

Beyond Techno-Economic Diffusion: A Systematic Review and Socio-Technical Audit of Agent-Based Models of Rooftop Solar PV Adoption

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Abstract

Agent-based modelling (ABM) is increasingly used to analyze rooftop solar photovoltaic (PV) diffusion, yet it remains unclear how existing models operationalize socio-technical mechanisms such as peer effects, grid constraints, policy uncertainty, and energy justice. This systematic review evaluates ABM architectures for rooftop PV diffusion through a three-layer evidence design: a mapping of 876 publications (2000–2025), a core set of 101 ABM-related studies, and structured coding of 50 focal ABMs using the Spatial–Economic–Mechanistic–Policy–Justice (S-E-M-P-J) framework, which tests whether mechanisms are formally implemented rather than narratively invoked. The coding reveals an uneven architecture: behavioural mechanisms are nearly universal (96%) and policy representations common (82%), yet only 2 of the 50 focal studies (4%) combine architectural embedding of justice-related variables with justice as a core evaluation criterion, and justice remains computationally isolated from the models’ economic, spatial, and policy machinery. The field shows signs of an integration plateau: the median model implements three of the five dimensions, unchanged for a decade, and only 3 of the 41 policy-implementing models treat policy as time-varying. Current models answer “how much and where”, but rarely “for whom”. The review distils a methodological agenda into a minimal justice-reporting standard for adoption ABMs.

Keywords: agent-based modelling; rooftop solar photovoltaics; distributed energy systems; socio-technical transitions; energy justice; systematic review



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1. Introduction

Rooftop solar photovoltaic (PV) systems are becoming a central component of low-carbon energy transitions, reshaping electricity systems from centralized infrastructure toward decentralized and prosumer-driven configurations [1]. Beyond their technical and economic characteristics, rooftop PV systems are embedded within complex socio-technical environments, where adoption is shaped by behavioural heterogeneity, spatial conditions, institutional arrangements, and access to capital [2–7]. Consequently, rooftop PV diffusion is not socially neutral. Throughout this review, justice denotes energy justice in its established three-tenet form: distributional justice (how the costs and benefits of adoption are shared), procedural justice (who participates in, and can influence, adoption-relevant

decisions), and recognition justice (whose needs and constraints are acknowledged) [8,9], a framing aligned with the equity commitments of the United Nations Sustainable Development Goals, most directly SDG 7 (affordable and clean energy) and SDG 10 (reduced inequalities) [10]. Empirical evidence shows that rooftop PV adoption can reinforce or mitigate existing socio-economic inequalities depending on how policies, markets, and social dynamics interact [2–5,11,12].

Conventional modelling approaches, which often treat adoption as the outcome of rational, representative agents responding to price signals, struggle to capture this societal complexity. In practice, households and firms operate under bounded rationality [13–16] and are shaped by the neighbourhood context, social visibility, and perceptions of procedural fairness [5,17,18]. This mismatch creates an important analytical gap: when models abstract away social heterogeneity, they risk producing policy insights that are efficient on paper yet socially regressive in practice, generating uneven cost redistribution and programme benefits that bypass disadvantaged groups [19,20].

Rooftop PV adoption depends not only on technical feasibility and economic performance but also on social norms, policy credibility, and geographic conditions. For this reason, agent-based modelling (ABM) has become increasingly relevant because it enables heterogeneous actors, behavioural rules, and spatial interactions to be represented within the same simulation environment [21–28].

Despite its growing use, two critical limitations persist in the ABM literature on rooftop PV. First, existing reviews remain fragmented, often focusing on innovation diffusion, technical grid integration, or economic feasibility in isolation, without systematically examining how behavioural mechanisms translate into broader societal outcomes [29,30]. Second, while concepts of energy justice and equity have become increasingly prominent in policy discourse, the extent to which these concerns are operationalized within simulation models rather than treated merely as contextual narratives remains unclear [8,9,31,32]. As a result, the societal and policy implications of modelling choices, rather than model outputs alone, remain largely underexplored.

Methodological transparency is a further concern: practices range from data-driven calibration and uncertainty analysis [33–35] to stylized behavioural assumptions, leaving the societal implications of ABM-based policy simulations difficult to assess [28,29,36].

The closest antecedents—end-to-end reviews of residential PV adoption research and the review of household energy technology adoption ABMs by [37]—map what models include rather than how modelling architectures structure socio-technical outcomes. While prior reviews have mapped ABM applications by topic, method, or policy setting, they have not systematically examined how model architectures encode the socio-technical mechanisms that shape socially differentiated adoption outcomes. What remains missing is an integrated review of how behavioural, spatial, policy, and justice-related assumptions are embedded within rooftop PV ABMs, and how these assumptions condition the policy relevance and societal legitimacy of model-based transition scenarios.

A note on emphasis is warranted. Justice receives particular attention in what follows not because the framework privileges it *a priori* but because it is where the audit reveals the largest implementation deficit. A justice-only review could not demonstrate this: the deficit becomes visible precisely in contrast to the four dimensions that the field does implement.

Consequently, this review is guided by three central research questions that interrogate the intersection of simulation practices and societal outcomes.

RQ1: How have ABM frameworks evolved from purely technoeconomic formulations toward representations of complex societal dynamics?

RQ2: How are energy justice considerations represented within current ABMs, and what are the implications of the remaining gaps?

RQ3: To what extent are policy uncertainty and institutional trust represented within current ABMs, and what are the implications of their limited representation for the validity of model-based transition scenarios?

This review makes four contributions. First, it introduces the spatial–economic–mechanistic–policy–justice (S-E-M-P-J) framework, an operational coding scheme that distinguishes rhetorical inclusion from computational implementation across five socio-technical dimensions, with a fully auditable study-level coding reported in Supplementary Table S1. Second, applying this framework to a three-layer evidence base—876 mapped publications, a core set of 101 ABM-related studies, and 50 focal ABMs coded in depth—it quantifies a normative–computational gap: justice-related variables are formally embedded in only a small minority of models and remain structurally isolated from the spatial, economic, and policy machinery in which other mechanisms are integrated. Third, it translates these architectural findings into a concrete methodological agenda—covering decision rule transparency, calibration and validation, policy volatility dynamics, and justice-sensitive agent attributes—for next-generation rooftop PV ABMs. Fourth, it distils this agenda into ODD+J, a minimal justice-reporting extension of the ODD (Overview, Design concepts, Details) protocol, proposed as a common transparency standard for future adoption models. Together, these contributions position the review as an integrated evaluation of modelling practice, linking simulation design choices to governance, legitimacy, and equity implications.

To clarify the analytical logic of the review, Figure 1 illustrates how the S-E-M-P-J framework is used not simply to classify model characteristics but to assess how ABM design choices shape simulated diffusion dynamics and their broader societal and policy implications. In this sense, modelling choices influence how equity and policy credibility are represented within transition analysis.

Table 1 highlights that existing reviews primarily focus on adoption drivers, modelling approaches, or policy mechanisms in isolation, whereas this study provides an integrated socio-technical evaluation of modelling practices and their implications. The four reviews compared in Table 1 are the closest antecedents—those that engage rooftop or household PV adoption modelling directly; the broader ABM and energy-modelling review literature [22,28,36] is engaged throughout Sections 2–4 rather than tabulated here.

Table 1. Comparison of the present review with existing literature on rooftop PV diffusion.

Study	Scope	Focus	Key Limitation	How This Review Differs
[29]	Residential PV adoption	Theories, drivers, and modelling approaches	Focuses on adoption drivers rather than modelling structure	Adds an implementation-level audit of model architectures, beyond adoption drivers
[30]	PV adoption modelling	Systematic review of modelling approaches	Limited discussion of socio-technical implications	Adds dimension-level (S-E-M-P-J) architectural evaluation
[37]	Household energy-technology adoption (ABM-focused review)	Barriers, policies, and agent-based modelling studies of household adoption	Centres on energy-efficiency technologies and adoption barriers; does not audit how socio-technical mechanisms are implemented within model architectures	Extends to rooftop PV and formally codes justice implementation

Table 1. Cont.

Study	Scope	Focus	Key Limitation	How This Review Differs
[38]	Innovation-diffusion ABMs (methodological review)	Empirical grounding, calibration and validation of diffusion ABMs	Focuses on empirical-grounding practice; no framework for socio-technical or justice completeness	Extends beyond calibration practice to socio-technical completeness, including justice
This study	Rooftop PV diffusion (ABM literature)	Integrated socio-technical synthesis using the S-E-M-P-J framework; proposes the ODD+J reporting standard	Focal S-E-M-P-J coding restricted to the 50 studies with codable full texts	—

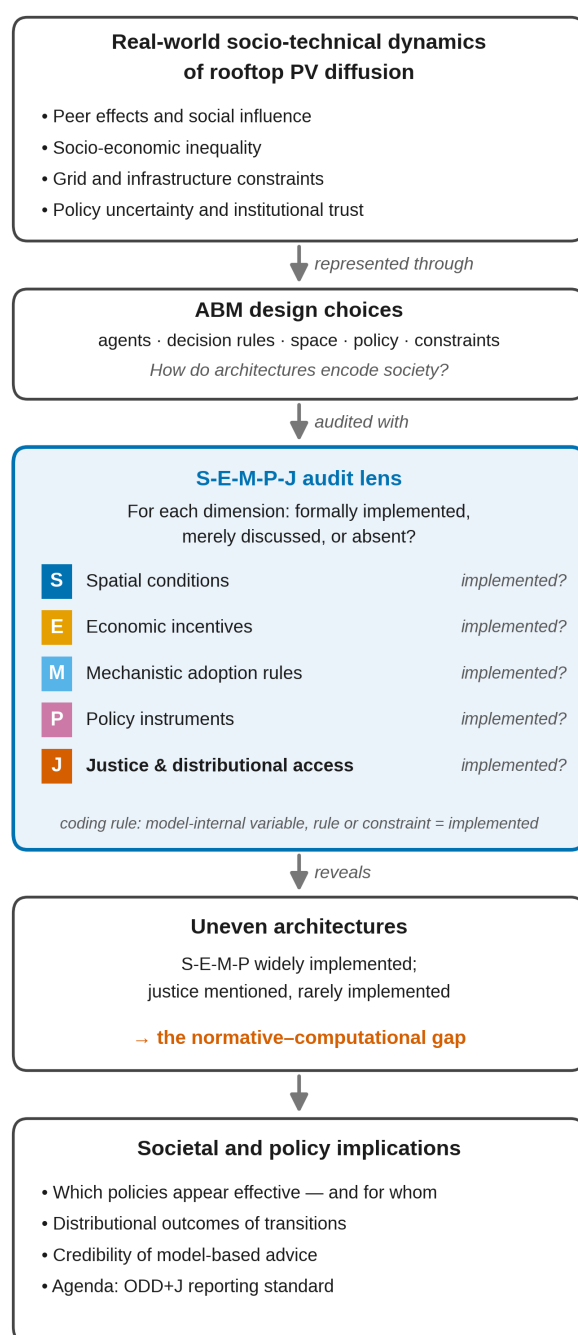


Figure 1. Analytical structure of the review and the S-E-M-P-J framework.

2. Methods

This study adopts a systematic review design, combining PRISMA-guided screening with structured thematic coding, to examine how agent-based modelling (ABM) studies represent rooftop solar photovoltaic diffusion. Rather than only classifying modelling techniques, the review evaluates how modelling architectures embed behavioural, spatial, economic, policy, and justice-related mechanisms. The methodological design therefore combines systematic literature screening with thematic coding to assess how simulation structures shape societal interpretation and policy relevance.

