

An integrated agent-based modelling and artificial intelligence framework for enhancing the experience of minority ethnic communities in digital energy services

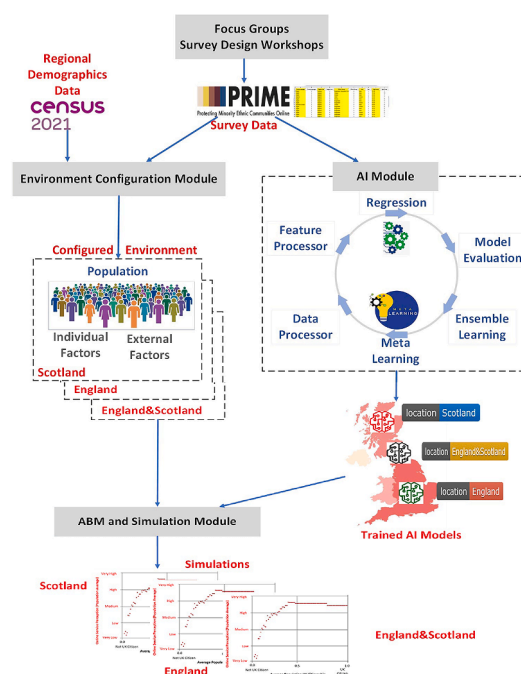
Mennan Guder^{*} , Nazmiye Balta-Ozkan

Faculty of Engineering and Applied Sciences, Cranfield University, Bedford, UK

HIGHLIGHTS

- First study extending ethnicity-based energy research to digital service access disparities.
- Novel ABM framework modelling user interactions with online energy services.
- ML-driven decision parameters derived from survey data to inform agent behaviours.
- Integrated AI-ABM approach combining predictive modelling with behavioural simulation.
- AI Module uses ensemble ML pipelines for region-specific models.
- Identifying key barriers for minority ethnic communities.

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:

Agent-based modelling
Online service experience
Artificial intelligence

ABSTRACT

Digitalisation plays a pivotal role in enhancing energy efficiency; however, it also highlights significant governance challenges and exacerbates various forms of energy injustice. This study explores how technological injustice exacerbates energy poverty, particularly via disparities in digital service access. The focus is on understanding and addressing challenges faced by minority ethnic (ME) communities, who often encounter

^{*} Corresponding author.

E-mail addresses: mennan.guder@cranfield.ac.uk (M. Guder), n.ozkan@cranfield.ac.uk (N. Balta-Ozkan).

<https://doi.org/10.1016/j.egyai.2025.100624>

Available online 22 September 2025

2666-5468/Crown Copyright © 2025 Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

Policy mitigation
Minority ethnic communities

heightened barriers to essential online energy services. While previous research has noted barriers ME communities face in energy markets, this study broadens this literature to analyse these issues for access to digital energy services.

The study integrates modelling, simulation, and AI to address these inequalities. The framework comprises three core modules: AI, Environment Configuration, and Agent-Based Modelling (ABM) and Simulation. Its primary aim is to identify effective strategies, policy changes, and adjustments that enhance online service experiences while addressing the unique challenges faced by these communities.

The AI Module uses ensemble-based ML pipelines to develop region-specific models. It addresses issues such as high dimensionality and overfitting by incorporating methods like Principal Component Analysis, Recursive Feature Elimination, and hyperparameter optimization.

The Environment Configuration Module supports tailored simulations by adapting datasets and regional characteristics, ensuring the accuracy and relevance of the simulations to the target communities.

The ABM and Simulation Module facilitates in-depth analysis of policy impacts and service provider attributes.

This framework offers valuable insights into improving online service delivery, promoting fairness, and addressing disparities in digital experiences. This work advances energy justice research by quantifying how socio-technical barriers disproportionately affect ME communities.

1. Introduction

Global electricity systems are undergoing a rapid transformation, driven by accelerating demand growth and the expansion of variable renewable generation. The IEA's Global Energy Review 2025 reports that electricity demand rose by 4.3 % in 2024, the fastest rate in three years, with more than 80 % of this increase met by low-emission sources [1]. While this surge in renewables is critical for decarbonization, it intensifies the challenge of maintaining system reliability and affordability, necessitating new tools for managing variability and consumer needs in real-time. In this evolving landscape, digitalisation has become an essential enabler, facilitating near real-time data sharing, predictive analytics, and system-wide optimization to build cost-effective and consumer-centred electricity systems [2].

The United Kingdom, the first country to legally commit to net-zero emissions, positions digitalisation as a cornerstone of its energy transition strategy [1]. UK policy highlights data and digital technologies as central to decarbonizing the energy system efficiently, ensuring benefits for all consumers—including the most vulnerable—and stimulating broader economic growth [3]. The energy regulator, Ofgem, has responded with guidance for network companies on developing digitalisation strategies [4], complemented by 'Data Best Practice' [5] and 'Consumer Vulnerability Strategy' documents [6].

Despite these policy ambitions, the consumer-centric potential of digitalisation remains largely unfulfilled. For example, the nationwide rollout of smart meters has been slowed by malfunctioning devices, delayed installations, and persistent consumer distrust [7], exposing a significant gap between policy goals and uptake. These challenges highlight ongoing issues of accessibility, trust, and usability, raising critical questions about the inclusivity of current digital strategies [8]. Such issues are particularly pronounced for minority ethnic (ME) communities, who face unique barriers—including language obstacles, digital literacy gaps, and culturally inappropriate engagement strategies—that are often overlooked in digital service design [9]. Qualitative research further reveals that widespread mistrust and privacy concerns among ME individuals lead to reluctant engagement with online energy services [10].

Previous studies have documented systemic inequalities in UK energy markets, including higher rates of fuel poverty and exposure to precarious tariffs among ME households. However, the digital dimension of these inequities remains underexplored [11]. Broader policy research stresses that digital inclusion must be embedded within the technical and regulatory frameworks of the energy transition [12]. This concern is echoed by the UK Government's data ethics and innovations report, which warns that digital exclusion risks exacerbating vulnerability among disadvantaged groups [13]. Together, these insights highlight the urgent need for research that accounts for heterogeneity and captures the complex experiences of ME households navigating

digital energy services.

ME communities, which make up 17 % of population in Great Britain,¹ are the focus of the UK research council-funded project, PRIME.² A growing literature documents structural inequalities linked to ethnicity and energy use [14], noting that ME households in England are more likely to experience fuel poverty than white households [15]. This precarity is exacerbated by rising energy costs and a higher likelihood of living in energy-inefficient homes [16]. The transition to digital services intensifies these challenges, as ME households often lack the necessary digital literacy, language support, or institutional trust to benefit from smart technologies and online energy management tools. Furthermore, marginalized communities are frequently excluded from decision-making processes related to energy policy and project design [17], creating a cycle of disengagement where services are not tailored to their needs and are therefore underutilized, perpetuating existing inequalities [9].

Within this context, technological injustice emerges as a critical but underexplored dimension of energy justice. ME households in low-income or remote areas may experience digital discrimination [18], where automated systems, biased algorithms, or poorly designed platforms further entrench inequities [19]. Such disparities limit the benefits of digitalisation, including efficient energy management and real-time monitoring, while undermining sector transparency. Although research in other sectors, such as healthcare, has examined service accessibility for ME communities [20], the application of these insights to digital energy services remains limited [21].

Building on this gap, this study investigates the overlooked dimension of technological injustice within the energy sector, focusing on disparities in access to online services among ME communities. It explores how inequitable access to online services can exacerbate existing inequalities, particularly affecting low-income households and those in remote areas with limited internet connectivity. Such disparities can lead to new forms of digital discrimination, where automated systems treat users unfairly based on data or system design, and biases in the design of online services can perpetuate discriminatory practices and unequal access [18]. Emerging research shows that algorithmically driven systems used for credit scoring or tariff recommendations can inadvertently disadvantage ME communities by relying on biased data proxies, thus codifying existing societal inequities into digital energy

¹ Census data for England and Wales is provided by Office for National Statistics for 2021 while data for Scotland comes from Scotland's Census for 2022. The share of ME communities is 7% in the latter while it's 18% in the former.

² Protecting Minority Ethnic Communities Online project is funded by UK Research and Innovation through the Strategic Priority Fund as part of the Protecting Citizens Online programme, initiated in response to the 2020 Online Harms White Paper. For further details, see <https://www.primecommunities.online/>

platforms [19]. This inequality limits digitalisation benefits while undermining sector transparency. Addressing these issues is crucial for promoting equity, empowerment, and inclusivity, ensuring that all individuals have fair and equitable access to energy resources. While studies have explored service accessibility challenges for ME communities in sectors like healthcare [20], the exploration of online service utilization among these communities remains underexplored, creating a significant gap in knowledge. A few recent studies have begun to quantify this gap, noting lower rates of smart meter adoption and engagement with digital energy tools among certain ME groups, but a comprehensive understanding of the driving mechanisms is still lacking [22].

Addressing this knowledge gap requires moving beyond traditional conceptual [14] and statistical approaches, which have identified recognition, distributional, procedural and social injustices [23] but fail to capture interactions between households, technology, and social networks [24]. Complex systems approaches, such as Agent-Based Modelling (ABM), offer a promising solution by simulating how individual households interact with technology and one another, generating emergent patterns and acceptance processes at the system level [25]. Although ABM is increasingly applied in energy research, accurately characterizing household behaviour remains challenging, particularly in the absence of large empirical surveys and frameworks tailored to ME communities [26].

This study addresses these challenges by making four key contributions:

1. **Application of an Integrated Data-Driven ABM to a Novel Domain:** While data-driven ABMs are established in other fields, this study pioneers their application to the critical yet understudied problem of technological injustice and digital exclusion in energy services for ME communities. The framework is tailored to capture the specific socio-technical barriers (e.g., digital literacy, language, trust) these communities face.
2. **Generating tailored empirical data:** To overcome the lack of representative evidence, the study develops a unique dataset through workshops, focus groups, and surveys with ME households. These inputs provide a robust foundation for modelling household behaviour and capturing lived experiences often absent from conventional datasets.
3. **Focus on Digital Service Disparities:** By explicitly examining accessibility to digital energy services, the framework highlights how technological inequities exacerbate energy poverty for ME communities—a dimension often overlooked in previous research.
4. **Policy-Relevant Insights:** The model provides insights for policy-makers and service providers, helping them understand how regional, socio-economic, and social factors shape digital service adoption and enabling the design of interventions that promote equity and inclusion.

Overall, the developed framework captures the complexity, high dimensionality, and interplay of individual, social, socio-economic, and socio-technical factors that shape household energy behaviours. It provides a robust foundation for exploring emergent system-level patterns, testing policy scenarios, and informing equitable design of digital energy services.

The remainder of this section presents a literature overview of ABM, including modelling approaches, key challenges, integration with data-driven and Machine Learning (ML) techniques, and applications within the energy domain.

