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# Customer enrollment and participation in building demand management programs: A review of key factors

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## ABSTRACT

Increasing the efficiency and flexibility of electricity demand is necessary for ensuring a cost-effective and reliable transition to zero-carbon electricity systems. Such demand-side management (DSM) resources have been procured by utilities for decades via energy efficiency and demand response programs; however, the key drivers of program enrollment and customer participation levels remain poorly understood — even as governments and grid planners seek to scale up the deployment of DSM assets to meet climate targets. Here we systematically review the evidence on multiple factors that may influence customer enrollment and participation in building DSM programs, focusing primarily on residential and commercial buildings. We examine the contexts in which relationships between DSM factors and outcomes are most often explored and with which methods; we also score the strength, direction, and internal consistency of each factor's reported impact on the enrollment and participation outcomes. We find that studies most commonly assess the effects of economic incentives for load flexibility on program participation levels, often using simulation-based methods in lieu of measured data. Few studies focus on program enrollment outcomes or regulatory drivers of either enrollment or participation, and gaps are also evident in the coverage of emerging DSM opportunities like load electrification. Removal of structural barriers (e.g., the lack of controls infrastructure) and the use of third party services (e.g., load aggregators) are the factors with the largest positive impacts on DSM outcomes, but no single factor emerges as clearly most impactful. For a given factor, the range of reported impacts typically varies widely across the relevant studies reviewed. Our findings provide a snapshot of the state of knowledge about building DSM and customer decision-making, and they expose key gaps in understanding that must be filled if building DSM is to expand as a critical resource for operating clean power grids.

## 1. Introduction

Governments around the world have committed to ambitious climate mitigation goals that center on reaching net-zero greenhouse gas (GHG) emissions economy-wide by mid-century. GHG reduction plans call for a rapid transition to a low-carbon energy system, and the integration of variable renewable energy (VRE) sources to decarbonize the electricity supply is the lynch pin of this transition. However, the weather dependence of VRE generation resources creates new operational challenges for electric utilities. Such challenges have renewed interest in complementary "demand-side solutions" [19]. These solutions modify the consumption of energy at its end use points — such as in buildings

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(e.g., [52]) — to balance energy supply and demand while minimizing the scale of additional generation, transmission, and distribution infrastructure investments that are needed to decarbonize the power system.

Demand-side solutions encompass multiple energy end-use sectors, diverse technologies, and a wide range of actors. In the context of electricity decarbonization and utility planning, such solutions fall under the traditional umbrella term “demand side management” (DSM). DSM denotes electric utility programs that are intended to affect the amount and timing of customer electricity usage [35], including programs for peak and annual demand reductions, load shifting and load building, and strategic load growth [30]. DSM strategies are broadly categorized as: energy efficiency improvements, including persistent reductions in energy demand through measures such as improving building envelopes or energy conversion systems, enhanced control algorithms, or system optimization; energy flexibility, including the shifting of energy demand profiles to satisfy grid and local objectives, for example through the re-scheduling of end use loads, the use of energy storage, and the incorporation of on-site renewable energy; and demand response (DR), which is considered a specific energy flexibility strategy that curtails end use electricity demand during times of grid stress [54]. Load electrification measures that convert fossil-fired heating, water heating, cooking, or drying equipment in buildings to run on electricity (preferably clean electricity) may also be considered DSM measures to the extent that the new electric load operates more efficiently and/or flexibly in coordination with power system needs.

For decades, utilities have procured DSM via energy efficiency and demand response programs, and the majority of program impacts have come from the buildings sector, which encompasses residential and commercial buildings. Buildings are the top source of global electricity demand among end-use sectors [38], and thus residential and commercial customers have historically been a primary target of DSM program administration [24]. Building DSM programs target the largest end use sources of residential and commercial building electricity demand — heating, cooling, and ventilation (HVAC), water heating, and commercial lighting and refrigeration. The potential flexibility from managing building loads is considerable but depends strongly on customer behavior [55], which enables or constrains program impacts in two ways: 1) customers decide to enroll in (or, in cases where they are auto-enrolled, to opt out of) the DSM program in the first place — e.g., by installing a certain type of enabling equipment, choosing a certain rate structure, or agreeing to respond to utility signals for load adjustment; and 2) customers' operational patterns and preferences determine the degree to which they are able to participate in the program once enrolled — e.g., the realized magnitude of changes in their load patterns.

Past studies of building DSM programs often assume that **economic incentives** — e.g., lump-sum payments, time-of-use tariffs or real-time pricing — act as the main driver for customers' program enrollment and participation (e.g., [13,29,36,77,84]). This assumption has been challenged by social science researchers (e.g., in Strengers [91], Shove et al. [86]), who point out that consumption patterns depend on the daily practices of households and businesses and that energy cost is therefore just one among many other elements influencing the magnitude and timing of energy demand [87,92]. This criticism is bolstered by recent evidence, for example, from a study that compares DR programs in Norway, Denmark and Austria. This study concludes that there is no simple causality between price schemes and DR actions and that price-sensitive DR depends on complex and interrelated elements such as consumer knowledge, the design of devices and the meanings associated with the schemes [16].

Other studies further highlight the non-economic factors that may be most important for customer DSM enrollment and participation. These include: **structural barriers**, including lack of availability of programs and enabling smart technology (e.g., grid-connected appliances or thermostats) [66,102,25,74,75,27]; utility partnerships with **third-party service** providers — including load aggregators, energy service companies (ESCOs), and software-as-a-service platforms — which may, for example, bundle incremental changes in load across many customers as an alternative to conventional generation resources, leverage social norms to increase participation, and/or enable peer-to-peer trading; **customer engagement** — including education and providing detailed feedback about energy consumption patterns — that increases environmental awareness and/or awareness of personal energy demand [53,62,98,106,42,108,13,57,12,60,77,99,29]; **customer segmentation**, which aligns DSM programs to customer characteristics — e.g., low-income customers [102,73] — to ensure sustained participation and avoid distributional consequences, such as higher bills or unhealthy conditions for low-income households [54,43,65,96]; and **regulatory instruments**, including mandatory rate structures, default rates, building and equipment codes and standards, and other rules and policy initiatives that support DSM measures [40,26,28,89].

A wide range of factors may therefore impact customer DSM enrollment and participation outcomes. However, a systematic understanding on the scope of evidence behind each factor and its potential impacts on DSM outcomes is lacking. Multiple recent reviews of DSM have been conducted, for example (e.g., [9,67,105,97,56] but these reviews place limited focus on the role of customer decision-making and behavior. The few studies that synthesize knowledge on DSM enrollment and participation factors are limited in scope and offer primarily qualitative assessments (e.g., [68,88]). More structured assessments of these factors across a wider range of contexts are needed to determine the feasibility of increasing DSM program deployment levels and load impacts to support a low-carbon power system.

Here we address this knowledge gap by systematically reviewing the available literature on factors that could increase customer enrollment and/or participation in utility DSM programs. Using a structured, multi-stage framework for retrieving, screening, and scoring relevant studies, we aggregate evidence about the impacts of several potential DSM factors on enrollment and participation outcomes. We also highlight the contexts in which relationships between the DSM factors and outcomes are most studied and uncover gaps in understanding that could hinder the broader adoption and use of DSM by utilities to meet power system decarbonization targets. Insights from the review, which is part of the authors' contributions to International Energy Agency Energy in Buildings and Communities Programme (IEA EBC) Annex 82: Energy Flexibile Buildings [39], can inform key considerations and areas for further investigation related to customer decision-making in the design and implementation of utility DSM programs.

## 2. Methods

### 2.1. Systematic review framework

The structure behind our systematic literature review is adapted from the Context-Intervention-Mechanism-Outcome (CIMO) framework [14]. This framework, which was originally developed for organization and management studies, has recently been translated to the context of energy policy by Peñasco et al. [71]. The study's research question is framed in terms of CIMO as follows:

- *What is known in the scientific and industry literature about the changes in DSM customer enrollment and/or level of participation **(O)** that arise from various market, policy, or other contextual factors **(I)** that may activate demand-side management resources **(M)** to facilitate electric grid decarbonization **(C)**)?*

Table 1 further defines each of the CIMO elements in the DSM review context. Here, we define six categories of DSM factors that are consistent with those identified in the Introduction. These factors could potentially be leveraged by electric utilities and/or policy makers to increase the scale and impacts of deployed DSM in buildings, by increasing the number of customers enrolled in DSM programs (“DSM enrollment,” outcome 1) and/or by increasing the potential response of

**Table 1**
Structure of systematic review of DSM factors, in terms of the four elements of the Context-Intervention-Mechanism-Outcome (CIMO) review framework.

| CIMO Element | Definition in Review Context |
|---|---|
| Context (C) | Need for greater demand-side management (DSM) to support the transition of the electric grid to low-carbon generation resources. |
| Intervention (I) | Market, policy, and other contextual factors that could be leveraged by utilities and other relevant stakeholders to increase enrollment and/or participation in DSM programs:<br>• **Incentives**: provide economic rewards for adjusting consumption (temporarily or permanently), for example, through lump-sum payments, customer equipment rebates or financing, time-varying electricity rates, etc.).<br>• **Structural barriers**: remove barriers to enrolling and/or participating in DSM programs by expanding program availability, increasing capabilities and the installed base of controls infrastructure and equipment that facilitates customer response.<br>• **Third-party services**: partner with aggregators, curtailment service providers, ESCOs, and other entities other than the utility to enroll customers and/or guide participation in DSM programs.<br>• **Customer engagement**: educate customers about DSM programs and provide feedback about their consumption or the consumption of peers.<br>• **Customer segmentation**: bin customers by common characteristics (e.g., socio-demographic factors, load adjustment preferences, etc.) to tailor engagement in DSM programs — for example, programs targeted at low-income customers.<br>• **Regulatory**: enact rules to compel customer enrollment and participation in DSM programs — e.g., mandated electricity rate structures, default time-of-use rates, other policy initiatives. |
| Mechanism (M) | Isolate the effect of an individual factor on DSM program enrollment and/or the potential level of load adjustments realized by program participants. |
| Outcome (O) | Change in **DSM program enrollment** (e.g., in total number of customers enrolled, rate of enrollment in eligible buildings, or other); change in **DSM program participation** (e.g., levels of load flexibility and/or energy efficiency impacts) achieved by participating customers. |

each customer that participates in these programs ("DSM participation," outcome 2). We quantify the reported direction, strength, and consistency of the reported relationship between these factors and outcomes via a paper scoring template that is further detailed in Section 2.4.

