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Advancing Inclusive Digital Energy Services through Integrated Artificial Intelligence and Agent-Based Modelling

Mina Takeda[1*], Haruto Suzuki[1]

Abstract

While digitalisation is crucial for advancing energy efficiency, it simultaneously raises significant governance dilemmas and deepens multiple strands of energy inequity. This investigation examines how technological injustice intensifies energy deprivation, particularly through unequal access to digital services. Emphasis is placed on identifying and confronting the difficulties that minority ethnic (ME) populations face, as they routinely encounter greater obstacles when seeking to access essential online energy services. Earlier scholarship has acknowledged the hurdles that ME populations confront in energy markets; this study extends that line of enquiry to scrutinise these challenges specifically in the context of digital energy service access. The work brings together modelling, simulation, and AI to tackle these asymmetries. The architecture is built around three principal modules: an AI component, an Environment Configuration component, and an Agent-Based Modelling (ABM) and Simulation component. Its overarching objective is to surface viable strategies, policy amendments, and refinements that elevate online service encounters whilst directly addressing the distinctive challenges these populations face. Within the AI Module, ensemble-based ML pipelines are harnessed to produce models calibrated for different regions. It addresses difficulties, including high dimensionality and overfitting, through techniques such as Principal Component Analysis, Recursive Feature Elimination, and systematic hyperparameter refinement. The Environment Configuration Module underpins bespoke simulations by adjusting input datasets and locational parameters, safeguarding their fidelity and applicability to the communities under investigation. Through the ABM and Simulation Module, the framework enables granular exploration of how policies and service-provider features shape outcomes. Overall, the framework yields meaningful guidance for refining digital service delivery, cultivating equity, and closing gaps in online experience. This contribution strengthens the field of energy justice by measuring the disproportionate socio-technical burdens borne by ME communities.

Keywords Artificial intelligence, Agent-based modelling, Online service experience, Policy mitigation, Minority ethnic communities

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Introduction

Electricity systems worldwide are in the midst of profound upheaval, powered by surging demand growth and the proliferation of variable renewable output. According to the IEA's Global Energy Review 2025, electricity consumption climbed 4.3% in 2024—marking the steepest annual increase in three years—with low-emission sources satisfying upwards of 80% of that additional need [1]. Though indispensable for decarbonisation, this upswing in renewables compounds the challenge of maintaining system stability and cost-effectiveness, calling for new instruments to manage variability and consumer demand on near-instantaneous time scales. Within this shifting context, digitalisation has

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emerged as a vital mechanism, enabling near-real-time information exchange, forward-looking analytics, and whole-system coordination to create electricity systems that are both affordable and attuned to consumers [2].

Having been the first country to adopt a legally binding net-zero commitment, the United Kingdom treats digitalisation as a linchpin of its energy transition agenda [1]. British policy identifies data resources and digital tools as pivotal to decarbonising the energy system cost-effectively, delivering benefits to all consumers—especially those in vulnerable circumstances—and spurring broader economic expansion [3]. The industry regulator, Ofgem, has responded by issuing directives to network operators on crafting digitalisation roadmaps [4], alongside guidance documents on 'Data Best Practice' [5] and the 'Consumer Vulnerability Strategy' [6].

Notwithstanding these policy aspirations, the promise of digitalisation to place consumers at the centre remains largely undelivered. The national smart meter rollout, for instance, has been hampered by equipment faults, installation backlogs, and enduring public mistrust [7], laying bare a sizeable disconnect between stated objectives and real-world adoption. These obstacles foreground long-standing concerns about accessibility, reliability, and ease of use, and prompt serious reflection on how inclusive existing digital strategies truly are [8]. Such concerns bear down disproportionately on minority ethnic (ME) communities, who run up against distinctive hurdles—spanning language barriers, shortfalls in digital know-how, and culturally misaligned outreach—that are regularly bypassed during the design of digital services [9]. Qualitative evidence further uncovers how deep-seated suspicion and unease about data privacy among ME individuals translate into guarded, reluctant engagement with online energy platforms [10].

Earlier studies have documented structural disparities in UK energy markets, including heightened rates of fuel poverty and disproportionate exposure to precarious tariff arrangements among ME households. The digital layer of these inequities, by contrast, has received comparatively scant attention [11]. Scholarship on the broader policy landscape emphasises that digital inclusion needs to be woven directly into the technical and regulatory fabric of the energy transition [12]. A parallel note of caution is sounded in the UK Government's report on data ethics and innovation, which warns that digital exclusion could magnify vulnerability among already disadvantaged segments of society [13]. These interconnected observations point to a pressing imperative for research capable of capturing diversity and faithfully representing the layered lived realities of ME households as they navigate digital energy services.

Accounting for 17% of the population of Great Britain,1 ME communities constitute the focal population of the UK research council-backed PRIME project.2 A mounting corpus of work records the structural inequities linking ethnicity and energy usage [14], with studies indicating that ME households in England face a greater likelihood of experiencing fuel poverty than their white counterparts [15]. This fragility is exacerbated by surging energy costs and a greater likelihood of occupying thermally inefficient homes [16]. The pivot towards digital delivery magnifies these pressures, given that ME households often lack the digital skills, language facilitation, or institutional confidence required to benefit from smart technologies and web-based energy management tools. What is more, peripheralised communities are frequently shut out of decision-making channels relating to energy policy and project design [17], thereby entrenching a self-reinforcing cycle of disengagement in which services are neither shaped by their needs nor fully taken up, locking in existing disparities [9].

Against this backdrop, technological injustice takes shape as a pivotal yet underexamined strand of energy justice. ME households situated in low-income or geographically remote localities may confront digital discrimination [18], in which automated decision systems, biased algorithms, or poorly conceived platform designs further calcify disadvantage [19]. These asymmetries curtail access to the gains promised by digitalisation—efficient energy management and live monitoring among them—whilst simultaneously chipping away at sectoral transparency. While inquiries in adjacent domains, most notably healthcare, have examined obstacles to service accessibility among ME populations [20], translating such insights into the realm of digital energy provision remains limited in scope and depth [21].

To address this lacuna, the present study focuses on the understudied phenomenon of technological injustice in the energy domain, specifically inequalities in online service access experienced by ME communities. It investigates the

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mechanisms by which unequal digital access can amplify pre-existing inequalities, with particularly acute consequences for low-income households and those in remote settings with patchy internet connectivity. Such disparities have the potential to give rise to novel forms of digital discrimination, in which automated systems treat individuals inequitably based on underlying data or architectural choices, and design biases embedded in online platforms perpetuate discriminatory outcomes and asymmetrical access [18]. Burgeoning evidence indicates that algorithmically governed systems used for tasks such as credit assessment or tariff recommendations can unintentionally penalise ME communities by drawing on biased proxy data, effectively encoding broader societal inequities into the operation of digital energy platforms [19]. This situation simultaneously narrows the distribution of digitalisation's benefits and diminishes sectoral transparency. Tackling these challenges head-on is essential to furthering equity, agency, and inclusion, so that all individuals can enjoy fair and balanced access to energy resources. While a body of research has examined the barriers to service accessibility faced by ME communities in fields like healthcare [20], the systematic examination of how these communities engage with online services remains sparse, leaving a significant evidence gap. A handful of emerging contributions have begun to quantify this shortfall, reporting lower levels of smart meter uptake and reduced interaction with digital energy tools among certain ME subgroups, yet a thorough understanding of the underlying causal mechanisms is still missing [22].

Bridging this evidence gap requires moving beyond established conceptual [14] and statistical paradigms, which have been effective in identifying recognition, distributional, procedural, and social injustices [23] but cannot adequately capture the interplay among households, technological systems, and social networks [24]. Complex systems methodologies, prominently Agent-Based Modelling (ABM), offer a compelling way forward by simulating the micro-level interactions of individual households with technology and with one another, thereby yielding emergent patterns and uptake dynamics at the systemic scale [25]. Even as ABM is increasingly applied in energy research, faithfully characterising household behaviour remains formidable, particularly in contexts where large-scale empirical surveys are absent and frameworks specifically attuned to ME communities have yet to be fully developed [26].

This investigation confronts these obstacles through four principal advances:

1. Transferring an integrated data-driven ABM into an uncharted setting: Although data-driven ABMs are widely used elsewhere, the present work marks their inaugural deployment in the pressing yet sparsely researched domain of technological inequity and digital marginality in energy provision for ME populations. The modelling architecture is purpose-built to capture the specific socio-technical impediments (including digital competence, linguistic accessibility, and institutional confidence) these groups must navigate.

2. Cultivating purpose-specific empirical material: Responding to the deficit of representative evidence, the inquiry constructs a distinctive corpus of data through collaborative workshops, facilitated focus groups, and structured questionnaires administered among ME households. These empirical foundations provide a reliable foundation for representing domestic behaviour and capturing experiential realities that conventional datasets often overlook.

3. Foregrounding asymmetries in digital service provision: By systematically scrutinising the ease of access to digital energy services, the modelling apparatus brings into sharp relief the mechanisms through which technological imbalances deepen energy hardship within ME populations—a line of inquiry that preceding scholarship has largely bypassed.

4. Actionable guidance for policy communities: The simulation yields insights directly relevant to regulators, government bodies, and utility operators, illuminating the pathways by which geographic, economic, and societal variables modulate the uptake of digital platforms, thereby equipping stakeholders to formulate interventions calibrated to foster fairness and broad-based participation.

Considered in its entirety, the constructed framework accommodates the layered intricacy, elevated dimensionality, and mutual conditioning among personal, communal, socio-economic, and socio-technical forces that structure household

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energy practices. It establishes a dependable base from which to probe system-scale emergent properties, stress-test alternative policy trajectories, and guide the inclusive configuration of digital energy platforms.

This segment presents a survey of the literature on ABM, covering paradigmatic strategies, persistent obstacles, convergence with data-informed and Machine Learning (ML) approaches, and illustrative cases drawn from the energy landscape.

Literature Review

The accelerating overhaul of power systems, conjoined with the deepening digitalisation of energy provision, has underscored the necessity of inventive analytical lenses to discern and mitigate gaps in service reach and consumer adoption. ABM has come to the fore as a formidable apparatus for rendering complex socio-technical configurations tractable, making legible the reciprocal influences between diverse, autonomous agents and the settings they inhabit. Allied with data-driven tools—ML prominent among them—ABMs can cast light on granular behavioural patterns, aggregate-level dynamical shifts, and the downstream consequences of regulatory choices. This review consolidates the existing body of work on ABM philosophies, modelling impediments, empirical augmentation strategies, and sector-specific energy applications, with particular emphasis on how these intellectual resources can orient the examination of digital energy access amongst ME groups. Via a critical synthesis of these threads, the section prepares the ground for the ML-augmented ABM architecture advanced here and locates the contribution within the wider terrain of scholarly and policy discourse.