2. Literature review

The rapid transformation of electricity systems, coupled with the increasing digitalisation of energy services, has highlighted the need for innovative approaches to understand and address disparities in access

and adoption. ABM has emerged as a powerful tool for simulating complex socio-technical systems, capturing interactions between heterogeneous agents and their environments. When combined with data-driven methods, including ML, ABMs can provide insights into individual behaviours, emergent system dynamics, and policy impacts. This literature review synthesizes existing research on ABM approaches, modelling challenges, data-driven enhancements, and applications within energy systems, with a particular focus on how these frameworks can inform the study of digital energy service access for ME communities. By critically examining these areas, the review establishes the foundation for the proposed ML-enhanced ABM framework and situates the study within current academic and policy debates.

2.1. Agent-based modelling approaches

ABM provides a powerful means of simulating complex systems by representing the interactions of autonomous decision-makers, or agents, whose behaviours collectively generate system-level outcomes [27]. By simulating interactions between agents, ABM can reveal macro-level patterns that emerge from micro-level behaviours. Each agent operates according to defined rules, yet the dynamics that emerge from their interactions are often non-linear and unpredictable, making ABM especially suited for capturing the complexity of socio-technical systems such as energy networks [28]. Unlike traditional modelling approaches that rely heavily on aggregated assumptions, ABM allows for the explicit representation of heterogeneous agents with diverse attributes, preferences, and constraints, thus offering a more realistic and granular perspective on system dynamics [27].

In recent years, ABM has been increasingly adopted across the social sciences and related fields to analyse emergent behaviour that are shaped by individual decision-making and social interactions [29]. Its flexibility enables researchers to integrate empirical data into models, ensuring that simulated behaviours reflect real-world beliefs, attitudes, and experiences. In the context of ME communities and digital energy services, such an approach provides a valuable lens for exploring how inequalities in access and engagement arise, evolve, and interact with broader socio-economic and institutional structures.

ABMs serve a variety of purposes, ranging from prediction and explanation to illustration, analogy, and social learning [24]. They are typically categorized according to the nature of agent behaviour, with models broadly grouped into physical, economic, and sociological types [30]. Socio-economic ABMs, in particular, have proven highly effective in examining household energy behaviours, where both social influences and economic constraints shape decision-making. For instance, research has demonstrated that household participation in demand-side management programs is strongly influenced by social learning, whereby peer recommendations and community norms significantly affect willingness to engage [31].

A further strength of ABM lies in its ability to represent bounded rationality, acknowledging that agents rarely have perfect information and instead make decisions under conditions of uncertainty and cognitive limitations. This feature allows researchers to examine adaptive behaviours and feedback processes within dynamic environments, illustrating how small-scale decisions can accumulate into large-scale systemic outcomes. Beyond analysis, ABMs also function as communication devices: they help to represent essential system components [32], facilitate shared understanding among stakeholders, simplify the communication of complex ideas, and provide multiple perspectives through analogy [33].

2.2. Modelling challenges

Despite its strengths, ABM faces enduring challenges, most notably validation [34], computational scalability [35], and behavioural realism [36]. Validation is particularly complex in socio-technical systems, where heterogeneous agents interact in high-dimensional environments

and produce emergent dynamics that are difficult to benchmark against real-world outcomes [37]. This limitation becomes particularly significant in ABM, where focusing only on individual-level behaviours obscure how agents' interactions generate emergent, system-level outcomes, potentially leading analyses—and the policy insights derived from them—to overlook critical structural and collective dynamics [38].

To address validation, researchers employ techniques such as docking, empirical comparison, and visualization as foundational checks, while advanced approaches—including bootstrapping, causal analysis, and inverse generative social science—offer deeper, system-level insight [34]. Global Sensitivity Analysis (GSA) plays a particularly important role, systematically identifying influential inputs in computationally intensive and high-dimensional settings [39].

Scalability represents another major barrier, as the computational demands of simulating large populations and detailed interactions grow exponentially with model complexity. This often limits the exploration of multiple scenarios, long-term dynamics, or robust sensitivity testing. At the same time, behavioural realism remains difficult to achieve: many ABMs still rely on simplified or theoretical assumptions that fail to capture the nuanced, diverse decision-making processes shaping socio-technical systems [34].

Addressing these limitations requires hybrid approaches that integrate data-driven methods with behavioural analysis during data collection and model construction. By embedding empirical evidence into agent behaviours, techniques such as ML can enhance predictive accuracy, improve behavioural fidelity, and account for regional variability and socio-economic diversity [40]. Such integration strengthens validation, mitigates scalability issues through data-informed parameterisation, and ultimately bridges the gap between theoretical abstraction and real-world complexity, making ABM a more robust tool for studying disparities in digital energy service access [41].

Evidence from a systematic review of 71 ABMs addressing household energy decisions highlights that, despite recent advances, agents are still often modelled with simple, rational decision rules, with only a limited range of data-driven constructs represented in decision-making [42]. As a result, many models risk failing to capture the diversity and complexity of real-world behaviours. For ABMs to reach their full potential in policy design, they must appropriately represent behavioural dynamics by strengthening the fit between behavioural determinants (e.g., trust) and the behaviour of interest (e.g., adopting digital services) [43].

2.3. Integrating behavioural analysis into ABM

To address the enduring challenge of behavioural realism in ABM, recent research advocates for a more structured integration of behavioural theory from the outset of model design [43]. A four-step framework has been proposed to bridge this gap: (1) identifying the target behaviour, (2) mapping its influencing factors, (3) grounding these factors in empirical data, and (4) systematically translating them into the ABM [43]. This process ensures that agent rules are directly informed by the factors that drive the behaviour in reality, moving beyond theoretical assumptions. Our framework adopts this approach, explicitly focusing on the "use" behaviour of digital services and employing the PRIME survey and the two design workshops to empirically ground the agents' decision-making parameters, thereby enhancing the model's validity and policy relevance.

2.4. Data-driven ABM models and AI

Data-driven ABMs represent an important methodological advance, as they leverage empirical data to inform agent behaviours, system structures, and simulation dynamics [44]. Unlike traditional models that rely on stylized assumptions, data-driven approaches calibrate decision-making processes with survey data, behavioural experiments, administrative datasets, and real-world observations, thereby improving

the realism and external validity of simulated outcomes [45]. This is particularly critical in socio-technical domains, where heterogeneous agents are influenced by diverse social, economic, cultural, and institutional factors.

Applications of data-driven ABMs span multiple domains. In online contexts, they have been employed to model public opinion dynamics and cyberbullying behaviours, offering insights into the social mechanisms underpinning harmful interactions and the effectiveness of targeted interventions [46]. In economics, probabilistic ABM extensions have been developed to infer latent micro-level variables, using algorithms such as gradient-based expectation maximization to enhance predictive accuracy in housing markets [47]. In environmental governance, ML-enhanced ABMs have evaluated policy interventions—such as payments for ecosystem services—revealing complex temporal effects, including initial increases in adoption followed by declines once incentives were withdrawn [48].

Recent developments illustrate the growing sophistication of data-driven ABMs. For instance, a high-resolution housing market ABM, calibrated with granular micro-level datasets and AI agents, demonstrated the system-wide influence of buy-to-let investors on boom-and-bust cycles [49]. Similarly, AI-enhanced conservation ABMs have combined ecological and evolutionary dynamics, providing adaptive decision-support tools [42]. These examples underscore how hybrid ABM–AI models can deliver actionable policy insights across domains.

Methodological innovations further demonstrate the role of AI in enhancing ABM. Frameworks that embed ML into ABM development allow for data-informed agent rules, improved behavioural fidelity, and transparent outputs [50]. Surrogate modelling, where ML algorithms approximate ABM outputs, enables rapid scenario evaluation in otherwise computationally infeasible settings [51]. Such approaches are especially valuable in high-dimensional policy spaces requiring extensive scenario testing.

Energy and environmental research has seen significant uptake of these hybrid approaches. Open-source modelling platforms have been used to provide data-driven simulations of electricity market dynamics at hourly resolution [52]. Hybrid methodologies combining ABM with bilevel optimization have been applied to real-time pricing in energy communities, demonstrating efficiency gains in battery storage management [53]. Studies of future energy scenarios indicate that aligning household storage decisions with market dynamics reduces costs and enhances renewable integration, in contrast to static pricing schemes. Similarly, multi-agent deep reinforcement learning has been employed to optimize peer-to-peer trading in decentralized markets, showing significant cost savings for households adopting adaptive strategies [54]. At the system level, agent-based co-simulation frameworks have been used to test smart grid demand response programs, confirming that even minor adjustments in building temperature set-points can mitigate district-level imbalances across large populations [55].

Taken together, these advances demonstrate the transformative potential of data-driven and AI-enhanced ABMs. By embedding empirical heterogeneity, scaling policy experimentation, and improving predictive accuracy, they move beyond abstract theorisation toward policy-relevant, context-sensitive insights. Within the scope of digital energy services for ME communities, such methods are uniquely suited to capture diverse user experiences, identify structural inequities, and simulate systemic effects of interventions.

Unlike existing approaches in socio-technical energy modelling that use data primarily for post-validation and rule extraction, the present study pioneers a data-driven ABM–AI framework grounded in the PRIME survey data. Here, ML models serve as the decision-making engines of agents, ensuring that the validity of the simulation is intrinsically linked to the predictive strength of empirical models. This ensures both robustness and behavioural realism, moving beyond abstract assumptions.

Our integrated framework addresses core modelling challenges by:

1. **Improving Behavioural Realism:** Replacing theoretical ABM assumptions with ML models trained on empirical data together with structural survey construction process to explicitly focus on the understudied "use" behaviour of digital services [56,57].
2. **Enhancing Validation and Scalability:** Combining GSA with ML approximations to strengthen validation and employing Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) [58] feature selection to manage high-dimensional data without overfitting.
3. **Ensuring Contextual Relevance:** Incorporating insights from behavioural analysis to guarantee that the selected features and ML-predicted behaviours are relevant to the specific context of digital service use.

This integration yields three critical advantages: capturing emergent dynamics through ML-enhanced ABM, enabling cross-regional analysis (England vs. Scotland) via data-driven simulations and contributing to the field of modelling habitual "Use" behaviours related to digital services by employing a data-driven approach to achieve behavioural realism [56,57]. The following section details the proposed ABM framework, its key components, functionalities, and the integration of these ML-driven decision processes.

3. Methodology

The primary objective of the proposed framework is to analyse the self-reported online service experiences of ME communities, with a focus on achieving behavioural realism. To this end, the ABM is developed using a structured four-step behavioural analysis approach [42], ensuring a systematic alignment between data collection, behavioural determinants, and simulation design.

3.1. Step 1: Identifying the target behaviour and survey construction

This framework concentrates on a specific yet underexplored behaviour: the habitual use of digital energy services (e.g., checking an app, paying bills online, submitting meter readings). Unlike one-off adoption decisions, this behaviour captures the continued and satisfactory use of services. The target behaviour is a shift from the baseline state of non-use or limited use (often due to perceived barriers) to sustained and satisfactory engagement with these services. Within the model, this is operationalised as each agent's perception score of their online service experience.

The PRIME survey was designed through an iterative co-design process involving the research team, ME community representatives, regulation authorities, and service providers. This participatory design ensured that the survey captured the most relevant behavioural determinants shaping digital service use [43]. The resulting dataset comprises 878 respondents, each represented by 138 features (socio-economic, cultural, and technological attributes) and a state variable reflecting satisfaction with online energy services. This direct alignment between survey construction and model design ensures a robust determinant-behaviour fit, grounding the ABM in empirically validated behavioural factors.