### 2.2. Review stages

We developed our final literature database through a five-stage review, screening, and scoring process:

1. Initial search of academic databases. Using the conceptual framing described in the previous section, we develop lists of key words to use in retrieving relevant papers from the Scopus and ScienceDirect academic literature databases. Key words exclude acronyms and focus on the assessment of outcomes, for example:
   - (buildings AND grid) AND ([instrument/factor] AND ("response" OR "outcome" OR "impact" OR "level" OR "incidence" OR "effect") AND ("evaluation" OR "appraisal" OR "assessment" OR "ex-post" OR "analysis").

   Paper metadata retrieved in this step were stored in a BibTex file for further processing.
2. Title and abstract screening and category tagging. Papers from the previous step were divided randomly across 6 reviewers for an initial screening. This screening followed two steps:
   i. A title screen removed duplicate papers in the database.
   ii. Paper abstracts were reviewed against a common set of inclusion and exclusion criteria (see Section 2.3). To facilitate this step, the BibTex database was uploaded to a Mendeley Research Group, where abstract data are translated to a graphical user interface for easier review. As each abstract was reviewed, the reviewer also made an initial assessment of which DSM factor(s) the paper focused on, and tagged the paper accordingly.

   Once the title and abstract screening were complete, a second, screened and tagged iteration of the BibTex database from step 1 was produced for further processing and review.
3. Parallel search for reports and key authors. Significant research on DSM programs is conducted outside the academic context — e.g., by utilities, regional grid planners and operators, governments, and companies. To ensure that our search did not exclude these valuable sources, we put out a parallel call across the full IEA EBC Annex 82 group for key non-academic studies and/or authors that should be included in our review. Once identified and abstract-screened, metadata from these studies were added to the BibTex database from step 2.
4. Detailed review and scoring of screened papers. Each paper and report in the database resulting from steps 2 and 3 was reviewed in depth by 7 reviewers, including all 6 who screened paper abstracts in step 2. As in that step, papers were randomly assigned to the reviewers. As part of this in-depth review, each paper was subjected to the inclusion and exclusion criteria a second time. Provided the paper passed the second screening, reviewers used a common template and instructions to enter detailed paper metadata across several categories of interest and to score the paper's reported effects of DSM factor(s) on DSM outcomes. Metadata and scores were entered into a shared spreadsheet for further data cleaning and processing (see Section 2.4).
5. Supplemental scoring. A final stage of review added information about the nature of customer control over participation in DSM programs (see Section 2.4), a topic which was apparent in many of the scored papers, where applicable. These scores were assigned by a single reviewer who was not involved in the preceding screening and scoring steps.

### 2.3. Screening criteria

Paper abstracts and full texts were screened according to a common set of conditions for inclusion or exclusion, enumerated below. These screening criteria were defined in advance of the review process described in the previous section.

- Inclusion criteria:
  – Published after the year 2000.
  – Scientific articles, reviews, and technical reports.
  – English texts only.
  – Must include focus on building electric loads (including residential, commercial, and/or industrial buildings), ideally in the context of power system needs.
  – Studies in which the relative impact of an individual DSM factor of interest on an individual DSM outcome or outcomes of interest was assessed.
- Exclusion criteria:
  – Studies that do not include a focus on building electric loads or which clearly do not relate to the context of power system needs.
  – Studies that do not report on at least one of the distinct DSM factor(s) AND at least one of the distinct outcome(s) of interest.
  – Studies in which the relative impacts of individual DSM factors on a DSM outcome/outcomes of interest cannot be isolated or are mixed with the effects of other types of factors.

**Table 2**
Paper metadata collected during detailed review and scoring stage. See supporting text in Section 2.4 for definitions of each row.

| Scoring Category | Scoring Options |
|---|---|
| Building Type | Residential; Commercial; Industrial; Other |
| Building Scale | Multiple Buildings; Single Building; Single and Multiple Buildings |
| Loads Assessed | Whole Building; HVAC; Water Heating; Lighting; Refrigeration; Electronics; Small Appliances; EVs; On-site PV; Battery; Other; Non-specific |
| Measure Type | Efficiency-equipment; Efficiency-envelope; Efficiency-controls; Efficiency-other; Flexibility; Electrification; Other; Non-specific |
| Assessment Method | Simulation/Modeling; Laboratory Testbed; Metered Customer Data; Longitudinal Survey(s); Cross-sectional Survey(s); Other Quantitative; Other Qualitative; Other |
| Participation Type | Passive; Active; Combination |

### 2.4. Scoring and post-processing

Tables 2 and 3 show, respectively: the categories used to collect metadata on each paper's focus and high-level characteristics; and the categories for scoring the direction, strength, and consistency of each paper's reported relationship between DSM input factors and outcomes of interest.

The following metadata categories were scored (Table 2):

- **Building type**. The focus of the review was on residential and commercial buildings, however, larger commercial buildings are sometimes lumped together with industrial buildings in analysis and reporting. Therefore, all types of buildings — residential, commercial, and industrial, were included in the possible scoring categories.
- **Building scale**. Studies may assess the impacts of DSM programs across a cluster of multiple buildings, at the scale of a single building, or at both scales.
- **Loads assessed**. We focus primarily on building end use loads, whether aggregated across a whole building/multiple load types or isolated for a single load of interest. Since DSM programs may engage both building loads and other onsite distributed energy resources (DERs) (e.g., onsite solar generation, battery storage, and/or EV charging/discharging), these load categories were also distinguished in the scoring framework.
- **Measure type**. DSM is defined broadly to encompass building energy efficiency, building demand flexibility and DR, and building load electrification measures. Efficiency measures include improvements to building equipment efficiency, improvements to building envelope component performance (e.g., windows, walls), or controls that both reduce energy waste and enable load flexibility.
- **Assessment method**. Studies may use simulation methods, metered load measurements, self-reported survey responses, or a combination of these methods to determine the impacts of various DSM factors on DSM outcomes.
- **Participation type**. For studies of DSM participation, the participation may occur actively; passively; or via a combination of both types of participation. The definition of active and passive participation intersects with measure types, as further described below, but emphasizes the degree to which customers have operational control over a given measure.
  - *Passive energy flexibility* involves the use of automated control algorithms to shift the energy demand of building loads (e.g., HVAC, water heating, lighting, etc.); to balance these loads with onsite generation and energy storage; and to enable smart grid interactions.
  - *Passive energy efficiency* involves building renovations or the purchase of more efficient appliances, including improvements that deliver energy savings at a district level. This concept excludes changes in operational behavior and/or the scheduling of building energy services.
  - *Active energy flexibility* involves customers' conscious demand shifting of building loads.
  - *Active energy efficiency* involves consciously reducing overall use of building energy services, e.g., via changes in operational behavior and/or scheduling of building energy services.
  - *Combined (passive plus active) energy flexibility* implies that customers influence the operation of automated control algorithms (e.g. by adjusting constraints of the algorithms or by overwriting automated control actions).
  - *Combined (passive plus active) energy efficiency* involves the combination of building renovations or more efficient equipment and the reduced use of this equipment.

**Table 3**
Scoring categories for DSM input factors, outcomes of interest, to describe effects of input factor(s) on outcome(s). See supporting text in Section 2.4 for definitions of each row.

| Scoring Category | Scoring Options |
|---|---|
| DSM Factor | Regulatory; Incentives; Customer Engagement; Customer Segmentation; Third Party Services; Structural Barriers |
| DSM Outcome | Program Enrollment, % Enrolled; Program Enrollment, Total Enrolled; Program Enrollment, Other Metric; Participation Level, Energy Use Impact; Participation Level, Peak Demand Impact; Participation Level, Other Metric; Other |
| Impact Direction | -1 (Negative); 0 (No Impact); 1 (Positive) |
| Impact Strength | 1 (Low); 2 (Medium); 3 (High); Unknown/Not Assessed |
| Impact Consistency | 1 (Mixed Evidence); 2 (Mostly Consistent Evidence); 3 (Consistent Evidence) |

In addition to these metadata, we score DSM factors, outcomes, and the relationship between the two as follows (Table 3):

- **DSM factor**. Scoring of DSM factors maps directly to the definition of these factors in Table 1. When a paper examined multiple factors and the effect of each factor on the DSM outcome(s) of interest was separately reported, we included a unique score for each DSM factor-DSM outcome pairing. As a result, some papers generate more than one score for the DSM factor-outcome relationship.
- **DSM outcome**. Within the primary DSM enrollment and participation outcomes identified in Table 1, different reporting metrics are distinguished in the scoring: changes in DSM enrollment may be reported in terms of percentages or total enrolled, for example, while changes in DSM participation may be reported in terms of en-

ergy use or peak demand impacts, or via non-energy metrics such as likelihood of enrollment or cost savings.

- **Impact direction**. Studies may report increases, decreases, or effectively no change in DSM enrollment or participation outcomes as a result of the implementation of one or more of the DSM factors of interest.
- **Impact strength**. The reported magnitude of impacts of DSM factors on DSM outcomes is binned into three categories, for studies that assess this: 1-Low (less than 10% change or not statistically significant or qualitatively described as minimal/negligible effect on outcome); 2-Medium (10-30% change or moderate statistical significance (p-value less than 0.05) or qualitatively described as medium/moderate effect); or 3-High (greater than 30% change OR high statistical significance (p-value less than 0.001) OR qualitatively described as large effect). These quantitative thresholds were determined based on the group's collective expert judgment of what might constitute low, medium, or high levels of impact from a utility perspective.
- **Impact consistency**. The impacts of DSM factors may be assessed for just one case, or may be compared across multiple buildings and/or sub-populations of interest. Strong effects that are observed consistently across multiple instances are more robust than those that are only assessed for one instance. We group the internal consistency of reported effect sizes into three categories: 1-Mixed Evidence (less than 70% same direction/comparable magnitude across multiple buildings/collections of buildings, or studies that only assess effects in one building); 2-Mostly Consistent Evidence (70-90% same direction/comparable magnitude); or 3-High (greater than 90% of cases in study demonstrate effect in the same direction and of comparable magnitude). These quantitative thresholds are consistent with those used in Peñasco et al. [71] to establish the consistency of observed energy policy interventions on promoting low-carbon energy transition.