Agent-based modelling approaches

ABM constitutes a versatile toolkit for replicating multifaceted systems by modelling the exchanges among self-directed decision-making entities—agents—whose cumulative actions crystallise into macroscopic regularities [27]. Through the simulation of inter-agent dynamics, ABM enables the identification of broad, system-level configurations that arise from localised, micro-scale activity. Individual agents behave according to prescribed operational protocols. Yet, the patterns born of their mutual engagement are commonly non-linear and resistant to simple extrapolation. This quality makes ABM particularly well-suited to untangling the dense fabric of socio-technical assemblages, such as energy infrastructures [28]. Standing apart from orthodox modelling traditions that rely predominantly on averaged or homogenised characterisations, ABM enables the direct incorporation of agent heterogeneity—spanning disparate traits, value orientations, and limiting conditions—thus providing a representation that is both more faithful to empirical reality and richer in granularity [27].

Over the last several years, ABM has been increasingly used within the social sciences and neighbouring disciplines to examine collective phenomena shaped by individual-level deliberation and social connectivity [29]. Its pliability allows modellers to embed observationally grounded content into simulations, helping to ensure that virtual behaviours track the attitudes, convictions, and situated experiences of real populations. When the analytical lens is trained on ME communities and their encounters with digital energy platforms, this orientation supplies a powerful heuristic for tracing how asymmetries in service reach and user involvement originate, mutate across time, and intertwine with encompassing socio-economic and institutional orders.

ABMs serve a spectrum of functions, from forecasting and causal clarification through to vivid illustration, analogical reasoning, and collective sense-making [24]. They are habitually sorted according to the underlying logic of agent behaviour, with accepted taxonomies distinguishing physical, economic, and sociological variants [30]. Socio-economic ABMs have shown particular explanatory traction in studies of domestic energy conduct, a domain in which peer influences and material constraints jointly channel decision pathways. Illustrative findings indicate, for example, that household enrolment in demand-side flexibility schemes is substantially modulated by vicarious learning, with neighbourly endorsements and locally shared expectations exercising a decisive effect on readiness to participate [31].

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An additional merit of ABM is its capacity to encode bounded rationality, recognizing that agents operate with incomplete information and must make choices under uncertainty and cognitive limits. This trait opens the door to analysing adaptive responses and recursive causal loops within fluid environments, revealing how modest, decentralised choices can cascade into extensive, system-spanning transformations. Extending beyond analytical utility, ABMs double as vehicles for dialogue and sense-making: they aid in delineating indispensable system components [32], cultivate common ground among disparate stakeholders, streamline the communication of intricate conceptual material, and afford multiple interpretive standpoints through analogical juxtaposition [33].

Modelling challenges

For all its advantages, ABM faces stubborn obstacles, most notably empirical corroboration [34], computational tractability at scale [35], and the faithful representation of human conduct [36]. Corroboration becomes especially demanding in socio-technical contexts, where variegated agents move through richly dimensioned spaces and generate emergent regularities that elude straightforward comparison with observational benchmarks [37]. This limitation assumes heightened importance in ABM, since an exclusive preoccupation with micro-level behaviours can conceal the relational processes through which agent interactions give rise to macro-scale patterns. This blind spot risks stripping analyses and the policy inferences they support of their capacity to register structural and collective forces [38].

To meet the corroboration challenge, scholars draw on procedures such as docking exercises, alignment with empirical data, and graphical inspection as preliminary diagnostic steps, while more elaborate protocols—including bootstrapping, causal decomposition, and inverse generative social science—deliver more penetrating, system-focused evaluation [34]. Global Sensitivity Analysis (GSA) commands a central role, enabling the methodical isolation of parameters that exert disproportionate influence in computationally intensive, high-dimensional modelling environments [39].

Scalability presents a further formidable bottleneck, as the computational burden of simulating numerous agents and their richly specified interactions grows faster than linearly with model detail. This reality frequently imposes limits on the range of scenarios that can be traversed, the temporal depth that can be simulated, and the thoroughness of sensitivity testing that can be sustained. In parallel, behavioural fidelity remains elusive: many ABMs rest on stylised or axiomatically derived premises that cannot adequately approximate the variegated, context-sensitive processes of judgement and choice that animate actual socio-technical systems [34].

Overcoming these constraints calls for blended approaches that interweave data-intensive techniques with behavioural diagnostics at both the stages of empirical collection and model construction. By grounding agent-level conduct in observational evidence, tools from the ML repertoire can improve predictive performance, deepen behavioural authenticity, and accommodate territorial heterogeneity and socio-economic pluralism [40]. Such methodological fusion shores up corroboration, relieves scalability strains through empirically guided parameter reduction, and, in the final analysis, narrows the gulf separating theoretical stylisation from the dense textures of the real world, thereby transforming ABM into a more resilient instrument for probing asymmetries in digital energy access [41].

Evidence harvested from a systematic synthesis of 71 ABM studies centred on domestic energy choices reveals that, despite incremental advances, agents remain overwhelmingly programmed with elementary, utility-maximising heuristics, and only a narrow repertoire of empirically anchored constructs feeds into their decision logic [42]. The upshot is that numerous models risk erasing the heterogeneity and complexity that characterise actual human practice. If ABMs are to deliver on their promise as aids to policy architecture, they must be equipped to faithfully represent behavioural mechanics by strengthening the correspondence between posited behavioural drivers (such as interpersonal trust) and the focal behaviour under examination (for example, the uptake of digital platforms) [43].

Weaving behavioural diagnostics into ABM construction

Responding to the persistent shortfall in behavioural credibility that has trailed ABM work, a growing chorus of scholars now presses for behavioural theory to be threaded into model architecture from the very outset rather than patched in

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retrospectively [43]. One systematic sequence of four stages has been proposed to span this divide: (1) demarcating the behaviour of interest with precision, (2) tracing the constellation of elements that shape it, (3) tethering those elements to concrete empirical evidence, and (4) translating them in a disciplined fashion into the operational logic of the ABM [43]. Executing this sequence ensures that the rules animating agents are fuelled directly by what demonstrably propels the behaviour in lived reality, breaking free from reliance on a priori speculation. Our modelling enterprise embraces this logic wholeheartedly, training its analytical gaze squarely on the "use" behaviour associated with digital platforms and mobilising both the PRIME survey instrument and the twin design workshops to furnish an empirical anchor for the decision-making parameters assigned to agents. This move demonstrably bolsters the model's trustworthiness and its resonance with policy concerns.

Empirically anchored ABMs and the role of AI

ABMs fed by empirical evidence represent a genuine methodological watershed, insofar as they mine real-world data to give form to agent dispositions, system topologies, and the trajectories that simulations trace over time [44]. Diverging sharply from legacy models erected upon idealised or conventional presuppositions, empirically fed strategies calibrate choice procedures against questionnaire returns, controlled behavioural experiments, institutional data repositories, and direct field observation, thereby lifting the verisimilitude and transferability of what simulations produce [45]. This point becomes particularly important in socio-technical contexts, where diverse agents are pulled in multiple directions by a tangled mesh of social, financial, cultural, and regulatory forces.

The reach of empirically anchored ABMs now extends into a remarkable diversity of application zones. In digitally mediated social spaces, they have been pressed into service to reconstruct how collective opinion coalesces and how online persecution propagates, surfacing fresh appreciation of the interpersonal dynamics that fuel toxic encounters and revealing how well-tailored remedial measures perform [46]. Turning to economic settings, probabilistically inflected ABM variants have been developed to recover micro-level variables that are difficult to observe, harnessing algorithms such as gradient-driven expectation maximisation to improve forecasting fidelity in residential property markets [47]. Meanwhile, within the environmental management domain, ML-augmented ABMs have subjected policy tools—illustratively, financial rewards for ecosystem stewardship—to rigorous appraisal, exposing subtle temporal signatures, including an early surge in enrolment followed by contraction once monetary incentives were discontinued [48].

The latest wave of innovation attests to the quickening refinement of empirically anchored ABMs. Consider, by way of illustration, a high-granularity housing market ABM that was tuned against richly detailed micro-data and populated with AI agents; it succeeded in bringing into full view the systemic footprint of buy-to-let actors upon the rhythmic swings of speculative heating and cooling [49]. Along parallel lines, conservation-oriented ABMs fortified with AI now knit together ecological dynamics with evolutionary pressures, furnishing nimble tools to guide decision-making under uncertainty [42]. Such vignettes serve to underscore how hybrid ABM–AI configurations can yield operationally meaningful intelligence for policy across an expansive range of sectors.

Methodological cross-fertilisation further illuminates the part AI plays in elevating ABM craftsmanship. Blueprints that integrate ML directly into the lifecycle of ABM creation open the door to agent protocols soaked in data, heighten the persuasiveness of simulated behavior, and keep output streams interpretable [50]. The practice of surrogate modelling—whereby ML approximations stand in for full-blown ABM runs—enables swift traversal of possibility spaces that would otherwise be computationally out of reach [51]. Such stratagems prove especially valuable in high-dimensional policy environments, where exhaustive scenario stress-testing is indispensable.

Energy and environmental investigations have registered particularly vigorous adoption of these blended toolkits. Platforms released under open-source licenses have been used to deliver empirically tuned renderings of electricity market fluctuations, resolved to the hour [52]. Hybrid designs that fuse ABM with bilevel optimisation have been applied to the design of real-time price signals within energy collectives, documenting efficiency windfalls in the orchestration of battery storage assets [53]. Exploratory analyses of future energy trajectories reveal that aligning household-level storage

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choices with market rhythms both trims expenditures and deepens the penetration of renewables. These outcomes stand in stark contrast to those observed under invariant pricing structures. In a complementary vein, multi-agent deep reinforcement learning has been deployed to refine peer-to-peer exchange within decentralised marketplaces, resulting in meaningful cost reductions for households willing to adopt adaptive trading strategies [54]. At the infrastructure tier, co-simulation frameworks grounded in agent-based logic have been trialled to assess demand-side response initiatives across intelligent grid architectures, demonstrating that even marginal recalibrations of building temperature thresholds can ease supply–demand tensions at the district scale when aggregated across large populations [55].

When viewed in synthesis, these lines of advance illuminate the genuinely transformative promise of data-soaked and AI-fortified ABMs. By encoding the empirical heterogeneity of real populations, magnifying the scope of policy-relevant experimentation, and sharpening the accuracy of forward projections, they leave behind disembodied conceptual exercises and move toward insights that are simultaneously policy-actionable and sensitive to local conditions. Transposed onto the terrain of digital energy service provision for ME constituencies, such techniques are singularly well-equipped to register the variegated textures of user lived experience, lay bare entrenched structural disadvantages, and simulate the cascading systemic consequences that flow from planned interventions.