3.2. Step 2: Mapping influencing factors

The PRIME survey results and co-design workshops were used to map influencing factors into individual and external categories. This mapping ensures the factors are relevant to the specific behaviour type, which involves both habitual (e.g., routine app checks) and reflective (e.g., trusting a platform with data) elements. These factors were operationalised as agent attributes and environment settings, ensuring contextual relevance and direct transfer into the ABM structure (see Table 1).

Table 1

Attributes of agents and environment.

Factors	Category	Socio-Economic Attributes	Socio-Technical Attributes
Individual	Demographics	- Employment Status - Highest Level of Education - Accommodation Type - Income Level (implied by employment) - Citizenship	- Technology Literacy
	Health & Living	- Housing Situation - Activity Limitations	- Access to Digital Devices
	Technology & Internet Use		- Used Devices - Internet Access Type - Internet Medium - Digital Skill Level - Online Service Usage Reason - Preferred Digital Platforms - Online Harm Experience - Trust in Digital Systems
External (Environment Attributes)	Online Service Usage	- Ability to Pay for Services	

3.3. Step 3: Grounding the model with empirical data

The mapped determinants were parameterised using the PRIME survey data, ensuring the model is empirically grounded. This step moves the ABM beyond theoretical abstraction by explicitly linking survey-derived features to agent behaviour. In next step, ML is applied to this survey data to capture the complex, non-linear relationships between influencing factors and the target behaviour. By doing so, the model directly addresses the challenge of behavioural data scarcity highlighted in ABM literature, as ML algorithms provide predictive mappings where traditional assumptions often fall short.

3.4. Step 4: Translating into the ABM framework (The integrated Ai-ABM modules)

The mapped and empirically grounded factors are translated into the simulation through our integrated three-module framework. The AI Module encapsulates the learned relationship between attributes (factors) and behaviour (perception score). The Environment Configuration Module sets the external factors (policies, population demographics). Finally, the ABM and Simulation Module executes the behaviour, allowing agents to interact and generate emergent outcomes.

- **The Environment Configuration Module** initializes the synthetic population and defines the external factors (policy parameters, regional characteristics) that form the context for the behaviour.
- **The AI Module** serves as the computational embodiment of the behavioural mapping. It generates the function $f(\text{attributes, environment}) \rightarrow \text{perception score}$ that acts as the 'brain' for each agent. This function is not a simple heuristic rule but a sophisticated, data-driven prediction model trained on the empirical PRIME survey data.
 - **Input:** The module is trained on the empirical **PRIME survey data**, which provides the ground truth for the relationship between agent attributes and their reported online service experience.
 - **Process:** The module employs automated ML pipelines to construct this predictive function efficiently and robustly.
 - **Output:** The final outputs are high-performing fused ensemble models for each spatial context (England, Scotland, and a combined England & Scotland model). These models are serialized (saved to disk), making them portable and transferable functions.

They are integrated into the ABM module to govern the perception and behaviour of every agent during simulation. The performance of each regional model is rigorously validated using holdout testing and cross-validation to ensure reliability and generalizability [59].

- **The ABM and Simulation Module** is where the behaviour is simulated. Each autonomous agent, governed by its AI-derived "brain," interacts with the environment and other agents. Its perception of the online service is dynamically computed based on its attributes and the state of the environment, allowing for a realistic simulation of the "use" behaviour over time.

4. The framework

The proposed framework consists of three interconnected modules: Environment Configuration, AI, and ABM & Simulation. Developed in Python, the framework offers flexibility in integrating ML models, generating diverse configurations, and adapting the model to different cultural and social contexts. This versatility allows it to be applied across regions or communities with distinct demographics, policies, or socio-technical characteristics. The architecture operationalizes the behavioural analysis approach, ensuring simulations are grounded in empirical patterns of service "use" rather than theoretical assumptions.

The framework workflow is illustrated in Fig. 1. The process begins with empirical survey data from the PRIME project, which feeds into the AI Module. Here, ensemble ML pipelines learn the complex, non-linear mapping between agent attributes and their online service perception, producing trained models that serve as the data-driven "brains" of the agents. The Environment Configuration Module then uses these models and regional demographic data to initialize a realistic population and define policy parameters, creating a Configured Environment (e.g., England, Scotland). Finally, the ABM & Simulation Module executes the core experiment: autonomous agents interact within this environment, generating emergent system-level outcomes from micro-level behaviours. These results are analysed to produce policy insights that directly address factors shaping digital service experiences among ME communities.

4.1. Environment configuration module

This module is responsible for **initializing the population and policy environment**, effectively defining the context in which agents

operate. Its main contributions are:

- **Population Initialization:** Constructs synthetic populations that mirror real-world demographic and socio-economic distributions.
- **Empirical Grounding:** Avoids unrealistic random distributions by incorporating real-world data, enhancing the model's fidelity and ensuring outputs reflect genuine socio-technical dynamics.

By allowing for **population diversity and context-specific policy inputs**, this module enables the framework to be applied across different regions, each with unique populations and service conditions.

4.2. AI module

The AI Module serves as the decision-making core of the framework, translating agent attributes and environmental conditions into predicted perceptions of online energy service use. The module follows a systematic, step-by-step workflow as outlined below:

Step 1. Data Pre-processing and Feature Engineering

Given the high-dimensional nature of the PRIME survey data (138 features for 878 respondents), the primary challenge was to mitigate the acute risk of overfitting and improve model interpretability. To address this, our pre-processing pipeline aggressively managed dimensionality. We employed rigorous feature selection techniques, including Extra Trees Pre-processing [60] and Select Percentile, to isolate and retain only the most predictive variables. Furthermore, we utilized feature extraction methods such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Feature Agglomeration to transform the feature space into a lower-dimensional set of components that capture the latent structures in the data [61]. This process was a necessary step to ensure the resulting models are robust, generalizable, and built on a clean, information-rich input set.

Step 2. Model Training Pipelines

Two complementary AutoML pipelines are used to optimise predictive models:

- **Auto-Sklearn Pipeline:** Auto-Sklearn employs Bayesian optimisation to evaluate a wide suite of regression algorithms, such as Random Forests, AdaBoost, Gradient Boosting Machines, XGBoost, LightGBM, CatBoost, ARD Regression, KNN, Gaussian Processes, and

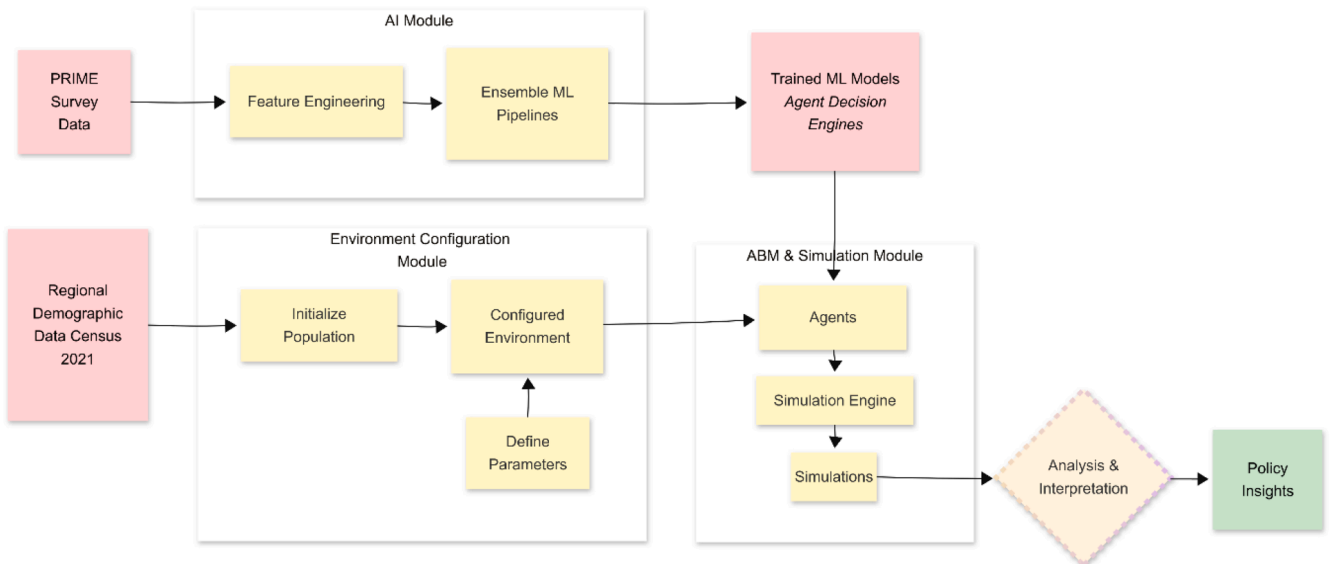


Fig. 1. Workflow of the integrated AI-ABM framework.

MLP. Bayesian optimisation and meta-learning are employed to select the best-performing models. Ensemble strategies, such as bootstrap aggregating (bagging) and stacking, further enhance predictive accuracy.

The Auto-Sklearn pipeline (Fig. 2) begins with raw data and applies pre-processing (cleaning, imputation, normalisation, and feature extraction). Bayesian optimisation systematically explores the hyperparameter space, evaluating candidate models with metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 . The ensemble prediction is defined in Eq. (1) where $\tilde{y}_i$ is the prediction from the i th model and w_i its assigned weight.

$$\tilde{y}_{\text{ensemble-sklearn}} = \sum_{i=1}^n w_i \tilde{y}_i \quad (1)$$

Table 2 reports the diverse models contributing to the final ensemble, highlighting the robustness of the Auto-Sklearn approach. For instance, Model 1 employs a Random Forest algorithm with mean imputation and quantile transformation, coupled with Extra Trees pre-processing for feature selection, achieving a significant weight of 0.28. In contrast, Model 4 uses ARD Regression with median imputation and normalization, utilizing feature agglomeration for extraction, and carries a weight of 0.14. This diversity in models and pre-processing strategies highlights the robust and meticulous approach of Auto-Sklearn in automating model selection and hyperparameter optimization to address challenges such as high-dimensional data and overfitting, enhancing prediction accuracy and model reliability. The outcome of this process includes an optimized final model and a data transformer, which are the key deliverables for effectively applying and utilizing the model.

- **Auto-Keras Pipeline:** In parallel, Auto-Keras performs Neural Architecture Search (NAS) to identify high-performing deep learning

architectures. The search space includes Dense Networks, Convolutional Neural Networks (CNNs), Residual Neural Networks (ResNet), and Recurrent Neural Networks (RNNs). Hyperparameters (e.g., number of layers, activation functions) are systematically tuned using algorithms such as Random Search, Bayesian Optimisation, Hyperband, Greedy Search, and NAS-RL [62].

