



A Data-Driven Approach to Understanding Online Service Access and Technological Energy Injustice Among Minority Ethnic Communities

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Abstract

In the energy domain, various forms of injustice manifest, spanning distribution, production, access, environmental, economic, social, inter-generational, technological, cultural, and governance realms. This paper delves into the technological injustice regarding online service access by energy suppliers, specifically focusing on its impact on energy poverty among minority ethnic communities. The Ofgem Consumer Impacts of Market Conditions Survey Wave 3 Report highlights significant challenges within the energy market, particularly affecting minority ethnic communities. Despite initiatives to investigate legal services for minority ethnic communities, exploration of online service utilization remains inadequate, creating a significant gap in understanding. This paper proposes a comprehensive examination of online service usage and perceptions within minority ethnic communities to address this research gap.

The proposed framework encompasses modules for survey construction, data analysis, Machine Learning (ML) integration, and Agent-Based Modelling (ABM) and simulation. Feature examination reveals correlations between accommodation type and online service satisfaction, influencing simulations. The ABM module simulates how changes in accommodation type affect online service satisfaction, with ML models predicting outcomes. Validation through empirical data and expert knowledge ensures model accuracy.

This research contributes to understanding online service experiences, particularly for minority ethnic communities, aiming to empower researchers and service providers to address inequalities effectively. Future work involves expanding the ABM to incorporate threat modelling concepts, providing a tool for assessing and fortifying the security posture of online services for minority ethnic communities.

CCS Concepts

• **Artificial Intelligence, Multiagent systems, Energy Infrastructure, Social and Professional Topics;**



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Keywords

Agent-Based Modelling, Machine Learning, Artificial Intelligence, Energy Justice, Energy Service Access

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1 Introduction

In the energy domain, various forms of injustice can manifest, spanning distribution, production, access, environmental, economic, social, inter-generational, technological, cultural, and governance realms [1]. Distribution injustice arises from the uneven allocation of energy resources and benefits among different populations or regions. Distributional injustices are evident even within the energy infrastructure itself, with certain resources being inherently unevenly distributed, such as wind resources in specific locations. Claims for justice necessitate combining evidence of inequality with arguments for fair treatment. Hence, empirical research avenues include examining the extent to which the placement of energy infrastructure contributes to distributional injustices [2].

Production injustice involves unfair labour practices or environmental harm caused by energy production processes. Research addressing production-oriented issues aims to shed light on the unjust placement of power plants near ethnic minority or indigenous communities, frequently resulting in their exclusion from decision-making processes [3]. Access injustice refers to limited or unequal access to affordable, reliable energy services. Environmental injustice entails disproportionate environmental impacts of energy activities on marginalized communities. Economic injustice reflects disparities in the distribution of economic costs and benefits related to energy policies and pricing. Social injustice encompasses discrimination or exclusion in energy decision-making processes. Inter-generational injustice concerns unfair distribution of energy-related benefits or harms between present and future generations. Cultural injustice involves disregarding indigenous or traditional knowledge and values in energy projects. Governance injustice denotes deficiencies in transparency, accountability, or democratic participation in energy governance structures. These injustices highlight the need for equitable and inclusive approaches to address social, economic, and environmental concerns in the energy sector.

Technological injustice concerns unequal access to and control over energy technologies. This paper will delve into the technological injustice regarding online service access by energy suppliers, shedding light on this overlooked aspect of the broader energy justice discourse. It will specifically focus on the impact of technological injustice on energy poverty among minority ethnic communities, examining disparities in online service access provided by energy suppliers.

The Ofgem Consumer Impacts of Market Conditions Survey Wave 3 Report, conducted between November and December 2022, highlights significant challenges within the energy market [4]. It provides extensive insights into various aspects including affordability concerns, government support awareness, security of supply issues, payment method preferences, and consumer attitudes toward the energy market, offering detailed findings and demographic analyses for each area. With 80% of consumers facing increased energy prices, many are adopting measures like reducing appliance usage to manage costs. Despite government support, confusion persists regarding the Energy Price Guarantee and its relationship to the price cap.