To support this analysis, a comprehensive literature dataset was constructed and systematically analyzed using an integrated thematic framework. This approach enables a consistent evaluation of modelling practices, allowing the review to move beyond descriptive classification toward an assessment of how simulation design choices shape socio-technical interpretations and policy relevance.

2.1. Scope, Analytical Logic, and Review Orientation

To avoid ambiguity between the different levels of analysis, this study used a three-layer evidence structure. The first layer is the broad screening universe of 876 publications used to identify the overall development and thematic structure of rooftop PV diffusion and ABM-related literature. The second layer was the core analytical set of 101 studies selected because they explicitly engaged with ABM or closely related agent-based simulation approaches in the context of rooftop or distributed PV adoption. The third layer is the focal set of 50 studies, selected from the 101-study core set for detailed thematic coding because they provide sufficient information on agent definitions, decision rules, calibration, validation, spatial representation, policy modelling, or justice-related mechanisms. The 876-publication layer therefore provides field-level context, the 101-study layer defines the ABM-specific evidence base, and the 50-study layer supports detailed claims about model design and operationalization.

The review covered peer-reviewed journal articles and selected conference proceedings published between 2000 and 2025, with the final database searches conducted in November 2025. While analytical mapping focuses on the period 2000–2024 to ensure temporal consistency in citation accumulation, studies published throughout 2025 were incorporated into the qualitative synthesis, where they offered substantive methodological innovations. This period captures both the early experimental use of ABM in energy research and its more recent consolidation as a mainstream analytical approach [39]. Three interdisciplinary principles guide the methodological orientation. First, ABM is conceptually heterogeneous: studies vary widely in how they define agents, formalize decision-making, and represent behavioural or spatial structures—even a single behavioural theory admits many divergent formalizations [40]. As a result, a simple enumeration of publications provides limited insight into how societal dynamics are modelled [22,41–43]. Second, rooftop PV adoption is inherently multidimensional and shaped by interacting economic, behavioural, spatial, regulatory, and equity-related factors.

These considerations motivate a sequential–iterative review design: broad retrieval, relevance screening, construction of a core analytical set, analytical mapping, and thematic synthesis.

Table 2 summarizes this S-E-M-P-J framework and serves as the analytical backbone for both the screening process and subsequent thematic synthesis.

In this review, S-E-M-P-J was used as an analytical coding framework, rather than as a prescriptive model-building template. The ordering of the letters is mnemonic rather than hierarchical, and the five dimensions are derived from the adoption-determinant literature as the principal channels through which outcomes become socially differentiated; candidate

constructs such as resilience, trust, or governance operate through these channels—trust via M and P, governance via P—rather than alongside them.

Table 2. S-E-M-P-J framework used for coding rooftop PV ABMs.

Dimension	Definition in ABM Context	Key Variables & Evidence Types Looked For
S—Spatial	Representation of physical space, geography, and infrastructure.	GIS data, building footprints, roof suitability, shading, network topology, neighbourhood clustering, distribution grid constraints.
E—Economic	Financial drivers and investment logic guiding agents.	Payback period, NPV, ROI, installation costs, electricity prices, income levels, budget constraints.
M—Mechanistic (Behavioural)	Representation of agent decision rules, cognitive bounds, and social interaction mechanisms (e.g., peer effects).	Bounded rationality, peer effects, social learning, risk perception, heuristic rules, habit formation.
P—Policy	Regulatory instruments and market rules affecting adoption.	Feed-in tariffs, net-metering, subsidies, regulatory uncertainty, institutional trust mechanisms.
J—Justice	Distributional equity, procedural fairness, and access disparities within the socio-technical system and whether these are represented as dynamic constraints within the agent’s decision-making architecture or merely as post-simulation metrics.	Income inequality, energy poverty, split incentives (renter/owner dilemma), access to credit, digital divide.

Each dimension is anchored in an established theoretical tradition, and that tradition also fixes its coding boundary. The spatial dimension (S) operationalizes the geography of diffusion and infrastructure constraint emphasized in spatial diffusion research [5]; its boundary is physical or network space represented inside the model, not merely spatially disaggregated input data. The economic dimension (E) reflects investment and discounting theory [44,45]; it requires an endogenous, agent-level financial calculation, not the mere mention of costs. The mechanistic dimension (M) draws on diffusion-of-innovations theory, behavioural intention frameworks such as the theory of planned behaviour, and bounded-rationality research [13,40,46]; it captures decision rules beyond pure financial optimization. This is also the boundary that separates M from E and establishes their conceptual independence: E specifies the financial inputs to a decision, whereas M specifies the behavioural rule that transforms those inputs, together with social signals, into a choice, and either can be present without the other. A model whose agents perform a full financial optimization with no behavioural rule implements E without M; a contagion model whose agents respond only to peer adoption implements M without E. The policy dimension (P) rests on instrument design and policy credibility research [47,48]; its boundary is an instrument that alters agent decisions inside the simulation, not policy motivation in the framing. The justice dimension (J) derives from the three-tenet energy justice literature [8,9,31]; its boundary is distributional structure implemented in the model, as elaborated in Sections 2.5 and 2.6 and graded in Section 2.6.

Each dimension was coded according to whether it was absent, conceptually discussed, or formally represented within the model structure. “Formal representation” refers to implementation through agent attributes, decision rules, constraints, spatial layers, policy scenarios, calibration variables, or simulation outputs. This distinction is important because many studies discuss socio-technical factors narratively, whereas fewer studies embed these factors directly into computational model structures. Therefore, the coding procedure distinguished between rhetorical inclusion and operational implementation. In the operational coding rubric (Section 2.6), this three-way reading (absent/conceptually

discussed/formally represented) is collapsed into a binary implemented/not-implemented indicator for the four technical dimensions, while for justice the graded five-level scale introduced in Section 2.6 preserves the intermediate forms explicitly.

To make this analytical contrast explicit, the distinction between conventional techno-economic adoption logic and the socio-technical representation evaluated in this review can be stated compactly. In a techno-economic formulation, adoption is treated as a deterministic threshold on an economic utility derived mainly from financial returns:

$$A_i = 1 \text{ if } U_i^E \geq \tau, \text{ else } 0, \quad U_i^E = g(NPV_i, PB_i) \quad (1)$$

A socio-technical S-E-M-P-J formulation instead embeds economic logic within behavioural, spatial, and policy conditioning, and gates the resulting adoption propensity by an access/justice term:

$$p_i^{eff}(t) = J_i(t) \cdot \sigma(\beta_0 + \beta_S S_i + \beta_E E_i + \beta_M M_i(t) + \beta_P P_i(t)) \quad (2)$$

where S, E, M and P denote the spatial, economic, behavioural (mechanistic), and policy terms, $\sigma(\cdot)$ is the logistic function, and $J_i(t) \in [0, 1]$ is a financial-access gate. Equation (2) is an illustrative, stylized synthesis constructed for this review rather than an estimated model: its purpose is to make explicit that access constraints can suppress adoption even when the perceived utility of adoption is favourable—precisely the mechanism that most reviewed ABMs do not represent. The gate term deliberately instantiates only the narrowest, distributional-access reading of justice; procedural and recognition tenets are not reducible to such a gate, which is one reason the coding rubric of Section 2.6 treats justice as a graded, multi-form construct rather than a single access term. The contrast between Equations (1) and (2) formalizes the central argument of this review.

2.2. Database Selection and Search Strategy

To ensure interdisciplinary coverage, a literature search was conducted using the Web of Science Core Collection and Scopus. Search queries combined terms related to agent-based or multi-agent simulations with keywords capturing solar photovoltaic technologies and distributed or residential adoption contexts. Boolean operators were applied to maximize recall while maintaining conceptual precision; the full search strategy for both databases is reported in the Supplementary Material (Database Search Strategy). The review followed established guidance for systematic literature review [49]. The search strategy relied on Boolean combinations of methodological keywords (e.g., “agent-based modelling”, “multi-agent simulation”) and domain-specific terms (e.g., “rooftop PV”, “distributed generation”, “solar adoption”). Search terms were deliberately constructed to capture not only technical modelling approaches but also studies engaging with behavioural dynamics, policy design, and distributional outcomes, in order to reflect the interdisciplinary scope of this review. While the review primarily focused on peer-reviewed journal articles, conference proceedings were retained only when they offered distinct methodological innovations not yet present in the journal literature ($n = 2$: the Springer proceedings chapter of Guo et al. [50] in the focal set, and Snape et al. [51], listed in Supplementary Table S2). In addition, three institutional reports [2,3,52] and one foundational book [46] were cited for conceptual and contextual grounding but were not part of the screened corpus; the remaining references consist of peer-reviewed journal articles.

Publications focusing exclusively on utility-scale PV, purely technical performance analysis, or energy system optimization without behavioural or adoption components were excluded. The database searches returned 1703 records (Web of Science: 886; Scopus: 817), exported on 3–6 November 2025. Block-level merging of the raw exports removed

213 exact duplicates, leaving 1490 records; cross-database deduplication then removed a further 614 records, leaving 876 unique publications that formed the basis of analytical mapping. All screening counts and coded results reported in this review derive from this November 2025 corpus; a later targeted verification search, used only as an out-of-corpus robustness check on the justice finding, is described in Section 5.

2.3. Screening and Construction of the Core Analytical Set

The screening proceeded in two stages. First, titles, abstracts, and author keywords were screened by the first author, supported by keyword harmonization in the bibliometrix/biblioshiny environment [53], to identify studies employing ABM or closely related agent-based simulation approaches, with rooftop or distributed PV adoption as a substantive focus [54]. Studies addressing generic renewable energy planning or smart grid optimization without explicit adoption dynamics were excluded at this stage.

Second, full texts were retrieved for the candidate records emerging from this screening, and eligibility for the core set was assessed against the inclusion criteria. Full texts were successfully retrieved for all core-set candidates, and no reports were excluded at the full-text stage; the separation between focal and non-focal core studies (Supplementary Table S2) reflects coding depth rather than exclusion. This process resulted in a deliberately inclusive core set of 101 studies, comprising agent-based models together with closely related simulation, empirical, and methodological studies of rooftop or distributed PV adoption, retained for field-level analysis; within this set, focal eligibility required ABM as the primary methodological framework, explicit modelling of rooftop or distributed PV adoption, and incorporation of behavioural, spatial, or policy mechanisms [4,16,55–58]. One additional study meeting all inclusion criteria was identified through citation searching rather than the database queries and was included in the core set [59]. From this core set of 101 studies, a focal subset of 50 studies was selected for in-depth thematic coding through a purposive, transparency-oriented procedure. Because the analytical claims about model design and justice operationalization depend on detailed, full-text information, selection prioritized studies whose full texts allowed the S-E-M-P-J dimensions to be assessed at the level of implementation rather than narrative mention. Specifically, a study was retained in the focal set when its full text reported (i) the agent definition and decision rules, (ii) at least one explicitly implemented modelling mechanism among the behavioural, spatial, policy, or economic components, and (iii) sufficient methodological detail (e.g., calibration, validation, scenario design, or data sources) to allow consistent cross-study coding. Studies that were not agent-based implementations (reviews, system dynamics models, and empirical or technical context studies), that engaged with rooftop PV ABMs only at a conceptual level, or that did not report enough implementation detail to code the S-E-M-P-J dimensions, were retained in the 101-study core set for field-level analysis but were not carried into the focal coding set. The complete list of these 51 non-focal core studies, with the reason each was not carried into focal coding, is provided in Supplementary Table S2. Selection was based on the transparency and codability of the reported model structure rather than on citation counts, journal outlet, or perceived quality. The 50 focal studies and their full dimension-by-dimension coding are reported in Supplementary Table S1, so that the basis for each inclusion is auditable; focal studies not cited elsewhere in this review are [60–62]. Figure 2 shows the systematic screening and selection process following the PRISMA guidelines, illustrating how the initial corpus was progressively refined into the core analytical set and the 50-study focal subset.