The NAS process (Fig. 3) involves dataset transformation, definition of architectural configurations, search and training of candidate models, and iterative refinement based on validation performance. The best-performing neural model is selected, with final prediction is given in Eq. (2) where m is the number of candidate models explored.

$$\tilde{y}_{\text{ensemble-keras}} = \max_{1 \leq j \leq m} \tilde{y}_j \quad (2)$$

4.2.1. Step 3: Model fusion

To combine the strengths of traditional ML and deep learning, the outputs of Auto-Sklearn and Auto-Keras are fused into a single hybrid ensemble as given in Eq. (3). This ensemble leverages the strengths of both traditional ML and neural network approaches to predict agents' perceptions of online service use.

$$\tilde{y}_{\text{final}} = \alpha \tilde{y}_{\text{ensemble-sklearn}} + (1 - \alpha) \tilde{y}_{\text{ensemble-keras}} \quad (3)$$

The fusion parameter α (where $0 \leq \alpha \leq 1$) controls the weighting between the two ensembles. To determine the optimal value for α , we performed a grid search over a range of values from 0 to 1 in increments of 0.1. The performance of each resulting fused model was evaluated on the validation set using the RMSE metric. The value of α that yielded the lowest RMSE was selected for the final model. The optimal α is found to be 0.82. This optimization process ensures the fused model achieves the best possible balance, leveraging the robust feature-based learning of

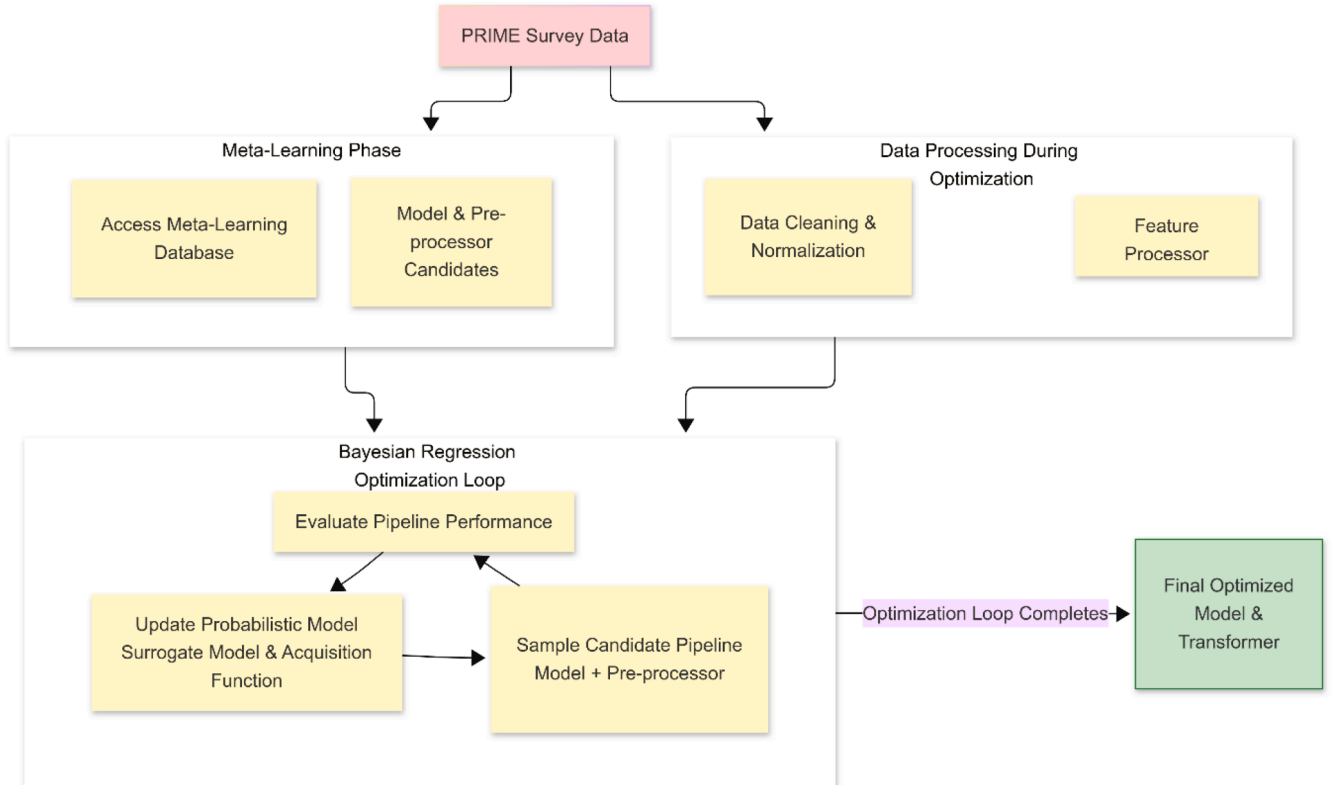


Fig. 2. Auto-sklearn pipeline.

Table 2
Auto-sklearn ensemble learning results.

	Regression Algorithm	Data Pre-processor	Feature Pre-processor	Weight
1	Random Forest	Mean imputation, Quantile Transformer (n_quantiles: 1344, output_distribution: uniform)	Extra Trees Pre-processing (Feature Selection)	0.28
2	Extra Trees	Mean imputation, Standardize	Select Rates (Feature Selection)	0.22
3	AdaBoost	Mean imputation, Normalize	Fast ICA (Feature Extraction)	0.16
4	ARD Regression	Mean imputation, Normalize	Feature Agglomeration (Feature Extraction)	0.14
5	MLP	Median imputation, Quantile Transformer (n_quantiles: 174, output_distribution: uniform)	Select Percentile (Feature Selection)	0.06
6	AdaBoost	Median imputation, Quantile Transformer (n_quantiles: 1904, output_distribution: normal)	Select Percentile (Feature Selection)	0.04
7	K-Nearest Neighbours	Mean imputation, Quantile Transformer (n_quantiles: 1000, output_distribution: normal)	Feature Agglomeration (Feature Extraction)	0.04
8	Gaussian Process	Mean imputation, Quantile Transformer (n_quantiles: 268, output_distribution: uniform)	Feature Agglomeration (Feature Extraction)	0.02
9	AdaBoost	Mean imputation, MinMax Scaling	Select Percentile (Feature Selection)	0.02
10	AdaBoost	Median imputation, Normalize	PCA (Feature Extraction)	0.02

Auto-Sklearn and the complex pattern recognition capabilities of Auto-Keras for final prediction.

Step 4. Spatially Distinct Models

To reflect regional differences, three distinct models are trained: one for England, one for Scotland, and a combined model. This allows for the exploration of demographic, policy, and digital access variations across contexts.

Step 5. Integration with ABM

The AI Module produces a predictive function,

$$f(\text{attributes}, \text{environment}) \rightarrow \text{perception score} \quad (4)$$

which is serialized and integrated into the ABM and Simulation Module. This function acts as the “brain” of each agent, replacing traditional rule-based decision logic with a data-driven, empirically grounded mechanism.

During simulation initialization, each agent is assigned a unique set of attributes. Whenever an agent interacts with its environment (e.g., encounters a new policy or service feature), its change in perception is computed by evaluating this shared prediction function. The function is implemented as a callable model within the agent class, ensuring that behavioural updates are consistent with the statistical patterns identified in the survey data.

Each perception value generated by the AI function is time lined throughout the simulation. From these timelines, simulation graphs are derived by tracking changes in attributes over time. For a given time step, the average perception score across the population is calculated and plotted as a point on the simulation graph. By iterating this process for all time steps, we obtain a detailed trajectory of population

perception dynamics. When all individual points are aggregated, the overall simulation graph emerges, illustrating how population-level perception evolves in response to selected environmental parameter changes (ex. increase in Citizenship) and policy interventions.

This integration offers three key advantages:

1. **Behavioural Realism:** Agent decisions are based on real-world data, moving beyond theoretical assumptions.
2. **Dynamic Adaptation:** Agents respond to changes in the environment or policy in a manner consistent with empirical trends, and population-level effects are dynamically reflected in the simulation graphs.
3. **Interpretability:** The drivers of agent behaviour are explicitly linked to features analysed by the ML models, enhancing the transparency and policy relevance of simulation outcomes.

Step 6. ML-Model Validation

The ensemble ML models were rigorously validated to ensure their robustness, reliability, and generalizability despite the high-dimensional data. We employed a strict holdout testing protocol and 10-fold cross-validation. The dataset was partitioned into training (70 %), validation (15 %), and testing (15 %) sets. The validation set was used for model selection and hyperparameter tuning during the automated ML process, while the final testing set was held back strictly for an unbiased evaluation of the best-performing model. This rigorous validation framework was essential to provide confidence that the models learned genuine predictive relationships rather than spurious correlations within the training data. Predictive accuracy was measured using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2).

The ensemble ML models were rigorously validated to ensure their robustness, reliability, and generalizability despite the high-dimensional data. We employed a strict holdout testing protocol and 10-fold cross-validation. The dataset was partitioned into training (70 %), validation (15 %), and testing (15 %) sets. The validation set was used for model selection and hyperparameter tuning during the automated ML process, while the final testing set was held back strictly for an unbiased evaluation of the best-performing model. This rigorous validation framework was essential to provide confidence that the models learned genuine predictive relationships rather than spurious correlations within the training data. Predictive accuracy was measured using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2).

Table 3 summarises the performance of twelve ML models tested: the Fused Model, Auto-Sklearn, Random Forest, Extra Trees, AdaBoost (Fast ICA), ARD Regression, Auto-Keras, Multi-Layer Perceptron (MLP), AdaBoost (Quantile 1904), K-Nearest Neighbours (KNN), Gaussian Process, and AdaBoost (MinMax Scaling).

The **Fused Model** outperformed all others, achieving an MAE of 0.082, MSE of 0.010, RMSE of 0.100, and R^2 of 0.92 on the independent test set. Auto-Sklearn ($R^2 = 0.89$) and Random Forest ($R^2 = 0.87$) followed closely, demonstrating the strength of automated and ensemble-based approaches. By contrast, AdaBoost with MinMax Scaling recorded the lowest performance ($R^2 = 0.66$).

The **baseline model**—a Random Forest with rule-based decision logic—was chosen because Random Forests are one of the most widely applied methods in ABM studies of energy domains, often serving as a benchmark due to their interpretability, robustness, and ease of integration into simulation workflows. Comparing our data-driven Fused Model ($R^2 = 0.92$) against this widely used baseline ($R^2 = 0.87$) highlights the added value of integrating automated ensemble approaches.

