Agency and Justice in the Smart Home: Interdisciplinary Approaches for Analyzing Automated Energy Systems

Agency and Justice in the Smart Home: Interdisciplinary Approaches for Analyzing Automated Energy Systems

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Abstract

As the energy system embraces intermittent and renewable energy sources to achieve decarbonization goals, the residential sector is expected to play a more active role in managing energy. Future visions of the system view the residential home as a distributed and flexible energy resource, capable of dynamically shifting energy use in time to align with the availability of renewables. This will be supported by the diffusion of smart technologies with enhanced information-based and automated features to control energy use more granularly. Such a shift raises numerous questions: who should be tasked with managing energy use in the home and for what purposes; how is control over energy use defined and how will the introduction of smart technologies in the home shift who has it; and who may face barriers to accessing the benefits of such programs as policy strives to advance a more equitable energy future.

This dissertation aims to address these questions through developing interdisciplinary tools and analyses to support a holistic understanding of how smart home energy management systems (SHEMS) might impact the grid as a whole and the people for whom it was built to serve. First, I conduct a systematic meta-review on the smart home energy management system literature to understand dominant discourse around the implementation of SHEMS. Results show a body of research skewed towards techno-centric approaches to smart home energy management and a lack of integration between the social and technical disciplines. Second, I propose a multidisciplinary taxonomy of control in the smart home which defines control as both a function of technical automation and relationships between actors in the energy system. The outcome is a scenario analysis tool which defines four characteristic types of control and highlights core issues for consideration in each scenario based on illustrative case studies. Finally, I explore how indicators used to identify disadvantaged communities predict patterns of household activities and adoption of enabling technologies related to demand flexibility. Results show that income, race, education, housing type and tenure, age and disability significantly correlate with activity patterns and technology access. Based on these findings, I offer recommendations on how policy can better center equity as demand flexibility initiatives expand. In aggregate, this body of research critically reflects on how the human dimensions of energy use are currently being situated in SHEMS and demand flexibility research. It offers reflections on how future research and practice can holistically evaluate the implications of new innovations for diverse actors in the energy system.

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For Eileen,

who showed me life never hands you more than you can handle

and there is always hope.

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Chapter 1

Introduction

1.1 Energy Systems in Transition

The energy system currently stands at a critical moment in its evolution. The United States has pledged to reduce net emissions 50-52% by 2030 [1] and the Department of Energy [2] recently released a blueprint for building decarbonization which seeks to achieve a 65% reduction in greenhouse gas emissions by 2035 and 90% by 2050 (compared to 2005) while striving for a net-zero emissions economy. At the same time, over 20 states have adopted policies striving for 100% renewable energy or zero-greenhouse gas emissions for their power sector or even their whole economy [3].

Driven by these ambitious federal and state decarbonization objectives, the grid has begun a significant transition. Achieving decarbonization goals will involve rapid deployment of renewable resources such as wind and solar [1,4], spurring a move away from centralized and stable generation, towards intermittent and often distributed resources. In parallel, decarbonization will involve electrification of key sectors including building and transportation. Electrification initiatives are projected to result in significant growth in electricity demand, potentially doubling demand by 2050 [1,4]. Demand is projected to increase overall and particularly at peak periods. The North American Electric Reliability Corporation projects peak demand could grow an estimated 12% over the next 10 years (91 GW in total) and even more aggressively in order to reach net zero-greenhouse gas targets by 2050 [5].

The convergence of these two drivers has emphasized the temporal aspects of both supply of and demand for electricity and to what extent they are (or aren't) aligned. A paradigm shift is occurring in grid planning and operation such that it is no longer sufficient to plan a system designed to meet peak energy demand. Instead, planning must now consider how much energy is being consumed, at what times, in what ways, and where, in coordination with resources supplying that demand. As a result, demand-side management (DSM) strategies seeking to influence when people use energy have become a central component of grid planning and policy initiatives [5,6]. DSM broadly includes tools such as energy efficiency and demand response [7]. Energy efficiency efforts provide persistent reductions in energy use through adoption of more efficient technologies or energy use behaviors. Demand response (DR) efforts seek to alter the timing and magnitude of energy use [8]. While DR has traditionally focused on curtailing energy use at times of peak demand, a more expansive focus on demand flexibility, emphasizing flexible operation of building energy use generally, has emerged [7].

Recent modeling [4,9] has illustrated the ability for DSM to provide numerous grid benefits, including increasing efficiency of power system operations, smoothing peak demands, aligning demand with renewable generation, reducing curtailment of resources and price volatility, and overall reducing annual electricity use. Such benefits could amount to an estimated 8% reduction in carbon emissions and 9-10% cost savings for grid system operation by 2050. This equals savings of upwards $10 billion in costs that would otherwise largely be passed to customers through electric rates [4]. Such efforts could also help mitigate costs with the expected grid infrastructure build out that will be required to support increasing demand, support resilience in the face of disruptive events, and advance equity-related outcomes if deployed intentionally [5].