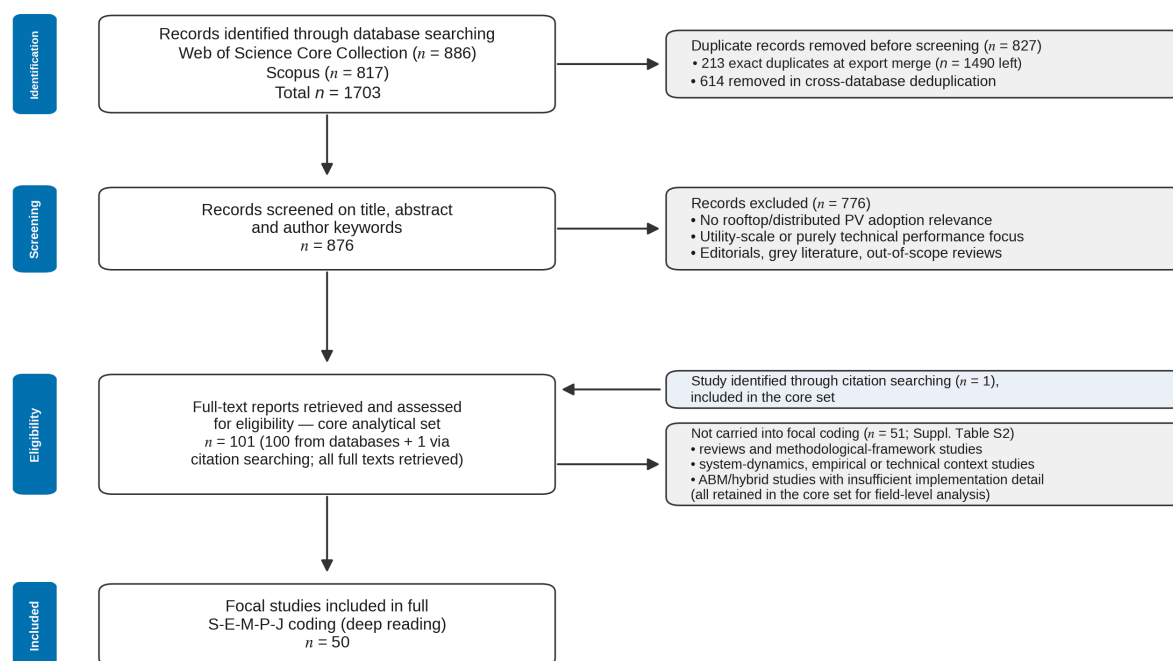


Figure 2. PRISMA flow diagram of the literature selection process [63].

These studies form the backbone of thematic synthesis, with key modelling dimensions summarized in Table 3 and a complete list provided in Supplementary Table S1. Rather than serving as a descriptive inventory of modelling techniques, Table 3 is used as an analytical device to reveal how dominant modelling choices structure societal outcomes in rooftop PV diffusion. Each modelling dimension is interpreted in terms of its social implications—specifically, how assumptions about behaviour, space, policy design, and access shape who adopts, who benefits, and which inequalities may be reproduced or mitigated through simulated transition pathways.

Table 3. Key modelling dimensions in the rooftop PV ABM-related literature.

Dimension	Modelling Approach	Key Mechanisms	Example Studies
Behavioural decision-making	Widely modelled	Bounded rationality, payback thresholds, heuristic decision rules	[5,16,23,56]
Social interaction and peer effects	Core modelling element	Neighbourhood contagion, network-based diffusion, visibility effects	[14,16,57,64]
Spatial representation	Increasingly common	GIS-based rooftop suitability, neighbourhood clustering, building-level spatial data	[6,33,65]
Grid and hosting-capacity constraints	Emerging but uneven	Feeder limits, transformer constraints, curtailment risk	[6,66,67]
Policy instruments	Common	Feed-in tariffs, net-metering schemes, subsidies, tariff reforms	[68–70]
Policy dynamics and uncertainty	Rare but growing	Dynamic incentives, policy shocks, expectation formation	[47,71]
Justice and equity	Limited but emerging	Income segmentation, credit constraints, tenure status	[57,72,73]
Calibration and validation	Highly heterogeneous	Stylised assumptions, sensitivity analysis, limited empirical calibration	[33,35,74]

Note: two cited examples are empirical (non-ABM) evidence anchors—Graziano and Gillingham in the behavioural row and Reames in the justice row—included as empirical grounding for the corresponding mechanisms rather than as ABM implementations.

2.4. Analytical Mapping of the Literature

The analytical mapping of the literature is descriptive in purpose: it contextualizes the growth and conceptual structure of the field, while all analytical claims about model design rest on the thematic coding described in Sections 2.5 and 2.6. Publication trend mapping and keyword co-occurrence analysis of the 876-record corpus were conducted in the bibliometrix/biblioshiny environment (R) [53]. Prior to analysis, author names and keywords exported from Web of Science and Scopus were harmonized to avoid fragmentation—for instance, consolidating “solar-PV”, “photovoltaic”, “solar photovoltaic” and “PV” under “solar PV”, and unifying “ABM”, “agent-based model” and “agent-based modelling”.

A core set of 101 studies was subjected to fine-grained structural analysis to map the evolution of modelling assumptions over time. This process prioritizes the identification of linkages between theoretical modelling choices (e.g., behavioural heuristics) and their real-world system implications, forming the empirical backbone of the subsequent synthesis on policy effectiveness and energy justice.

2.5. Thematic Synthesis Protocol

To move beyond surface-level categorization, the review employed a structured thematic synthesis informed by the innovation-diffusion and network-diffusion literature [13,75]. The coding focused on five analytical dimensions: modelling purpose, agent heterogeneity, decision logic, spatial representation, and policy realism. This five-lens scheme served field-level tagging of the core set; the formal dimension-level coding of the focal studies used the S-E-M-P-J rubric defined in Section 2.6. In addition, each study was tagged with its jurisdictional context to capture institutional and socio-economic conditions, shaping both modelling assumptions and policy relevance. This included coding the country/region of the empirical setting (or intended application), whether the case primarily reflects Global North or Global South conditions, and the stability of the policy environment, as reported in the study (e.g., stable incentive regimes versus volatile or shock-prone settings). These contextual tags are used in Section 3 to interpret geographic concentration patterns and assess how transferable justice- and policy-related insights are across different institutional environments.

The 101-study core set was characterized at field level using the thematic and jurisdictional tags described above, while full dimension-level S-E-M-P-J coding was applied to the 50 focal studies to examine how equity and justice considerations are operationalized. Justice was operationalized only if the model explicitly included vulnerability parameters (e.g., credit constraints for low-income agents or split-incentive structures for tenants), rather than merely referring to justice in narrative discussions. The variables named here—income, tenure, credit access—are illustrative rather than exhaustive: any formally implemented vulnerability dimension, such as ethnicity, education, energy burden, or digital access, satisfied the criterion equally. Under this deliberately strict coding rule, narrative references to equity, descriptive subgroup comparisons, or post hoc distributional commentary were not considered sufficient for classification as justice-operationalized unless justice-related variables were formally embedded within agent attributes or decision constraints, with distributional outcomes evaluated as a core criterion of the study. This stricter threshold was adopted to distinguish qualitative recognition of justice from computational implementation within the model architecture. This definition is adopted for reliability and cross-study comparability rather than as a claim to being the uniquely correct reading of justice; any broader definition would raise the count only by conflating stated intent with implemented model behaviour. Accordingly, the resulting estimate should be interpreted as a conservative indicator of formal operationalization rather than a claim that broader

distributional awareness is absent from the literature. Applying this predefined operational criterion systematically across all 50 focal studies (see Supplementary Table S1 for study-level coding), only 2 models (4%) were classified as formally embedding justice-related variables within agent attributes or decision constraints. This operational criterion corresponds to level J4 of the graded justice scale defined in Section 2.6; intermediate forms (narrative mention, covariate-level heterogeneity, and equity-targeted scenario tests) are distinguished explicitly at levels J1–J3 rather than being conflated with either absence or full implementation. To assess coding reliability, two of the authors independently coded all 50 focal studies. For the four technical dimensions (S, E, M, P), coded as binary implemented/not-implemented indicators, initial disagreements were resolved through discussion and documented consensus, and all 200 cell judgements were subsequently re-verified sentence-by-sentence against the full texts during the revision of this review, yielding ten documented cell-level corrections whose study-level rationales are reported in Supplementary Table S1; all frequencies reported in Section 3 reflect this verified coding. For the justice dimension, both coders independently applied the five-level scale defined in Section 2.6 to all 50 studies: agreement was 47/50 (94.0%), Cohen’s $\kappa = 0.91$ (linearly weighted $\kappa = 0.95$), all three disagreements lay on the J1–J2 boundary; none involved the J3 or J4 levels on which the headline finding rests, and each was resolved through documented consensus. Therefore, the final coding reflects a conservative interpretation of the reported model structures rather than an expansive reading of the authors’ broader policy motivations.

Importantly, the analytical and thematic results were interpreted iteratively, rather than sequentially. Themes identified through close reading were mapped back onto analytical clusters, allowing the review to examine how dominant modelling paradigms align or fail to align with emerging societal concerns. This verification step strengthens the robustness of the justice operationalization labels applied in thematic synthesis.

2.6. S-E-M-P-J Operationalization and Coding Rubric

To ensure that the S-E-M-P-J classification reflects implemented model structure rather than narrative mention, each of the 50 focal studies was coded as implementing (✓) or not implementing (✗) each dimension according to the operational criteria below. A dimension was coded as present only when it was represented as a model-internal variable, decision rule, or constraint. The full dimension-by-dimension coding for all 50 studies is reported in Supplementary Table S1, so that every inclusion is auditable.

Binary coding of the justice dimension, while reliable, compresses qualitatively different intermediate positions (narrative concern, covariate-level heterogeneity, and equity-targeted scenario tests) into a single negative class. To preserve these gradations, justice was additionally coded on a five-level ordinal scale (Table 4), in which each level corresponds to a distinct position of distributional structure within the model architecture.

Table 4. Five-level justice implementation scale (J0–J4) applied to the 50 focal ABMs. Study-level codes and supporting evidence sentences are given in Supplementary Table S1.

Level	Operational Definition	n (of 50)	Focal Examples
J0—Absent	No justice, equity, or distributional content; no group-differentiated variable.	14	—
J1—Narrative mention	Equity or distributional concern is discussed (framing, discussion, policy implications), but the model computes no distributional quantity and contains no group-differentiated structure.	6	[56,76]

Table 4. *Cont.*

Level	Operational Definition	<i>n</i> (of 50)	Focal Examples
J2—Covariate/outcome level	Socio-economic agent attributes (e.g., income, education, tenure) serve heterogeneity or calibration, or group-based adoption outputs are reported; no equity-targeted instrument is tested and equity is not the evaluation frame.	24	[6,68,77]
J3—Equity-targeted instrument (scenario level)	An instrument targeted at a disadvantaged group is tested at scenario level and distributional outcomes are measured for that group; justice is not the core evaluation framework of the study.	4	[16,35,62,78]
J4—Architectural embedding + core criterion	A vulnerability or access mechanism is embedded in the core decision architecture and justice/distributional metrics are core evaluation criteria of the study.	2	[57,72]

Applying the scale to the 50 focal studies yields J0: 14, J1: 6, J2: 24, J3: 4, and J4: 2. The binary indicator of Table 5 corresponds to level J4: the headline figure of 2/50 (4%) therefore denotes architectural embedding with justice as a core evaluation criterion, while a further four models (8%) test an equity-targeted instrument at scenario level (J3) without making justice the core evaluation frame. The full study-level five-level coding, together with the supporting evidence sentence for each study, is reported in Supplementary Table S1.