This comparative analysis, detailed in The ensemble ML models were rigorously validated to ensure their robustness, reliability, and generalizability despite the high-dimensional data. We employed a strict holdout testing protocol and 10-fold cross-validation. The dataset was

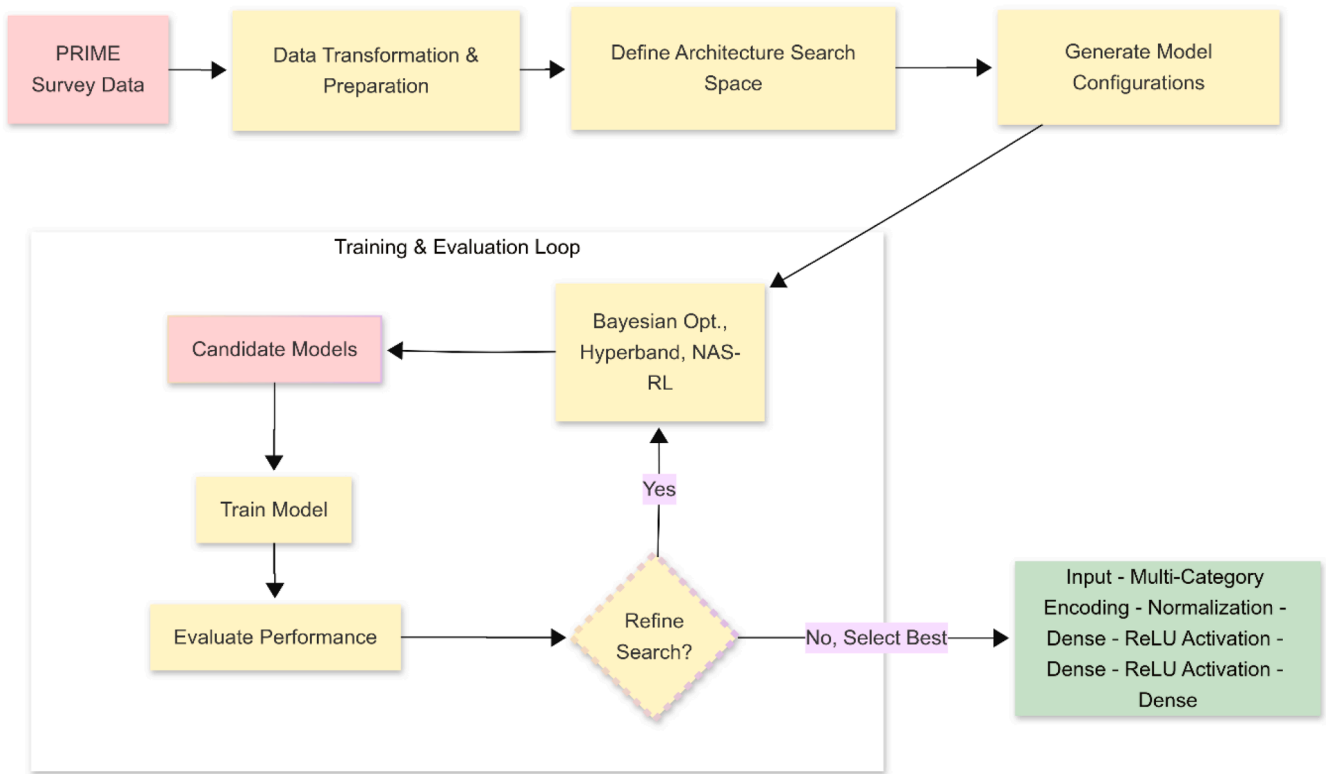


Fig. 3. Auto-keras pipeline and best model.

Table 3
Performance for ML Strategies.

Model	MAE	MSE	RMSE	R ² Score
Baseline (Standard Random Forest)	0.105	0.014	0.118	0.87
Fused Model	0.082	0.010	0.100	0.92
Auto-Sklearn (Table 2)	0.095	0.012	0.110	0.89
Extra Trees	0.115	0.016	0.126	0.85
AdaBoost (Fast ICA)	0.125	0.018	0.134	0.83
ARD Regression	0.140	0.021	0.145	0.80
Auto-Keras	0.150	0.023	0.152	0.78
MLP	0.165	0.026	0.161	0.75
AdaBoost (Quantile 1904)	0.170	0.027	0.164	0.73
K-Nearest Neighbours	0.175	0.028	0.167	0.72
Gaussian Process	0.190	0.031	0.176	0.68
AdaBoost (MinMax Scaling)	0.195	0.032	0.179	0.66

partitioned into training (70 %), validation (15 %), and testing (15 %) sets. The validation set was used for model selection and hyperparameter tuning during the automated ML process, while the final testing set was held back strictly for an unbiased evaluation of the best-performing model. This rigorous validation framework was essential to provide confidence that the models learned genuine predictive relationships rather than spurious correlations within the training data. Predictive accuracy was measured using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R²).

Table 3, confirms that our integrated AI-ABM framework provides a significant increase in predictive accuracy and behavioural realism, moving beyond rule-based simplifications that dominate many current ABM applications in energy research.

4.3. ABM and simulation module

The ABM and Simulation Module serves as a decision-support tool that enables policymakers and researchers to systematically examine the

effects of policy interventions and parameter modifications (e.g., mandating that all providers offer multilingual digital interfaces). Through this module, users can simulate a wide range of scenarios to understand how policy changes, population characteristics, and service provider attributes jointly influence perceptions of online energy services.

The ABM and Simulation module serves as a sophisticated tool for decision makers, enabling them to systematically examine the effects of policy changes or parameter modifications (for example, introducing a requirement that all providers must offer multilingual digital interfaces). This module allows for the simulation of various scenarios to understand how changes in the environment, driven by policies, population characteristics, and online service provider attributes, can influence the overall perception of online services. The interaction flow among household agents, policy, and the environment in the context of online services in the energy sector is illustrated in Fig. 4. The simulation environment is shaped dynamically by two main elements:

- 1. Policy Changes:** These are mandates or regulations set by policy-makers that shape the operating environment of online energy services. For example, a policy requiring all energy service providers to offer mobile applications would directly influence how digital services are delivered and accessed. Such policy adjustments act as levers that can shift population-level responses by altering the decision pathways modelled in the AI and agent-based systems.
- 2. Population Characteristics:** The demographic and regional attributes of the population play a crucial role in shaping online service perception. Factors such as technology access, digital literacy, and socioeconomic status are considered to understand how different segments of the population interact with online services.

For example, when a new policy mandates energy service providers to offer multi-language support on their digital platforms, agents interact with these enhanced services. Their perceptions of the online

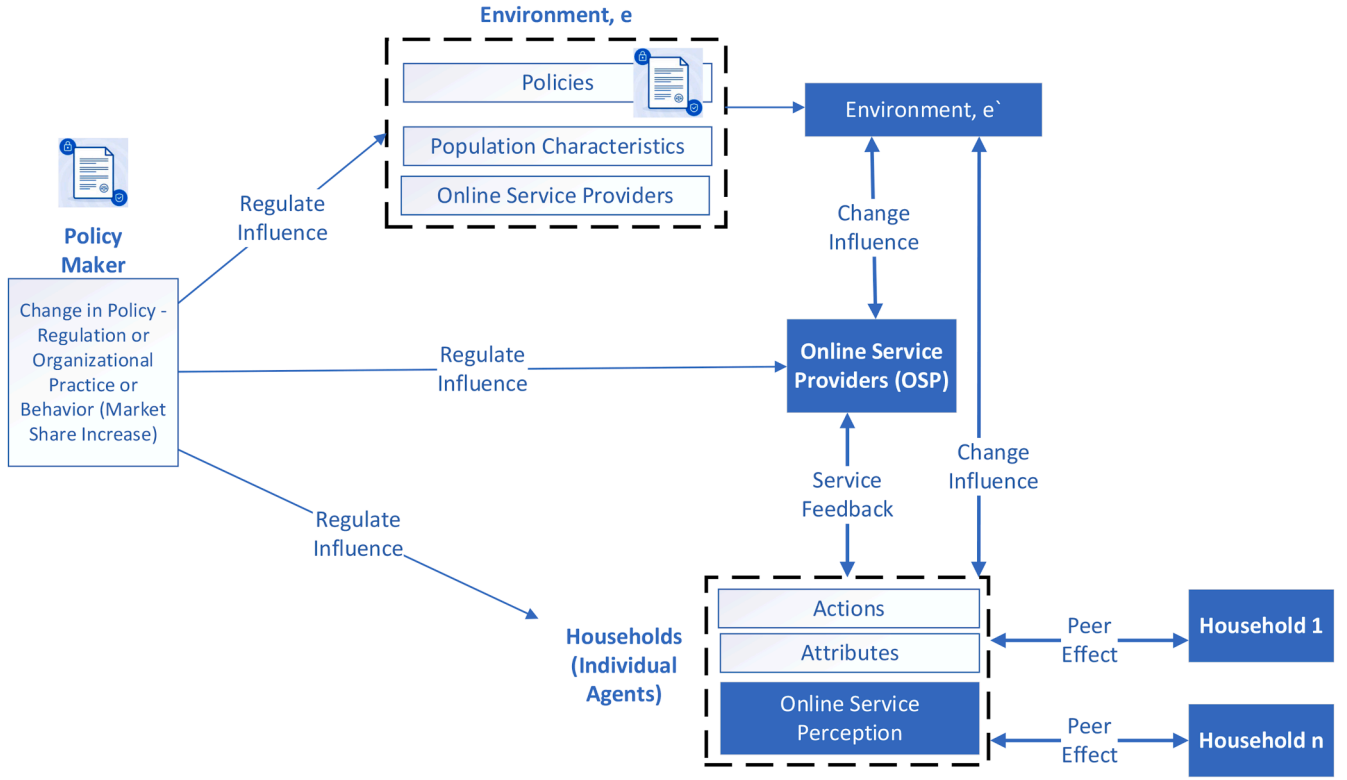


Fig. 4. Policy, household and environment interaction.

service are influenced not only by the accessibility of the service (e.g., availability in their preferred language) but also by their personal characteristics, such as language proficiency and past experiences with digital platforms. This policy change can significantly improve engagement and satisfaction among ME communities, particularly for those who face language barriers when accessing online energy services.

4.3.1. Modelling policy impact with linear diffusion functions

The simulation module employs diffusion functions to model gradual transitions in system parameters by calculating incremental changes at discrete time points. To simulate a desired change in any policy or consumer characteristics (e.g., mobile service usage) ΔL across the population over a specified number of simulation points, we distribute this change evenly across the simulation points. Here's how we calculate the number of individuals k to be selected for each simulation point to achieve this change.

- **Define the Desired Total Change ΔL :** The total change that you want to achieve across the entire simulation period.
- **Determine the Number of Simulation Points:** Let n be the total number of simulation points.
- **Calculate the Change per Simulation Point:** The change per simulation point ΔL_{point} in Eq. (5) is given below. This represents the average change in mobile service usage that should be achieved at each simulation point.

$$\Delta L_{point} = \frac{\Delta L}{n} \quad (5)$$

- **Determine the Average Change per Individual:** Let $\Delta L_{individual}$ be the change for each individual selected for change.
- **Calculate Required k for Each Simulation Point:** To achieve the desired change ΔL_{point} in Eq. (6) at each simulation point, calculate the number of individuals k needed:

$$k = \frac{\Delta L_{point} * P}{\Delta L_{individual}} \quad (6)$$

- ΔL_{point} is the change required at each simulation point,
- P is the total population size,
- $\Delta L_{individual}$ is the change in mobile service usage for everyone.

4.3.2. Simulation graphics

In this submodule, the results of the simulation data are visually presented through charts, offering a comprehensive view of evolving dynamics and policy impacts. Simulation data is collected and analysed at various points to illustrate changes over time. By presenting these simulations through detailed graphics, the simulation tool provides policymakers and researchers with critical insights into the impact of various factors and policy changes. This dual-functionality tool serves two primary purposes, each enhancing decision-making and strategy formulation:

1. **Evaluating the Possible Effects of Policy Changes:** The simulation tool allows users to foresee the potential impacts of policy modifications on online service perception. By analysing these projections, policymakers can anticipate outcomes, mitigate risks, and make data-driven decisions to improve service delivery and user satisfaction.
2. **Understanding Existing Patterns in Online Service Perception and Customer Attributes:** Beyond evaluating policy changes, the simulation tool is invaluable for analysing current trends and patterns in online service perception. By examining the interactions between various demographic factors (such as age, ethnicity, and accommodation type) and service attributes, researchers can identify key determinants of service perception. This understanding aids in recognizing which factors contribute most significantly to user

satisfaction, enabling the development of targeted strategies to enhance the overall online service experience.