Marking a departure from standard operating procedure in socio-technical energy modelling—where data are typically conscripted only at the back end for validation and rule extraction—the present investigation stakes out new methodological ground with a data-driven ABM–AI apparatus built from the foundations up on the PRIME survey corpus. Within this arrangement, ML models operate as the cognitive engines driving agent decisions, binding the credibility of the simulation directly to the forecasting muscle of empirically estimated models. This architecture simultaneously guarantees sturdiness and behavioural plausibility, taking a decisive step away from untethered theoretical abstraction.

Our unified framework grapples with foundational modelling hurdles by way of the following avenues:

1. Amplifying behavioural plausibility: Swapping out theoretically derived ABM conventions for ML models schooled on empirical observations, in conjunction with a deliberately structured survey-building process that keeps the neglected "use" facet of digital service interaction squarely in focus [56, 57].

2. Fortifying corroboration and computational feasibility: Wedding GSA to ML-driven surrogates to deepen validation, while enlisting Principal Component Analysis (PCA) alongside Recursive Feature Elimination (RFE) [58] to curate feature sets and discipline high-dimensional data without succumbing to overfitting.

3. Preserving Real-World Applicability: Assimilating lessons from behavioural investigation to warrant that the features retained and the ML-generated behavioural outputs stay tightly coupled to the concrete circumstances surrounding digital service engagement.

This synthesis generates three pivotal gains: surfacing emergent aggregate behaviours by way of ML-augmented ABM, empowering cross-jurisdictional comparative scrutiny (England set against Scotland) through simulations fuelled by empirical data, and pushing forward the scholarly understanding of routinised "use" conduct vis-à-vis digital platforms by adopting a data-centric orientation to secure behavioural realism [56, 57]. The portion that follows lays out in full the proposed ABM framework, its constitutive modules, their functions, and the mechanics through which these ML-steered decision processes are incorporated.

Materials and Methods

The central thrust of the proposed framework lies in the systematic examination of self-reported online service encounters among ME populations, with attaining behavioural authenticity as the guiding preoccupation. In pursuit of this objective, the ABM is assembled according to a methodical four-phase behavioural analysis protocol [42], thereby establishing a

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rigorous chain of correspondence linking empirical data collection, the factors that govern behaviour, and the simulation's architecture.

Step 1: Pinpointing the behaviour of interest and crafting the survey instrument

The framework fixes its analytical gaze on a circumscribed yet woefully under-investigated category of conduct: the routinised interaction with digital energy interfaces (for example, repeatedly visiting a supplier's application, discharging bills through web-based gateways, transmitting meter readings). In contrast to one-shot adoption episodes, this behavioural category captures the ongoing, gratifying pattern of platform use. The behavioural transition under scrutiny spans a baseline state of disengagement or constrained interaction (typically triggered by sensed barriers) to stable, satisfied immersion in these service environments. Within the model's architecture, this is rendered quantifiable through each agent's self-assessed perception rating regarding their online service experience.

The PRIME survey instrument was developed through an iterative, cooperative design trajectory that brought together the research investigators, delegates from ME community organisations, regulatory watchdogs, and commercial service providers around the same table. This collaborative development framework ensured that the instrument captured the most consequential behavioural determinants shaping digital service interaction [43]. The finalised dataset comprises 878 respondents, each profiled across 138 characteristics (spanning socio-economic circumstances, cultural positioning, and technological disposition), along with an outcome variable capturing the degree of contentment with online energy provision. This intimate knitting together of survey architecture and model configuration ensures a robust harmony between posited determinants and actual behaviour, firmly mooring the ABM in empirically substantiated behavioural factors.

Step 2: Charting the configuration of influencing factors

The outputs of the PRIME survey and the cooperative design workshops were used to categorize influencing factors into those at the individual level and those in the external setting. This sorting procedure verifies that the factors remain apposite to the distinctive behavioural category under the lens, one that blends automatic or habitual components (think of the unreflective checking of an application) with more contemplative elements (such as deciding whether to confide personal data to a given platform). These factors were subsequently transposed into agent-level attributes and environmental parameters, preserving their contextual relevance and enabling seamless integration into the ABM structure **(Table 1).**

Table 1. Attributes of agents and environment.

Factors	Category	Socio-Economic Characteristics	Socio-Technical Characteristics
Individual	**Demographic Profile**	• Work Status• Educational Attainment• Type of Residence• Earnings Level (inferred from employment status)• Nationality/Citizenship	• Level of Technological Proficiency
	Health and Living Conditions	• Residential Circumstances• Functional or Activity Restrictions	• Availability of Digital Devices
	Technology and Internet Engagement	—	• Devices Utilized• Type of Internet Connectivity• Mode of Internet Access• Digital Competency Level

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External (Environmental Factors)	**Use of Online Services**	• Financial Capacity to Afford Services	• Purpose for Using Online Services• Preferred Digital Channels and Platforms• Experiences with Online Risks or Harm• Confidence in Digital Technologies and Systems

Step 3: Tying the model to real-world observations

Each determinant identified and catalogued was subsequently given quantitative form using information from the PRIME survey, thereby anchoring the model in a solid empirical foundation. Carrying out this stage propels the ABM well beyond theoretical speculation by establishing a direct, traceable link between the characteristics measured in the survey and agents' behavior in the simulation. When the analysis moves to the next stage, ML techniques are applied to the same survey dataset to learn the tangled, non-linear webs of influence that connect driving factors to the focal behaviour. Adopting this tactic allows the model to tackle head-on a difficulty that the ABM research community has repeatedly flagged—the severe shortage of behavioural data—since ML methods can generate predictive linkages in exactly those situations where standard idealised assumptions break down.

Step 4: Moving into the ABM structure (The combined AI-ABM modules)

The determinants that have been both mapped and securely grounded in evidence are then carried across into the simulation environment via the integrated three-component modular design. The AI Module contains the learned correspondence between agent traits (the determinants) and conduct (the perception score). The Environment Configuration Module fixes the boundary conditions—policy instruments and the demographic makeup of the population. Finally, the ABM and Simulation Module brings the behaviour to life, allowing agents to interact reciprocally and produce system-level phenomena that no single agent intended.

• The environment configuration module breathes life into the synthetic populace. It establishes the parameters that sit outside any individual agent's control (policy choices, regional attributes), thereby supplying the situational stage upon which behaviour plays out.

• The AI module represents the algorithmic incarnation of the behavioural mapping exercise. It yields the mathematical relationship f(attributes, environment) → perception score, which serves as the cognitive engine inside every agent. This is no simple rule of thumb; rather, it constitutes a sophisticated, data-schooled predictive instrument trained from the ground up on the empirical PRIME survey records.

○ What enters the module: Training draws on the empirical PRIME survey corpus, which provides the authoritative benchmark documenting how agent characteristics relate to their self-reported experiences with online platforms.

○ What happens inside the module: The module marshals automated ML pipelines to assemble this predictive mapping function in a manner that is both computationally efficient and statistically robust.

○ What the module produces: The end products are high-accuracy fused ensemble models purpose-built for each geographical frame (England alone, Scotland alone, and a merged England & Scotland variant). These models undergo serialisation (they are written to persistent storage), a step that makes them portable artefacts that can be transferred across computational contexts. Once complete, they are embedded in the ABM module, where they shape each agent's perceptions and resulting conduct at every tick of the simulation clock. The predictive strength of each region-specific model is rigorously tested through holdout and cross-validation procedures, which attest to both its reliability and its capacity to perform well beyond the data on which it was trained [59].

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• The ABM and Simulation Module constitutes the stage on which behaviour actually unfolds. Each autonomous agent, governed by the cognitive apparatus provided by the AI pipeline, interacts with both the surrounding environment and other agents. Its subjective evaluation of the online service is recomputed dynamically as a function of its own attributes and the evolving state of the environment, enabling a realistic unfolding of "use" behavior across the full time horizon of the simulation.

The Framework

The architecture put forward here knits together three interdependent modules: environment configuration, AI, and ABM and simulation. Constructed entirely within the Python programming ecosystem, the design offers considerable latitude for incorporating diverse ML model types, spawning heterogeneous simulation configurations and reshaping the model to speak to markedly different cultural and societal milieus. This flexibility means the framework can be fielded across regions or population subgroups distinguished by contrasting demographic structures, regulatory frameworks, or socio-technical characteristics. The architecture gives concrete operational expression to the behavioural analysis methodology, ensuring that what happens within the simulation remains tethered to empirically observed regularities in how services are actually "used," rather than drifting into untested theoretical abstraction.

The sequence of operations executed by the framework is illustrated schematically in **Figure 1.** The chain commences with the empirical survey dataset generated by the PRIME initiative, which is fed directly into the AI Module. It is here that ensemble ML workflows internalise the complex, non-linear transformation connecting agent characteristics to their online service perceptions, yielding fully trained models destined to become the data-driven cognitive cores of the simulation's agents. The environment configuration module then steps in, using these trained models alongside regionally disaggregated demographic intelligence to generate a realistic synthetic population and adjust policy parameters, culminating in a Configured Environment (England and Scotland serving as the primary illustrations). At the final juncture, the ABM and simulation module execute the central experimental run: autonomous agents transact with one another inside this carefully prepared environment, and their decentralised micro-level behaviours coalesce into emergent, macro-scale regularities. These simulation outputs are subsequently mined to extract actionable policy intelligence that speaks directly to the constellation of forces moulding digital service experiences among ME populations.

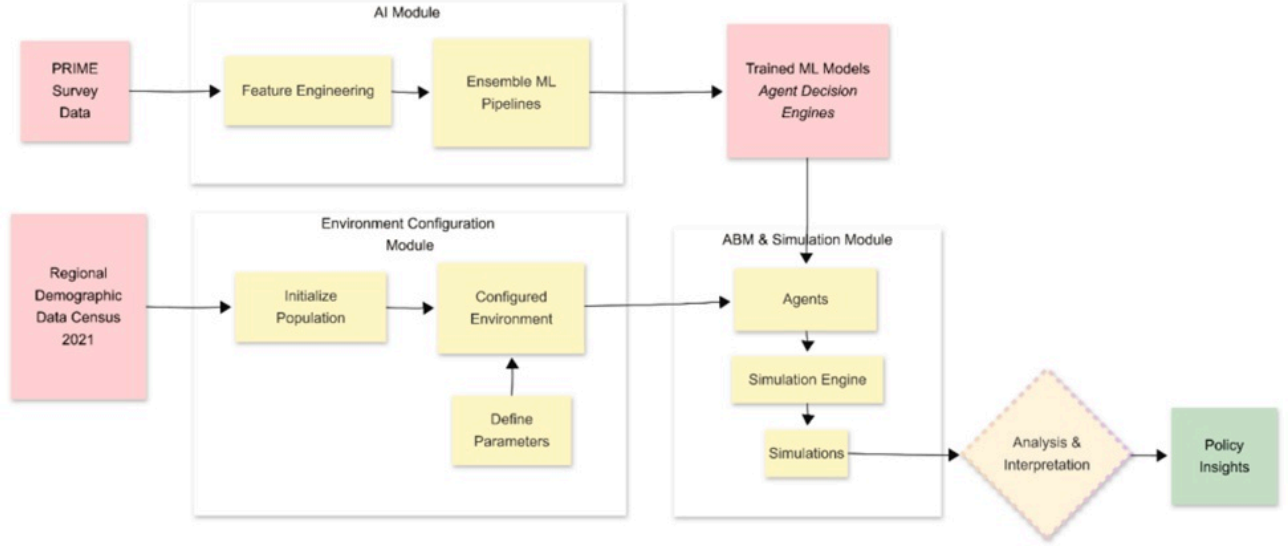

Figure 1. Workflow of the integrated AI-ABM framework.