Given these myriad benefits, there has been increasing policy attention towards growing resources, particularly around demand flexibility. The Department of Energy's Decarbonization Blueprint [2] set an objective of tripling demand flexibility potential by 2050 compared to 2020. Similarly, in 2023, the California Energy Commission adopted a goal of procuring seven Gigawatts of flexible load resources - equivalent to the amount of electricity capable of powering seven million homes - by 2030 to support transitioning to 100% clean energy [10]. In Vermont, transmission planning efforts assume 75% of all electric vehicle demand will be controllable during peak hours when estimating where potential grid infrastructure may need to be upgraded [11]. In order to achieve such ambitious objectives, policymakers, planners, and utilities envision the residential sector will play a significantly more active role in grid management during this transition occurs [2, 6, 12].

1.2 The Role of the Residential Sector in Energy Transitions

More active participation of the residential sector will be enabled by the diffusion of emerging smart technologies into the home. These technologies, broadly described as smart home energy management systems (SHEMS) or smart home technologies, include a variety of hardware and software components that allow more granular control over residential electricity demand. Technologies include smart appliances and space conditioning controls, bidirectional EV charging, battery or thermal storage, customer electric panels, and residential solar generation, and whole building monitoring and sensing networks [2, 13].

In combination with the evolution of the smart grid and Internet of Things, these technologies offer advances in data collection, processing, and monitoring, user interfaces and engagement, and automation capabilities [14–16]. They are expected to provide an influx of data on how people and buildings use energy, two-way communication capabilities to share this information between customers and utilities, and enhanced automation features to allow for more granular opportunities to manage energy use in homes.

Estimates of future electricity use in buildings by Langevin and colleagues [9] suggest the residential sector will account for the largest share of annual electricity use and summer and peak demand, accounting for between 1.4 and 1.7 times more peak load than commercial buildings. Space heating and cooling in particular, in addition to water heating, refrigeration, and home electronics and "miscellaneous loads" not otherwise specified are expected to significantly contribute to both annual and peak demand. However, while this sector is expected to significantly contribute to growing demand, it also is expected to have significant potential to reduce annual and peak loads, potentially accounting for more than 50% of the estimated potential for demand reductions from energy efficiency and demand flexibility [9]. Despite this modeled potential, few real-world programs have been deployed at scale. The vast majority of efforts to estimate demand flexibility potential stem from simulation models [7]. Real-world demonstrations to date show mixed results with regards to energy savings and other benefits likely to accrue to residents like comfort and convenience [17]. As emphasis on such initiatives continues to grow, many questions remain around how smart technologies will be deployed and what energy-related impacts they will have, how they will implicate agency and control over energy use in socio-technical ways, and what populations might be disproportionately impacted by efforts to shift timing of energy use.

1.3 Understanding the Human Dimensions of Smart Home Energy Systems

There are differing visions for how SHEMS will or should be deployed in order to support DSM efforts. Focus tends to center on the advanced information-based and automation functionalities of these technologies and how they can promote either behavior-based or technical approaches to managing energy use [18]. Technical approaches are often conceptualized as enhancements in "direct control", offering opportunities for SHEMS to manage appliances in a way that reduces energy use either through algorithmic control or remote control by a user [15, 16]. Alternatively, SHEMS activity or behavior-based approaches focus on opportunities to provide the user in-depth information about their energy consumption and market prices and encourage them to change energy use patterns [13, 18]. The extent to which technical and social aspects of energy systems are considered has historically been skewed along disciplinary lines [18,19] and investigated separately instead of as parallel paths integrated into a holistic understanding of energy use and how to shift it [20].

Policy and research often focus on technical solutions towards managing demand with appliances in residential homes seen as capable of providing critical grid assets needed to manage increased energy use and peak demand [2, 5]. For example, in2022 the California Public Utility Commission [21] argued "For large numbers of customers (both residential and commercial) to adopt flexible demand management solutions at the scale necessary to support the future electricity grid, automation technologies for controlling various end-uses and DERs must be inexpensive and ubiquitous. For this to be true, there must exist a robust and stable policy pathway that is standardized, easy to implement, and allows the industry to develop low-cost, flexible demand management capabilities and integrate them into smart end-use devices and DERs by default for use by all customer classes." (2) Yet critical assessments of the potential for SHEMS to advance grid objectives call for greater attention to the social dimensions of smart home systems to fully understand and develop effective smart systems [22].

As smart technologies are deployed to the residential sector, home energy management strategies increasingly intersect with everyday life and shift the ways people experience and interact with buildings [23]. Although this raises questions of agency [24–26] and energy justice [27,28], there has been surprisingly little investigation of these critical issues to date.