4.3.3. ABM model validation

The validation of the proposed ABM model was conducted using a multi-step framework that integrates empirical evidence, expert evaluation, ML model validation, and sensitivity analysis techniques. Procedures for ML model validation are described separately in the ML-Model Validation section. This subsection focuses on the agent-based validation, employing GSA and correlation-based cross-checking.

GSA is used to identify which factors have the greatest influence on model outcomes. By computing Sobol indices, it is possible to quantify both the direct effects of individual parameters (first-order indices) and their interactions with other factors (total-order indices). Sobol indices are derived by decomposing the variance of the model output into contributions from each input parameter and all possible interactions [70]. First-order indices measure the proportion of output variance caused by a single parameter alone, while total-order indices capture the overall contribution of a parameter, including all its interactions. This approach not only identifies the key drivers of model behaviour but also supports expert validation, ensuring that the simulation dynamics are interpretable and consistent with expected real-world patterns.

The ABM validation process consists of the following steps:

1. **Parameter Space Sampling:** Using Latin Hypercube Sampling, diverse parameter sets are generated to explore the input space comprehensively [63]. This ensures broad representation of potential variations in agent characteristics and online service interactions.
2. **ABM Execution and Sensitivity Analysis:** The ABM is executed for each sampled parameter set, producing outputs that form the basis

for sensitivity analysis. Sobol indices are then computed to assess the influence of each input parameter. First-order indices measure the direct effect of a single parameter on the output, capturing how changes in that parameter influence results. Total-order indices reflect the cumulative effect of a parameter, including both direct effects and interactions with other parameters [70]. This dual assessment provides a comprehensive understanding of which factors drive model behaviour and how parameter interactions shape simulation outcomes, supporting robust and interpretable results.

3. **Correlation Analysis and Validation:** To complement the insights obtained from GSA, Sobol index results were cross-verified using correlation analysis. All correlations were calculated with respect to the Persistence Score, a continuous measure ranging from -1 to 1 , derived from user perceptions and gathered in interviews (0–5). The correlation method was chosen based on the type of variable: continuous or count variables (e.g., English reading score, digital skill level) were analysed using; binary variables (e.g., UK Citizenship: Yes/No) were analysed using Point-Biserial correlation; and ordinal variables with more than two ordered categories (e.g., Highest Level of Education, Immigrant Status, Accommodation Type, Working Status, Past Online Harm Experience) were analysed using Spearman's rank correlation. This approach ensures that the relationships between agent attributes and persistence are measured appropriately, reflecting both linear and monotonic trends, and provides a robust cross-validation of the simulation results.

The Sobol indices from GSA were found to be consistent with the statistical correlations calculated directly from the survey data (Table 4). Parameters with high first-order and total-order Sobol indices (e.g., accommodation type and highest education level, past online harm experience) also exhibit strong correlations with online service

Table 4

Sobol indices and correlation (Online Service Perception) values for agent parameters.

Parameter	Encoding	Region	First-Order Index	Total-Order Index	Correlation (Persistence Score)
UK Citizen	Yes: 1, No: 0	England	0.10	0.28	0.62
English Level (Reading)	Not at all confident: 0 Not very confident: 1 Fairly confident: 2 Very confident: 3	Scotland	0.03	0.08	0.15
		England	0.09	0.31	0.40
		Scotland	0.07	0.26	0.38
Immigrant Status	Asylum Seeker: 1 Refugee: 2 Humanitarian Protection: 3 Not-Settled EU Citizen: 4 Visa Holder: 5 Settled EU Citizen: 6 Indefinite Leave to Remain: 7 Citizen: 8	England	0.09	0.25	0.38
		Scotland	0.02	0.05	0.23
Highest Level of Education	No qualifications: 1 Primary: 2 Secondary: 3 First degree: 4 Postgraduate: 5	England	0.13	0.32	0.44
		Scotland	0.14	0.35	0.46
Accommodation	Homeless: 1 Temporary accommodation: 2 Shared housing: 3 Living with parents: 4 Social housing: 5 Private rented housing: 6 Own home: 7	England	0.13	0.30	0.55
		Scotland	0.09	0.22	0.27
Past Online Harm Experience	Count of Previous Online Harm Experience [0–5]	England	0.11	0.27	−0.64
		Scotland	0.11	0.29	−0.64
Working Status	Not Working: 1 Unemployed: 2 Semi-Retired: 3 Retired: 4 Student: 5 Self-employed: 6 Employed: 7	England	0.10	0.28	0.52
		Scotland	0.12	0.29	0.58

Footnote: Correlation values are computed using **Pearson correlation** for continuous/count variables, **Point-Biserial correlation** for binary variables, and **Spearman's rank correlation** for ordinal variables.

perception scores. This consistency indicates that parameters with strong direct or interaction effects in the simulation correspond to real-world behavioural trends. Furthermore, the first-order indices often align closely with correlation magnitudes, confirming that the direct effect of individual parameters observed in the ABM matches the linear or monotonic relationships seen in the data. Total-order indices, which include interaction effects, typically exceed first-order indices for parameters that interact strongly with others, explaining why some variables may have moderate correlations with outcomes but still show high total-order contributions in the simulation. This agreement validates the simulation model and strengthens confidence that ABM results are both realistic and interpretable.

By applying this framework, the most influential parameters identified by the ABM can be confirmed to align with real-world behavioural patterns, enhancing model reliability and interpretability. Sensitivity trends that correspond with empirical data and theoretical expectations provide confidence in the simulation outputs and their relevance for policy decision-making.

The results from GSA confirm that certain parameters significantly impact online service perceptions. Notably:

- **UK Citizenship** strongly influences perceptions in England but has a weaker effect in Scotland.
- **English Language Skills (Reading)** are crucial across both regions.
- **Accommodation Type** and **Highest Level of Education** emerge as highly influential factors in shaping online service interactions.
- **Past Online Harm Experience** exhibits a strong negative correlation with online service perceptions, suggesting that individuals with prior negative experiences may engage less with digital services.

This multi-step validation process ensures the accuracy, robustness, and interpretability of the ABM. The insights gained from GSA support targeted policy interventions and service optimizations, helping mitigate digital inequalities among ME communities. Furthermore, this validation framework enhances the credibility of the model for future decision-making in online energy service accessibility.

5. Case study: UK citizenship versus online service perception

In this case study, we examine the relationship between UK citizenship and online service perception across three contexts: England, Scotland, and a combined case of both regions. For each of these contexts, we constructed regression models and conducted corresponding simulations. Fig. 5 illustrates the simulation graphs for each of the three regional simulations.

The goal of this study is to analyse both the regional and overall effects of UK citizenship on online service perception. The strong positive correlation (0.62, Table 4) supports the claim that citizenship is an enabler. This disparity highlights the need to address these barriers to ensure equitable access and inclusivity for all users, regardless of citizenship status.

In comparing the regional effects, the simulations reveal a notable divergence between England and Scotland. In England (Fig. 5b), UK citizenship is associated with a clear positive effect on online service perception; however, this relationship demonstrates diminishing marginal improvements as individuals progress along the path to citizenship. While initial integration leads to noticeable gains in perception, further advancement yields smaller incremental benefits. In contrast, Scotland (Fig. 5c), shows higher but varying degree of satisfaction at the beginning of the citizenship journey which may be linked to access to public services from the first day of entry into Scotland and ambition for ‘multiculturalism’ compared to England’s focus on ‘community cohesion’ [64]. This is supported further by a more positive sentiment towards immigration where a higher proportion of the Scottish public (38 %) would like immigration to increase rather than decrease (28 %) [65].

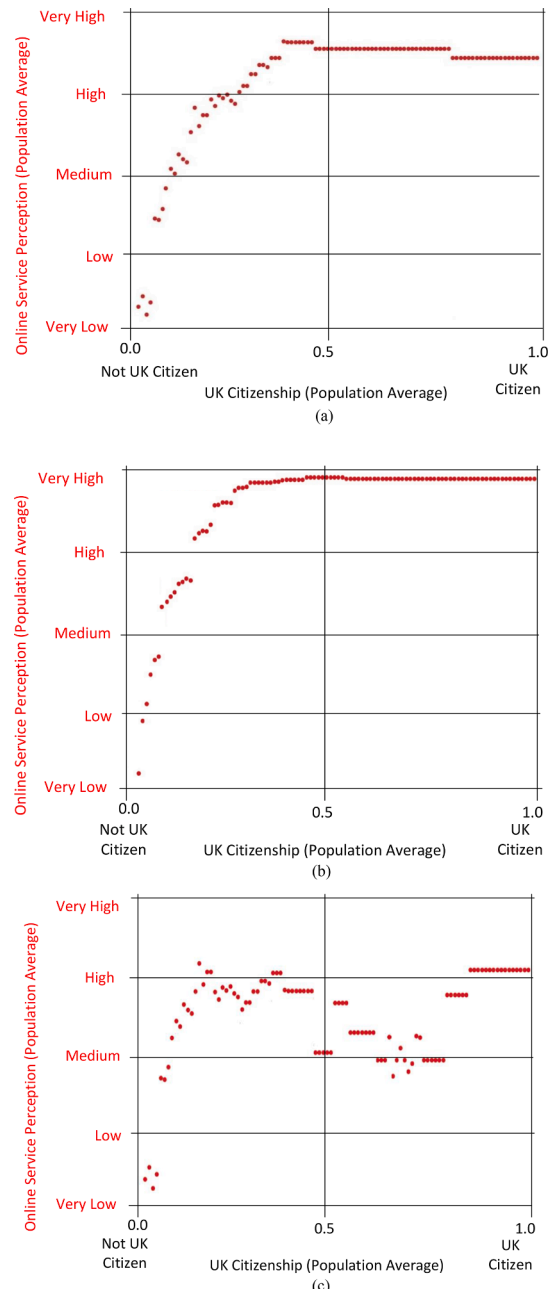


Fig. 5. UK citizenship versus online service perception simulation graphs: (a) England and Scotland, (b) England, (c) Scotland.

6. Discussion

This study developed an integrated AI-ABM framework to analyse and address the digital service access disparities faced by ME communities in the UK energy sector. The discussion reflects on the key findings, their implications, and how they advance the understanding of technological injustice.

The results from the GSA and correlation studies provide robust, empirical evidence for the socio-technical barriers that significantly impact online service perception. The strong negative correlation between Past Online Harm Experience and service perception underscores that cyber security and trust are not peripheral concerns but central to energy justice. For ME communities, a prior negative online experience is a major deterrent to engaging with digital energy services, highlighting an urgent need for providers to implement and communicate robust security and privacy measures.