For the purposes of exploring the overall impacts of a given DSM input factor on a given DSM outcome, we combine the scores for the three impact variables above — direction, strength, and consistency — into a composite impact score, $I$:

$$I = D * S * C \tag{1}$$

Where $D$, $S$, and $C$ are the scored direction, strength, and consistency of a given DSM input factor's impact on a given DSM outcome, respectively. Scores of 0 indicate no impact; 1 indicates low magnitude with mixed evidence; 4 indicates moderate magnitude with mostly consistent evidence; and 9 indicates high magnitude with robust evidence. Scores in between these benchmarks indicate a mix of levels of reported strength and consistency. Negative scores indicate that a given DSM input factor resulted in a DSM outcome changing in a non-beneficial direction (e.g., *increases* in demand or energy, or *reductions* in enrollment).

### 2.5. Implementation

Fig. 1 diagrams the sequence and timing with which key components of the systematic review were implemented, including the five review stages outlined in Section 2.2 as well as efforts to develop and implement a paper scoring framework, post-process scoring data, and compile a final database of results. The group finalized the systematic review approach in January 2022; conducted the initial database search and screening and parallel search of key authors and reports by April 2022; further screened and scored the papers passing the initial screen by November of 2022; and conducted scoring data analysis and supplementation in 2023. Given this timeline, the review does not include any papers that were published after March of 2022.

A data record is available in Langevin et al. [50] that includes the specific search strings used, bibliographic information for screened and scored papers, the scoring template and categories, and final scoring data.

## 3. Results

### 3.1. Characteristics of reviewed papers

A total of 730 unique papers were initially retrieved from the academic database keyword search; of these, 202 papers passed the abstract screen, an additional 16 papers were added via the parallel search of key reports and authors, and 80 papers were ultimately scored and contributed to the final set of findings (Fig. 2). Scored papers skew heavily towards recent publication dates (Fig. 3a)—more than 80% of the papers were published after 2015. This indicates growing research interest in studying DSM enrollment and participation, likely due to the acceleration of VRE deployment and other trends related to power system decarbonization that have increased the potential value of DSM measures for grid planners and operators. Of the papers that report a specific country of focus, most are from the United States (USA, Fig. 3b), which has a long history of DSM program administration. The European Union and its member states are the next most common places of focus.

#### 3.1.1. Prevalence of DSM factors

Fig. 2 shows that economic incentives (e.g., time-varying electricity rates, lump sum payments, or other financial rewards for customer load adjustments) are commonly the primary DSM factor that studies explore (29 of the scored studies), followed by structural factors (e.g., availability of required communication/control infrastructure; 19 studies) and involvement of third party services (e.g., aggregators; 14 studies). Regulatory approaches for increasing DSM enrollment and/or participation (e.g., mandated rate structures, defaulting to time-of-use rates, etc.) are the least commonly studied factor in the database (4 studies).

Among incentive-focused studies, many focus on time-of-use or real-time pricing schemes (e.g. [15], [33], [62], [31], [79], [58]), sometimes combined with the use of controls and various technologies that enable DR participation — including thermostats, shading, lighting controls, photovoltaics, battery storage, electric vehicles, electric heat pumps, and/or hybrid heating systems (see subsequent discussion of loads and measure types of focus). Given that incentives have a long history of use for encouraging energy efficiency retrofits [95], [32], it is not surprising that these are also commonly used for DR.

After incentives, the next most commonly explored DSM factors include structural barriers, third party services, and customer engagement. Research efforts that focus on addressing structural barriers include incentivizing less profitable retrofits [32] and utilizing advanced energy management, control systems, and smart grid technology to reduce uncertainties and enable improved communication between the grid and buildings [72], [107], [83], [84], [110]. Research on third-party entities include efforts by demand response aggregators and Energy Service Companies (ESCOs). These papers discuss control strategies and frameworks such as blockchain, peer-to-peer trading, and game-theory controls to support efficient decentralized energy management and energy exchange among users for cost and peak demand reduction [20], [37], [93]. They also discuss optimizing energy usage among multiple buildings and/or building systems (e.g. heat pumps), with a target of providing the most efficient outcome for all participants and for the DR program [20], [37], [93], [109], [95], [45]. Finally, studies of customer engagement generally provide real-time feedback on energy consumption, such as through smart meters and/or home energy monitoring systems. These feedback devices promote increased energy awareness, adoption of energy-efficient technologies and optimizing energy usage to align with grid capabilities [5], [60]. Additionally, behavioral interventions such as the use of competitions, social norms, and/or building-to-building comparisons may improve the awareness of residential customers and engage them in more sustainable behaviors [57], [99], [108].

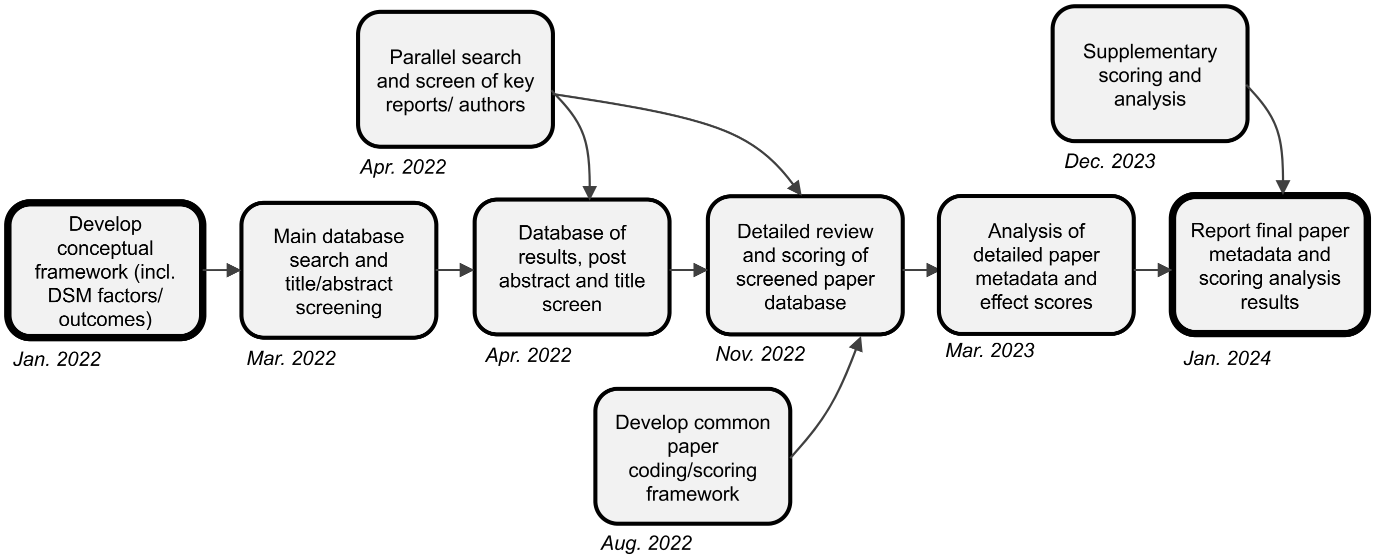


**Fig. 1.** Systematic literature review steps and implementation timing.

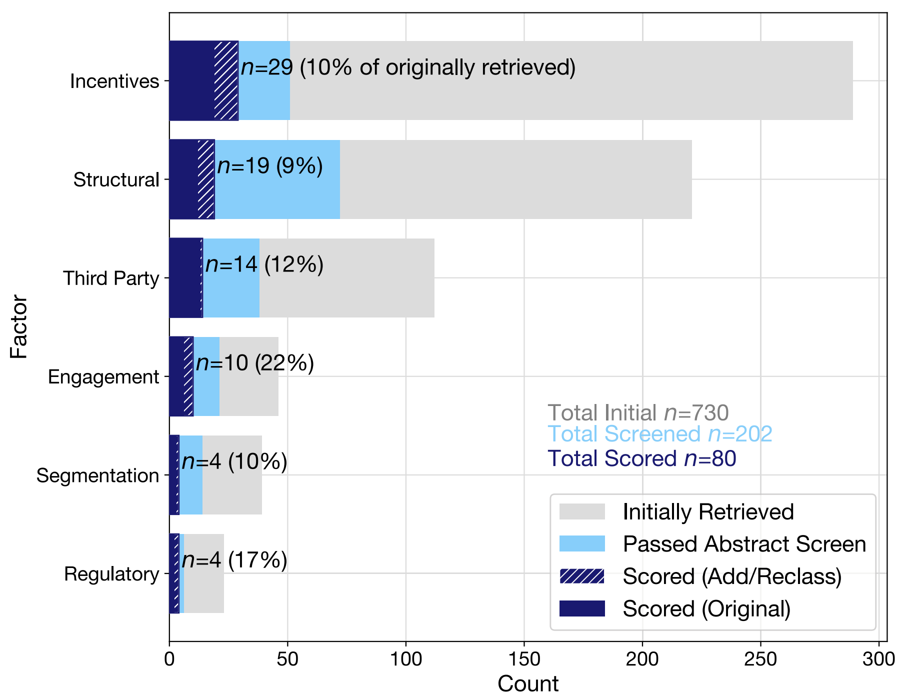


**Fig. 2.** Paper screening results by primary DSM factor examined after initial retrieval; title and abstract screening; and detailing scoring steps. Final number of papers retrieved for each factor is shown to the right of each bar, along with the ratio of final vs. initially-retrieved paper counts for the factor.