Energy poverty and injustice affect the entire population, but their impact and prevalence are particularly pronounced within ethnic communities. In October 2021, it was estimated there were 4.5 million UK households in fuel poverty [5]. Trust in energy suppliers also remains low, with only 46% trusting fair treatment and 42% trusting fair pricing [4]. Studies indicate that ethnic minorities, with reference to the white population, are significantly more likely to experience some degree of energy insecurity, with an odds ratio of 2.3 [6]. Ethnicity emerges as one of the most influential factors contributing to energy poverty [6, 7].

The following research effort contributes to a more comprehensive understanding of consumer experiences and lays the groundwork for addressing the challenges faced by minority ethnic communities in the digital realm. Steven Schmidt et al. investigate the quality of experience influenced by network degradations by exploring online mobile gaming services [11]. Simultaneously, Sumin Han et al. explore the impact of customer usage on coffee shop mobile app engagement, employing the Unified Theory of Acceptance and Use of Technology model and online reviews to provide strategic recommendations amid increased non-face-to-face interactions due to COVID-19 [12]. In another study, authors investigate how online customer reviews influence purchasing intentions, presenting a Perceived Derived Attributes model that extends beyond virtual attributes, providing insights into their impact on customer behaviour [13].

This paper will specifically delve into the technological injustice and its impact on energy poverty faced by minority ethnic communities, particularly focusing on the disparities in online service access provided by energy suppliers. This aspect, often overlooked in the broader discourse on energy justice, warrants attention due to its significant implications for individuals and communities belonging to minority ethnic groups. The inequity in accessing online services from energy suppliers can exacerbate existing inequalities, disproportionately affecting vulnerable populations such as low-income households and those in remote areas with limited internet connectivity, especially within minority ethnic communities. Moreover, this disparity perpetuates a cycle of energy poverty

by hindering individuals from effectively managing their energy usage, accessing support services, and benefiting from available resources. Furthermore, unequal access to online services undermines transparency and accountability within the energy sector, limiting consumers' ability to make informed decisions and hold suppliers accountable. Addressing these injustices related to online service access is crucial for promoting equity, empowerment, and inclusivity within the energy sector, particularly for minority ethnic communities, and ensuring fair and equitable access to energy resources for all.

1.1 Online Energy Service Access Model

In the analysis of attributes and data from the PRIME survey to comprehensively examine online service inequalities, a flexible and comprehensive modelling framework becomes essential. Among various modelling approaches, three common techniques are employed to analyse complex systems: ABM, Event-based Modelling (EBM) [14], and System Dynamics Modelling (SDM). EBM focuses on discrete events at specific time points, suitable for systems where events are pivotal [15]. It finds common application in systems engineering, allowing researchers to program different states a system undergoes to understand its underlying behaviour. In contrast, SDM emphasizes continuous variables and feedback loops to understand the long-term behaviour of dynamic systems, frequently used in economics and ecology [16]. ABM, gaining prominence in modelling human behaviour, delves into interactions among autonomous agents, making it effective for studying heterogeneous systems and emergent phenomena in social sciences and various fields [16]. The selection among these methods depends on the system under study, the desired level of detail, and specific research objectives.

Empirical comparison suggests that an agent-based approach is better suited for achieving a characterization model with successful validation. ABMs provide a descriptive understanding of system behaviour without specifying optimal actions [17]. ABM is a computational approach designed to simulate complex systems by modelling interactions of autonomous entities, termed agents, within a defined environment. These agents possess specific attributes, behaviours, and rules governing their interactions, leading to emergent patterns at the system level [18]. ABMs are classified based on agent behavior into physical, economic, and sociological categories, as well as by intended usage, encompassing prediction, understanding, and optimization [19]. The proposed model in this paper is characterized as a socio-economic model, as online service perception intertwines sociological and economic dimensions. Agents in this proposed ABM possess beliefs about the environment and a desire to obtain satisfactory online service.

Agent-based models anticipate specific aspects of unknown data, establish causal chains for complex phenomena, partially represent crucial system aspects, aid in theory development, simplify communication of ideas, offer diverse perspectives through analogy, and facilitate shared understanding among various groups. The primary purposes of ABM applications encompass prediction, explanation, description, theoretical exposition, illustration, analogy, and social learning [23].