The divergent impact of UK Citizenship between England and Scotland offers a nuanced understanding of how regional policy contexts shape digital inclusion. The diminishing marginal gains in service perception with citizenship progression in England suggest that initial integration support is crucial, but its effectiveness plateaus. In contrast, Scotland's initially higher and more variable satisfaction levels may be attributed to its distinct immigration and integration policies, such as earlier access to public services and a stronger policy focus on multiculturalism, as supported by public attitude surveys [71,72]. This finding moves beyond anecdotal evidence, providing a quantifiable basis for advocating regionally tailored, context-sensitive policies rather than one-size-fits-all national mandates.

Furthermore, factors such as Highest Level of Education, English Language Skills, and Accommodation Type were confirmed as critical determinants. The correlation between higher education levels and positive service perception emphasises the role of digital literacy, while the link between unstable housing and negative perception points to the deep-seated socio-economic dimensions of digital exclusion. This suggests that improving digital energy access requires interventions that address these broader structural inequalities, not just technical service delivery.

The successful application of the integrated AI-ABM framework itself is a key finding. By moving beyond traditional rule-based ABM approaches and using ensemble ML models trained on empirical survey data (the Fused Model achieved an R^2 of 0.92), this study demonstrates a significant advance in behavioural realism for simulating complex socio-technical systems. The framework successfully captures the high-dimensionality and non-linear interactions between individual attributes and environmental factors, providing a powerful tool for predicting emergent outcomes of policy interventions.

7. Conclusion and policy implications

This study set out to pioneer a novel, data-driven framework for investigating technological injustice in the digital energy landscape, with a specific focus on Minority Ethnic communities. The integrated AI-ABM approach has successfully quantified how specific socio-technical barriers—such as language proficiency, digital literacy, past online experiences, and citizenship status—disproportionately affect the online service perception of ME households.

Beyond these specific findings, a key methodological contribution of this work is the development and validation of a robust, integrated AI-ABM framework. By moving beyond theoretical assumptions and replacing simple rule-based agent behaviours with machine learning models trained on rich empirical data, this approach sets a new standard for behavioural realism in simulating complex socio-technical systems. The framework provides a powerful and transferable toolkit for researchers and policymakers to analyse disparities, test interventions, and generate evidence-based insights in contexts defined by high dimensionality and heterogeneity.

The main substantive conclusion is that digital exclusion in energy services is not a monolithic issue but a complex problem rooted in a confluence of socio-economic, cultural, and regional factors. Addressing it effectively requires moving beyond generic digitalisation strategies towards targeted, evidence-based interventions. The framework developed here provides the necessary methodological toolkit for generating such evidence, enabling a shift from theoretical assumptions to data-driven policy design.

Based on our findings, we propose the following concrete policy implications:

1. **Mandate Multi-Lingual and Digital Literacy Support:** Energy regulators (e.g., Ofgem) should incorporate requirements for multi-lingual support and digital literacy programs into their consumer vulnerability and digitalisation strategies. Service providers should

be incentivised to co-design these programs with ME communities to ensure cultural and linguistic appropriateness.

2. **Embed Security and Trust-by-Design:** Policy must mandate high standards of transparency, security, and data privacy for digital energy tools, especially those targeting vulnerable groups. Demonstrating clear accountability for preventing and addressing online harm is essential for building trust.
3. **Enable Region-Specific Policy Interventions:** Devolved administrations and local authorities should be empowered with the flexibility to design digital inclusion programs that reflect their unique demographic compositions and socio-political contexts, as evidenced by the differences between England and Scotland.
4. **Promote Proactive and Inclusive Service Design:** Digital energy services should be designed for accessibility from the outset, considering users with limited internet access, lower digital skills, and those in precarious housing situations. This aligns with the principle of 'leaving no one behind' in the energy transition.

In summary, this research provides both a robust methodological framework and a strong evidence base for crafting more equitable and effective digital energy policies. By directly linking agent behaviours in the simulation to empirical data, we have enhanced the realism and predictive power of policy modelling. The insights gained pave the way for reducing technological injustice and ensuring that the benefits of the digital energy transition are shared equitably across all segments of society.

The UK citizenship case study presented here is one of several applications of this framework. Future work will explore a wider range of policy scenarios to demonstrate the full versatility of the AI-ABM framework in addressing diverse aspects of digital exclusion and providing a richer set of evidence for policymakers. We also plan to extend this framework to include threat modelling and data-sharing scenarios, further enhancing its utility for creating secure and resilient online service environments for diverse communities.

CRediT authorship contribution statement

Mennan Guder: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Nazmiye Balta-Ozkan:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Mennan Guder reports financial support and article publishing charges were provided by UK Research and Innovation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the Engineering and Physical Sciences Research Council, part of the UK Research and Innovation (UKRI), under the grant number EP/W032082/1.

Data availability

The data that support the findings of this study are openly available in the Heriot-Watt University Research Portal at: PRIME survey dataset of minoritised ethnic peoples' engagement with online energy services

[66].

References

- [1] International Energy Agency, Electricity - global energy review 2025, (2025). <https://www.iea.org/reports/global-energy-review-2025/electricity> (accessed September 11, 2025).
- [2] National Energy System Operator (NESO), Digitalisation strategy and action plan, (2024). <https://www.neso.energy/news/2024-digitalisation-strategy-and-action-plan-published> (accessed September 11, 2025).
- [3] GOV.UK, Digitalising the energy system, (2024). <https://www.gov.uk/government/publications/digitalising-the-energy-system> (accessed September 11, 2025).
- [4] Ofgem, Digitalisation strategy and action plan guidance, (2021). https://www.ofgem.gov.uk/sites/default/files/2021-11/Digitalisation_Strategy_Action_Plan_Guidance_v1.pdf (accessed September 11, 2025).
- [5] Ofgem, Data best practice guidance team: energy system data regulation, (2024). https://www.ofgem.gov.uk/sites/default/files/2024-10/Track_Changes_Data_Best_Practice_Guidance_v301728394292260.pdf (accessed September 11, 2025).
- [6] Ofgem, Consumer vulnerability strategy, (2025). <https://www.ofgem.gov.uk/sites/default/files/2025-04/Final%20CVS%2015042025-20250414111309.pdf> (accessed September 11, 2025).
- [7] Uswitch, UK smart meter statistics, (2025). <https://www.uswitch.com/gas-electricity/studies/smart-meter-statistics/> (accessed September 11, 2025).
- [8] Kavan M., How different households use energy and how much it costs them, (2024). <https://www.nesta.org.uk/project/finding-ways-to-deliver-cheaper-electricity-by-rebalancing-leaves/how-different-households-use-energy/> (accessed September 11, 2025).
- [9] Djatmiko GH, Sinaga O, Pawirosu S. Digital transformation and social inclusion in public services: a qualitative analysis of e-government adoption for marginalized communities in sustainable governance. *Sustainability* 2025;17:2908. <https://doi.org/10.3390/su17072908>.
- [10] Quyoum A, Wong M, Ghosh S, Shahandashti SF. In: Proceedings of the USENIX symposium on usable privacy and security; 2025. <https://doi.org/10.48550/arXiv.2506.06062>.
- [11] CREDS, Energy injustice and ethnic minorities in the United Kingdom, (2022). <https://www.creds.ac.uk/energy-injustice-and-ethnic-minorities-in-the-united-kingdom/> (accessed September 11, 2025).
- [12] Chambers J, Robinson C, Scott M. Digitalisation without detriment: a research agenda for digital inclusion in the future energy system. *People Place Policy Online* 2023;16:177–92. <https://doi.org/10.3351/ppp.2022.5254227477>.
- [13] GOV.UK, CDEI AI barometer, (2020). <https://www.gov.uk/government/publications/cdei-ai-barometer/cdei-ai-barometer> (accessed September 11, 2025).
- [14] Bouzarovski S, Burbidge M, Sarpotdar A, Martiskainen M. The diversity penalty: domestic energy injustice and ethnic minorities in the United Kingdom. *Energy Res Soc Sci* 2022;91:102716. <https://doi.org/10.1016/j.erss.2022.102716>.
- [15] GOV.UK, Households in fuel poverty, (2025). <https://www.ethnicity-facts-figures.service.gov.uk/housing/housing-conditions/households-in-fuel-poverty/latest> (accessed September 11, 2025).
- [16] López I, García-Valdecasas JI, Monge Lasiera C. Household strategies for coping with energy poverty: technological and socio-familial dilemmas. *Energy Build* 2025;329:115117. <https://doi.org/10.1016/j.enbuild.2024.115117>.
- [17] Loginova J, Landauer M, Joona J, Datta R, Joona T. Enabling indigenous-centred decision-making for a just energy transition? Lessons from community consultation and consent in the circumpolar Arctic. *Energy Res Soc Sci* 2025;120:103928. <https://doi.org/10.1016/j.erss.2025.103928>.
- [18] Chen CF, Chen WA, Greig J, Robinson C. When concentrated disadvantage happens: exploring the nexus of energy and internet insecurities among vulnerable households. *iScience* 2024;27:109895. <https://doi.org/10.1016/j.isci.2024.109895>.
- [19] Prepayment energy meters disproportionately impact vulnerable UK households, (2023). <https://fideres.com/jingle-bills-jingle-bills-jingle-all-the-way/> (accessed September 11, 2025).
- [20] Nwokoroku SC, Neil B, Dlamini C, Osuchukwu VC. A systematic review of the role of culture in the mental health service utilisation among ethnic minority groups in the United Kingdom. *Glob Ment Health* 2022;9:84–93. <https://doi.org/10.1017/gmh.2022.2>.
- [21] UNECE, Digitalization in energy, (2025). https://unece.org/sustainable-energy/energy-efficiency/digitalization-energy?utm_source=chatgpt.com (accessed September 11, 2025).
- [22] Yue Q, Zhang M, Song Y. Impact of digital divide on energy poverty across the globe: the mediating role of income inequality. *Energy Policy* 2024;195:114349. <https://doi.org/10.1016/j.enpol.2024.114349>.
- [23] Shan S, Li Y, Yang Y, Zhang H, Li J. Quantifying social justice in energy transition: a policy-driven assessment framework for China. *Systems (Basel)* 2025;13:201. <https://doi.org/10.3390/systems13030201>.
- [24] Bouzarovski S, McKenzie P, Lonie A, Sarpotdar A, Mattioli G, Martiskainen M. The determinants of double energy vulnerability: a geospatial analysis. *Geogr J* 2025;191:e12610. <https://doi.org/10.1111/geoj.12610>.
- [25] Elsenbroich C, Polhill JG. Agent-based modelling as a method for prediction in complex social systems. *Int J Soc Res Methodol* 2023;26:133–42. <https://doi.org/10.1080/13645579.2023.2152007>.
- [26] Mishra S, Silva TL, Hellemo L, Jaehnert S, Egner LE, Petersen SA, Signer T, Zimmermann F, Bordin C. Agent-based modeling: insights into consumer behavior, urban dynamics, grid management, and market interactions. *Energy Strategy Reviews* 2025;57. <https://doi.org/10.1016/j.esr.2024.101613>.
- [27] Mazzetto S. Interdisciplinary perspectives on agent-based modeling in the architecture, engineering, and construction industry: a comprehensive review. *Energy Build* 2024;14:3480. <https://doi.org/10.3390/buildings14113480>.
- [28] Gao C, Lan X, Li N, Yuan Y, Ding J, Zhou Z, Xu F, Li Y. Large language models empowered agent-based modeling and simulation: a survey and perspectives. *Humanit Soc Sci Commun* 2024;11:1–24. <https://doi.org/10.1057/s41599-024-03611-3>.
- [29] Arnejo Z, Gaudou B, Saqalli M, Bantayan N. Communicating agent-based models to stakeholders: a scoping review. *J Artif Soc Soc Simul* 2025;28:2025. <https://doi.org/10.18564/jasss.5623>.
- [30] Zhang G, Li H, He R, Lu P. Agent-based modeling and life cycle dynamics of COVID-19-related online collective actions. *Complex Intell Syst* 2022;8:1369–87. <https://doi.org/10.1007/s40747-021-00595-4>.
- [31] Golmaryami S, Nunes ML, Ferreira P. The role of social learning on consumers' willingness to engage in demand-side management: an agent-based modelling approach. *Smart Energy* 2024;14:100138. <https://doi.org/10.1016/j.segy.2024.100138>.
- [32] Baustert P, Navarrete Gutiérrez T, Benetto E, Rasouli S. Propagating uncertainty through coupling of agent-based modelling and life cycle assessment. *J Clean Prod* 2025;493:144788. <https://doi.org/10.1016/j.jclepro.2025.144788>.
- [33] Grimm V, Berger U, Meyer M, Lorscheid I. Theory for and from agent-based modelling: insights from a virtual special issue and a vision. *Environ Model Softw* 2024;178. <https://doi.org/10.1016/j.envsoft.2024.106088>.
- [34] Collins AJ, Koehler M, Lynch CJ. Methods that support the validation of agent-based models: an overview and discussion. *J Artif Soc Soc Simul* 2024;27. <https://doi.org/10.18564/jasss.5258>.
- [35] Ionescu Ștefan, Delcea C, Chiriță N, Nica I. Exploring the use of artificial intelligence in agent-based modeling applications: a bibliometric study. *Algorithms* 2024;17:21. <https://doi.org/10.3390/a17010021>.
- [36] Rizzati M, Landoni M. A systematic review of agent-based modelling in the circular economy: insights towards a general model. *Struct Change Econ Dyn* 2024;69:617–31. <https://doi.org/10.1016/j.strueco.2024.03.013>.
- [37] Crespi C, Scollo RA, Fargetta G, Pavone M. A sensitivity analysis of parameters in an agent-based model for crowd simulations. *Appl Soft Comput* 2023;146:110684. <https://doi.org/10.1016/j.asoc.2023.110684>.
- [38] Chater N, Loewenstein G. The i-frame and the s-frame: how focusing on individual-level solutions has led behavioral public policy astray. *Behav Brain Sci* 2023;46:e147. <https://doi.org/10.1017/s0140525X22002023>.
- [39] Gamal Y, Heppenstall A, Strachan W, Colasanti R, Zia K. An analysis of spatial and temporal uncertainty propagation in agent-based models. *Philos Trans R Soc A* 2025;383. <https://doi.org/10.1098/rsta.2024.0229>.
- [40] Bemthuis RH, Lazarova-Molnar S. Towards integrating process mining with agent-based modeling and simulation: state of the art and outlook. *Expert Syst Appl* 2025;281:127571. <https://doi.org/10.1016/j.eswa.2025.127571>.
- [41] Koid E, Van Der Voort H, Warnier M. Agent-based modeling for data-driven enforcement: combining empirical data with behavioral theory for scenario-based analysis of inspections. *Data Policy* 2025;7:e6. <https://doi.org/10.1017/dap.2024.34>.
- [42] Willoughby JR, Lamka GF, Dunning KH, Narine L, Belsare A, Sundaram M. Using AI enhanced agent-based models to support management of wild populations. *Landscape Ecol* 2025;40:1–8. <https://doi.org/10.1007/s10980-025-02149-2>.
- [43] Rietkerk-van der Wijngaart M, de Jager L, Scholz G, Chappin E, de Vries G. Bridging behavioral theory and household energy decisions: enhancing agent-based models with behavioral analysis. *Front Psychol* 2025;16:1568730. <https://doi.org/10.3389/fpsyg.2025.1568730>.
- [44] Schünemann C, Johanning S, Reger E, Herold H, Bruckner T. Complex system policy modelling approaches for policy advice—comparing systems thinking, system dynamics and agent-based modelling. *Political Res Exch* 2024;6. <https://doi.org/10.1080/2474736X.2024.2387438>.
- [45] Zhang N, Bahsoon R, Tziritas N, Theodoropoulos G. Knowledge equivalence in digital twins of intelligent systems. *ACM Trans Model Comput Simul* 2024;33. <https://doi.org/10.1145/3635306>.
- [46] Wang R, Lu T, Zhang P, Gu N. Data-driven agent-based model for public opinion propagation simulation in cyberbullying. *Big Data Min Anal* 2025;8:794–819. <https://doi.org/10.26599/bdma.2024.9020042>.
- [47] Monti C, Pangallo M, De Francisci Morales G, Bonchi F. On learning agent-based models from data. *Sci Rep* 2023;13:1–12. <https://doi.org/10.1038/s41598-023-35536-3>.
- [48] Ravaoli G, Domingos T, Teixeira RFM. Data-driven agent-based modelling of incentives for carbon sequestration: the case of sown biodiverse pastures in Portugal. *J Environ Manage* 2023;338:117834. <https://doi.org/10.1016/j.jenvman.2023.117834>.
- [49] Mérő B, Borsos A, Hosszú Z, Oláh Z, Vágó N. A high-resolution, data-driven agent-based model of the housing market. *J Econ Dyn Control* 2023;155:104738. <https://doi.org/10.1016/j.jedc.2023.104738>.
- [50] Taghikhah F, Voinov A, Filatova T, Polhill JG. Machine-assisted agent-based modelling: opening the black box. *J Comput Sci* 2022;64:101854. <https://doi.org/10.1016/j.jocs.2022.101854>.
- [51] Spahić L, Filipović N. Development of a surrogate model for predicting atherosclerotic plaque progression based on agent based modeling data. *Technol Health Care* 2025;33:1221–31. <https://doi.org/10.1177/09287329241309771>.
- [52] Schimeczek C, Nienhaus K, Frey U, Sperber E, Sarfarazi S, Nitsch F, Kochers J, El Ghazi AA. AMIRIS: agent-based market model for the investigation of renewable and integrated energy systems. *J Open Source Softw* 2023;8:5041. <https://doi.org/10.21105/joss.05041>.