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Environment configuration module

This module shoulders the responsibility of bootstrapping the population and the policy setting, in effect painting the backdrop against which all agent activity will unfold. Its central deliverables are as follows:

• Population instantiation: Synthesises artificial populations whose demographic contours and socio-economic distributions faithfully mirror those observed in actual communities.

• Empirical mooring: Steers clear of implausible stochastic scatter by feeding real-world data into the initialisation process, a step that boosts the model's representational accuracy and ensures its outputs remain true to genuine socio-technical dynamics.

By accommodating population heterogeneity alongside policy inputs tailored to specific contexts, this module prepares the framework for application across different regions, each with its own distinctive population profile and service landscape.

AI module

The AI Module serves as the decision-making heart of the entire framework, translating agent attributes and environmental states into forecasted perceptions of online energy service use. The module proceeds along a carefully ordered, stepwise trajectory as described below:

Step 1. Data pre-processing and feature engineering

Faced with the considerable dimensionality of the PRIME survey dataset—138 features measured across 878 respondents—the immediate, most pressing challenge was to mitigate the acute threat of overfitting while simultaneously rendering the resulting models more interpretable. Our pre-processing pipeline met this challenge by taking an assertive approach to dimensionality management. We deployed rigorous feature selection routines, including Extra Trees Pre-processing [60] and SelectPercentile, to winnow the full set of predictors to only those carrying genuine prognostic value. Beyond mere selection, we also enlisted feature extraction methodologies—Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Feature Agglomeration—to project the original feature space into a new coordinate system of substantially lower dimension, one whose axes capture the latent organising principles buried within the data [61]. This preparatory labour was an unavoidable prerequisite for ensuring the downstream models would prove resilient, generalise beyond their training sample, and rest upon a clean substrate stripped of noise and rich in information.

Step 2. Model training pipelines

Two complementary AutoML workflows operate in tandem to hone predictive models to their sharpest edge:

• Auto-sklearn pipeline: Auto-Sklearn deploys Bayesian optimisation to sift through a broad palette of regression techniques—Random Forests, AdaBoost, Gradient Boosting Machines, XGBoost, LightGBM, CatBoost, ARD Regression, KNN, Gaussian Processes, and MLP all fall within its purview. Bayesian optimisation, coupled with meta-learning, aims to identify the strongest candidate models. Ensemble-building strategies, most notably bootstrap aggregating (bagging) and stacking, are then applied to squeeze additional predictive performance from the candidate pool.

The Auto-Sklearn pipeline **(Figure 2)** accepts raw data as its input and immediately applies a sequence of pre-processing operations—data cleansing, imputation of missing values, normalisation, and feature extraction. Bayesian optimisation then systematically probes the hyperparameter landscape, evaluating each contender against a battery of metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2. The ensemble-level prediction is formalised in **Eq. 1**, where $\tilde{y}_i$ captures the forecast issued by the ith model and w_i its corresponding weight allocation.

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

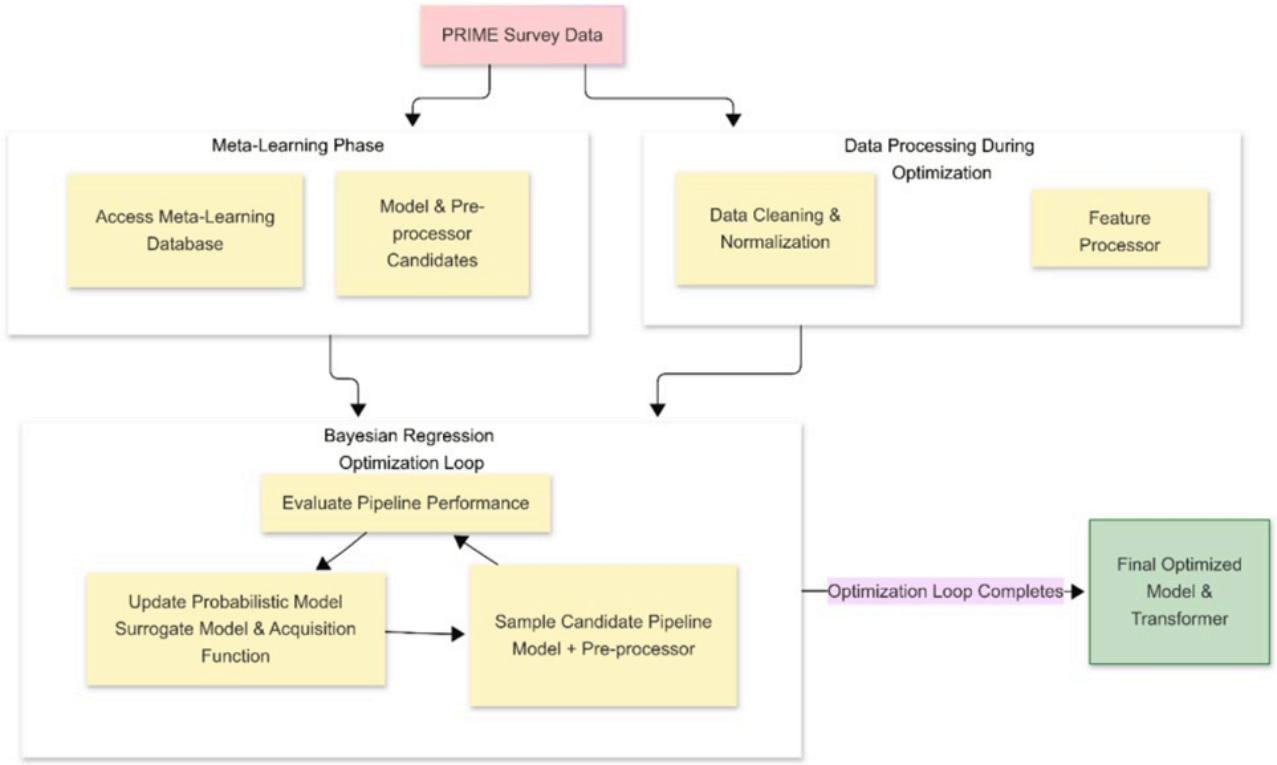

Figure 2. Auto-sklearn pipeline.

Table 2 presents the diverse collection of models that feed into the terminal ensemble, highlighting the robustness that the Auto-Sklearn methodology delivers. By way of illustration, Model 1 mobilises a Random Forest algorithm buttressed by mean imputation and quantile transformation, coupled with Extra Trees pre-processing for feature triage, and it commands a substantial weighting of 0.28. Model 4, standing at the opposite end of the methodological spectrum, employs ARD Regression with median imputation and normalisation, leans on feature agglomeration for extraction, and receives a more modest weight of 0.14. This pronounced diversity—spanning model families, imputation strategies, transformation techniques, and feature handling approaches—throws into sharp relief the meticulous, comprehensive character of the Auto-Sklearn machinery as it automates the twin challenges of model selection and hyperparameter refinement, thereby prevailing over obstacles such as high-dimensional data and overfitting while boosting both predictive accuracy and model dependability. What emerges from this entire process is an optimised final model together with a data transformer; these two artefacts constitute the essential deliverables for the subsequent application and operational deployment of the model.

• Auto-keras pipeline: Operating alongside its Auto-Sklearn counterpart, Auto-Keras carries out Neural Architecture Search (NAS) to surface deep learning configurations that deliver standout performance. The search space is expansive, encompassing Dense Networks, Convolutional Neural Networks (CNNs), Residual Neural Networks (ResNet), and Recurrent Neural Networks (RNNs). Hyperparameters—the number of layers, the choice of activation functions, and kindred design decisions—are subjected to systematic tuning via an arsenal of search algorithms: Random Search, Bayesian Optimisation, Hyperband, Greedy Search, and NAS-RL [62].

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The NAS procedure **(Figure 3)** unfolds through several distinct steps: the dataset is reshaped into the required format, architectural templates are specified, candidate designs are explored and trained, and a cycle of iterative refinement is driven by how well each candidate performs on the validation set. The neural configuration that yields the best performance is then selected, and the final prediction is expressed in **Eq. 2,** where m denotes the total number of candidate models explored during the search.

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

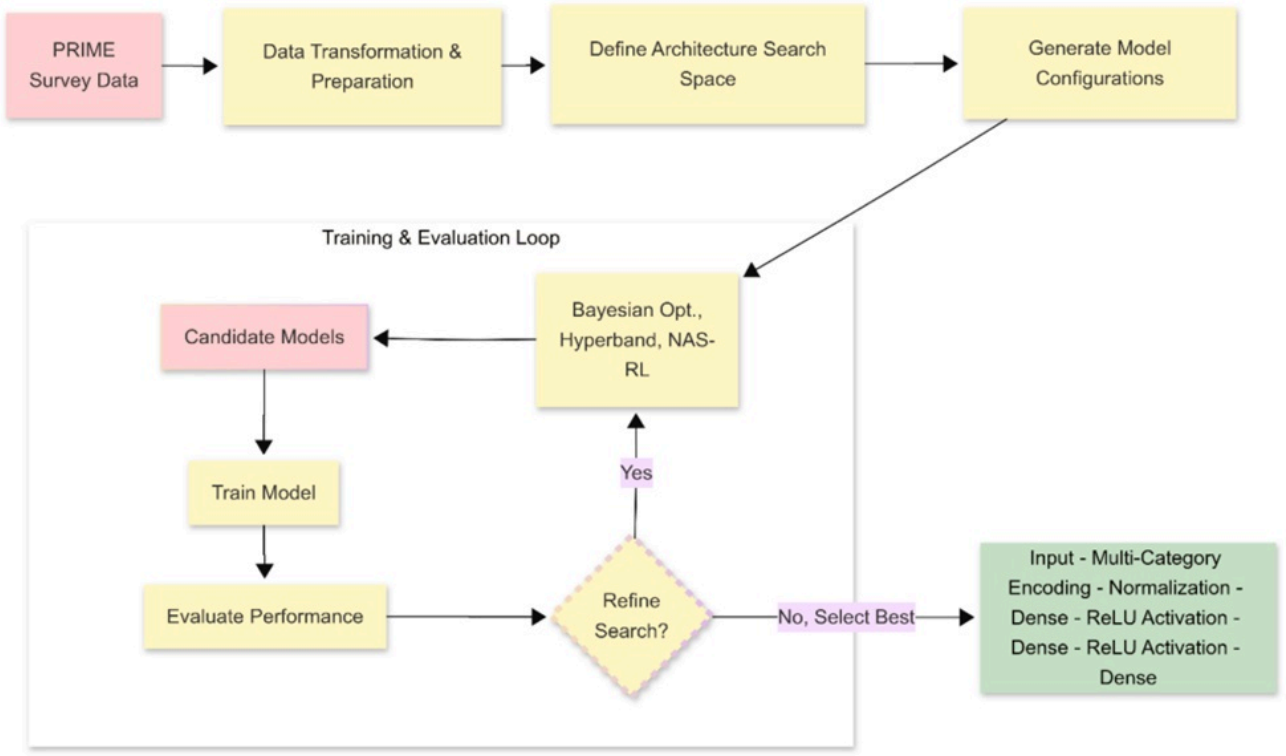

Figure 3. Auto-keras pipeline and best model.