Segmentation and regulatory inputs are among the least common inputs considered in the research that was reviewed, together comprising the focus of approximately 10% of studies. For studies focused on customer segmentation, segmentation dimensions include a customer's building type [44], demographics and socioeconomic variables [60], [62] and program type [44]. The limited number of studies concerning regulatory levers for DSM include one that develops recommendations for energy efficiency and renewable integration measures on the basis of simulated energy savings and existing municipal regulations [32], as well as another that develops a decision support system for policymakers to use in designing effective DR programs and informing effective regulatory constraints [98].

*3.1.2. Outcomes and methods*

Fig. 4a shows that most (86%) of the paper scores reflect an assessment of DSM participation — typically via the metric of peak demand impacts, though energy use impacts are also often studied, sometimes alongside the peak impacts. Only 7% of paper scores (N = 8) include assessment of a DSM enrollment outcome. Most enrollment studies explore the effects of incentives on enrollment, and via metrics other than direct enrollment rates or numbers such as self-reported likelihood to enroll from survey data. The "Other" output metrics reflected in Fig. 4a include cost savings, customer comfort, and greenhouse gas emissions, among others.

Relative peak demand and energy impacts vary widely across studies that report these outcome metrics. Specifically, relative peak impacts

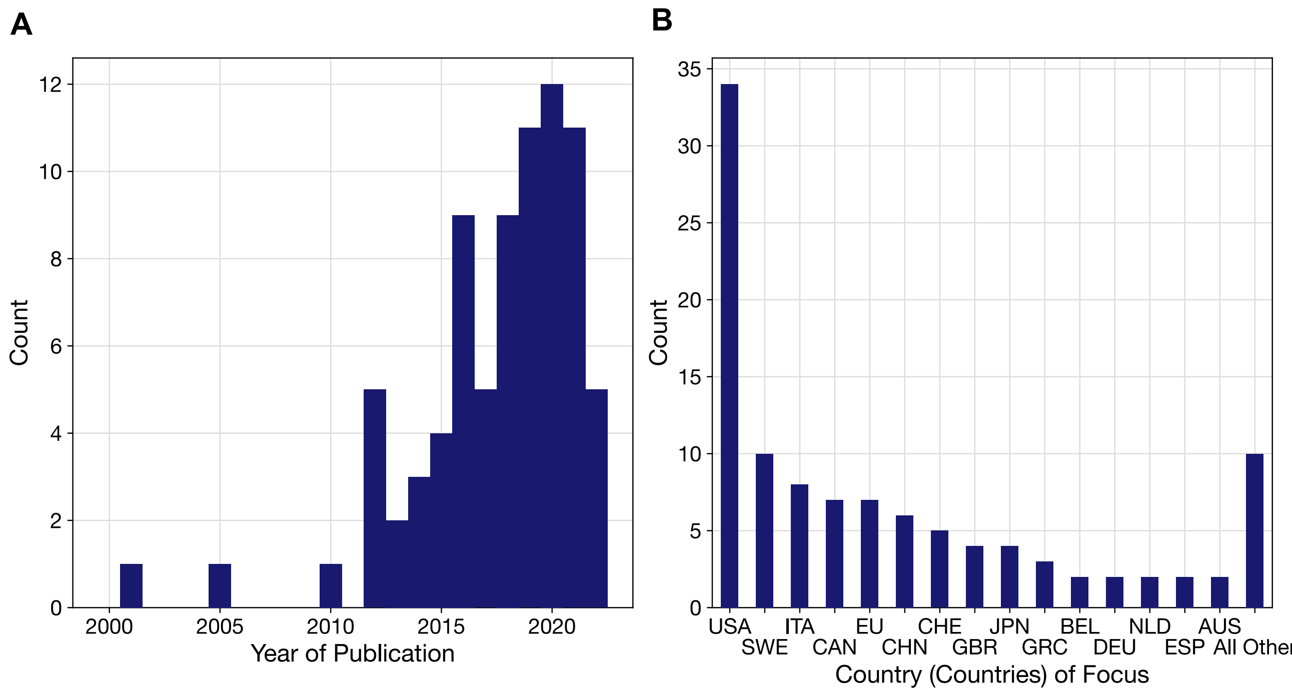


**Fig. 3.** a) Distribution of publication years for scored papers. Note that the analysis does not consider papers published after March of 2022, when the initial literature database search and screening was conducted (see Fig. 1.) b) Distribution of scored papers by country of focus.

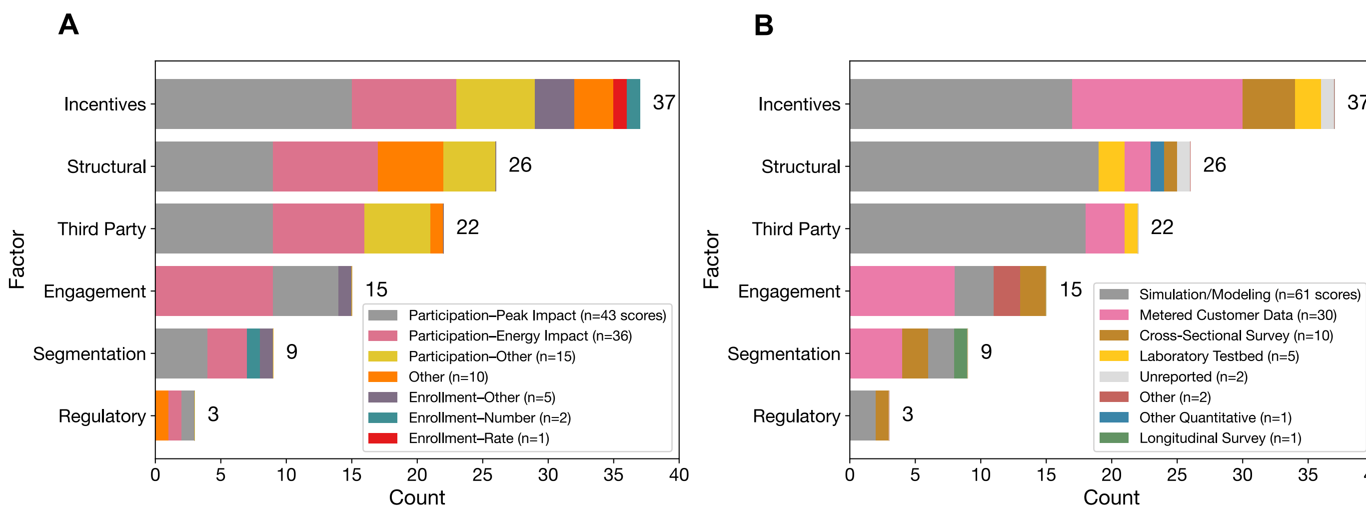


**Fig. 4.** a) DSM enrollment or participation outcome assessed by studies, by DSM input factor type. b) Primary study methodology by DSM factor type.

range from 1% in Bartusch and Alvehag [11], a long-term estimation of residential demand reduction from time-of-use electricity pricing, to 80% in Rotger-Griful et al. [81], a simulation-based study in which the authors indicate low potential for achievement of the reduction in practice. Relative energy impacts range from 2.5% of overall consumption in Chrysopoulos et al. [17], a study of small commercial buildings, to 73% of monthly costs [95], which uses model predictive control to support integration of micro-scale concentrated solar power and thermal energy storage with HVAC operations. A few studies report negative peak and energy impacts, for example in Geneidy and Howard [33], which explores control strategies under incentives and penalties and suggests the trade-off between increased cost for demand reduction and the penalty for no demand reduction is the reason for the negative impacts. Within the smaller set of studies that report outcomes related to DSM enrollment, [63], [102] and [59] use surveys to understand why some customers participate in demand response and/or their preferences for different electric service plans.

Additionally, Fig. 4b shows that most studies rely on simulation or modeling to characterize DSM impacts, though methods differ notably by DSM factor examined. For example: simulation is by far the most commonly used method to explore structural barriers and third party services, while most studies of customer engagement and/or segmentation rely on metered customer data, and simulation and metering are used about equally in studies of DSM incentives. Survey methods are infrequently observed overall in the scoring data, but are disproportionately used to explore enrollment outcomes (e.g., self-reported likelihood to enroll in a program), constituting 5 of the 7 instances in which enrollment outcomes were explored and a primary study method could be discerned.

Studies that use simulation and modeling methods use both bottom-up and top-down approaches [51]. Common tools for bottom-up ap-

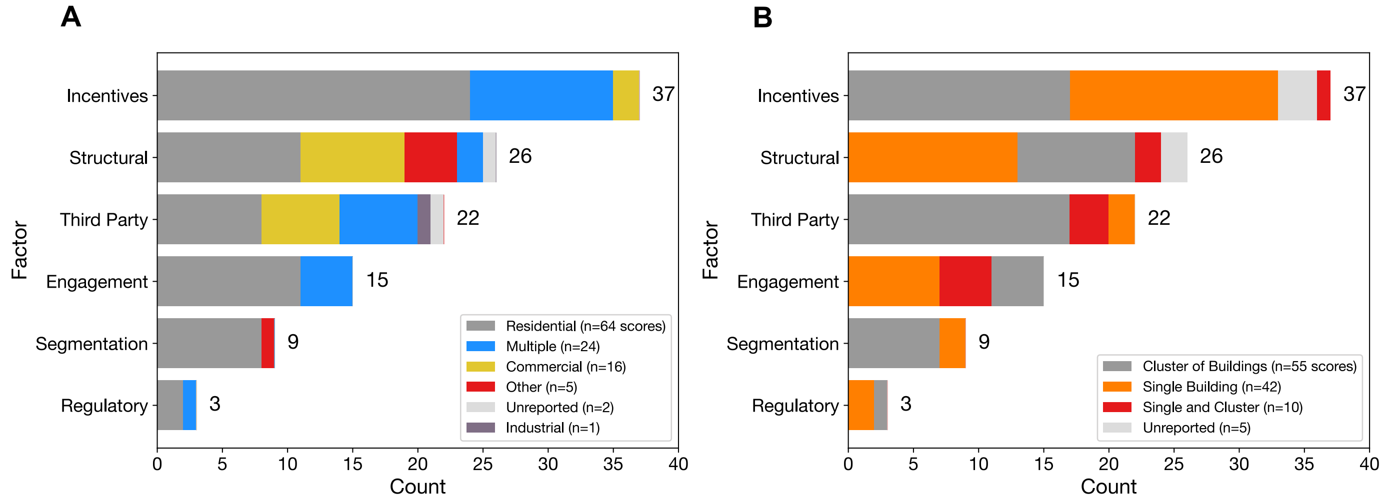


**Fig. 5.** a) Study building type(s) of focus by DSM input factor type. b) Scope of study focus (i.e., individual vs. multiple/clusters of buildings) by DSM factor type.