The remainder of this section provides a detailed literature overview of ABM, covering modelling approaches, challenges, data-driven models, and ML applications, as well as applications of ABM across energy, domain.

1.2 Modelling Challenges

Effectively addressing the challenges inherent in modelling involves tackling model design, variable size, and validation [26]. Model design poses a significant challenge in ABM, requiring the formulation of processes into rules at an appropriate level of detail to meet the model's objectives [27]. In our proposed model, integrating ML plays a crucial role in streamlining system-specific ABM rules, alleviating the difficulties associated with rule creation.

Model validation is critical for constructing accurate ABMs, involving historical or empirical data and expert knowledge [32]. In [33], nine methods useful for ABM validation are reviewed, covering foundational topics like docking, empirical validation, sampling, visualization, and role-playing. Common validation strategies include observing model behaviour under extreme parameter values and modified behavioural rules. Assessing validity and involving subject matter experts in the modelling process contribute to robust validation [32]. Additionally, empirical validation is employed. In our paper, we utilize both empirical validation and expert examination, evaluating ML model accuracies since they serve as the underlying decision sources.

1.3 Data-Driven Models and Machine Learning

A data-driven ABM utilizes empirical data to inform its structure and behaviour [34]. These models show promise in various areas such as data science learning, autonomy through adaptation, and smart sensing system design [34]. They rely on real-world data, often collected through surveys, for validation [35].

Existing applications of data-driven ABMs typically involve extracting rules from data and integrating them into the model [36]. However, this rule-learning approach doesn't always meet the demands of a versatile modelling framework. It faces challenges in abstracting unbiased rules from data without simplifications or assumptions. By incorporating ML to infer optimal rules, ABMs can overcome this challenge [37]. Navigating the intricacies of ABM presents challenges in abstracting and formulating rules from data without bias, simplifications, and assumptions. Yet, by integrating ML to aid in inferring optimal, system-specific rules, the challenge of rule creation is mitigated.

The fusion of ABM with ML brings advancements across various domains, including healthcare, environmental science, and marketing [36, 38, 39]. This integration revolutionizes the simulation of complex systems by addressing challenges in rule definition and decision-making processes [37]. However, despite its potential, the use of ML in ABMs remains limited, particularly in feature examination [38].

In the energy sector, ABMs are widely used for market analysis, consumption modelling, and trade simulations. For example, Guimarães et al. (2021) investigated consumer participation in peer-to-peer energy trading within smart grids, providing insights into its economic impact and renewable energy integration [39]. Fatras et al. (2022) developed a modular ABM for electricity markets,

addressing uncertainties faced by price-sensitive consumers [40]. Khalil et al. (2022) utilized an ABM integrated with ML to study changes in residential energy consumption during the COVID-19 pandemic [41].

In summary, the literature review highlights gaps in understanding online service experiences, particularly for minority ethnic communities. Our proposed ABM framework, coupled with ML models, aims to address these gaps by empowering researchers and service providers to tackle online service inequalities effectively. The versatility and domain independence of ABMs position them as valuable tools for analysing online energy service satisfaction across diverse ethnic communities.

2 METHOD

The primary objective of the proposed framework is to develop effective strategies for safeguarding minority ethnic communities in online environments. This involves conducting a comprehensive examination of online energy service satisfaction, with a focus on understanding their characteristics and potential challenges. By identifying factors that either enhance or hinder online service experiences, the framework aims to support researchers in analysing and visualizing the effects of these factors on different ethnic minority groups. Ultimately, the goal is to empower service providers to demonstrate accountability and transparency in online service delivery.

The study aims to develop a versatile agent-based model focusing on individuals' online service perception. The proposed model achieves adaptability, domain independence, customization capabilities, and avoids assumptions through its modular structure. Domain independence allows for seamless adaptation to new domains without reconstruction, while the customization capabilities facilitate tailored simulations with specific population characteristics. Importantly, no assumptions are embedded in the model; instead, agent characteristics, behaviours, and interactions, as well as environmental changes, are solely determined by survey data.