Table 2. Auto-sklearn ensemble learning results.

No.	Regression Model	Data Processing Method	Feature Engineering Method	Weight
1	Random Forest	Mean-value imputation followed by a Quantile Transformer (*n_quantiles* = 1344, *output_distribution* = uniform)	Extra Trees-based Feature Selection	0.28
2	Extra Trees	Mean-value imputation with standardization	Select Rates Feature Selection	0.22
3	AdaBoost	Mean-value imputation and normalization	Fast ICA Feature Extraction	0.16
4	ARD Regression	Mean-value imputation and normalization	Feature Agglomeration-based Feature Extraction	0.14

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5	MLP	Median-value imputation followed by a Quantile Transformer (*n_quantiles* = 174, *output_distribution* = uniform)	Select Percentile Feature Selection	0.06
6	AdaBoost	Median-value imputation with a Quantile Transformer (*n_quantiles* = 1904, *output_distribution* = normal)	Select Percentile Feature Selection	0.04
7	K-Nearest Neighbours	Mean-value imputation followed by a Quantile Transformer (*n_quantiles* = 1000, *output_distribution* = normal)	Feature Agglomeration-based Feature Extraction	0.04
8	Gaussian Process	Mean-value imputation with a Quantile Transformer (*n_quantiles* = 268, *output_distribution* = uniform)	Feature Agglomeration-based Feature Extraction	0.02
9	AdaBoost	Mean-value imputation combined with Min–Max scaling	Select Percentile Feature Selection	0.02
10	AdaBoost	Median-value imputation and normalization	Principal Component Analysis (PCA) Feature Extraction	0.02

Step 3. Model fusion

To unite the respective virtues of classical ML and deep neural computation, the predictions generated by Auto-Sklearn and Auto-Keras are merged into a single composite ensemble according to the formulation laid out in **Eq. 3.** This blended construct capitalises on what each paradigm does best—the feature-centred learning prowess of traditional ML and the sophisticated pattern-recognition faculties of neural architectures—to arrive at estimates of how agents will regard their digital service encounters.

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

A mixing parameter, denoted α and bounded within $0 \le \alpha \le 1$, determines the proportional contribution drawn from each of the two ensemble sources. Discovering the most favourable setting for this parameter involved conducting an exhaustive sweep across the entire permissible range, sampled at intervals of 0.1. At each sampled point, the performance of the corresponding blended model was measured against the validation partition using the RMSE statistic. The α value that produced the smallest RMSE was subsequently adopted for the definitive model configuration; the optimal value was 0.82. Carrying out this calibration ensures the amalgamated construct reaches the most advantageous trade-off, simultaneously exploiting the resilient, feature-driven learning provided by Auto-Sklearn and the subtle pattern-detection capacity offered by Auto-Keras to generate the final forecast.

Step 4. Spatially distinct models

To reflect the reality of regional variation, three independent model specifications are estimated: one devoted exclusively to England, a second customised for Scotland, and a third that pools observations from both nations. Adopting this tripartite structure enables investigation of how demographic profiles, policy regimes, and digital connectivity circumstances diverge across these settings.

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Step 5. Integration with ABM

The end product delivered by the AI Module amounts to a predictive transformation,

$$f(attributes, environment) \rightarrow perceptionscore \quad (4)$$

Which undergoes serialisation before being embedded directly into the ABM and Simulation Module. This transformation serves as the cognitive apparatus housed within every agent, displacing older styles of rule-driven choice logic with a procedure that is simultaneously nourished by data and moored in empirical observation.

During the initialisation phase of a simulation run, each agent is endowed with a distinctive profile of characteristics. Whenever that agent later comes into contact with an alteration in its surroundings—whether through the enactment of a new policy instrument or the rollout of an unfamiliar service feature—the ensuing shift in its perception is derived by calling upon this common predictive transformation. The function is implemented as an invocable entity within the agent class, a structural decision that keeps behavioural updating tightly coupled to the statistical regularities detected in the survey corpus.

Every perception datum emitted by the AI transformation is preserved in a chronological record extending across the entire simulation. These individual temporal traces are then aggregated into simulation graphs, constructed by observing the drift of attributes as time steps advance. At each discrete step, the mean perception value across the full population is computed and displayed as a single marker on the simulation graph. Carrying this operation forward across all time steps produces a richly resolved trajectory capturing the movement of population-wide perception. When the totality of these individual markers is assembled, the full simulation graph materialises, laying bare how perception at the collective scale responds to chosen shifts in environmental variables—a rise in Citizenship, for example—and to the introduction of policy measures.

Embedding the AI function in this fashion brings three decisive advantages:

1. Behavioural verisimilitude: The choices agents make are grounded in observational evidence from actual populations, marking a clean departure from unverified theoretical conjecture.

2. Dynamic responsiveness: Agents react to perturbations in their environment or to policy shifts in a manner consistent with empirical tendencies, and the consequences unfolding at the population scale are dynamically reflected in the simulation graphs.

3. Interpretability: The factors that propel agent conduct are transparently traceable to the features scrutinised by the ML models. This property enhances both the clarity and the applicability of the simulations' findings.

Step 6. ML-model validation

The ensemble ML constructs were subjected to an intensive validation protocol to verify their resilience, trustworthiness, and performance on unseen data, despite the elevated dimensionality of the predictor space. This involved applying a rigorous holdout testing framework alongside 10-fold cross-validation. The complete dataset was split into three non-overlapping portions: a training segment (70%), a validation segment (15%), and a test segment (15%). The validation portion was used for model selection and hyperparameter tuning during the automated ML procedure. In contrast, the testing portion was kept strictly sequestered to deliver an impartial assessment of the top-performing model. Implementing such a stringent validation framework proved essential to ensure that the models had identified genuine predictive relationships rather than capitalising on chance associations in the training data. Predictive performance was quantified through Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2).

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Table 3 brings together the outcomes registered across twelve ML configurations that were subjected to empirical testing: 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).

Table 3. Performance for ML Strategies.

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

The Fused Model surpassed every competing specification, recording an MAE of 0.082, MSE of 0.010, RMSE of 0.100, and an R^2 of 0.92 when evaluated on the independent test partition. Auto-Sklearn (R^2 = 0.89) and Random Forest (R^2 = 0.87) ranked second and third, respectively, results that attest to the effectiveness of automated and ensemble-driven methodologies. At the far end of the performance distribution, AdaBoost combined with MinMax Scaling returned the lowest R^2 (0.66).

The choice of baseline—a Random Forest governed by rule-based decision logic—was motivated by the fact that Random Forests represent one of the most commonly deployed techniques within ABM studies situated in the energy domain, frequently functioning as a reference standard owing to their combination of interpretability, robustness, and straightforward integration into simulation environments. Placing our data-driven Fused Model (R^2 = 0.92) alongside this

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widely adopted benchmark (R^2 = 0.87) highlights the additional value gained from incorporating automated ensemble strategies.

This comparative appraisal, detailed below, shows that the ensemble ML constructs underwent an intensive validation protocol to assess their resilience, trustworthiness, and performance on unseen data, despite the high dimensionality of the predictor space. This involved applying a rigorous holdout testing framework alongside 10-fold cross-validation. The complete dataset was split into three non-overlapping portions: a training segment (70%), a validation segment (15%), and a test segment (15%). The validation portion was used for model selection and hyperparameter tuning during the automated ML procedure. In contrast, the testing portion was kept strictly sequestered to deliver an impartial assessment of the top-performing model. Implementing such a stringent validation framework proved essential to ensure that the models had identified genuine predictive relationships rather than capitalising on chance associations in the training data. Predictive performance was quantified through Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2).

Table 3 confirms that the integrated AI-ABM architecture advanced here yields a meaningful improvement in both predictive precision and behavioural authenticity, thereby decisively moving beyond the rule-based simplifications that still hold sway across a considerable fraction of contemporary ABM applications in energy research.

ABM and simulation module

The ABM and Simulation Module functions as a decision-support apparatus, enabling policy practitioners and academic investigators to systematically explore how policy interventions and parametric adjustments—an illustrative instance being the imposition of a requirement compelling all providers to supply multilingual digital interfaces—produce their effects. Through this module, users can stage a broad range of counterfactual scenarios, thereby arriving at an enriched understanding of how policy shifts, the compositional features of the population, and the characteristics of service providers jointly sculpt perceptions of online energy platforms.

The ABM and Simulation Module functions as a decision-support apparatus, enabling policy practitioners and academic investigators to systematically explore how policy interventions and parametric adjustments—an illustrative example being the imposition of a requirement that all providers supply multilingual digital interfaces—produce their effects. This module enables users to enact a diversity of hypothetical scenarios, thereby allowing them to grasp how alterations in the surrounding environment, driven by regulatory decisions, demographic configurations, and the properties of online service providers, can, in combination, shape the overarching perception of digital platforms. The pattern of mutual influence circulating among household agents, policy frameworks, and the ambient environment within the sphere of online energy provision is rendered visible in **Figure 4**. The simulation context receives its evolving form from two principal streams of influence:

1. Policy adjustments: These comprise directives and regulatory requirements issued by governing authorities that structure the operational environment in which online energy services are delivered. For instance, a regulation requiring every energy service provider to make a mobile application available to its customer base would directly shape the channels through which digital offerings are supplied and accessed. Levers of this policy variety function as instruments that can shift population-wide response patterns by reconfiguring the decision routes encoded within AI and agent-based systems.

2. Population characteristics: The demographic and geographic profile of the population strongly influences how online services are perceived. Elements such as access to technological infrastructure, competence with digital environments, and socio-economic standing are incorporated to represent the distinct ways in which different segments of the population engage with online platforms.