proaches, which begin at the individual building level, include EnergyPlus (e.g., [47,10]), MATLAB (e.g., [1,6,4]) and other optimization tools (e.g., [8]). Often these studies use model prototypes to represent the common types of buildings across a region of interest [4]. For example, [15] analyzed the impact of various demand response strategies on utility cost savings, peak demand reductions, and indoor comfort using several types of small commercial buildings across 14 U.S. locations, considering different climate zones and utility rate schedules. Other studies use top-down approaches (e.g., [72,36]). For example, [72] created and optimized an artificial neural network (ANN) model to improve forecasts of building-based PV output to reduce demand uncertainty and decrease customer cost.

In studies that use metered customer data, utility smart meter data are commonly used for evaluation, though many customer engagement studies collect customer feedback using in-home displays (IHDs) in combination with metered energy use data (e.g., [99,57,60,77]). Some such studies suggest that IHDs encourage residential customers to reduce overall electricity usage [77]. Other customer engagement research uses survey responses to evaluate engagement in social competition that rewards effective energy management [42]. Studies focused on customer segmentation also commonly rely on measured electricity savings and/or load shifting capability [94]; [2]. Survey research is sometimes conducted directly by utilities and/or grid operators. For example, [63] evaluated participation in price-responsive load programs, using a survey for program participants and non-participants.

### *3.1.3. Building type and scope*

Residential contexts are a predominant focus of the studies across DSM input factors (Fig. 5a), particularly in studies that explore customer engagement and segmentation approaches to increasing DSM enrollment and/or participation. Studies that explore the effects of structural or third party factors on DSM outcomes more commonly focus on commercial buildings. As mentioned, these two factors encompass availability of centralized controls infrastructure and use of load aggregator services, both of which are currently more prevalent in commercial than in residential settings.

Most residential studies focus on single family attached or detached homes (e.g., [64,78,58]). Some include multifamily buildings (e.g., [94,17]), a combination of multiple residential building types (e.g., [11,29]), or do not specify building characteristics beyond them being residential (e.g., [106,82]). Regarding commercial contexts, the large majority of commercial buildings considered are office buildings (e.g., [110,4,18,100,3]). Most of the commercial building-focused studies in the structural or third-party input factor categories appear to be focused on optimal control strategies for building systems (e.g., [4,107,95]), in some cases driven by load aggregators (e.g., [93,10,100]).

Studies also explore a variety of building scopes across DSM factors (Fig. 5b) — both individual buildings and clusters of buildings. Overall, clusters of buildings are more often examined, and this is particularly the case for studies that examine factors related to load aggregation — third party services and customer segmentation (where “segments” are often collections of customers with similar load profile characteristics). Cluster sizes in studies of third party services range from as small as 3 buildings to as large as 4000 buildings; cluster sizes in customer segmentation studies are somewhat larger, ranging from 200 to 5487 buildings. Many studies of building clusters in the context of third party services investigate the behavior of a control strategy or algorithm across the cluster (e.g., [10,100,90]).

### *3.1.4. Technology and measure types*

Most studies report the impacts of DSM programs at the whole building level or otherwise across multiple technology types (Fig. 6a). When multiple load types are studied, DSM of HVAC equipment is often one of them — HVAC is included in over half of all instances where multiple loads were investigated (33 of 61 instances). Moreover, of the studies that do isolate the impacts of a single load, HVAC is most commonly the focus, and particularly so for studies of third party aggregator involvement in DSM programs. Few studies isolate the participation profiles of DERs that would intersect with building load operations, such as electric vehicles (EVs), battery storage, and onsite generation. However, DERs are addressed in many of the studies that focus on multiple technologies or the whole building.

Examples of combinations of technologies in the DSM literature include: HVAC (heat pump, electrical heaters), batteries, and hot water storage [110]; HVAC, lighting, on-site PV, and water heating [32]; EVs, appliances, and HVAC [2]; and HVAC with battery or other types of storage [46,72,45,79,20,78,61]. As an example study focused on HVAC only, [80] assessed the demand response potential of ventilation fans in a 12-story building.

Regarding DSM measure types, studies examine demand flexibility measures most frequently —— both in isolation and in conjunction with energy efficiency measures (Fig. 6b). When efficiency measure impacts are reported alongside demand flexibility measure impacts, these measures typically consist of control schemes that reduce waste in the scheduling and use of energy services (e.g., services provided when occupants are not home) while also enabling targeted adjustments to operations at certain hours to provide flexibility to the grid. Notably, none of the reviewed studies addressed DSM in the context of load electrification measures that convert fossil-fired heating, water heating,

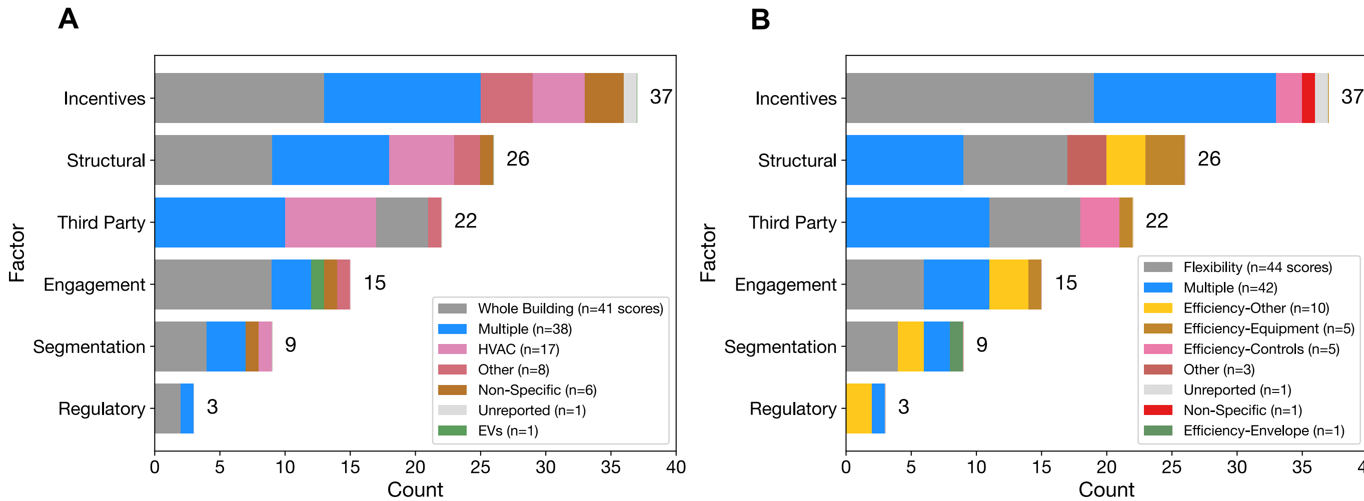


**Fig. 6.** a) Study technology or technologies of focus by DSM input factor type. b) Study measure type(s) of focus by DSM factor type.

cooking, or drying equipment to run on electricity. This is despite the central role that building electrification is expected to play in meeting countries' economy-wide decarbonization goals. Efficiency-only measures were less commonly observed across all DSM factors studied.

Flexibility in the reviewed studies is achieved by either the use of energy storage (e.g. battery, thermal, EV) or solar panels (e.g. [49]; [48]), by modifying when energy-consuming devices are being used (e.g. [84]), or a combination of both. In other cases, a time-of-use or DR scheme is implemented without specifying how demand flexibility is met (e.g. [1]). For studies that focus on multiple DSM measures, most papers combine DR with energy efficiency measures. Such combinations include smart home energy management with TOU pricing [78]; [98], efficient control of appliances/HVAC with dynamic pricing [79]; [62], high-efficiency HVAC systems used with DR [79], decentralized control of HVAC with incentive-based DR [93]; [95]; [20], renewable installations with incentive-based DR [95]; [32]; [85], installation of solar to reduce operation costs [32], and use of artificial intelligence (AI) and Internet of Things (IoT) approaches to support demand flexibility and equipment operational efficiency [85]; [78]. The smaller number of papers that focus just on efficiency primarily report on retrofits of public [32]; [3] and multifamily [94] buildings. Such studies cover a range of efficiency strategies such as insulation improvements, window upgrades, LED lighting, installing high efficiency HVAC systems, and purchasing EnergyStar appliances, among others. Another study used gamified platforms to encourage energy savings engagement with smart devices [108], an example of a controls-focused efficiency measure.

*3.1.5. Participation type*

Fig. 7 shows that most studies focus on passive (e.g., automated and/or remotely controlled) customer participation in DSM programs (53 scores, or 55% of all scores for this metric). A smaller number of studies explore active/manual customer control and participation (18 scores, 19%) as well as programs that combine active and passive participation elements (11 scores, 11%). Some studies also directly compare active vs. passive participation ("Multiple," 15 scores, 16%). Studies not addressing a participation type focus mainly on customer enrollment and willingness to provide demand response.