The proposed framework, illustrated in Figure 1, encompasses four pivotal modules: Survey Construction, Data Analysis, ML Integration, and ABM and Simulation Modules. Modules are developed primarily in Python, which offers flexibility in integrating ML models and experimenting with diverse initial population generations. This versatility enables the model and framework to be utilized for analysing various cultures or social distributions effectively.

The Survey Construction Module serves as a meticulous framework for crafting and analysing surveys. It begins by defining clear survey objectives, identifying the target audience, and tailoring the survey's content and format accordingly. Subsequent phases involve meticulous design, distribution through appropriate channels, and systematic compilation and organization of responses. The collected data undergoes thorough cleaning and processing, ensuring accuracy and reliability for subsequent analysis. Ultimately, the organized dataset provides valuable insights, driving informed decision-making processes. The final PRIME survey contains 878 respondents, where each individual agent has 138 features and a state variable representing online energy service satisfaction.

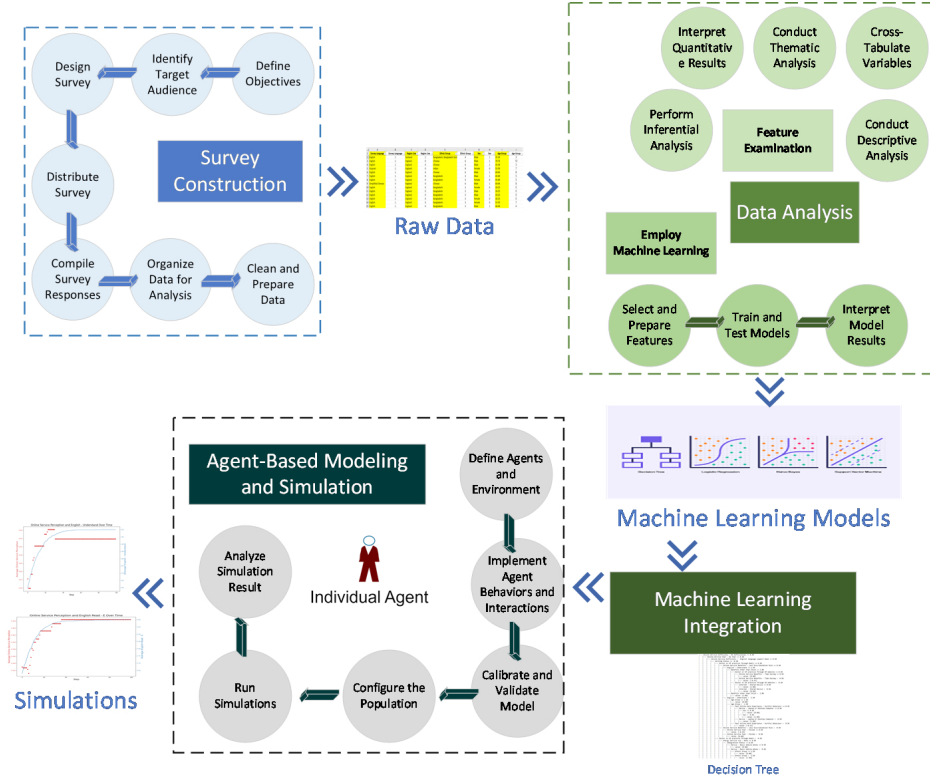


Figure 1: Modules in the proposed framework.

The Data Analysis Module is a comprehensive component designed to thoroughly dissect and understand datasets. It explores relationships and correlations, conducts inferential analysis, and employs ML techniques for predictive analysis. The module interprets quantitative results, identifies recurring themes, and summarizes key data characteristics. ML models are trained and tested, with their results interpreted to gauge predictive capabilities and identify influential features, providing actionable insights for decision-making.

The ML Integration Module serves as a bridge between ML models and the ABM and Simulation Module. It leverages the output of ML models as a service for simulations, with models trained to forecast online service experiences and associated probabilities. These probabilities play a crucial role in optimization calculations during simulation steps.

The ABM and Simulation Module defines agents and their interactions, constructs corresponding populations, and leverages ML models for decision-making. It facilitates simulations that analyse the impact of attribute changes over time on online service perception. The results of these simulations are visualized through charts, offering a comprehensive understanding of evolving dynamics and policy effects.