While the ability to more granularly control energy use in homes is a central focus of the deployment of SHEMS, little attention has focused on how their modes of deployment influence agency in smart home systems. Yet as noted by Adams and colleagues [26], DSM programs employing smart technologies "could be seen as exemplary social and technical experiments in their efforts to redistribute agency between users, grid operators, and energy companies." (3) and recent work has called for a greater understanding of household agency in smart energy transitions [29]. Consideration of agency raises questions of how control is defined, what objectives SHEMS are being deployed to achieve, who is identifying and setting those objectives, and what roles actors are expected (or not expected) to play in the control of home energy use moving forward. If control-based solutions are to be deployed rapidly at scale, deep considerations of how control is defined and who possesses the agency to wield it are imperative. As state and federal policies increasingly look to advance the vision of the future energy systems with rapidly increasing amounts of energy flexibly managed through technical automation of home devices, it remains unclear what level of public support exists for this vision [26]. Affective influences such as control, uncertainty and trust influence innovative technology rejection [30] and people are more likely to participate in automated demand-side management efforts if they align with their values, fit within current daily schedules, and understand how and why energy use is being managed [26]. Even among experts, conceptualizations about the role of control in the smart grid differ and at times conflict regarding who will hold control in future systems [31].

As agency questions emerge, the previous decade has also shown significant growth in scholarship and policy focus on energy justice [32, 33]. In 2021, the Biden Administration initiated the Justice40 initiative via Executive Order 14008 [34], which seeks to direct 40% of the investments in climate and energy towards disadvantaged communities. At the state level, as of 2022, nearly half of states in the US had taken some action to advance energy and environmental equity through avenues such as legislation, executive orders, or Public Utility Commission activity [33]. Additionally, arguments have been made by researchers [35] and practitioners [5] that innovations in the electric system offer opportunities to simultaneously decrease emissions and advance equity and justice considerations if intentionally deployed. However, there is also the risk of exacerbating inequities if not carefully considered [36]. There is currently a limited but growing body of research at the intersection of demand flexibility and energy justice, which recognizes that the ability to be flexible in the way energy is used requires some capacity, dependent on both social and technical aspects of energy use and daily life [27]. This work is largely focused on the inequitable distribution of this capacity [27, 37] and how that manifests in different communities experiencing inequitable financial and nonfinancial impacts of these initiatives.

However, a critical first step in understanding distributional impacts of programs and policies in modeling and analysis is identifying who may be at risk of experiencing disproportionate shares of burdens [38]. Despite initial evidence of inequitable distribution across populations, there has been less attention on who might be impacted both in research [37] and policy [33], a critical first step to accurately understanding how they might be impacted and to what magnitude. This has been identified as a key area for future research in order to inform procedural efforts to bring more diverse and the most impacted voices to the decision-making table and into the structures of analyses. This is necessary to accurately estimate and evaluate impacts experienced, and develop strategies to mitigate them [38].

1.4 Approaches to Date to Address these Issues

For a typically slow-moving industry, new technologies, the needs of the grid, and consumer adaptations to ongoing changes are evolving quickly. Although the first published demonstration of a fully automated, energy-smart home appeared over 30 years ago [39], seemingly little definitive evidence exists to show the impact of SHEMS in the residential sector [36]. Few large-scale, real-world deployments in DSM programs exist to provide data on realistic potential energy impacts [7, 40]. Empirical studies that have occurred continue to show mixed results regarding the ability for these programs to deliver tangible benefits to residents [17] and suggest potential inequities are possible without specific attention to how programs are deployed [28, 36].

With a shortage of real-world evidence, energy models, data science, and decision support tools will play a powerful role in aiding utilities and policymakers as they explore new DSM opportunities. Such tools have long supported decision-making in the energy industry, but often reflect predominantly technical perspectives [41] with growing calls for better representation of people in modeling and analysis to better understand interactions between people, technologies, the built environment, and broader energy systems [7, 23, 42]. Misrepresentation and simplistic consideration of the social aspects of the smart home energy system or the complexity of societal activity patterns could lead to inaccurate assessments of energy savings strategies [22], inherently limit the capacity for such efforts to holistically explore promising program opportunities [41,43], and potentially perpetuate existing inequities instead of addressing them [38]. As such, a need exists for a suite of new tools and frameworks, rooted in a socio-technical understanding of the complex drivers of energy consumption and experiences in energy systems, to support decisions in the future. Such frameworks will need to be capable of illustrating the complex interactions of people and technologies in the energy system and envision the many paths forward.