Table 5. Operational coding rubric for the S-E-M-P-J dimensions.

Dimension	Operational Definition	Coded ✓ When the Model...
S—Spatial	Explicit spatial or grid representation of agents/infrastructure	places agents in GIS/spatial units, or represents feeder, transformer or hosting-capacity geography
E—Economic	Endogenous economic decision variable	computes payback/NPV/LCOE, tariffs, financing or price response as a driver of adoption
M—Mechanistic	Behavioural decision mechanism beyond pure optimization	implements peer effects, thresholds, heuristics, bounded rationality or attitudinal rules
P—Policy	Policy instrument represented as a model input	encodes feed-in tariff, net-metering, subsidy, tax or regulatory change that alters agent decisions
J—Justice	Endogenously coupled distributional structure	embeds distributional structure endogenously in the adoption mechanism (vulnerability or access attributes coupled to decision rules) and evaluates distributional metrics as a core outcome (level J4 in Table 4); heterogeneity covariates alone do not qualify

2.7. Transparency and Methodological Boundaries

All database queries, screening criteria, and coding procedures were documented to support reproducibility. The review protocol was not prospectively registered. Nevertheless, this review is subject to the limitations inherent in the literature. English-language restrictions may not fully capture region-specific modelling efforts, and inconsistent reporting of ABM design and calibration limits the feasibility of quantitative meta-analyses [42,43]. Consequently, the synthesis emphasizes analytical interpretation over statistical aggregation, focusing on how modelling choices shape societal narratives of technological diffusion.

3. Results: Literature Trends and Socio-Technical Patterns

This section synthesizes the analytical patterns and thematic structures emerging from the three-layer evidence structure. The 876-publication map provides a macro-level view of the field; the 101-study core set is used to trace how modelling architectures have shifted from predominantly techno-economic logic toward richer socio-technical representations; and the 50 focal studies support the detailed coding claims about model design and justice operationalization. Throughout the results, claims are attributed to the corresponding evidence layer so that the underlying evidence base remains explicit. The results are organized into four parts: publication trajectories, conceptual structures, thematic evolution, and the operationalization of behavioural, spatial, policy, and justice-related mechanisms. Analytical mapping is used not as an end in itself but as a means to contextualize shifts in modelling paradigms and to identify how emerging societal concerns are, or are not, reflected in dominant simulation practices.

The results should be interpreted as a structured synthesis of reported modelling practices rather than a statistical meta-analysis of model outputs. Because ABM studies differ substantially in scale, data availability, agent definitions, calibration practices, and reporting detail, the review focuses on how modelling choices are represented and justified across the literature.

3.1. The Rise of Social Simulation in Energy Research

3.1.1. Growth of the Broad Literature (876-Paper Universe)

The publication trajectory derived from the 876-paper dataset shows a pronounced expansion of research linking distributed solar PV adoption with behavioural and computational modelling approaches over the past two decades (Figure 3). Between 2000 and 2010, the annual output remained limited, with only sporadic contributions addressing PV adoption through simulation-based or behavioural lenses. This early period reflects the marginal role of prosumer-oriented PV technologies in global energy systems.

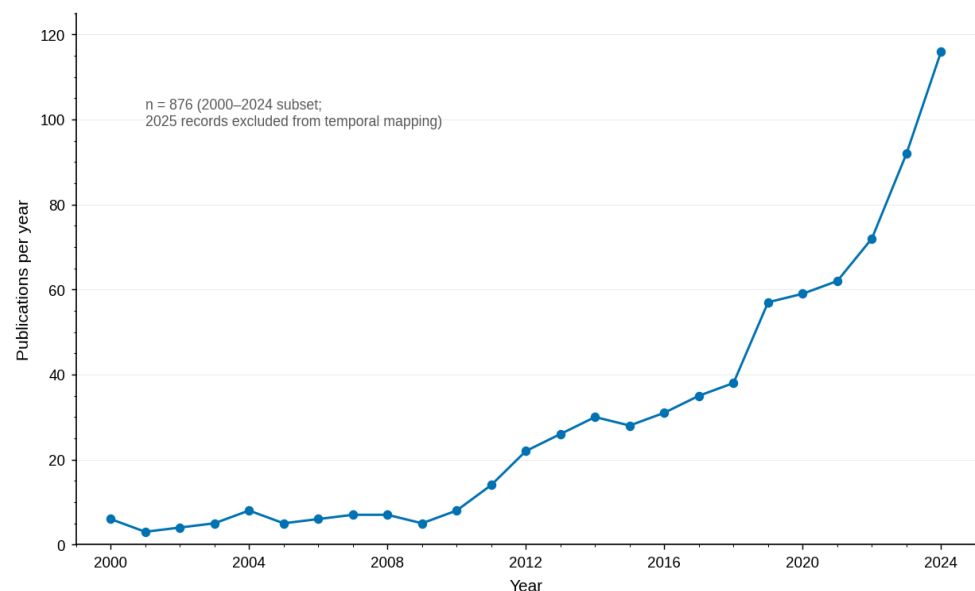


Figure 3. Annual publication trend of the screening universe, 2000–2024 subset (full universe $n = 876$; records published in 2025 are excluded from temporal mapping, cf. Section 2.1).

From 2010 to 2012, publication activities began to accelerate, driven by increased policy attention to residential PV incentives, declining technology costs, and the diffusion of innovation frameworks applied to energy technologies. After 2015, growth became markedly steeper, coinciding with the maturation of both PV markets and agent-based and

behavioural modelling tools. By the early 2020s, rooftop PV adoption had emerged as a prominent research cluster within the broader renewable energy literature. The scale and continuity of this growth indicate that the field has moved beyond isolated case studies, providing sufficient critical mass to warrant a structured synthesis.

3.1.2. Growth of the Core ABM-Related Literature (101-Study Core Set)

A similar but more focused trend is observed within the subset of studies that explicitly employ agent-based or multiagent modelling frameworks. Prior to 2010, only a small number of studies had applied ABM to households or small-scale PV adoption. From 2015 onward, annual publication counts increased sharply, reflecting a broader shift toward modelling prosumer behaviour, social influence, and interactions between adoption and distribution grids.

Beyond publication volume, the consolidation of ABM as a methodological approach is reflected in recurring analytical assumptions across the core literature. The growing prominence of ABM appears closely linked to its ability to represent heterogeneous decision-makers, locally clustered diffusion processes, and interacting behavioural mechanisms that unfold over space and time. These features are particularly salient in residential PV adoption, where decisions rarely follow uniform economic logic [7,34].

3.1.3. Geographic Concentration and Representational Gaps

Beyond temporal growth, the literature exhibits clear geographic concentration in terms of where ABM applications are empirically grounded. A substantial share of core studies are calibrated to, or motivated by, policy and market conditions in relatively stable, high-income contexts, where adoption is supported by well-defined incentive regimes, high data availability, and comparatively predictable regulatory environments. This geographic concentration introduces a systematic bias in model assumptions, where models implicitly assume high-trust institutional environments, formalized housing markets, and stable middle-class financial profiles as universal baselines for energy transitions.

When disaggregated by jurisdictional context, the core ABM-related literature is predominantly calibrated to stable, high-income Global North settings characterized by predictable policy regimes and high data availability, while only a small subset explicitly engages with structurally constrained Global South contexts marked by income volatility, informal tenure arrangements, credit constraints, and policy instability. This imbalance limits the external validity of model-based policy insights in heterogeneous institutional environments. In frequency terms, 35 of the 50 focal models are calibrated to a named jurisdiction while 15 are generic, theoretical, or unspecified; among the named settings, the United States (9), the United Kingdom (4), Switzerland (3), and Germany (2, plus one joint Canada–Germany study) together account for more than half, whereas non-OECD and emerging-economy settings appear only sporadically (China $\times 2$, Qatar $\times 2$, the wider Arabian Gulf region $\times 1$, Türkiye $\times 1$). The full jurisdictional tagging underlying these counts is provided in Supplementary Table S1.

The patterns summarized in Table 6 are derived from the jurisdictional context coding described in Section 2.5 (Thematic Synthesis Protocol). For the 50 focal studies, the underlying jurisdiction frequencies are reported in Section 3.1.3 and are auditable study-by-study in Supplementary Table S1; for the wider 101-study core set, the patterns reflect a comparative qualitative interpretation rather than strict frequency counts.

This analysis demonstrates that the jurisdictional context functions as a structuring condition within ABM architecture, shaping how equity, policy effectiveness, and legitimacy are represented across different socio-political environments. Consistent with qualitative systematic review practices [49,63], Table 6 synthesizes these patterns by distinguishing

between models calibrated to stable, high-income policy regimes and those engaging with structurally constrained adoption contexts.

Table 6. Jurisdictional patterns in rooftop PV ABMs.

Dimension	Global North–Dominant ABMs	Global South-Oriented ABMs
Policy regime assumptions	Stable, long-term incentives; predictable regulatory frameworks	Volatile incentives; policy reversals; institutional uncertainty
Socio-economic representation	Middle- to high-income homeowners; stable employment	Income volatility; informal employment; heterogeneous affordability
Tenure structures	Owner-occupiers implicitly assumed	High renter shares; informal or insecure tenure
Access to finance	Easy access to credit and capital	Credit constraints; limited formal financing
Justice operationalization	Predominantly distributional (income-centric), failing to capture structural vulnerability.	Largely limited to narrative framing, with few models formally embedding tenure or credit constraint parameters.
Implications for modelling outcomes	High diffusion potential; policy efficiency focus	Underestimated barriers; equity and access risks underexplored

3.2. Conceptual Structure: From Economics to Behaviour

3.2.1. Dominant Paradigms in the Global Literature

The thematic structure of the rooftop PV literature reveals four dominant research clusters. The first cluster, centred on innovation diffusion and behavioural mechanisms, brings together concepts such as peer effects, social influence, and the diffusion of innovation, signalling a growing integration of behavioural science into energy research. The second cluster focuses on distributed energy systems and grid integration, incorporating terms related to hosting capacity and network constraints, and highlights the increasing relevance of infrastructure-level considerations as PV penetration increases. The third cluster, policy evaluation and tariff design, reflects sustained attention to regulatory instruments, such as feed-in tariffs and net metering. Finally, the computational modelling cluster encompasses agent-based modelling, system dynamics, and related simulation approaches.

Together, these clusters indicate that rooftop PV research has evolved into an interdisciplinary research field rather than a unified modelling approach. Behavioural diffusion, policy design, grid integration, and computational methods appear to be closely connected, yet analytically differentiated, underscoring the pluralistic nature of the field.

3.2.2. Thematic Consolidation in Agent-Based Modelling

Four main clusters are observed. The behavioural mechanisms and social interaction cluster captures peer effects, social learning, bounded rationality, and neighbourhood influence, highlighting the ABM's capacity to simulate social contagion processes [56,70,79]. Economic feasibility and investment decision-making remain central, with financial metrics such as payback and tariff structures continuing to anchor adoption decisions [4,23,44,59,80]. Spatial modelling and grid constraints form a distinct cluster, reflecting the growing attention to infrastructural realism through GIS-based representations and hosting-capacity considerations [6,33,65,66,81–85]. Finally, policy scenarios and regulatory design constitute a cluster where ABMs function as policy analysis tools, testing alternative tariff regimes and regulatory shocks under heterogeneous agent behaviour [58,69,70,86–88].