2.1 FORMULIZATION

The Environment (E) in ABM serves as a comprehensive framework that encapsulates crucial elements, including policies, population

distribution, and interaction points. It is the backbone of the simulation, exerting a central influence on the behaviours exhibited by autonomous agents within the model. All agents observe the global environment $e, e \in E$.

Agents are autonomous entities represented as software entities that operate within a simulated environment. Each agent possesses the ability to make decisions based on its internal state, which includes a set of attributes defining its characteristics, behaviour, and perceptions. Each agent i possesses a state, $s_i \in S$ composed of attributes a_i^j , $0 < j < n$, representing both inherent agent characteristics and online service experience perception. a_i^j is the j^{th} attribute of i^{th} agent where n is the attribute count.

Agents in ABM are typically designed to interact with each other and respond to changes in the environment based on some decision model. In proposed approach ML models are used as the source of decisions.

Action (X) is the points of engagement within the model, accessing online services is the corresponding action in the proposed case. When an agent i , engages in an action $x \in X$ where X is the set of actions, together with a change in environment e , to $e' \in E$. It undergoes a state transformation, the corresponding transition function TS is defined as

$$s'_i = TS(x, s_i, e') = \{a_i^j\}'_{0 < j < n}.$$

i^{th} agent has a state s_i , $s_i \in S$ formed by the attributes a_i^j , $0 < j < n$. s_i' represents the new state of agent i after taking action x , with a probability $P(s_i'|x, s_i, e')$.

The utility function (u) within the proposed ABM framework linked to enhancements in online service experience perception. The primary objective is to design the utility function such that it encourages environment changes (actions are assumed to independent of changes) that lead to highest increase in online service experience perception. The agent receives a utility $u(s_i, x, e, e') : S \times X \times E \times E$ for taking action x in state s_i together with a change in environment $e, e' \in E$.

V value function represents the expected cumulative utility when starting from a particular state and following a certain policy to reach another state.

$$u(s_i, x, e') = V_i(s_i, e) - V_i(s_i', e')$$

By aligning the utility function with the goal of optimizing online service experiences, the ABM framework aims to simulate and analyse agent behaviours that contribute to improved perceptions of online services over time. The utility function serves as a guiding principle, steering agents towards actions that yield the highest utility value and, consequently, fostering a dynamic and responsive system within the simulated environment.

2.2 DATA ANALYSIS MODULE

The Data Analysis Module is a central component aimed at thoroughly examining and comprehending PRIME survey data. It comprises various subcomponents tailored to thoroughly explore data relationships and correlations, as well as utilize ML methods for predictive analysis.

In this module, ML algorithms are utilized to develop models that serve as the primary source of intelligence for agents in the system. These ML models significantly influence the outcomes of simulations within the ABM module. The ML model's role is to predict the online service experience of individual agents based on specific attributes and the given environment. It not only forecasts an online service experience value but also estimates the associated probability. Each domain, such as energy, requires its own tailored ML model to effectively capture the intricacies of the target variable, which falls within the continuous range of $[-1, 1]$. Therefore, regression models are selected due to their suitability for handling continuous variables.

Developing ML models tailored to online energy service satisfaction enables a nuanced understanding of the relationships between features and the target variable.

2.3 ABM AND SIMULATION MODULE

In the ABM and Simulation module, ML models dedicated to each domain determine the outcomes of agents' actions and update online service perceptions accordingly. This module dynamically adjusts the environment based on simulation projections, shaping agent behaviour, and determining online service perception values through ML models.

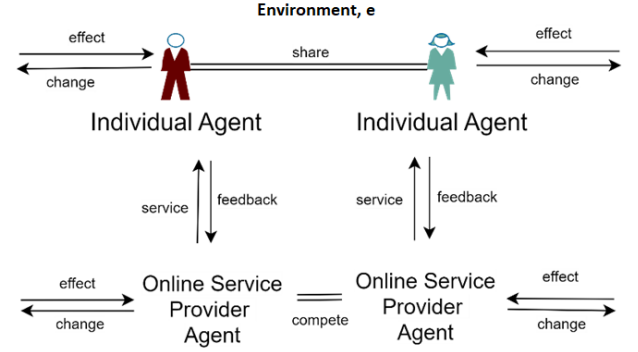


Figure 2: ABM and Simulation Module.