- [53] Sarfarazi S, Sasanpour S, Bertsch V. Integration of energy communities in the electricity market: a hybrid agent-based modeling and bilevel optimization approach. *Energy Rep* 2024;12:1178–96. <https://doi.org/10.1016/j.egy.2024.06.052>.
- [54] Pereira H, Gomes L, Vale Z. Peer-to-peer energy trading optimization in energy communities using multi-agent deep reinforcement learning. *Energy Inform* 2022; 5:1–18. <https://doi.org/10.1186/s42162-022-00235-2>.
- [55] Nweye K, Sankaranarayanan S, Nagy Z. MERLIN: multi-agent offline and transfer learning for occupant-centric operation of grid-interactive communities. *Appl Energy* 2023;346. <https://doi.org/10.1016/j.apenergy.2023.121323>.
- [56] Lichand G, de Paula Serdeira A, Rizardi B. Behavioral insights for policy design: a new framework for understanding wicked social problems and designing policies for real citizens. Springer International Publishing; 2023. <https://doi.org/10.1007/978-3-031-33034-6>.
- [57] Wijermans N, Scholz G, Chappin É, Heppenstall A, Filatova T, Polhill JG, Semenik C, Stöppler F. Agent decision-making: the elephant in the room - enabling the justification of decision model fit in social-ecological models. *Environ Model Softw* 2023;170:105850. <https://doi.org/10.1016/j.envsoft.2023.105850>.
- [58] Bulut O, Tan B, Mazzullo E, Syed A. Benchmarking variants of recursive feature elimination: insights from predictive tasks in education and healthcare. *Information* 2025;16:476. <https://doi.org/10.3390/info16060476>.
- [59] Seraj A, Mohammadi-Khanaposhtani M, Daneshfar R, Naseri M, Esmaili M, Baghban A, Habibzadeh S, Eslamian S. Cross-validation. *Handb Hydroinform* 2023; 89–105. <https://doi.org/10.1016/b978-0-12-821285-1.00021-x>.
- [60] Petmezas G, Papageorgiou VE, Vassilikos V, Pagourelas E, Tachmatzidis D, Tsaklidis G, Katsagelos AK, Maglaveras N. Enhanced heart failure mortality prediction through model-independent hybrid feature selection and explainable machine learning. *J Biomed Inform* 2025;163. <https://doi.org/10.1016/j.jbi.2025.104800>.
- [61] Natarajan K, Baskaran D, Kamalanathan S. An adaptive ensemble feature selection technique for model-agnostic diabetes prediction. *Sci Rep* 2025;15:1–12. <https://doi.org/10.1038/s41598-025-91282-8>.
- [62] Alaiad A, Migdady A, Al-Khatib RM, Alzoubi O, Zitar RA, Abualigah L. Autokeras approach: a robust automated deep learning network for diagnosis disease cases in medical images. *J Imaging* 2023;9:64. <https://doi.org/10.3390/jimaging9030064>.
- [63] Borisut P, Nuchitprasittichai A. Adaptive Latin hypercube sampling for a surrogate-based optimization with artificial neural network. *Processes* 2023;11:3232. <https://doi.org/10.3390/pr11113232>.
- [64] GOV.SCOT, New Scots refugee integration strategy, (2024). <https://www.gov.scot/publications/new-scots-refugee-integration-strategy-2024/> (accessed September 11, 2025).
- [65] Sarah Kyambi, R. Kay, Attitudes to immigration in Scotland: cautious pragmatism?, (2024). <https://www.migrationpolicyscotland.org.uk> (accessed September 11, 2025).
- [66] Netto, G. (Creator), Baillie, L. (Creator), Pang, W. (Creator), Shahandashti, S. (Creator), Rizvi, M. (Creator), Yuan, Y. (Creator), Lewinska, P. (Creator), Dodd, C. (Creator), Islam, F. (Creator), Hasan, S. (Creator), Whyte, L. J. (Creator), Song, J. (Data Manager) (7 Apr 2025). PRIME Survey Dataset of Minoritised Ethnic People's Engagement with Online Services. Heriot-Watt University. PRIME_Data(.zip). [10.17861/db813826-e45d-4274-b4c3-7ecdbf2336a5](https://doi.org/10.17861/db813826-e45d-4274-b4c3-7ecdbf2336a5).



DSPACE

<https://dspace.org/>

An integrated agent-based modelling and artificial intelligence framework for enhancing the experience of minority ethnic communities in digital energy services

Guder, Mennan; Balta-Ozkan, Nazmiye

2025-12

Elsevier

<https://doi.org/10.1016/j.egyai.2025.100624>

Guder M, Balta-Ozkan N. (2025) An integrated agent-based modelling and artificial intelligence framework for enhancing the experience of minority ethnic communities in digital energy services. Energy and AI, Volume 22, December 2025, Article number 100624