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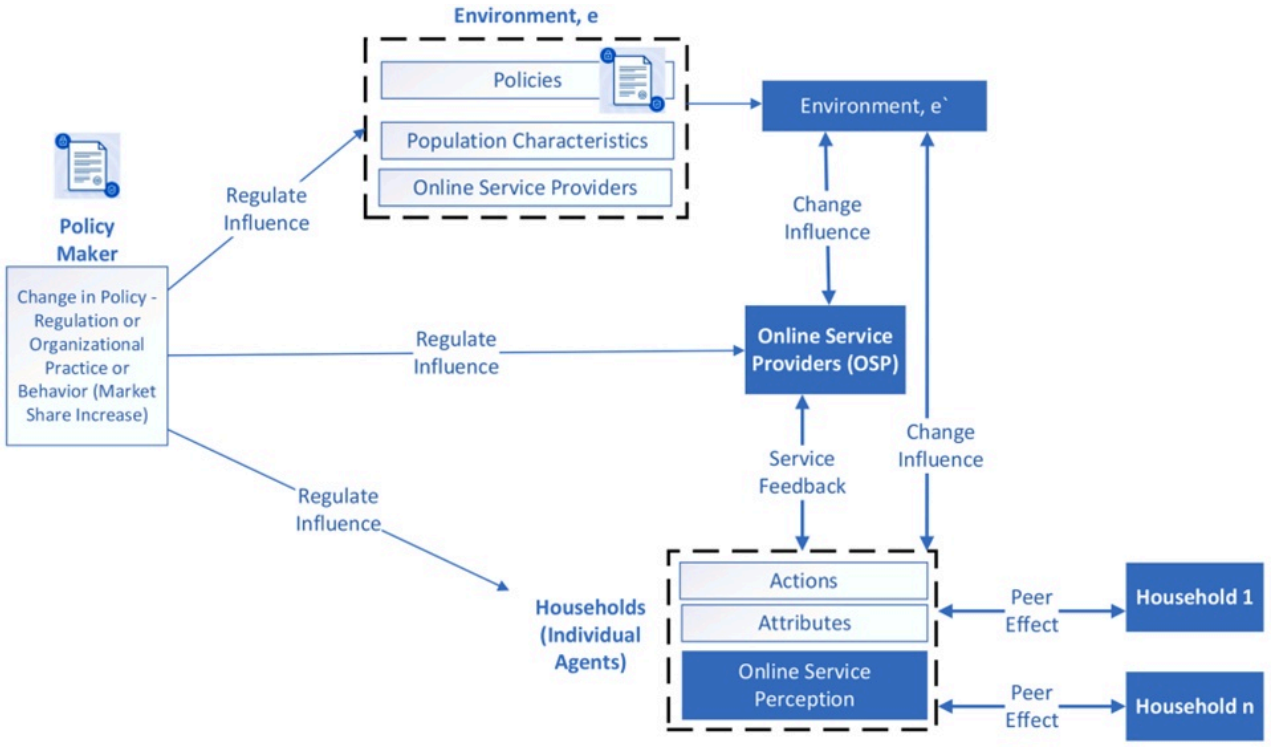

Figure 4. Policy, household and environment interaction.

To take a concrete illustration, were a newly introduced regulatory measure to oblige energy providers to embed multi-language support within their digital platforms, agents would then engage with these augmented service environments. The perceptions those agents form of the online service are conditioned not only by how readily the service can be reached—for example, whether the interface accommodates their preferred language—but also by their individual endowments, including linguistic fluency and prior experience with digital platforms. A policy adjustment of this nature has the potential to substantially raise levels of engagement and satisfaction within ME communities, with particularly pronounced effects among individuals who routinely encounter language-related obstacles when seeking to use online energy services.

Capturing policy effects via linear diffusion formalisms

To simulate gradual rather than instantaneous changes in system parameters, the simulation machinery uses diffusion functions that compute incremental adjustments at each discrete time step. Suppose the aim is to bring about a predefined shift in a policy variable or a consumer characteristic—mobile service engagement being a representative case—where the cumulative change sought over the entire population across a specified run of simulation steps amounts to ΔL. In that scenario, this aggregate alteration is divided equally among the steps that constitute the simulation horizon. The question of how many individuals (k) must be flagged for modification at each step to ensure the intended total materialises is resolved in the sequence that follows.

• Fix the aggregate target shift ΔL: The complete extent of change one intends to accomplish by the conclusion of the simulation period.

• Fix the tally of simulation steps: The symbol n represents the total number of simulation steps into which the horizon is partitioned.

• Arrive at the per-step quantum of change: The quantum of change to be realised within any single simulation step, designated ΔL_{point}, is furnished by **Eq. 5** displayed beneath. This figure captures the average alteration in mobile

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service uptake that should materialise at each step.

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

• Specify the average alteration per affected individual: Let $\Delta L_{Individual}$ stand for the magnitude of the shift each person selected for modification experiences.

• Determine the necessary k for every simulation step to deliver the sought-after adjustment ΔL_{point} at each step, as expressed in **Eq. 6**, one solves for the requisite number of individuals k:

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

• ΔL_{point} is the targeted adjustment to be met at each simulation step,

• P gives the total size of the population under study,

• $\Delta L_{Individual}$ denotes the shift in mobile service uptake attributable to each selected person.

Simulation graphics

The function of this submodule is to translate the numerical output of simulation experiments into graphical depictions through an array of charts, thereby affording a panoramic perspective on the dynamical trajectories that unfold and the imprint left by policy decisions. Data points harvested at multiple time points throughout the simulation are collated and scrutinised to shed light on the temporal evolution. The conversion of these simulation records into meticulously crafted visual formats puts vital knowledge about the weight of various variables and policy changes into the hands of policy practitioners and academic analysts. This instrument performs two core roles simultaneously, each one reinforcing the broader activities of deliberation and strategic design:

1. Anticipating the plausible fallout from policy modifications: Operators of the simulation tool are positioned to foresee the downstream effects that policy adjustments might trigger in perceptions of online services. Through careful study of these anticipatory pictures, decision-makers can prepare for likely outcomes, avoid adverse developments and anchor their choices in data-driven insights, all in the service of improving how services are delivered and raising the satisfaction of those who use them.

2. Making sense of established configurations linking online service perception to customer profiles: The utility of the simulation tool extends beyond forward-looking evaluation of policy shifts; it is equally valuable as a lens through which to scrutinise contemporary tendencies and enduring structural patterns in the perception of online services. By teasing apart the reciprocal influences at work among an assortment of demographic dimensions—chronological age, ethnic identity, housing type, and related categories—and the characteristics of the services themselves, those engaged in research can zero in on the decisive factors that govern how services are perceived. This diagnostic purchase helps pinpoint which elements bear the greatest responsibility for shaping user satisfaction, thereby opening the way for the deliberate development of finely honed strategies to enhance the overall digital service experience.

ABM model validation

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Confirming the soundness of the ABM formulation advanced here was undertaken through a stratified, multi-pronged procedure that braids together observational grounding, judgement from domain specialists, performance checks on the ML components, and sensitivity-testing methods. The steps followed for verifying the ML models are given a separate, extended treatment in the section entitled "ML-Model Validation." The focus of the discussion in the present subsection is instead on the agent-level strand of validation, which calls upon GSA in combination with cross-verification grounded in correlation statistics.

The purpose of deploying GSA is to determine which of the numerous inputs exert the greatest influence on the model's outputs. By evaluating Sobol indices, one gains the ability to put a number both on the contribution that each parameter makes when acting alone—this is the province of first-order indices—and on its fuller contribution once every synergistic entanglement with fellow parameters is folded in, as summarised by total-order indices. The derivation of Sobol indices rests upon partitioning the total variance observed in the model's output and assigning portions of that variance to each separate input parameter and to every feasible interaction among them. First-order indices estimate the fraction of output variance that can be exclusively credited to a solitary parameter operating in the absence of interactions. In contrast, total-order indices capture the complete signature of a parameter, sweeping in all interaction effects of whatever order in which that parameter participates. Performing this analysis serves the dual purpose of unmasking the chief levers that steer model behaviour and of providing a platform for expert-led validation, since it allows a check that the dynamical patterns generated by the simulation remain both intelligible and congruent with expectations derived from real-world regularities.

The ABM validation protocol is built from the following sequential stages:

1. Traversal of the parameter landscape: Latin Hypercube Sampling is used to generate a richly varied ensemble of parameter configurations, enabling an exhaustive sweep across the input domain [63]. Adopting this sampling strategy guarantees that the possible spread of variation in agent properties and in the characteristics of online service interactions is represented in a balanced and comprehensive manner.

2. Running the ABM and carrying out a sensitivity analysis: For each sampled parameter configuration, the ABM is launched and allowed to run its course; the outputs generated serve as the evidential basis for the subsequent sensitivity analysis. Sobol indices are then calculated to gauge the influence of each input parameter. First-order indices register the unmediated effect that a parameter, considered in isolation, has upon the output, thereby capturing the extent to which variation in that single parameter alone is transmitted through to variation in the results. Total-order indices encompass the entire footprint of a parameter, combining its direct effect with all interactions in which it is implicated. The availability of this paired diagnostic—direct effect alongside full effect—provides a well-rounded picture of which factors function as the primary engines of model dynamics and of how interdependencies among parameters jointly sculpt the simulation's outputs. This picture, in turn, supports robust, interpretable conclusions.

3. Correlation analysis as a cross-validation tool: To complement and corroborate the picture that emerged from the GSA, the Sobol indices were subjected to a further round of verification using correlation analysis. Every reported correlation coefficient was calculated with the Persistence Score serving as the reference variable; this score is a continuous metric ranging from −1 to 1 and is ultimately rooted in user perceptions recorded during interview encounters (on a response scale anchored at 0 and 5). The choice of which specific correlation coefficient to apply in each instance was governed by the measurement characteristics of the predictor variable under examination: for variables that are continuous or that represent counts (English reading proficiency score and digital skill level are two pertinent illustrations), Pearson correlation was employed; for variables that take only two possible values (UK Citizenship: Yes/No is the paradigm case), the Point-Biserial correlation was employed; and for ordinal variables whose categories follow a ranked order extending beyond a simple binary split (Highest Level of Education, Immigrant Status, Accommodation Type, Working Status, and Past Online Harm Experience all fall within this class), Spearman's rank correlation was employed. This deliberate matching of correlation technique to variable type ensures that the linkages connecting agent attributes to persistence are captured in a statistically appropriate manner, remaining sensitive to linear associations where warranted and to

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monotonic associations where the data demand it, and the whole exercise delivers a sturdy cross-validation of the patterns observed in the simulation results.