Agents and their interactions are precisely defined within this module, and the incorporation of ML models facilitates simulations. These simulations enable researchers to examine the consequences of attribute changes over time on online service perception, visually presented through charts for comprehensive understanding of evolving dynamics and policy impacts.

Moreover, the module includes diffusion functions for each attribute and a legal adjustment period for policy simulation. A probability of change is computed aligned with the policy's legal adjustment period or desired simulation duration, adapting the population to the final state based on this probability and prevailing distribution.

The inner components of the ABM and Simulation module are illustrated in Figure 2, which categorizes individuals accessing energy services as Individual Agents and online service providers as Online Service Provider Agents. Each entity interacts, leading to dynamic environment changes.

Agents play a pivotal role in shaping the environment, influenced by both the environment and interactions. The main action revolves around accessing online services, leading to changes in concerns and developing new perceptions. "Agent" denotes software autonomy and decision-making based on environment-derived information, while "environment" is the simulated context where agents operate and learn.

Each agent has attributes influencing its decision-making, while the environment defines policies and population distribution. The ABM and Simulation module generate charts visualizing attribute relationships with online service experience over time.

The module models policy changes and their diffusion through environmental parameters, reflecting adaptation to policy changes over the environment through configurable legal adjustment periods. Derived agent subtypes cater to additional requirements, enhancing adaptability beyond the initial scope. Spatial diversity is considered, reflected in environmental context and diverse outcomes observed. Leveraging additional data sources and scaling agent types enhance model representation and applicability across diverse geographic contexts.

The validity of the ABM model is assessed through expert evaluation and by examining the accuracy and precision values of the underlying ML models used as the decision source. Each feature is

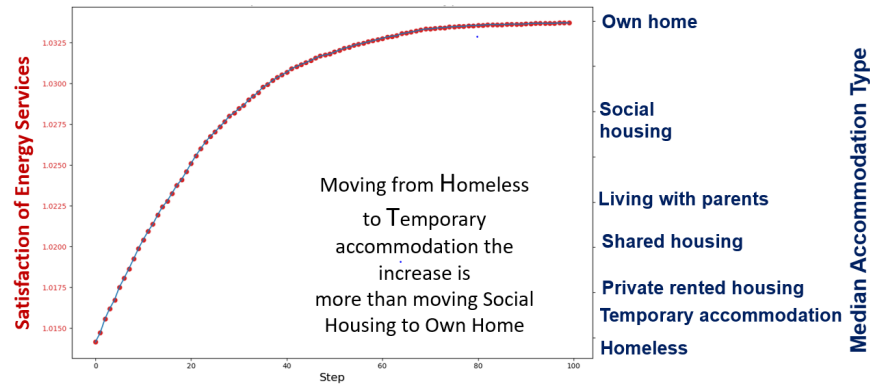


Figure 3: Levels of Satisfaction of Energy Services by Accommodation Type Simulation

scrutinized individually, which has led to instances where statistically insufficient data is available. For example, in the case of ‘age’, we have revised the ML models by aggregating larger groups of age clusters. Instead of using 5-year age ranges, we have transitioned to 10-year intervals or even broader categories to ensure robustness and reliability in the model’s predictions.

2.4 ABM and SIMULATION CASE STUDY

We employ ABM to explore the relationship between types of service usage, levels of concern about such services, and residence in different types of accommodation.

In the following paragraph, we will utilize the module to simulate the relationship between individuals’ online service satisfaction and their accommodation type. Starting with the Homeless category, we will gradually transition through the median accommodation types of the population, emphasizing the progression from Homeless to Temporary accommodation, then to Private rented housing, Shared housing, Living with parents, Social housing, and Own Home. By conducting simulations based on these transitions, we aim to examine how changes in accommodation type affect the population’s level of online service satisfaction. It begins with a population skewed towards homelessness and gradually increases house ownership to observe its effect on online service perception over 100 steps. This analysis will be facilitated by ML models, enabling us to predict and simulate the impact of accommodation type changes on online service satisfaction levels within the population.