Breaking this variable down by input factor type in Fig. 7, it is notable that studies of third party services all explore passive participation in DSM programs. These studies typically concern remote aggregation of loads to meet grid needs — e.g., across different building types [6], across diverse load profiles within a single building [109], or across households with varying degrees of willingness to provide demand response [61]. Passive participation schemes are also common in studies that explore the effects of incentives — several of which simulate the energy cost savings of different rate structures (e.g., [69,84,15]) — and in studies concerning structural barriers, which often develop smart energy management systems to enable balancing of energy demand, renewable energy sources and storage (e.g., for aggregated loads [22]; heating and hot water storage [22,95,110]; and electric vehicles [48]). Studies of smart systems rarely investigate active customer participation in isolation, though they do in some cases layer active participation on top of passive control approaches.

Active customer participation is most frequently investigated in studies of incentives (e.g., [11,59,12,13,62,76]). These studies demonstrate the importance of customer awareness of variations in energy prices over time, as well as the increased uncertainty in level of response that comes with active customer participation [103]. Active customer participation is also relatively common in studies of customer engagement (e.g., via education [62], feedback [29,57,77], or both [99] and in studies that seek to increase levels of customer response via segmentation (e.g., by accounting for differences in customer preferences [59] or level of interest in energy services [106]. Furthermore, regulatory instruments that enable competition in the electricity market may create lower prices and more cost savings for customers, therefore stimulating active participation [98].

*3.2. Impacts on DSM outcomes*

Fig. 8 plots the distribution of direction, strength, consistency, and composite impact scores across all DSM input factors and outcomes. Impact scores are mostly positive (Fig. 8a), tend to be of low to moderate strength (Fig. 8b), and have no clear trend for internal consistency (Fig. 8c). Composite scores (Fig. 8d) most commonly mix the low and moderate or moderate and high levels of impact strength and consistency ($I = 2$ and $I = 6$, respectively in Fig. 8d). Relatively few composite scores indicate both a high magnitude and consistency of impact ($I = 9$, 10 scores in Fig. 8d).

*3.2.1. Impacts by input factor*

Fig. 9 breaks out composite impact scores by each of the DSM factors of interest, summarizing the range of scores observed for each factor. Fig. 9a pools impacts across all DSM enrollment, participation, and other outcomes, while Figs. 9b-d show impacts for each of these outcomes in isolation. In Fig. 9a, the median and interquartile ranges of scores are relatively higher for the third party services, structural barrier, and customer engagement factors, but not clearly so. Indeed, differences in the mean composite scores are generally small across factors. The distribution of composite scores does vary by factor, most notably for the

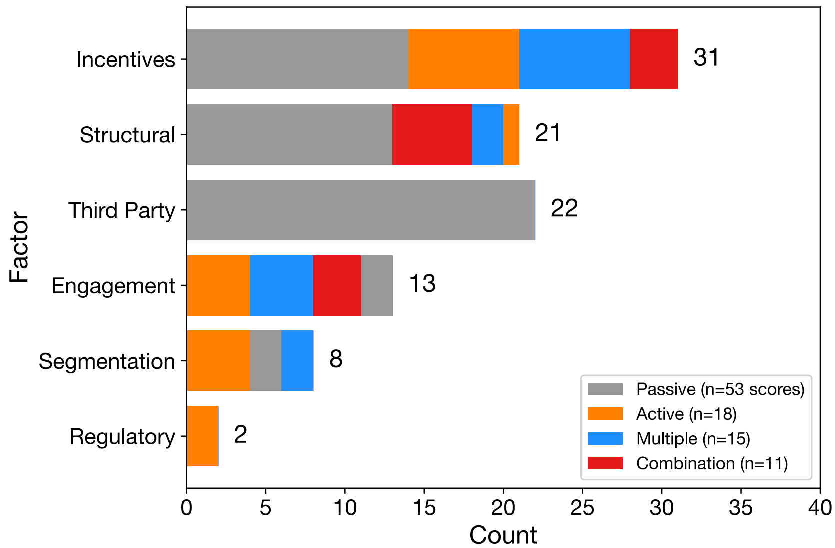


**Fig. 7.** Examination of passive occupant control, active occupant control, a combination of passive and active occupant control, or both individually ("Multiple"), by DSM input factor type. Note that such a dimension is generally only relevant to studies of DSM participation.

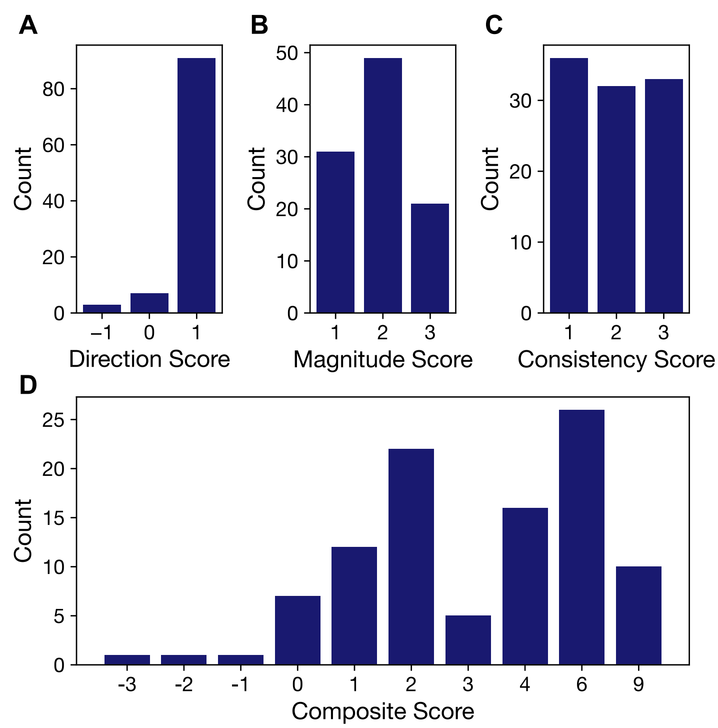


**Fig. 8.** Histogram of impact scores, across all DSM input factors and outcomes, for: a) direction (-1 = negative; 0 = no impact; 1 = positive), b) strength (1 = low; 2 = moderate; 3 = high), c) consistency (1 = mixed; 2 = mostly consistent; 3 = high), and d) the composite of a*b*c (<0 = negative impact; 0 = no impact; 1 = low impact, mixed evidence; 4 = moderate impact, mostly consistent evidence; 9 = high impact, robust evidence).

incentives factor, for which there is disagreement across studies about impacts from incentives — some studies report strongly positive and consistent impacts, while others show negative impacts, and the median impact size is relatively low for incentives compared to the aforementioned DSM factors.

Examining the other plots in Fig. 9, the wide range of reported impacts for the incentives factor is driven by studies of DSM participation (Fig. 9c), for which a similarly wide range of incentive impacts is observed, from weakly negative to strongly positive. In these studies, negative incentive impacts often signify time-varying rates that result in new, slightly larger peaks in energy demand and/or rebounds in hourly demand succeeding peak pricing periods that result in small increases in overall energy use. For example, [1] found that the implementation of Real-Time Pricing - Hour Ahead (RTP-HA) and instantaneous demand control methodologies for industrial and commercial customers created a new peak due to simultaneous RTP-response across all buildings. Geneidy and Howard [33] observed that RTP-HA may lead to demand spikes before the peak price periods (60% increase in peak demand), as homes preheat during off-peak periods.

By contrast, a small number of studies (N = 8) that examine the impacts of incentives on enrollment tend to have larger, more consistent positive impacts of incentives on enrollment outcomes (Fig. 9b)). These positive outcomes reflect increased participation in Time-of-Use (TOU)/dynamic pricing and incentive-based programs [12]; [31]; [102], as well as increasing adoption of the energy efficient equipment that is incentivized by programs [63], among other trends.