3.3. Evolution of Research Themes Across Time

The conceptual focus of this field has shifted through three distinct evolutionary phases, reflecting the maturation of energy transition research. During the emergence phase (2010–2015), research focused primarily on techno-economic feasibility and early diffusion concepts with limited engagement with spatial or policy-rich ABMs. The expansion phase (2016–2020) saw rapid growth in peer effects research, increased use of GIS-based spatial modelling, and rising attention to grid constraints and prosumer dynamics. In the most recent maturation phase (2021–2024), justice-, equity-, and access-related terms became more visible alongside increasingly sophisticated representations of agent heterogeneity and a broader range of spatial scales, from neighbourhoods to national systems.

3.4. Operationalizing Societal Dynamics in Models

3.4.1. Behavioural Modelling Approaches

Decision-making models were clustered into three broad categories across the 101 core studies. Early contributions relied primarily on economic decision rules, such as pay-back thresholds or utility maximization, which remain in use but are increasingly augmented by behavioural components [45]. A substantial share of the literature incorporates bounded rationality and heuristic decision-making, including satisficing behaviour, risk aversion [15,21,34,78], and threshold-based rules [26,56,85,89,90]. Survey-parameterised household ABMs, in which agent decision functions are fitted directly to stated-preference data, provide particularly transparent examples of this class [91,92]. Social influence and peer effects have become particularly prominent, with many models employing network-based contagion mechanisms to generate more realistic diffusion trajectories and spatial clustering [4,16,17,56–58,64]. These behavioural representations show how bounded rationality and peer influence can amplify neighbourhood clustering, producing unequal adoption patterns that aggregate or representative-agent models typically fail to detect.

3.4.2. Spatial Representation and Grid Constraints

A substantial number of core ABM-related studies incorporate explicit spatial logic, ranging from simple adjacency-based neighbourhood structures to GIS-derived representations of roofs and buildings. More recent models increasingly integrate hosting-capacity constraints, feeder and transformer limits, shading, orientation, and neighbourhood clustering effects [66,67,82–84,93]. At the national scale, some studies couple rooftop PV adoption with bulk-power system planning—for example linking an agent-based rooftop adoption model (dSolar) with capacity expansion modelling (ReEDS) to capture how distributed adoption interacts with system-level expansion [93]. Across these studies, spatially explicit representations tend to produce slower diffusion dynamics and more realistic adoption plateaus than non-spatial formulations. Spatially explicit modelling shows how infrastructure constraints can generate first-come, first-served dynamics that exclude late adopters and reinforce socio-economic inequalities.

3.4.3. Policy Modelling Approaches

Policy representation within the core ABM-related literature spans a wide spectrum from stylized static parameters to detailed scenario comparisons. Common approaches include simulations of feed-in tariffs, net metering schemes, subsidies, and tariff reforms. While some studies incorporate transaction costs or administrative barriers, explicit modelling of dynamic policy shocks remains relatively rare, although it has begun to appear in more recent works. Concretely, of the 41 focal models that implement a policy dimension, only three represent policy as time-varying or adaptive—through adaptive feed-in schedules, dynamic community solar tariffs, or subsidy reduction paths—while the re-

maintaining 38 encode instruments as static parameters or discrete scenario comparisons (Supplementary Table S1) [48]. Overall, the literature indicates that policy volatility and regulatory uncertainty are insufficiently captured despite their well-documented influence on real-world investment behaviour [47,70,86,94,95]. From a societal perspective, this omission matters because policy uncertainty is not merely an economic risk factor but is also closely tied to institutional trust, shaping whether households perceive energy transitions as credible, fair, and worth participating in.

Across the reviewed models, policy instruments are typically evaluated in terms of aggregate adoption efficiency; however, their distributional implications have received limited attention. Feed-in tariffs and tax credits, for example, are frequently modelled as universally accessible despite empirical evidence that such instruments disproportionately benefit higher-income homeowners with access to capital and stable tenure [11,12]. The absence of differentiated access assumptions means that many ABMs implicitly assume uniform policy access, obscuring which groups benefit from or are excluded by specific regulatory designs.

3.4.4. Treatment of Justice and Equity

Only a limited subset of rooftop PV-related studies explicitly operationalize justice-relevant variables within modelling or empirical assessment frameworks, most commonly through income segmentation, access disparities, or tenure-related constraints [57,72,73]. Here, operationalization is understood strictly as the formal embedding of justice-related mechanisms within agent attributes or decision constraints, with distributional metrics evaluated as a core criterion, rather than their inclusion as contextual motivation or normative framing. Following established energy justice framing, justice-sensitive modelling can be understood across distributional justice (who receives costs/benefits), procedural justice (who participates and how decisions are made), and recognition justice (whose needs and constraints are acknowledged). In contrast, recognition justice—concerned with whether the specific needs and constraints of marginalized groups are acknowledged within modelling frameworks—remains almost entirely absent from current ABM implementation. Across the reviewed ABMs, distributional proxies (e.g., income segmentation, credit access) appear sporadically, procedural dimensions are rarely formalized beyond stylized participation assumptions, and recognition justice remains largely absent as a computational mechanism rather than a narrative concern [8,9,31,32]. Simultaneously, thematic synthesis reveals that justice-related considerations have become increasingly discussed in recent ABM literature. Most ABMs treat equity as a post-simulation output rather than as an ex ante decision constraint. Under this definition, the majority of studies that reference equity or justice do so discursively without incorporating these concerns into the computational structure of the model itself. When models abstract away from the specific constraints of renters or low-income households, they may overlook how unequal access conditions influence adoption outcomes across different social groups. At present, this remains an emerging and largely prospective concern in rooftop PV ABMs but warrants early methodological attention. Applying this deliberately strict operational criterion, only 2 of the 50 focal ABM studies (4%) were classified as formally embedding justice-related variables within agent attributes or decision constraints. On the graded scale of Section 2.6, these two studies sit at level J4; a further four studies (8%) test an equity-targeted instrument at scenario level (J3), and twenty-four (48%) include socio-economic covariates or group-level outputs without any equity-targeted mechanism (J2). Therefore, this figure should be interpreted as a conservative estimate of computational operationalization, rather than as evidence that broader normative concern with equity is absent from the field.

3.4.5. Quantitative Synthesis of S-E-M-P-J Implementation

Across the 50 focal ABMs, socio-technical representation is highly uneven (Figure 4). A behavioural or mechanistic decision layer is nearly universal (M: 96%, 48/50); policy representation is common (P: 82%, 41/50); spatial representation appears in roughly two-thirds of the models (S: 64%, 32/50), and explicit economic decision variables in roughly three-quarters (E: 74%, 37/50). In sharp contrast, only two of the 50 models (4%) combine architectural embedding of a distributional dimension with justice as a core evaluation criterion (level J4); covariate- and scenario-level forms (J2–J3) remain decoupled from the models' evaluative core. Deep justice implementation is therefore not a minor gap but a near-structural absence in the computational core of the field.

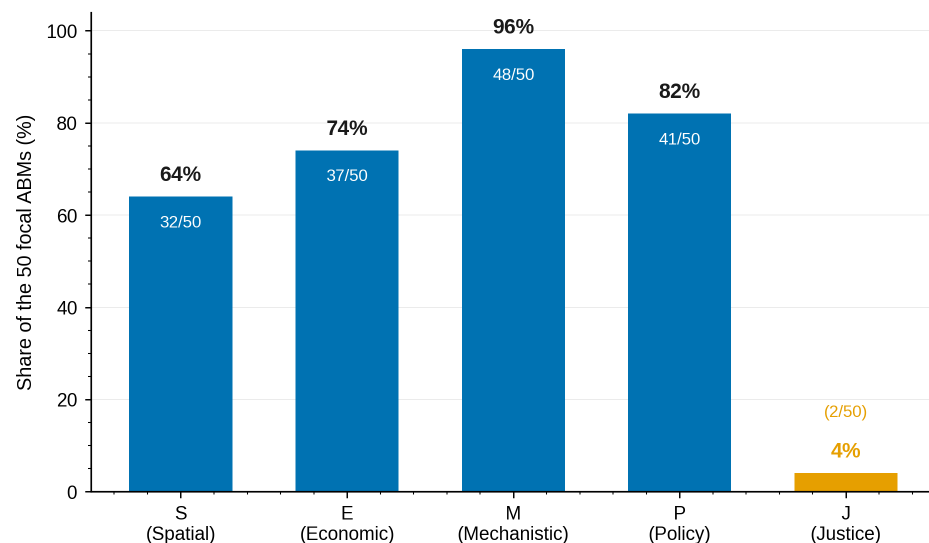


Figure 4. Implementation frequency of the five S-E-M-P-J dimensions across the 50 focal ABMs ($n = 50$). Justice (4%) is the clear outlier.

Integration across dimensions is shallow. The median model implements three of the five dimensions; only one of the 50 models implements all five, while 21 implement four—and those four are almost always the technical set S-E-M-P, with justice excluded. This is confirmed by the co-occurrence structure (Figure 5): the technical dimensions cluster tightly (M and P together in 39 models, S and M in 32, E and P in 35), whereas justice co-occurs with any other single dimension in at most two models. Justice is thus isolated from the economic, spatial, policy and behavioural machinery rather than integrated with it.

This pattern shows no sign of deepening over time. The number of dimensions implemented per model is essentially flat across periods: mean 3.3 (median 3, IQR 3–4) for the $n = 3$ studies up to 2014 (indicative only), mean 3.3 (median 3, IQR 3–4) for 2015–2019 ($n = 21$), and mean 3.1 (median 3, IQR 2–4) for 2020–2025 ($n = 26$); justice inclusion has never exceeded 5% in any period (0/3, 1/21, and 1/26, respectively). Given the very small earliest stratum and the width of these interquartile ranges, no statistically established time trend is claimed; the plateau is advanced as a cautious descriptive observation, whose force lies in what the distributions rule out: any sign of deepening cross-dimensional integration over time. The field has broadened topically without becoming more integrative: additional studies have added breadth, not socio-technical depth. We term this pattern the integration plateau: horizontal growth in models and topics without architectural deepening. The plateau does not imply an absence of methodological innovation. Innovation is abundant within dimensions—spatial resolution, behavioural calibration, and policy detail have each advanced markedly—but it accumulates inside dimensional silos rather than across them; what has stagnated is the coupling of dimensions within single architectures. This

reframes the review’s contribution from description to diagnosis—the limitation is not that any single dimension is missing but that the dimensions are modelled in separable silos. Economic and policy levers are wired into behavioural and spatial structure, yet distributional outcomes are neither generated by nor fed back into that structure. Current rooftop-PV ABMs can therefore answer “how much and where” but not “for whom”, and closing this gap requires justice to be operationalized as a model-internal variable rather than appended as post hoc discussion.