Through feature examinations, it has been revealed that accommodation type is highly correlated with online service satisfaction. Figure 3 presents a simulation depicting the impact of change in accommodation type on the Levels of Satisfaction of Energy Services. Online service satisfaction is quantified on a scale from -1 to 1, where -1 denotes the worst satisfaction and 1 signifies the best.

Consistent with the findings in feature examinations, escalating homeownership contributes to an enhancement in online service satisfaction. If homeownership increases, online service perception increases accordingly. Moving from Homeless to Temporary accommodation results in a greater increase than moving from Social Housing to Own Home. Social housing occupants tend to express more concerns regarding various factors related to energy service

compared to other accommodation types. Conversely, those in own homes exhibit lower levels of concern across these factors.

The validation of the proposed ABM model is achieved through a combination of empirical data and expert knowledge. Given that the sole decision source is the ML models, we assess the mean square error of the regression predictors as the empirical success measure for ABM models, employing cross-validation for robust evaluation.

In the realm of expert examination, researchers explore various combinations of features, constraints, and enablers to observe their effects on online service perception. Throughout this process, they scrutinize the proposed model, questioning its accuracy and modelling capabilities, all with the goal of identifying areas for improvement.

3 DISCUSSIONS

The proposed modelling framework addresses existing gaps in the literature by cantering on the online energy service satisfaction of Minority Ethnic communities. By integrating ML models into the ABM framework, it enhances comprehension and offers valuable insights for policy decisions and service providers.

Within the PRIME project context, the developed Machine Learning-utilized ABM framework has yielded significant contributions. Researchers can effectively examine, simulate, and analyse enablers and constraints for minority ethnic communities seeking online services. Initial findings highlight low English proficiency as a major constraint, underscoring the importance of proposing language support as a crucial intervention with potential for substantial impact.

The ML Module’s role in influencing simulation outcomes enables unbiased rule derivation from survey data, thereby enhancing predictive capabilities and promoting data-driven decision-making.

The ABM and Simulation Module’s precise definition of agent interactions and thorough examination of attribute changes over time provide a comprehensive understanding of the dynamics influencing online service perception. Given the literature’s emphasis on the need for extensive research into online service experiences among Minority Ethnic communities, the proposed ABM framework emerges as a versatile tool for addressing this research gap.

A planned future contribution involves integrating an optimization structure into the framework to examine optimal environments and policies through Belman equations. This optimization aspect aims to provide insights into the most effective configurations for achieving equitable outcomes in energy domain, thereby enhancing the research's practical value for policymakers and service providers.

In summary, the research advocates for the dual role of ABM in informing policy decisions and guiding service providers, with an emphasis on ML models for fairness in decision-making. The proposed framework offers a comprehensive and data-driven approach, paving the way for inclusive policies and improved service delivery for Minority Ethnic communities.

As part of our future work, we aim to expand our existing ABM for online service perception to specifically address threat modelling within the context of online service access for minority ethnic groups. Building upon the foundational structure of our current ABM, we intend to enhance and adapt it to incorporate the complexities of potential security threats and vulnerabilities within online service environments. This extension will maintain the same agent-centric framework, utilizing identified agents, including individual agents and service provider agents.

To enhance the model's fidelity in capturing diverse threat scenarios, we will introduce subtypes of service provider agents, each representing different types of online service providers. Additionally, recognizing the importance of comprehensive and up-to-date data in threat modelling, we plan to integrate additional data about online service providers. This augmentation aims to enrich the agent profiles, enabling a more nuanced representation of the services offered, security measures in place, and potential vulnerabilities specific to minority ethnic communities.

As part of the ABM for threat modelling, we will systematically identify and incorporate threat vectors relevant to the unique characteristics and challenges faced by minority ethnic groups. The extended ABM will simulate and analyse how these threats manifest and propagate within the online service ecosystem, allowing for a proactive understanding of security risks.

By extending our ABM to encompass threat modelling concepts, we aim to provide a valuable tool for organizations and policymakers to assess and fortify the security posture of online services catering to minority ethnic communities. This future work aligns with our overarching goal of contributing to the development of inclusive, secure, and resilient online service environments for diverse user groups.

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