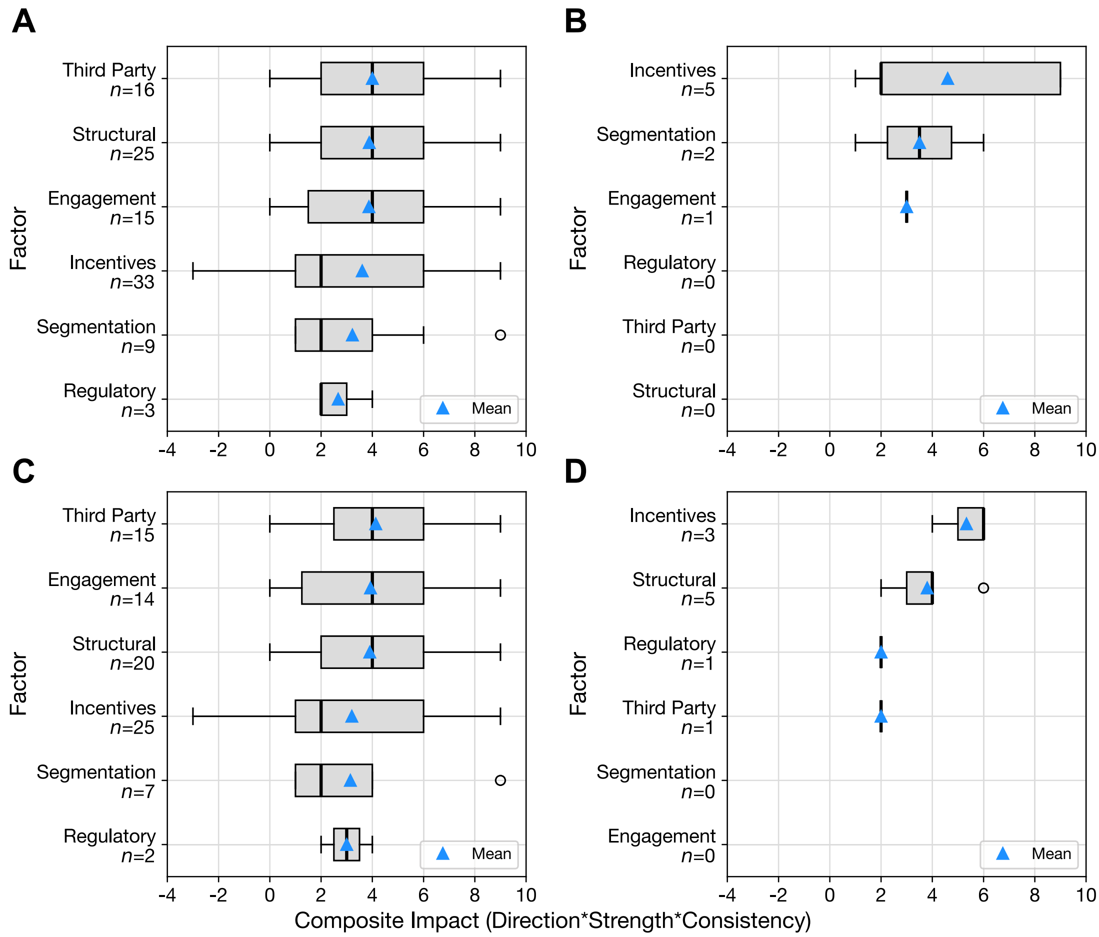


**Fig. 9.** Reported composite impact score of the study on DSM outcomes of interest (direction*magnitude*consistency) by DSM input factors. Shown are the impact scores for: a) all DSM outcomes of interest (enrollment/participation/other), b) DSM enrollment outcomes only, c) DSM participation outcomes only, and d) Other (non-enrollment/non-participation) DSM outcomes only. Box plots are presented in descending order from top to bottom based on the mean composite score for the given input factor on the y-axis. The number of scores behind each box plot is shown below the y-axis label for each factor. Composite score interpretation: <0 = negative impact; 0 = no impact; 1 = low impact, mixed evidence; 4 = moderate impact, mostly consistent evidence; 9 = high impact, robust evidence.

### 3.2.2. *Impacts by metadata variable*

Fig. 10 further explores whether scored impacts differ by each of the study metadata variables summarized in Figs. 4–7. Differences in mean composite scores, while again muted overall, are most apparent between study methods (Fig. 10b), measure types (Fig. 10f), and — for those studies that focus primarily on DSM participation outcomes — whether the participation is active, passive, or a combination of those types (Fig. 10g).

Regarding differences across study methods, simulation studies have the highest mean and median composite impact scores, followed by survey studies; both of these types of studies have median scores in the moderate range. It is important to note that most simulation studies do not conduct model validation and that many of these studies focus on assessing potential. This may help explain the higher impacts that tend to be reported in simulation-based studies. Simulation studies that report *potential* impacts include those that focus on cost savings, demand reduction and/or energy efficiency improvements through HVAC system optimization for DR [103]; [34]; [80], direct-load control [69], and/or thermal energy storage [18]; [8]; [107]. Other simulation studies examine the potential for RTP efficacy over TOU and fixed tariffs [7]; [78], and predicted behavioral responses to DR events [66], among other issues related to potential impacts.

Compared with simulation studies, composite scores for metering studies appear lower, due to several such studies reporting low impacts and/or few instances where impacts are observed to be robust across multiple building samples. Notably, metering studies focus more often than simulation studies on energy use as a DSM participation marker (in 43% of scores for metering studies vs. 26% of scores for simulation studies, respectively) and observe minimal energy conservation through this metric, whether for single loads like HVAC [90] or across a whole building [62]; [99]. Both simulation and metering studies generate wide ranges of reported impacts that suggest disagreement across these types of studies. These ranges include reports of neutral impacts, as well as reports of negative impacts in the case of the simulation studies.

Regarding differences across measure types, studies that examine flexibility measures alone or in combination with efficiency measures report the highest impacts on DSM outcomes, again in the moderate range of the composite score. These studies often report temporary reductions in hourly demand during peak periods that tend to be larger than energy reductions measured across longer time periods (e.g., monthly or annual), though as mentioned, in a few instances peak reductions are outweighed by new increases in demand in pre-conditioning or recovery periods outside the peak window, resulting in a negative score (e.g., in [1,33]). Efficiency-only measures tend to have lower scores, particularly those that implement controls (e.g., thermostat setbacks), which are more sensitive to occupant behavior and comfort constraints.

Finally, DSM participation schemes that combine passive occupant participation with the option for active intervention (e.g., control schemes that allow a utility to remotely adjust smart thermostats while offering occupants the option of manual override) show the strongest positive impacts on DSM participation, in the moderate to high range of the composite score. Several studies find that when energy demand is

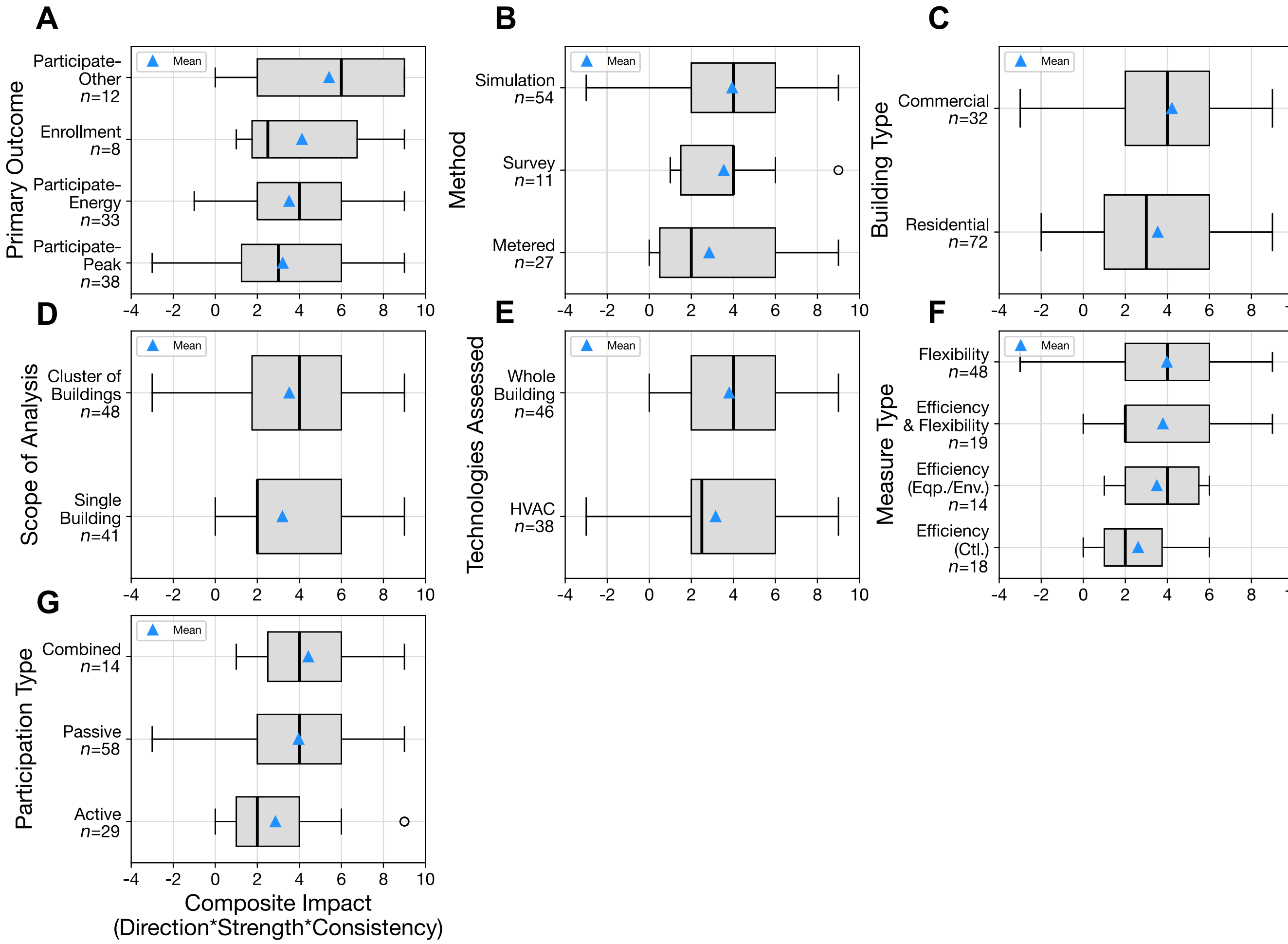


**Fig. 10.** Reported study effect sizes on DSM outcomes of interest (direction*magnitude*consistency) across all DSM input factors, broken out by a) primary outcome (DSM enrollment or participation); b) study method, c) building type, d) scope of analysis (single building vs. cluster of buildings), e) technologies assessed, f) measure type, and g) participation type. Breakout categories are generally only shown when they produce at least 10 scoring data points. Box plots are presented in descending order from top to bottom based on the mean composite score for the given metadata category on the y-axis. The number of scores behind each box plot is shown below the y-axis label for each category. Composite score interpretation: <0 = negative impact; 0 = no impact; 1 = low impact, mixed evidence; 4 = moderate impact, mostly consistent evidence; 9 = high impact, robust evidence.

shifted, consumer acceptance is improved with controllers that enable both types of participation (e.g., [41,53,66,81,107,108]). The mean impacts of purely passive DSM participation schemes are comparable, if slightly lower than the combined participation cases, but can also range widely and include negative impacts.

Studies that examine active DSM participation report substantially smaller impacts than for the combined and passive schemes — most scores are in the low range on the composite scale — which suggests that over-reliance on manual occupant scheduling and intervention in DSM programs could limit the impacts of customer participation in these programs. The handful of studies that directly compare active and passive participation further underscore this finding. For example, [77] observes that during critical peak pricing programs, event load reductions ranged from 13 to 20% in case of active participation in the residential sector; with control technology, which could raise thermostat levels or switch off equipment, the reductions increased to between 23 and 49%. Bernard et al. [12] compare participants whose thermostat is controlled remotely during peak shaving events with those that were able to reprogram their thermostat. They observe that the energy demand reductions of households that managed the thermostats themselves during events were considerably lower, though still statistically significant. Finally, [62] observes that in certain regions and under certain rate structures, significantly higher peak energy demand reductions occur for households that participate passively compared to those that participate actively in dynamic pricing programs.