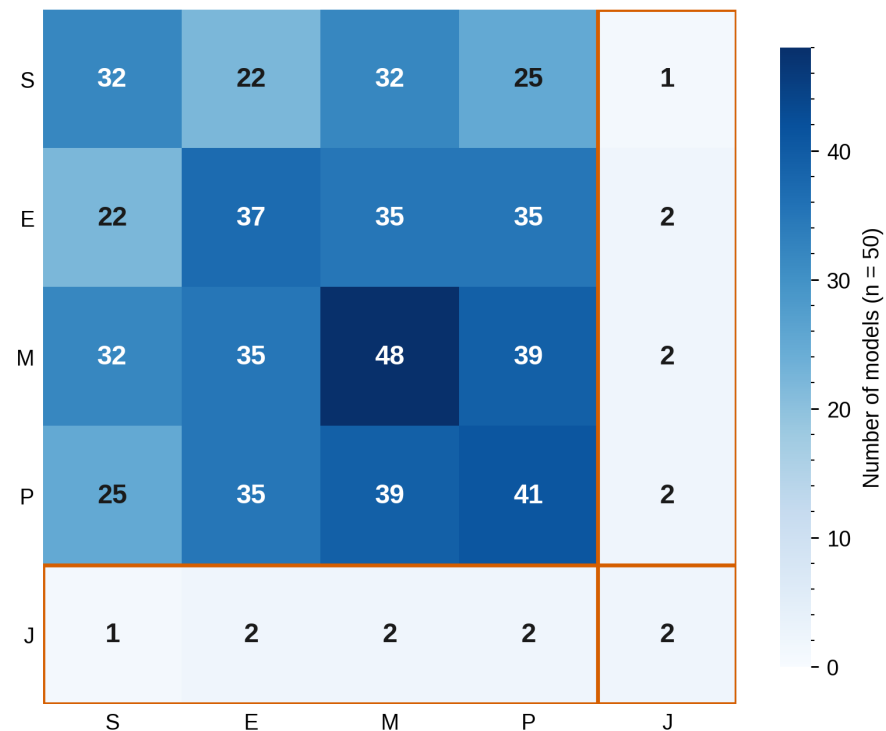


Figure 5. Co-occurrence of the S-E-M-P-J dimensions across the 50 focal ABMs (diagonal = number of models implementing each dimension; off-diagonal = joint implementation). Note the isolated justice row and column.

4. Discussion

Three findings organize this discussion. First, rooftop PV ABMs have genuinely evolved: economic optimization no longer monopolizes adoption logic, and behavioural and spatial realism are now mainstream (Sections 3.4.1 and 3.4.2). Second, this evolution is architecturally uneven—policy dynamics and, above all, justice remain rare as implemented mechanisms, and where justice appears it is disconnected from the models’ economic and spatial core (Section 3.4.5). Third, these are not merely technical omissions: what a model implements determines which policy questions it can answer, and current architectures can address “how much and where” but rarely “for whom”. Unlike previous review studies that focus on cataloguing modelling approaches or adoption drivers, this study therefore provides a structured evaluation of how modelling architectures shape socio-technical interpretations of energy transitions. Throughout, S-E-M-P-J functions as an analytical audit lens, not as a normative modelling standard.

The combined analytical and thematic results demonstrate that agent-based modelling (ABM) of rooftop solar PV diffusion has undergone a methodological evolution. Early studies framed household PV adoption primarily as an economic optimization problem [35,68], whereas contemporary literature increasingly recognizes adoption as the outcome of interacting behavioural, social, spatial, regulatory, and justice-oriented mechanisms [6,16,31]. This evolution reflects broader changes in how distributed energy transitions are modelled

and interpreted [96]. The observed shift aligns with long-standing findings in innovation- and network-diffusion research [13,75] and with perspectives on innovation diffusion and socio-technical change [46,97], indicating that ABM has moved beyond exploratory simulation toward a more central role in assessing the societal impacts of technological change. Although this study does not introduce a new computational model, it provides an integrated evaluative framework for assessing the social robustness of transition simulations. By clarifying how modelling practices condition the societal interpretation of energy transitions, this review serves as a methodological intervention to improve the integration of behavioural and social dimensions into energy modelling. This shift increases the relevance of ABM for evaluating governance-sensitive energy transition strategies.

4.1. From Economic Rationality to Behavioural Realism

The synthesis confirms that while economic rationality remains an important component of adoption modelling, it no longer dominates the conceptual landscape. Contemporary studies increasingly show that rooftop PV uptake is shaped by interacting behavioural, social, and regulatory mechanisms rather than by financial incentives alone [6,16,31]. This perspective echoes long-standing arguments in innovation-diffusion research, which emphasize that adoption cannot be reduced to a uniform investment decision across heterogeneous actors [28,46].

From a policy perspective, models that rely exclusively on financial metrics, such as payback periods or net present value, risk overestimating the responsiveness of households to subsidies, while underestimating non-monetary barriers. Empirical evidence demonstrates that models incorporating “soft” factors, including social visibility, neighbourhood contagion, and risk perception, reproduce diffusion trajectories that more closely resemble observed adoption patterns than those based on purely cost-optimizing assumptions [4,16,17]. Importantly, this behavioural turn does not reject economic reasoning; rather, it embeds financial logic within broader decision architectures, offering a more credible interpretation of adoption as the product of interacting societal motivations [23,44,98].

4.2. Energy Justice as a Structural Modelling Blind Spot

A central finding of this review, based on systematic coding of the 50 focal ABMs, is that while energy justice has become an increasingly prominent normative expectation, only a small minority of models formally translate justice principles into computational constraints, creating a measurable normative–computational gap. Importantly, this gap should not be interpreted as a lack of normative concern among researchers but as a structural limitation rooted in how justice-related concepts are translated into computational rules. Although justice-related concepts appear with increasing frequency in keyword networks, they are rarely operationalized within simulation architectures. In contrast, recognition justice, which concerns whether the specific needs and constraints of marginalized or vulnerable groups are acknowledged, is almost entirely absent from current ABM implementations. For instance, recognition justice can be directly encoded into models by defining the specific energy needs of elderly households or individuals with medical device dependencies as a weighted constraint in decision rules. This reflects a broader modelling bias toward representative agents, limiting the visibility of structurally vulnerable groups. Among the 50 focal ABM studies examined in depth, only two combine architectural embedding of justice-related variables with justice as a core evaluation criterion (level J4), operationalized through income segmentation or tenure status, while a further four test equity-targeted instruments at scenario level (J3), while empirical disparity analyses provide complementary distributional evidence [57,72,73]. This assessment follows the operational definition specified in Section 2.5, which requires justice to be formally

embedded within agent attributes or decision constraints, with distributional metrics as a core evaluation criterion, rather than referenced solely at the narrative or motivational level.

Nor does this pattern appear unique to rooftop PV. In the closest adjacent evidence base—agent-based studies of household energy technology adoption, as reviewed by Heselink and Chappin [37]—equity likewise appears largely as motivation rather than as implemented model structure, and a parallel critique has long been directed at integrated assessment models for aggregating away within-region distributional heterogeneity [99]. Read against these neighbouring studies, the 4% figure is best interpreted not as the shortcoming of a single niche but as a symptom of a broader culture in computational energy modelling that treats distributional structure as post-processing rather than architecture; the post-window studies noted below suggest this culture is beginning to shift.

Consequently, integrating justice-related constraints into model structures may improve the policy relevance of rooftop PV simulations [32,73,100,101]. Three candidate explanations for this gap can be distinguished, and they carry different implications. The first is a data gap: agent-level income, tenure, and energy burden variables are rarely available at the resolution ABMs require. The second is a formalism gap: peer influence has canonical computational templates (Bass-type contagion, network diffusion) and behaviour has the theory of planned behaviour, but justice has no equivalent, readily importable formalism. The third is an incentive gap: the representative-agent tradition and the modularity of publishable model extensions reward adding technical detail over distributional structure. The evidence assembled here is most consistent with the first two operating jointly; notably, both justice-implementing focal models are calibrated to data-rich United States settings, exactly as the data-gap explanation predicts. The two exceptions are themselves instructive: Brugger and Henry [72] show that the equity outcome of incentive programmes depends on how targeting interacts with social-network position, and Sundaram et al. [57] show that flat tax credits reproduce existing exclusion whereas network-aware seeding improves inclusive access—yet both operationalize distributional justice only, encoding neither procedural participation nor the recognition of group-specific needs. Whether procedural and recognition justice can be meaningfully formalized at agent level, or instead mark an epistemic boundary of household-scale simulation, is in our view the central open conceptual question of this literature. Very recent work published after our search window, cited here as post-window context only, outside the coded corpus (Section 5), supports this trajectory: pecuniary-externality modelling of adoption inequity [102] and subsidy reform simulations with explicit equity and fiscal outcomes [103] embed distributional structure directly in ABM architectures, suggesting that the normative–computational gap identified here is beginning to attract methodological responses.

4.3. Policy Volatility and Static Policy Representation

Beyond agent behaviour, the literature reveals a persistent disconnect between the volatility of real-world policy environments and the static representation of policies in most ABMs. Earlier studies frequently assumed stable subsidy regimes, whereas more recent studies highlighted that regulatory frameworks often oscillate between supportive and restrictive orientations. Empirical evidence indicates that investment decisions are strongly influenced by the perceived durability and credibility of policy incentives over time [47].

However, policy uncertainty is rarely formalized within the models [71,95,104]. Such dynamics are particularly salient in the volatile policy environments common to emerging and middle-income economies, where shifting regulatory signals and institutional credibility play a central role in shaping investment expectations. Instead, policies are commonly implemented as static parameters rather than as dynamic processes shaped by regulatory change, political risk, or institutional delay. This limitation is consequential: when

households anticipate retroactive tariff cuts or regulatory instability, adoption is postponed, even when economic conditions appear favourable. As a result, ABMs that neglect these expectational dynamics may systematically overestimate diffusion rates, failing to capture the link between policy credibility and institutional trust [7,58,70,86].

4.4. From Technical Validation to Social Legitimacy

Finally, the review identified substantial methodological heterogeneity that challenges the credibility of ABM as a policy support tool. Although spatial realism has improved through the integration of granular GIS data, thereby revealing how hosting-capacity limits and feeder constraints shape adoption outcomes [6,26,105], validation practices remain uneven. Many studies continue to rely on stylized assumptions owing to data limitations, with only a minority employing empirically grounded calibration or back-casting against observed adoption curves [74]. Illustrative exceptions include data-driven calibration [35], survey-parameterised designs [91,92], and empirically informed hybrid models [33,34]; this assessment is qualitative, reflecting reported practice across the corpus rather than a coded distribution.

This fragmentation weakens the extent to which policy conclusions can be transferred across different contexts. A key implication is that rooftop PV adoption must be understood as a spatially embedded process, rather than a uniform national trajectory. Spatially explicit ABMs demonstrate that neighbourhood topology and feeder structure can generate pronounced clustering and lock-in effects, even under identical incentive schemes [6,33,105]. There is a clear need for standardized reporting practices and transparency frameworks for ABMs to evolve from academic exercises to robust decision support instruments [42,43,106]. Without rigorous validation against both behavioural data and physical grid constraints, policymakers may remain reluctant to rely on ABM outputs as legitimate evidence for infrastructure and energy planning decisions [31].

A further validation priority concerns the relationship between theory-driven and data-driven ABMs. Data-driven approaches that learn agent decision parameters directly from large-scale adoption micro-data provide a complementary benchmark against which the behavioural assumptions of theory-driven models can be tested, and systematically contrasting the diffusion patterns produced by the two offers a practical route to stronger empirical validation [35].

These modelling improvements also involve important trade-offs. Greater spatial resolution, richer behavioural rules, dynamic policy representation, and justice-sensitive agent attributes can improve realism, but they also increase the data requirements, computational burden, parameter uncertainty, and validation difficulty. For this reason, the argument of this review is not that every rooftop PV ABM should include all S-E-M-P-J dimensions in maximum detail. Rather, model complexity should be matched to the research question, available data, and intended policy use. Therefore, the S-E-M-P-J framework is best understood as a diagnostic tool for making modelling choices explicit rather than as a requirement for a maximally complex simulation design.