The Sobol index values from the GSA were consistently related to the statistical correlations computed directly from the survey dataset **(Table 4)**. Those parameters for which both first-order and total-order Sobol indices register at elevated levels—accommodation type, highest education level, and past online harm experience supply clear examples and are also the parameters that display marked correlations with the scores reflecting online service perception. The presence of this consistency carries an important implication: parameters whose direct or interaction-mediated effects bulk large within the artificial world of the simulation correspond, in a faithful way, to the behavioural tendencies observed in the real-world data. A further noteworthy observation is that the first-order indices are often close to the absolute magnitudes of the corresponding correlation coefficients. This pattern confirms that the isolated effect of any individual parameter within the ABM closely mirrors the linear or monotonic relationships manifest in the empirical record. Total-order indices, by virtue of the fact that they additionally incorporate interaction contributions, routinely exceed their first-order counterparts for those parameters that enter into pronounced interdependencies with other variables; this observation helps to explain why certain variables may exhibit only moderate correlations with the outcome of interest and yet still register high total-order contributions when the simulation is run. The convergence between these two independent lines of evidence—the GSA on the one hand and the correlation analysis on the other—authenticates the simulation model. It reinforces confidence in the proposition that the ABM outputs are simultaneously faithful to empirical reality and open to meaningful substantive interpretation.

Table 4. Sobol indices and correlation (Online Service Perception) values for agent parameters.

Parameter	Coding Scheme	Region	Correlation (Persistence Score)	Total-Order Sensitivity Index	First-Order Sensitivity Index
UK Citizenship	Yes = 1, No = 0	England	0.62	0.28	0.10
		Scotland	0.15	0.08	0.03
English Reading Proficiency	Not at all confident = 0Not very confident = 1Fairly confident = 2Very confident = 3	England	0.40	0.31	0.09
		Scotland	0.38	0.26	0.07
Immigration Status	Asylum Seeker = 1Refugee = 2Humanitarian Protection = 3Non-settled EU Citizen = 4Visa Holder = 5Settled EU Citizen = 6Indefinite Leave to Remain = 7Citizen = 8	England	0.38	0.25	0.09
		Scotland	0.23	0.05	0.02
Educational Attainment	No Qualifications = 1Primary Education = 2Secondary Education = 3Bachelor's Degree = 4Postgraduate Qualification = 5	England	0.44	0.32	0.13
		Scotland	0.46	0.35	0.14
Housing Status	Homeless = 1Temporary Housing = 2Shared Accommodation = 3Living with	England	0.55	0.30	0.13

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	Parents = 4Social Housing = 5Private Rental = 6Home Ownership = 7				
		Scotland	0.27	0.22	0.09
Previous Online Harm Exposure	Number of prior online harm incidents (0–5)	England	−0.64	0.27	0.11
		Scotland	−0.64	0.29	0.11
Employment Status	Not Working = 1Unemployed = 2Semi-Retired = 3Retired = 4Student = 5Self-Employed = 6Employed = 7	England	0.52	0.28	0.10
		Scotland	0.58	0.29	0.12

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.

By putting this framework into operation, one can verify that the parameters flagged as most consequential by the ABM do indeed mirror behavioural regularities observed in the real world, a correspondence that fortifies both the model's trustworthiness and the clarity with which its results can be parsed. When the directional patterns unearthed through sensitivity testing harmonise with the empirical record and the predictions of established theory, the outcome is a strengthened conviction that the simulation outputs are credible and meaningful to the concerns of policy formulation.

What the GSA brings into sharp focus is that a restricted set of parameters leaves an outsized footprint on the way online services are perceived. The following deserve particular emphasis:

• Holding UK citizenship emerges as a factor that powerfully shapes perception within the English context, yet its influence proves considerably less when the lens is turned on Scotland.

• Proficiency in English language skills (Reading) is a critical element regardless of the regional setting.

• Accommodation type, together with the highest level of education, emerges as a particularly powerful determinant shaping the nature of interactions with online services.

• The presence of past online harm experience in an individual's history shows a strong inverse relationship with how online services are perceived, a pattern suggesting that those who have endured adverse online experiences may display heightened reluctance to interact with digital platforms in the future.

The multi-layered validation sequence adopted in this work attests to the exactness, sturdiness, and interpretability of the ABM. The diagnostic intelligence extracted through GSA opens the door to crafting carefully targeted policy responses and service-level adjustments, efforts that can help shrink the digital divides affecting ME populations. In addition, the validation architecture itself enhances the model's standing as a trusted tool that can guide future decisions on the accessibility of online energy services.

Case Study: UK Citizenship Versus Online Service Perception

The analytical lens of this case study focuses on the bond between UK citizenship status and perceptions of online services, explored through three analytical windows: England alone, Scotland alone, and a consolidated treatment that

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brings both nations under a single umbrella. For each of these three analytical windows, tailored regression models were estimated, and matching simulation runs were conducted. The graphs depicting the simulation outputs for all three regional treatments are presented in **Figure 5.**

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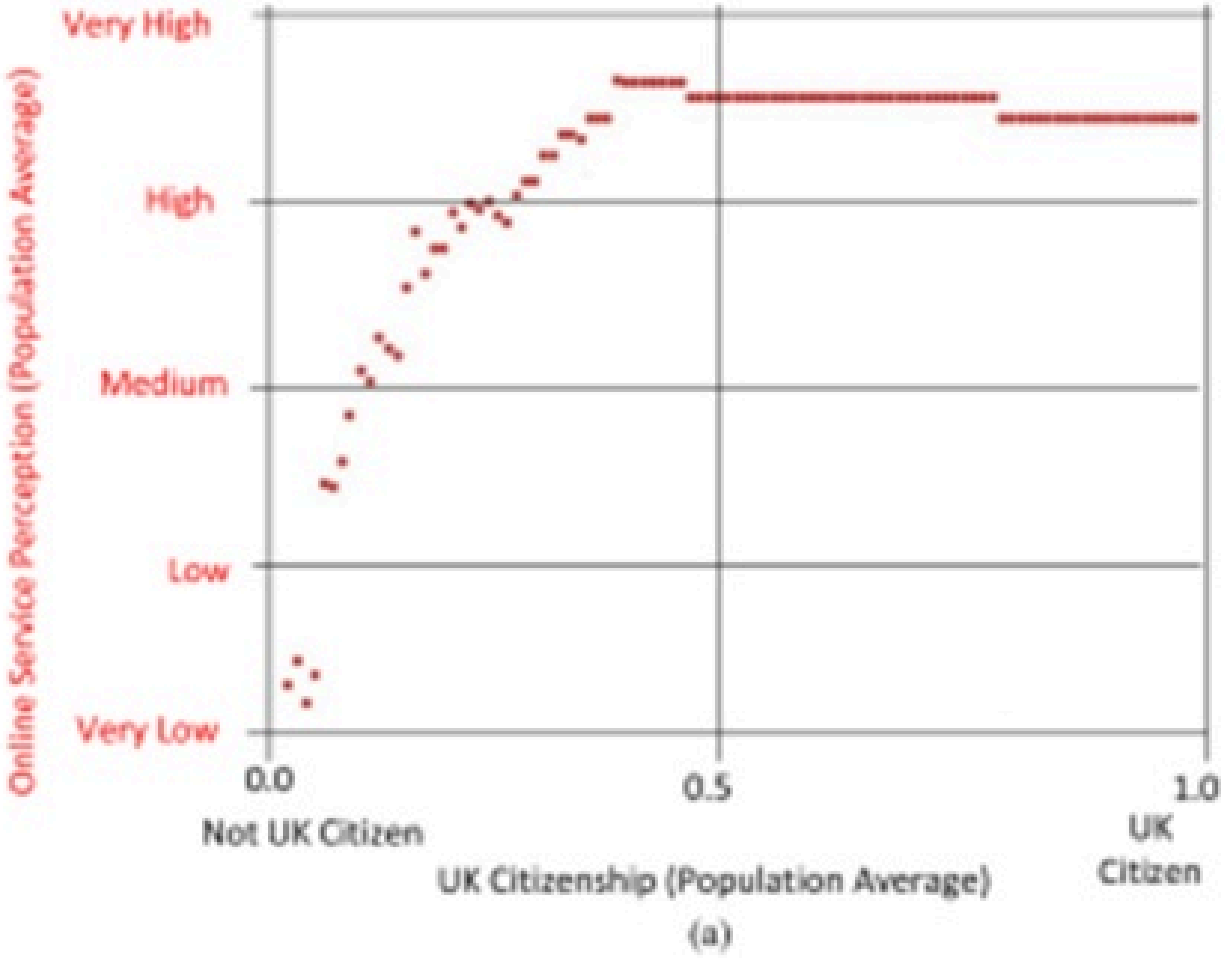
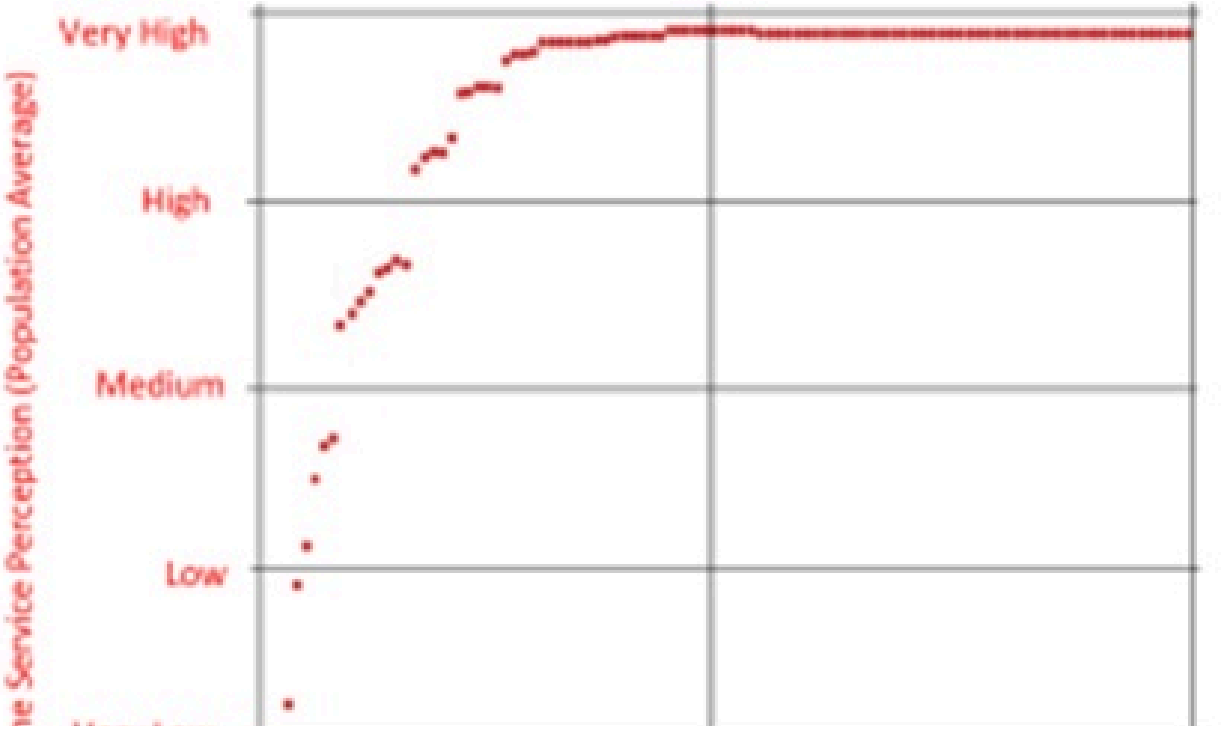