## 4. Discussion

Through a systematic review and scoring of existing literature concerning DSM enrollment and participation factors, we reveal a number of common themes with broader significance to utilities, grid planners, and other decision-makers who would seek to increase DSM program deployment and efficacy to facilitate deep decarbonization of the buildings and power sectors:

1. **A prevailing focus on economic incentives and DSM participation, often explored through simulation.** While many studies examine DSM participation outcomes, few studies focus on DSM enrollment. Here, methodological constraints may come into play: it's easier to measure or model changes in loads and corresponding financial signals than it is to track enrollment outcomes across DSM programs that may be highly diverse in their scopes, timing, and potential benefits to consumers. Moreover, while countries like the United States have long histories with DSM program implementation, in many other regions DSM programs are not yet widespread. In such contexts, simulations that demonstrate DSM participation

potential may serve as prerequisites for eventual DSM program design and customer enrollment.

2. **A muted hierarchy in DSM impacts across influencing factors and other relevant dimensions.** While third party services and the removal of structural barriers score the highest overall impacts on DSM participation, the hierarchy is muddled by the wide ranges around scored impacts and the heavy reliance on simulated results, which add uncertainty by tending to explore theoretical potential and simplifying real-world dynamics. This inconclusive picture is to be expected in a review that spans DSM participation across a wide diversity of contexts and which attempts to combine qualitative and quantitative estimates of relative impact across studies that also use different types of metrics to characterize impact. Nevertheless, it underscores the need for further research that can directly compare the relative impacts of the various DSM factors under a shared set of conditions and evaluation metrics.
3. **The clear role of automated control technologies.** Increasing availability of controls is a key strategy for removing structural barriers to DSM participation — which our review found is an important factor — and is also an enabling condition for other factors, notably the use of remote third party load aggregation services and the implementation of time-varying rate signals for load flexibility. Moreover, greater automation of DSM controls — e.g., to allow more passive participation of customers in DSM programs — appears to have larger positive impacts on participation outcomes than fully active (manual) control schemes, though more research is needed to confirm this finding. The highest impact is observed when both types of participation are combined, meaning that customers retain the ability to override automated and/or remote control settings. This finding echoes previous evidence for the importance of perceived risk and control, as well as level of complexity and effort as key enablers or barriers for DSM program participation [68].
4. **Limited understanding of DSM factors with high importance for energy system decarbonization pathways.** Very few studies examine potential regulatory avenues for increasing building DSM enrollment or participation, despite the importance of policy and regulatory factors in earlier reviews of DSM adoption [89] and the expectation that regulatory instruments will be central to accelerating DSM deployment alongside low-carbon building technology adoption. Similarly, none of the reviewed studies specifically examined the intersection of DSM enrollment or participation and building load electrification, despite the widespread view that building electrification is a key pathway for energy system decarbonization and could cause significant changes in seasonal profiles of electricity demand on the electric grid (e.g., [70,104,101]).

   Such gaps may reflect the relative immaturity of both of these key decarbonization levers. In the case of regulatory tools, while innovative approaches are expanding historical support for energy efficiency — e.g., through new types of building codes and appliance or performance standards — the lack of common, readily measured DSM metrics has hindered the incorporation of specific provisions in such regulatory measures. In the case of load electrification, utilities and policy makers are only just beginning to explore program and/or rate structures that may drive further adoption, and approaches for stacking and maximizing incentives for DSM and load electrification are currently still under debate.

Given these findings, we recommend the following points of focus going forward for utilities, grid planners, and other researchers to improve the understanding of what drives customer enrollment and participation in DSM programs:

- **Improve tracking of DSM enrollment and link enrollment to participation data.** Future DSM enrollment will likely look different than in the past, for example as utilities and regulators turn to "opt-out" approaches to increase enrollment and new business models like virtual power plants (VPPs) are supported that simplify enrollment by streamlining enrollment with the purchase of enabling equipment [23]. Incorporating standardized data reporting requirements into the development of such programs and including both cross-sectional and longitudinal measurements can simplify the study of enrollment trends and allow researchers to explore the full sequence of customer DSM behavior, from enrollment through to actual adjustments in load patterns.
- **Increase comparability of DSM enrollment and participation impacts across potential factors and reduce dependence on simulations.** With the exception of other higher-level reviews, the studies we examine in this paper tend to isolate the effects of single DSM enrollment or participation factors on these outcomes and to rely on different metrics for characterizing impacts. Going forward, study designs should prioritize parallel assessment of multiple DSM factors at once, so that the reported impacts of each factor are all tied to a common set of conditions and evaluation metrics, thus facilitating apples-to-apples comparisons. Confidence in such comparisons would be further improved by prioritizing measured vs. simulated data, though real-world resource and sample size constraints may limit the ability to study multiple types of DSM interventions at once, and simulations are useful in exploring schemes that have yet to be implemented [21]. Confidence in and comparability of simulation results can be improved by including comprehensive reporting metrics and by flagging model limitations to consider when relying on simulated results to inform DSM program design.
- **Further examine the effects of regulatory instruments and the intersection of DSM and load electrification.** As mentioned, policy makers are expanding the scope of traditional regulatory instruments, such as codes and standards, to accelerate the adoption of both energy efficiency and electrification measures in buildings. These approaches can also accelerate the deployment of DSM assets more broadly — indirectly, by encouraging the installation of more efficient electric equipment that is also grid-connected and enables participation in DSM programs; or directly, by explicitly requiring the installation of equipment and/or controls with smart features. Consideration of such interactions is discouraged by the traditional siloing of DSM programs — energy efficiency and DR programs have historically been administered separately. Going forward, however, the interdependence of DSM, electrification, and the policy and regulatory approaches that can catalyze widespread deployment of both will be an important point of focus for researchers.

### 4.1. Study limitations

While our review provides comprehensive insights into recent literature on DSM enrollment and participation factors, it is non-exhaustive for two reasons. First, the review only accounts for literature published by March of 2022, when the initial paper retrieval and screening stage was completed. Given the rapid growth in publications concerning DSM in recent years and continued improvements in available DSM program data, subsequent studies that we did not include may shed further light on our key findings. Our review and scoring framework should thus be leveraged to conduct periodic re-reviews that demonstrate how the DSM evidence base is changing over time.

Second, it's likely that much of the evidence base for DSM enrollment and participation factors exists in the gray literature, which includes policy and utility studies. Given that gray literature lacks the centralized data repositories that facilitate systematic search and retrieval of academic studies, our retrieval of gray literature was limited to manual internet searches and IEA EBC 82 expert word-of-mouth about which additional studies to include. Improving approaches for systematically examining this important but opaque body of evidence on DSM would be a fruitful area of focus for future reviews.

The current iteration of this review's paper scoring framework does not assess the durability of DSM enrollment and/or participation outcomes over time. Evidence on the durability of such DSM outcomes could become increasingly important as demand-side resources are called upon more frequently and for longer time periods to support power system operations under high variable renewable energy penetration. Moreover, in seeking to isolate the effects of individual DSM factors on DSM outcomes, the scoring framework does not account for the use of multiple, mutually-reinforcing instruments to drive greater customer DSM enrollment and response. Interest in such multifaceted approaches may increase as decision-makers are tasked with broadening and scaling DSM programs to support decarbonization goals; direct assessment of multi-faceted approaches could therefore be included in future updates to this systematic review.

Finally, while both the structure and scope of our review are key innovations of this work, such features sacrifice some of our ability to take a more flexible and nuanced view of the existing literature on DSM enrollment and participation. For example, insights from individual studies which fall outside the metadata categorization and impact scoring criteria we used may be overlooked and/or discarded, though such studies may provide valuable context for interpreting our key findings. Moreover, while impact scoring followed a common set of detailed instructions across reviewers, the mapping between study results and scoring bins was not always clear cut and sometimes required additional layers of interpretation; each reviewer brought their own particular perspective in handling such cases.

## 5. Conclusion

We conducted a systematic review of evidence on factors that could increase customer enrollment and/or participation in utility DSM programs, ultimately focusing on 80 relevant studies from an initially retrieved set of 730 that were published over the course of the last two decades.

Results show that although studies of DSM enrollment and participation have increased in recent years, the evidence base for this topic area remains thin — particularly for DSM enrollment, potential regulatory drivers for DSM, and emerging DSM measures such as load electrification with flexibility. Even for relationships that are more commonly studied, such as that between economic incentives and DSM participation, impacts on DSM outcomes appear highly context-dependent and range widely in strength, direction, and internal consistency across studies. Moreover, reported impacts are commonly simulated, rather than measured or investigated through surveys, adding to uncertainty about real world impact potential.

Of the investigated DSM enrollment and participation factors, third party services (e.g., load aggregation), customer engagement, and removal of structural barriers (e.g., deploying enabling controls infrastructure) have the highest scored impacts on DSM participation. However, impact ranges overlap across factors and no factor clearly emerges as being most impactful. We find some evidence for contextual differences in impacts — notably, DSM impacts tend to be larger in schemes that rely on fully- or partially- automated participation instead of customers' active participation, and are larger for measures deployed to provide energy flexibility compared to energy efficiency measures.

While our findings lack the precision needed to guide specific utility strategies for increasing DSM enrollment and participation in a particular service territory, our study produced a useful snapshot of the state of knowledge about DSM and customer behavior, and it exposes key gaps in understanding that must be filled if DSM is to expand as a reliable resource for building and grid decarbonization in the coming years.

## CRediT authorship contribution statement

**Jared Langevin:** Writing – review & editing, Writing – original draft, Visualization, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Kristen Cetin:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sara Willems:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis. **Jeonga Kang:** Writing – original draft, Visualization, Formal analysis. **Roohany Mahmud:** Writing – original draft, Visualization, Formal analysis. **Toke Haunstrup Christensen:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Conceptualization. **Rongling Li:** Supervision, Investigation. **Armin Knotzer:** Supervision, Investigation, Conceptualization. **Opeoluwa Wonuola Olawale:** Investigation, Conceptualization. **Dirk Saelens:** Supervision. **Sarah O'Connell:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

A data record for this article is available: https://doi.org/10.17632/vhs8rwm5ws.1.

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