4.5. Societal and Policy Implications

The findings of this review have direct implications not only for energy policy design but also for how technological change is governed, legitimized, and socially negotiated. From a modelling perspective, ABMs can function as policy analysis tools in which alternative incentive designs, grid constraints, behavioural assumptions, and access barriers are tested under heterogeneous adoption conditions.

The reviewed literature shows that policy instruments interact nonlinearly with peer influence and regulatory expectations [16,68]. Therefore, ABMs function as simulation-

based analysis instruments for exploring distributional risks, behavioural feedback loops, and unintended societal consequences of policy designs [19,76,107]. In volatile incentive environments, “wait-and-see” dynamics may dampen investment, even under favourable economic conditions [47].

Crucially, this review highlights that neglecting spatial and justice dimensions leads to systematically suboptimal outcomes. Models that integrate feeder-level constraints demonstrate that uncoordinated deployment can trigger voltage bottlenecks before national capacity targets are reached [6,52,82]. Similarly, reliance on financial incentives alone often reinforces socio-economic inequalities, concentrating adoption among higher-income households while structurally excluding renters and lower-income groups [23,57,73,108]. Policy instruments, such as community solar and shared ownership schemes, therefore, emerge as critical mechanisms for broadening access and mitigating exclusion [109]. Table 7 synthesizes these insights by linking dominant modelling findings to the risks of conventional assumptions and outlining actionable pathways for socially inclusive policy design. The table is intended as an executive-level synthesis that translates modelling insights into governance-relevant design principles. In volatile policy environments, particularly in emerging and middle-income economies, the reviewed simulation studies indicate that institutional trust strongly influences investment expectations. Without credible and transparent policy trajectories, the reviewed studies suggest that even favourable returns may be discounted by perceived regulatory risk, producing diffusion patterns that standard models tend to miss.

Table 7. Policy Implications Derived from Rooftop PV ABMs.

Dominant ABM Insight	Risk of Traditional Assumption	Unintended Societal Consequence	Implication for Policy Design
Nonlinear Response: Adoption is driven by thresholds; small incentive changes can trigger disproportionate uptake or stagnation due to peer effects [4,68].	Linearity Assumption: Assumes adoption scales proportionally with subsidy levels.	Overshooting or Inefficacy: Unexpected subsidy booms (budget overrun) or failure to trigger uptake in target segments.	Adaptive Incentives: Apply capacity-dependent degression with targeted low-income bonuses to ensure social contagion benefits diverse segments, not just early wealthy adopters.
Spatial Constraints: Distribution grid constraints [6,66].	“Copper Plate” Grid: Assumes uniform diffusion and unlimited grid capacity.	Infrastructural Inequality: Local congestion creates “first-come, first-served” access barriers for late adopters.	Locational Signals: Use hosting-capacity maps to steer deployment, prioritizing grid access equity for late adopters in structurally constrained neighbourhoods.
Expectation Dynamics: Agents delay investment if they perceive regulatory instability or anticipate policy changes [47].	Static Policy View: Assumes agents react only to <i>current</i> prices, ignoring future uncertainty.	Erosion of Institutional Trust: “Stop-start” diffusion cycles that damage installer supply chains and consumer trust.	Credible Commitment: Establish long-term tariff trajectories to build institutional trust, reducing the ‘wait-and-see’ inertia caused by policy volatility.
Structural Exclusion: Financial incentives alone are insufficient to address disparities; adoption concentrates among high-income groups [57,72,73].	Representative Agent: Assumes all households have equal access to capital and ownership rights.	Regressive Redistribution: Public funds subsidize high-income homeowners, widening the energy equity gap.	Equity-Sensitive Policy Design: Replace flat tax credits with ownership-agnostic instruments (e.g., community solar) to bypass capital barriers and enhance procedural legitimacy.

The findings suggest that rooftop PV diffusion should be understood not only as a techno-economic optimization problem but also as a governance and legitimacy challenge.

Financial incentives alone are unlikely to deliver socially balanced outcomes unless accompanied by stable institutional arrangements, credible policy trajectories, and procedurally fair implementation. In this respect, policy effectiveness depends not only on the level of incentives or payback periods but also on how policy regimes are perceived in terms of stability, fairness, and long-term commitment.

5. Limitations

While this review provides a robust synthesis of agent-based modelling applied to rooftop PV adoption, several limitations shape the scope and interpretation of its conclusions. These constraints arise from the trade-offs inherent in combining analytical mapping with a critical thematic analysis. In addition, potential publication bias may influence the representation of well-documented modelling practices over less transparent studies.

Scope and Selection Limitations:

First, this review prioritizes analytical depth over exhaustive coverage by focusing on a core set of empirically grounded studies. Consequently, grey literature, non-indexed regional studies, and broader transition models with limited rooftop PV focus may be underrepresented. In addition, restricting the review to English-language publications indexed in Web of Science and Scopus may limit coverage of region-specific modelling efforts. In addition, title–abstract–keyword screening was performed by a single reviewer, and inter-rater reliability was quantified only at the focal coding stage; screening-stage reliability is therefore unmeasured. Because focal-set selection prioritized the codability of reported model structures, well-documented models—disproportionately calibrated to Global North settings—were more likely to enter the focal set, which may amplify the geographic concentration described in Section 3.1.3. By construction, the studies not carried into focal coding are those whose reported model structure could not be coded reliably; coding them would add “unclear” labels rather than usable observations, and the reported percentages should therefore be read as shares of codable models. Supplementary Table S2 documents the reason for every non-focal classification, so that this boundary is itself auditable.

Heterogeneity in Model Reporting:

Second, the field exhibits substantial inconsistencies in the documentation and validation practices. Despite the availability of protocols such as ODD, many studies have provided limited transparency regarding decision rules, calibration strategies, or empirical grounding. This heterogeneity constrains the feasibility of direct quantitative meta-analysis and complicates the comparisons across studies. Therefore, the synthesis reflects reported modelling practices rather than a statistical comparison of simulation outcomes.

Interpretation of Energy Justice:

Third, the treatment of energy justice relies on a proxy-based reading of the literature. Justice-related dimensions were identified through explicit terminology (e.g., equity, poverty, distribution) and modelled variables such as income segmentation or tenure status. Some studies address equity implicitly without employing explicit justice language. Therefore, the limited representation of justice-related variables should be interpreted as a structural characteristic of current modelling practice rather than as a complete absence of equity awareness in the literature or a limitation of the review itself. In addition, because classification relied on the reported model structure, the limited documentation in some studies may have contributed to the under-identification of justice-related mechanisms. The observed scarcity of formal justice operationalization, therefore, likely reflects both modelling omission and reporting omission to some extent. A further caveat concerns the search design: none of the four Boolean blocks contained justice- or equity-specific terms, so field-level observations about the visibility of justice discourse should be read as conser-

vative. The central quantitative finding is, however, largely insulated from this limitation: it reports the share of rooftop PV adoption ABMs that formally operationalize justice, and any such ABM—justice-focused or not—is captured by the method-and-technology block of the search irrespective of its justice vocabulary. Consistent with this, the corpus retrieved justice- and equity-focused studies where they exist [11]. All corpus construction, screening counts, and coded results in this review derive exclusively from the November 2025 searches described in Section 2.2; the corpus was frozen at that date and was not re-run. Separately from the corpus, a supplementary targeted verification search (Scopus, July 2026), combining justice and equity terms with ABM and PV vocabulary, was conducted solely as an out-of-corpus robustness check on the justice finding: it returned 14 records, and none published within the original search window met the focal inclusion criteria beyond studies already included. Two studies published after the search window [102,103] are cited in Section 4.2 as post-window context only; they enter no count, figure, or coded result of this review.

Contextual Generalisability:

Finally, agent-based models are inherently context specific, reflecting the regulatory, spatial, and behavioural conditions of particular jurisdictions [110]. Behavioural rules calibrated for households in stable policy environments may not translate directly to volatile contexts, such as Türkiye, Brazil, or South Africa. These regions represent emerging economies in which rapid market growth often coincides with high policy uncertainty and distinct socio-economic segmentation, differing significantly from the stable institutional settings of the Global North. Accordingly, the policy implications derived from this review should be understood as heuristic rather than as universally transferable laws of diffusion.

6. Future Research Directions for Next-Generation Rooftop PV ABMs

The trajectory of agent-based modelling in rooftop PV research reveals a field that is expanding in thematic scope but lagging in methodological consolidation. Future research should focus on improving empirical grounding, spatial realism, and behavioural representation in rooftop PV ABMs. Particular attention should be given to volatile policy environments and emerging economies, where institutional trust and financing barriers strongly influence diffusion dynamics.

6.1. Improving Empirical, Spatial, and Grid Representation

The primary priority is the integration of high-resolution empirical data into the ABMs. Although coupling with GIS data is becoming more common, future models must move beyond stylized spatial representations to incorporate satellite-derived building footprints and empirically grounded hosting-capacity constraints. Such advances enable a more accurate representation of local saturation effects and spatial spillovers [66,83,84,111]. At the same time, behavioural realism requires further development. Moving beyond deterministic payback thresholds toward representations informed by cognitive psychology and risk perception would better capture the roles of trust, administrative burden, and social norms in adoption decisions [50,56]. Therefore, greater use of survey data and experimental evidence is essential for improving the predictive credibility [71].

6.2. Embedding Behavioural and Justice-Sensitive Agent Attributes

Future ABMs should more explicitly represent financing constraints, tenure structures, and differentiated access to incentives. Pioneering contributions, such as the equity-oriented ABM of Sundaram et al. [57] and the empirical disparity analysis of Reames [73], demonstrate that when these variables are included, models reveal regressive outcomes that are concealed by standard aggregate diffusion curves. By embedding these equity

dimensions, models can move beyond efficiency-based optimization to assess the social legitimacy of transition pathways, which is a critical requirement for long-term policy effectiveness. By explicitly linking modelling choices to questions of legitimacy, fairness, and social acceptance, future ABM research can help ensure that technological diffusion pathways align not only with efficiency goals but also with broader societal expectations and long-term policy acceptance. In parallel, models should increasingly capture the co-evolution of PV with complementary technologies, including storage, electric vehicles, heat pumps, and peer-to-peer trading platforms. These interactions generate feedback loops that static or single-technology models are unable to represent [112–115], yet they are central to understanding future distribution grid dynamics [116].

6.3. Modelling Policy Volatility and Context-Specific Adoption Barriers

Finally, there is a clear need to test the generalizability of diffusion mechanisms across diverse regulatory and socio-economic contexts. Most core studies, ranging from zero-energy communities [6,23,33] and GIS-coupled diffusion models [65] to policy portfolios [70,80] and equity-focused analyses [72,77,100], have been calibrated for relatively stable Global North settings. This leaves a significant gap in understanding diffusion dynamics in emerging economies characterized by policy volatility and rapid market growth [7,117]. Future research should focus on volatile policy environments, where institutional trust and informal housing tenure reshape diffusion pathways in ways that models calibrated to stable EU/US settings cannot capture. The S-E-M-P-J lens itself maps the transferability failure modes involved: informal tenure undermines justice-related assumptions (J), policy volatility invalidates static policy representations (P), and data scarcity weakens spatial calibration (S)—the framework can therefore serve as a checklist when adapting Global North-calibrated architectures to structurally different settings [118]. Future models should test lower institutional-trust assumptions and stronger financing constraints in settings characterized by policy volatility, economic uncertainty, and insecure tenure, rather than assuming the stable regulatory expectations typical of many Global North-oriented ABMs.

