an EWISe solution offers several other potential benefits and opportunities to stakeholders, such as:

- ✓ reducing information asymmetry between landlords and tenants in terms of the energy performance of a particular residence;
- ✓ empowering community or utility leaders to address energy poverty needs within their community through embedding initiatives such as energy sharing or gifting; and
- ✓ providing valuable insights for government agencies through a high-level, real-time view of energy poor areas that may benefit from specific interventions and assistance.

4.3 Issues to Consider

The design and development of an EWISe system to tackle energy hardship must consider a variety of issues, particularly around data and the AI models (see Table 1). Data collection, storage and aggregation should consider issues such as privacy, security, openness, data provenance, and trust. Appropriate mechanisms should be put in place to ensure these issues are considered right from the conceptual phase of the system to its final deployment and use. Additionally, the use of AI models can introduce challenges and concerns that need to be addressed. For example, the developed models should not be biased towards certain groups of households. This may arise due to the nature of features considered in developing these models. Other issues, such as bias and explainability, should also be considered during the development process.

Table 1 Considerations for EWISe Design

Category	Issue	Description
Data-related issues	Privacy	Keeping household/community data private – not revealing identifiable information that is considered private by households/communities to external parties
	Security	Keeping data safe with appropriate authentication, authorization features and also employing encryption/decryption algorithms
	Data Openness	The ability for anyone to use the data freely and then to redistribute the data subject to the appropriate terms of use (e.g., for research purposes and/or commercial use). Open data promotes transparency, enables citizen science, and facilitates innovation.
	Data Provenance	Tracing the origin of a piece of data/information held in an organization to determine the chain of custody of the data. It informs the origin of the data, changes to the data, and details supporting the confidence or validity (and non bias) of data.

	Trust	Related to provenance, trust ensures that the data being considered is valid and hence trustworthy. This can enable data "collaboration between organizations to make that journey faster, less costly, and less risky".
AI-related issues	Bias	When the algorithm used produces biased results as a consequence of erroneous assumptions of the learning processes. Bias leads to user mistrust of the system.
	Explainability	Ability of the algorithm to explain how it computed its results (i.e., its logic) to the humans in a way that "makes sense." Explainability improves the transparency of the system.

5. A People-centric Approach to Energy Hardship

In developing any technological solution, we must remember that energy hardship is not an abstract concept, but a problem with very tangible consequences on people. Households in situations of energy poverty are comprised of individuals and families that are unable to meet their basic energy needs for heating/cooling, cooking, washing and many others that are often taken for granted by those who have a high-level of energy wellbeing. Thus, consistent with the value of energy justice, proposed solutions must maintain and strengthen individual and collective agency and respect the rights of all people. Moreover, solutions must leverage human intelligence to optimize artificial intelligence solutions and address a number of the issues outlined above. One approach for doing this is to adopt human-in-the-loop practices in the design, development and implementation of an EWISe solution.

Since the goal of EWISe is to provide recommendations for different stakeholders (households, community and utility leaders, and government agencies and policy makers), involving human in-the-loop (HITL) is an important consideration for its successful operationalization. With HITL practices, humans are involved in training the ML models and improving the accuracy and correctness of outcomes. To explain how HITL can improve EWISe, we consider the issue from two perspectives – the *users* of the system and its outputs and the *modelers* who create the AI models that offer insights to the different stakeholders (users).

5.1 EWISe Users

At the household level of the EWISe solution, the results are presented to household members so that can choose a course of action from the suggestions (e.g., following suggested device-schedule, moving to a new provider and signing up to receive energy gifts). While some of these can be automated (e.g., integrating with a smart home system, changing energy providers) through web services, others will require interactions with other people (e.g., changing behaviors, joining an energy cooperative). At the community/utility level, the recommendations made by EWISe will invariably require community and utility leaders to make decisions (e.g., setting up energy microgrids) with direct impacts on community members. Inclusive and participative approaches that take into account the knowledge, creativity and perspectives of different stakeholders will help to validate and augment the decisions suggested by the system. Similarly, at the national/regional level, different government agencies and policy makers will have to operationalize certain options (e.g., setting energy rebates or energy payment holidays during critical events) which will require inputs and buy-in from the whole range of stakeholders. In critical situations (e.g., heat waves), time is of the essence, thus consultative structures and trusting relationships must be established in advance to permit agile responses to mitigate the most severe consequences.