(a)



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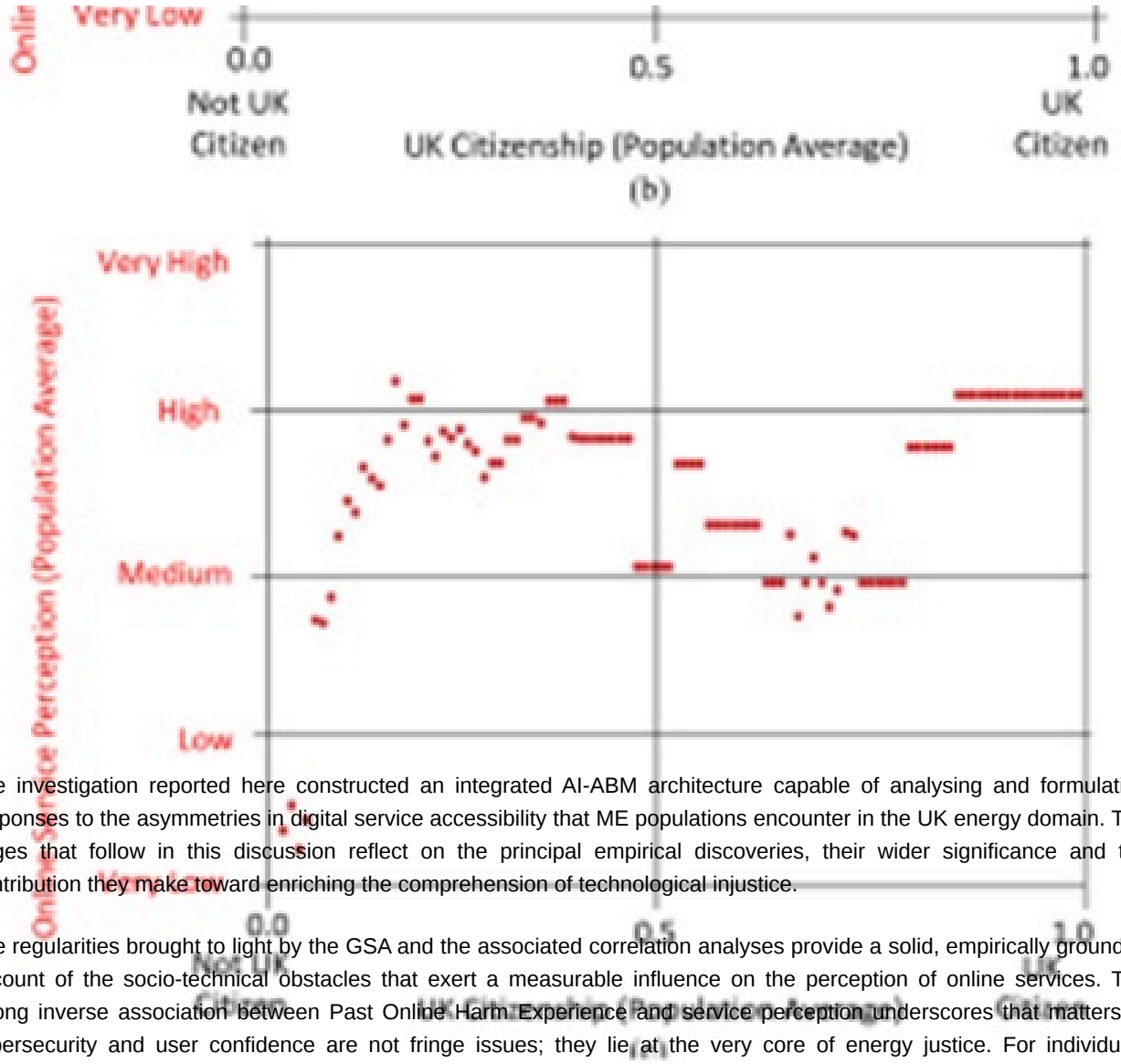

The investigation reported here constructed an integrated AI-ABM architecture capable of analysing and formulating responses to the asymmetries in digital service accessibility that ME populations encounter in the UK energy domain. The pages that follow in this discussion reflect on the principal empirical discoveries, their wider significance and the contribution they make toward enriching the comprehension of technological injustice.

The regularities brought to light by the GSA and the associated correlation analyses provide a solid, empirically grounded account of the socio-technical obstacles that exert a measurable influence on the perception of online services. The strong inverse association between Past Online Harm Experience and service perception underscores that matters of cybersecurity and user confidence are not fringe issues; they lie at the very core of energy justice. For individuals belonging to ME communities, the memory of a prior adverse encounter in the digital realm serves as a formidable disincentive to engaging with digital energy platforms. This realisation points to an acute necessity for service providers to implement—and to publicly convey the existence of—rigorous protections covering security and the handling of personal information.

The divergent roles assumed by UK Citizenship when the English and Scottish settings are placed alongside one another furnish a more textured appreciation of how regional policy landscapes mould the contours of digital inclusion. The pattern of diminishing incremental returns in service perception that accompanies the progression toward citizenship in the English instance signals that, while the support furnished during early integration carries genuine importance, its effectiveness eventually levels off. In marked contrast, the initially elevated—and more widely variable—satisfaction levels recorded in the Scottish instance may plausibly be assigned to Scotland's distinctive portfolio of immigration and integration measures, prominent among them faster eligibility for public services and a more pronounced policy orientation toward multiculturalism, an account that receives backing from surveys canvassing public sentiment. This finding takes the discussion beyond anecdotal terrain, laying a quantifiable foundation for advocating policies calibrated to regional particularities and responsive to local circumstances, rather than uniform national prescriptions.

In addition to these regionally differentiated patterns, further determinants—among them Highest Level of Education, English Language Skills, and Accommodation Type—were validated as playing a determining role. The linkage between

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higher educational credentials and more favourable perceptions of online services spotlights the significance of digital literacy, even as the connection between insecure housing conditions and lower perception scores exposes the deep socio-economic underpinnings of digital exclusion. This signals that any meaningful effort to broaden the reach of digital energy services must incorporate interventions that address these broader structural disparities, rather than narrowing the focus solely to the technical delivery of services.

The successful operationalisation of the integrated AI-ABM framework constitutes, in its own right, a notable finding. By discarding traditional ABM designs built on manually specified rules and embracing ensemble ML models trained on empirical survey data—the Fused Model reached an R^2 of 0.92—this piece of scholarship exemplifies a consequential advance in achieving behavioural authenticity when simulating intricate socio-technical arrangements. The framework demonstrates the ability to handle high dimensionality and nonlinear feedback loops that connect individual-level traits to properties of the surrounding environment, thereby equipping researchers and policymakers with a powerful tool for anticipating emergent outcomes triggered by policy interventions.

Conclusion

The ambition that launched this inquiry was to break new ground by developing a data-driven methodology for probing technological injustice in the digital energy domain, with particular focus on Minority Ethnic populations. Through the fused AI-ABM methodology, the work has succeeded in measuring the extent to which particular socio-technical impediments—encompassing language competence, digital fluency, prior online encounters, and citizenship status—unequally shape the online service perceptions held by ME households.

Moving beyond these individual empirical contributions, a central methodological advance of this investigation lies in the creation and corroboration of a robust, unified AI-ABM architecture. By setting aside abstract postulates and substituting simplistic rule-governed agent behaviour with machine learning constructs trained on dense empirical data, this methodology raises the bar for behavioural authenticity in simulating intricate socio-technical configurations. The architecture provides a powerful and adaptable set of tools that scholars and decision-makers can deploy to dissect asymmetries, test remedial measures, and produce observationally anchored insights in settings marked by high dimensionality and pronounced heterogeneity.

The overriding substantive inference to be drawn is that digital marginalisation in the sphere of energy services does not present itself as a uniform phenomenon but rather as a layered predicament stemming from the intermingling of socio-economic, cultural, and geographically specific currents. Mounting an effective response demands a departure from all-purpose digitalisation blueprints and a turn toward precisely focused, evidence-grounded measures. The architecture elaborated in these pages provides the requisite methodological apparatus for generating such evidence, thereby enabling a transition from theoretical conjecture to policy formulation grounded in data.

Drawing upon the evidence assembled here, we advance the following actionable policy directions:

1. Require multi-lingual provision and digital literacy assistance: Bodies charged with energy oversight (Ofgem being a case in point) ought to embed stipulations for multi-lingual provision and for digital literacy initiatives within their consumer vulnerability frameworks and digitalisation roadmaps. Operators of energy services should be offered incentives to jointly craft these initiatives with ME populations to ensure their cultural resonance and linguistic suitability.

2. Embed security and trust by design: Regulatory instruments must require higher standards of openness, security, and data confidentiality for digital energy instruments, especially those aimed at at-risk segments of the population. The visible demonstration of unambiguous responsibility for preventing and remedying online harm is an indispensable prerequisite for cultivating trust.

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3. Facilitate regionally differentiated policy responses: Devolved governing bodies and municipal authorities should be given the latitude to devise digital inclusion initiatives that reflect their distinctive demographic profiles and socio-political settings, a necessity borne out by the contrasting patterns observed between England and Scotland.

4. Champion proactive and inclusive service conception: Digital energy platforms ought to be conceived with accessibility built in from the very earliest design stages, taking into account those who contend with restricted internet connectivity, lower levels of digital dexterity, and unstable housing circumstances. Such an orientation coheres with the precept of 'leaving no one behind' as the energy transition unfolds.

To distil the contribution, this investigation delivers simultaneously a resilient methodological architecture and a weighty body of evidence upon which to erect policies for digital energy that are both fairer and more efficacious. By directly tethering agent conduct in the simulation to empirical observations, we have amplified the verisimilitude and prognostic capacity of policy modelling. The understanding harvested through this work lays the groundwork for reducing technological injustice and securing an equitable distribution of the gains from the digital energy transition across every stratum of society.

The case study centred on UK citizenship, set out in the foregoing pages, represents merely one among a broader family of applications to which this architecture lends itself. Investigations planned for the future will encompass a broader array of policy scenarios, an undertaking intended to showcase the full adaptability of the AI-ABM architecture in confronting various facets of digital exclusion and to place a richer compendium of evidence at the disposal of those charged with crafting policy. It is also our intention to broaden the architecture to encompass threat modelling alongside data-sharing vignettes, thereby further augmenting its capacity to contribute to the development of secure and resilient online service environments suited to the needs of heterogeneous communities.

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Conflict of interest

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

Mennan Guder reports that UK Research and Innovation provided financial support and article publishing charges. 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.

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None

Conclusion

None

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