Table 8 summarizes this agenda by linking key research gaps to methodological priorities, data requirements, and anticipated societal benefits.

Table 8. A strategic research agenda for next-generation rooftop PV agent-based models.

Identified Research Gap	Methodological Priority	Data/Modelling Requirement	Expected Societal Benefit
Stylised Agents: Models rely on simple payback logic, missing psychological barriers.	High: Behavioural realism & validation.	Micro-surveys, discrete choice experiments, adoption micro-data.	Credible Forecasts: More accurate prediction of uptake under different incentive schemes.
Spatial Abstraction: Grid constraints are often ignored or simplified.	High: GIS & Socio-spatial integration.	Satellite imagery, feeder topology, hosting capacity maps.	Infrastructural Equity: Proactive identification of congestion hotspots that may exclude late adopters.
Justice Blind Spots: Equity is rarely operationalized beyond income.	High: Justice-sensitive parameters.	Tenancy status (split-incentives), credit scores or financing proxies, demographic distribution data.	Inclusive Design: Prevention of regressive outcomes and energy poverty traps.
Technological Silos: PV is modelled in isolation from storage/EVs.	Medium: Multi-tech co-evolution.	Load profiles for EVs/Heat pumps, battery cost curves.	System Resilience: Understanding synergies between prosumer tech and grid flexibility.
Geographic Bias: Lack of models for volatile/emerging markets (e.g., Türkiye, Brazil, South Africa).	Medium: Cross-country transfer & adaptation.	Local regulatory history, inflation data, specific housing typologies.	Robust Governance: Policy insights tailored to unstable or rapidly growing markets.

6.4. Operationalizing S-E-M-P-J: Practical Guidance for Modellers

The quantitative synthesis shows that the field's central limitation is shallow, siloed operationalization rather than any single missing dimension. The following recommendations translate each dimension into concrete, implementable modelling choices, drawing on approaches already demonstrated in the reviewed literature.

Spatial (S). Move beyond adjacency dummies to infrastructure-aware geography: place agents on GIS-derived building stock and couple adoption to explicit hosting-capacity, feeder and transformer limits, as in the GIS-data-mining and neural network agent-based designs of Lee and Hong [65] and of Alderete Peralta et al. [33]. The spatial resolution and the grid constraint mechanism should be reported explicitly to support reproducibility.

Economic (E). Represent the adoption decision with an explicit, agent-level financial calculation—payback or net present value under prevailing tariffs, financing terms and incentives—and make discounting behaviour explicit rather than assuming a single social discount rate, following De Groote and Verboven [45] and Borenstein [44]. Where uncertainty is material, incorporate it into the payoff, as in Bauner and Crago [95].

Mechanistic (M). Combine a utility or threshold core with empirically grounded behavioural mechanisms—peer effects, social-network exposure and bounded rationality—rather than pure optimization, as integrated by Rai and Robinson [16] and by Stavrakas et al. [34]. Behavioural parameters should be calibrated to survey or revealed-preference data where available, in the spirit of Rai and Henry [47].

Policy (P). Model policy instruments as structural changes to agent incentives and constraints, not merely as exogenous parameter shocks: encode feed-in tariffs, net-metering and subsidy schedules with their real eligibility and timing, and test policy volatility explicitly, as in Nuñez-Jimenez et al. [88], Pearce and Slade [96], and Castaneda et al. [48]. Reporting how each instrument maps to specific decision variables improves the credibility of scenario results.

Justice (J). This is the dimension most in need of operationalization. Rather than treating equity as post hoc commentary, distributional structure should be embedded inside the model: assign agents income, tenure (owner or renter) and energy burden attributes, and couple a distributional outcome metric—for example adoption by income quintile, a Gini coefficient of installed capacity, or explicit split-incentive exclusion—to the adoption mechanism, so that “who adopts” is generated endogenously. The equity-oriented designs of Reames [73], of Brugger and Henry [72], and of Sundaram et al. [57] provide starting points; note that the first is an empirical disparity analysis whereas the latter two are agent-based implementations.

Calibration, validation and transparency. Across all dimensions, out-of-sample validation, sensitivity analysis of key behavioural parameters, and ODD-style documentation should be standard practice; data-driven calibration approaches such as that of Zhang et al. [35] offer a template for empirically disciplining agent behaviour. Modellers should also report the computational cost of added spatial or behavioural detail, since higher resolution trades off against tractability and calibration feasibility—a trade-off that itself warrants explicit justification.

To consolidate this guidance into a reportable standard, Table 9 proposes a minimal justice-reporting extension to the ODD protocol (“ODD+J”): four items that any rooftop PV ABM can report regardless of its primary research question. ODD is the natural host for this extension because it is already the most widely used reporting protocol in the reviewed literature and demands the least of authors; heavier documentation frameworks aimed at comprehensive validation evidence would raise the adoption barrier for what is intended as a minimal disclosure standard, and model-design strategies such as pattern-oriented modelling address how models are built rather than how they are reported. ODD+J is offered

as a complementary extension of this widely adopted protocol, not as a replacement for existing ABM reporting standards. In this respect ODD+J follows the precedent of ODD+D, which extended the protocol to make human decision-making explicit [119]; ODD+J does the same for distributional structure. The two extensions are complementary rather than competing in scope: ODD+D specifies how agents decide (decision theory, heterogeneity, learning, and uncertainty), whereas ODD+J specifies for whom outcomes differ, that is, where distributional attributes, access constraints, and outcome metrics sit within the architecture. Because ODD+D’s decision-oriented elements do not require distributional structure to be reported, a model can be fully ODD+D-compliant while leaving the position of justice, including its deliberate omission, undocumented; ODD+J closes precisely this gap with four reportable items while keeping the additional reporting burden minimal. The intention is not to require justice-focused models but to make the position of justice within each architecture—including its absence—explicit and comparable across studies. Justice, rather than any other dimension, is the appropriate extension because it is the only S-E-M-P-J dimension that is simultaneously near-absent from implementations (4%) and invisible in standard reporting: spatial, economic, behavioural and policy choices are already covered within the existing ODD structure, whereas the position of distributional structure, including its deliberate omission, is not. The marginal transparency gain of extending the standard is therefore largest precisely here.

Table 9. ODD+J: a proposed minimal justice-reporting extension for rooftop PV agent-based models.

Item	What to Report	Illustrative Example
Agent attributes	Income, tenure (owner/renter) and energy-burden attributes: distributions and data sources	Income deciles from census microdata; renter share by district
Position of access constraints	Where justice enters the architecture: exogenous attribute, decision constraint/gate, endogenous feedback, or outcome metric only	Credit constraint as an adoption gate; adoption–tariff–exclusion feedback loop
Distributional outcome metric	At least one distributional metric coupled to the adoption mechanism	Adoption by income quintile; Gini coefficient of installed capacity; split-incentive exclusion rate
Justice scope statement	Which justice tenets are represented (distributional, procedural, recognition) and which are not	“Distributional only; procedural participation not modelled”

7. Conclusions

This review makes four distinct contributions by moving beyond descriptive review approaches and introducing a socio-technical audit of modelling practices in agent-based simulations of rooftop PV diffusion. First, it introduces the S-E-M-P-J framework as a structured approach for evaluating the socio-technical completeness of ABMs. Rather than serving as a descriptive taxonomy, the S-E-M-P-J framework offers a socio-technical audit lens for assessing whether ABM architectures capture the principal mechanisms through which diffusion outcomes become unevenly distributed, politically conditioned, and socially differentiated. The S-E-M-P-J framework has not been proposed as a prescriptive modelling checklist but as a diagnostic tool for examining how simulation structures represent modelling assumptions. Second, it empirically demonstrates a persistent gap between justice discourse and computational implementation in rooftop PV simulation. Third, it translates modelling design choices into governance-relevant policy implications, linking simulation architecture to legitimacy and institutional trust. Fourth, it proposes ODD+J (Table 9), a minimal justice-reporting standard through which the position of justice in any adoption ABM—including its absence—becomes explicit and comparable across studies.

These contributions answer the three research questions directly. In answer to RQ1, the field has moved from cost threshold formulations to behaviourally and spatially rich architectures,

without a corresponding deepening of cross-dimensional integration (Sections 3.3 and 4.1). In answer to RQ2, energy justice reaches architectural embedding with a core evaluative role in only 2 of the 50 focal models (level J4), appears at covariate or scenario level in a further 28 (J2–J3), and remains computationally isolated from the economic, spatial and policy machinery (Sections 3.4.4, 3.4.5 and 4.2). In answer to RQ3, policy uncertainty is only rarely represented as a dynamic mechanism: only 3 of the 41 policy-implementing focal models encode time-varying instruments. Institutional trust, which operates through the perceived credibility of such instruments, is correspondingly almost never modelled as an explicit variable, and the absence of both tends to inflate simulated diffusion and weaken the validity of model-based transition scenarios (Sections 3.4.3 and 4.3).

This systematic review demonstrates that the diffusion of rooftop solar PV systems is not merely a technological or economic process but a socio-technical process shaped by modelling choices that encode assumptions about behaviour, equity, and governance. Synthesizing evidence from 876 publications and a core set of 101 studies, the analysis confirms a decisive shift from stylized economic representations toward richer socio-technical models that account for behavioural heterogeneity, spatial constraints, and policy design. However, this evolution is uneven. While social interaction, grid limitations, and spatial dynamics are increasingly recognized [65,66,120], regulatory uncertainty and distributional equity remain insufficiently operationalized within most simulation frameworks. By systematically linking modelling practices to societal outcomes, this study demonstrates that agent-based models do not merely simulate diffusion trajectories but also shape how policy outcomes are evaluated within energy transitions.

Methodologically, the field continues to exhibit pronounced heterogeneity in decision rules, calibration strategies, and validation practices, thereby limiting cumulative learning and cross-context comparability. Therefore, advancing the field requires next-generation ABMs that integrate behavioural science with high-resolution infrastructure data and explicitly represent policy volatility and justice-sensitive parameters. Greater convergence toward transparent reporting standards and open validation practices is also essential for strengthening the credibility of model-based policy advice, which is important for improving the reliability of policy-oriented modelling.

Ultimately, this review provides a consolidated foundation for advancing the ABM-based analyses of distributed energy transitions. As rooftop PV becomes an increasingly central component of global energy systems, improving the usefulness of ABMs for long-term policy analysis will depend on deeper integration of behavioural, spatial, economic, and justice dimensions. Future ABMs would benefit from more systematic integration of behavioural, spatial, and equity-sensitive mechanisms. The evidence assembled here substantiates the claim of our title: current models answer “how much and where” with growing sophistication, while “for whom” remains, with only two J4-level exceptions in fifty models, outside their computational architecture.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/en19153611/s1>, The complete database search strategy—the Boolean search strategy for Web of Science and Scopus, block-level record counts, export dates, syntax notes, and a dated note on the July 2026 out-of-corpus verification search—is provided as a separate supplementary file (Supplementary Material: Database Search Strategy). Supplementary Table S1 presents the study-level, dimension-by-dimension S-E-M-P-J coding of the 50 focal agent-based modelling studies examined in this review, together with their descriptive characteristics, the five-level justice coding (J0–J4) with a supporting evidence sentence for each study, and a change log documenting the cell-level corrections made during revision; the coding criteria are given in Tables 4 and 5 of the main text. Supplementary Table S2 lists the 51 core-set studies that were not carried into focal coding, together with the reason for each. A completed PRISMA 2020

checklist, indicating the location of each reporting item in the manuscript, is provided as a separate supplementary file (PRISMA 2020 Checklist).

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