5.2 Modelers

Those involved in developing EWISe solutions hold an important responsibility because their work can have immediate and direct effects on the lives of many people. In particular, programmers and AI modelers will create AI models (e.g., those that detects energy hardship) across the three levels which will then be made available to the different stakeholders. Modelers are also responsible to testing the quality of insights generated by these models. At different levels of granularity, EWISe modelers will need to work closely with representatives of households, community groups, utilities, and government agencies to identify key features needed to create models. This work is often iterative in nature, where models are developed, tested based on test data and validated using real data, over several iterations, until the required level of model performance is met (e.g., the model is 95% accurate across varied datasets). To build good models, AI modelers and EWISe solution designers and developers will require a strong comprehension of energy well-being and energy hardship as well as sensitivity to the potential for bias that could undermine the intent of the solution. Thus, it will be important during the design and development of the EWISe system, that users and modelers work closely to create better models that can then be used by a large swathe of different stakeholders. Also, once the models have been deployed, requirements to model new scenarios are likely to arise. By listening carefully to system users and involving them in the process of defining requirements and testing outputs, modelers will be better positioned to deliver solutions with positive impacts.

6. Conclusion

No one should have to give up basic necessities in order to pay for energy or live in a dwelling that is kept at an unhealthy or unsafe temperature. Yet, millions of people – both in developing and developed countries face this situation and experience some level of energy hardship, or, in the extreme, energy poverty. Although the problem is complex and multifaceted, we suggest that it is possible to leverage human and artificial intelligence through an EWISe solution to provide a holistic view of the problem and potential solutions to a wide range of stakeholders from individual households and utilities to regional and national government policy makers. With concerted effort and collaboration our hope is that we can make energy poverty a thing of the past.

For Further Reading

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Biographies

Jacqueline Corbett is with Université Laval, Canada. She is Professor of Management Information Systems in the Faculty of Business Administration at Université Laval in Quebec City, Canada. She holds a Ph.D. from Queen's University at Kingston, Canada. Jacqueline's research takes a multidisciplinary and multi-method approach to investigate questions related to emerging digital technologies in the areas of clean energy, sustainable development, and Indigenous business. Her research is funded in Canada by both the Natural Sciences and Engineering Research Council (NSERC) and the Social Sciences and Humanities Research Council (SSHRC), and has been published in highly regarded scholarly journals, such as Journal of Business Ethics, Strategic Entrepreneurship Journal, Journal of the Association of Information Systems, Information Systems Journal, International Journal of Information Management, IEEE Transactions in Engineering Management, and Energy Research & Social Science. Jacqueline holds leadership roles as President of the Association for Information System's special interest group in Green IS, and Director of the Centre for Research and Cocreation in Innovation and Sustainable Indigenous Business at Université Laval.

Bastin Tony Roy Savarimuthu is with Otago University, New Zealand. He is Professor of Computing at the University of Otago, in Dunedin, New Zealand. He received his PhD from the University of Otago. His research interests are in the fields of Artificial Intelligence, Software Engineering and Information Systems. His work focuses on social aspects of computing including designing socially aware software and studying social aspects in software development teams such as social norms, personality types and decision-making. His works in the Information Systems domain focus on developing AI-based artefacts (e.g., models) and systems that enable sustainable practices. In the energy domain, his works have focussed on simulation of coalition formation strategies in microgrids and the role of social norms in energy conservation. His papers appear in the top-conferences in the three fields his research including International Joint Conference on Artificial Intelligence (IJCAI), International Conference on Software Engineering (ICSE) and International Conference on Information Systems (ICIS). He has been a Senior Programme Committee (SPC) member for the top conferences in these three fields. He has been a program chair and general chair of several international conferences.