1.5 This Research

This dissertation aims to address the identified gaps in research and policy and critically reflect on how the human dimensions of energy use are currently situated in SHEMS research. Through three research chapters, I develop interdisciplinary tools and analyses to support a holistic understanding of how smart home energy management systems (SHEMS) might impact the grid as a whole and the people for whom it was built to serve.

In my first paper (Chapter 2), I conduct a systematic meta-review on the smart home energy management system literature to understand dominant discourse around the implementation of SHEMS. The results show a body of research skewed towards techno-centric approaches to smart home energy management and a lack of integration between the social and technical disciplines.

In the second paper (Chapter 3) I propose a multidisciplinary taxonomy of control in the smart home which defines control as both a function of technical automation and relationships between actors in the energy system. The outcome is a scenario analysis tool which defines four characteristic types of control. Review of illustrative case studies of each type reveal a number of considerations for future policy and program development including the extent to which dominant views of SHEMS-enabled control shift agency over energy use away from residents.

In the final paper (Chapter 4), I explore how indicators used to identify disadvantaged communities predict patterns of household activities and adoption of enabling technologies related to demand flexibility. Results show that income, race, education, housing type and tenure, age and disability significantly correlate with activity patterns and technology access. I reflect on how this may impact capacity of these populations to engage in demand flexibility initiatives and the need for more nuanced understandings of customers in programs and policies seeking to advance these efforts.

In Chapter 5, I conclude by reflecting on the development of this body of research and how the results of this work collectively offer insights on the need for future research and policy to holistically evaluate the implications of new innovations for diverse actors in the energy system.

Chapter 2

Of impacts, agents, and functions: An interdisciplinary meta-review of smart home energy management systems

[1]

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Abstract

Smart home energy management technologies (SHEMS) have long been viewed as a promising opportunity to manage the way households use energy. Research on this topic has emerged across a variety of disciplines, focusing on different pieces of the SHEMS puzzle without offering a holistic vision of how these technologies and their users will influence home energy use moving forward. This paper presents the results of a systematic, interdisciplinary meta-review of SHEMS literature, assessing the extent to which it discusses

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the role of various SHEMS components in driving energy benefits. Results reveal a bias towards technical perspectives and controls approaches that seek to drive energy impacts such as load management and energy savings through SHEMS without user or third-party participation. Not only are techno-centric approaches more common, there is also a lack of integration of these approaches with user-centric, information-based solutions for driving energy impacts. These results suggest future work should investigate more holistic solutions for optimal impacts on household energy use. We hope these results will provoke a broader discussion about how to advance research on SHEMS to capitalize on their potential contributions to demand-side management initiatives moving forward.

2.1 Introduction

Many new technologies are expected to play a significant role in the ongoing transition towards a clean energy future. Smart home energy management technologies (SHEMS) in particular, such as automated home systems and connected appliances, have long been viewed as promising opportunities to enhance the residential sector's ability to contribute grid resources required to support this transition [8, 44] while providing households with valued services like enhanced comfort and convenience [45–47]. As such, visions of the future energy system often conceptualize the residential sector as a powerful distributed energy resource (DER), enabled by the deployment of SHEMS and coupled with advances in the Internet of Things and broader smart grid capabilities.

With the potential to provide a dynamic combination of production, storage, and flexible demand, many industry stakeholders expect households to become more active participants in the energy system moving forward [12, 48–50]. Yet, exactly how they will participate remains to be seen. As SHEMS continue to emerge uncertainty remains regarding their ability to deliver on hypothesized energy impacts. These uncertainties include what types of energy services SHEMS will be best suited to provide, what functionalities will prove key to unlocking these energy services, and which parties - such as homeowners, utilities, or the technologies themselves - will drive these potential benefits. Seeking to address these uncertainties, a proliferation of research on SHEMS has emerged in the last decade to better understand their role in the grid of the future. However, as noted by Christensen and colleagues [12], "the high degree of 'interpretive flexibility' associated with the 'smart grid' means that is it imbued with very different and sometimes conflicting interpretations of how solutions should be designed" (345). To date, few people have lived in a home defined by smart energy solutions [51] and the research on SHEMS has emerged across a variety of different disciplines. The result has been a scattered body of research that often presents findings on different pieces of the SHEMS puzzle, emphasizing some over others, without offering a clear, holistic vision of how these technologies and their related energy management strategies could impact energy use in the home moving forward.

Seeking to help put the pieces of that puzzle together, this research surveys and analyzes the dominant discourses in SHEMS research on key questions regarding the energy impacts of SHEMS. Specifically, the analysis aimed to assess the disciplinary perspectives involved in this research and the energy impacts, key actors, and technological functionalities expected to play fundamental roles in the future energy system. We believe this research provides several key contributions to the literature. To the authors' knowledge, it is the first review seeking to explicitly assess the extent to which different disciplines contribute to SHEMS research and quantify the relative prevalence of research regarding different pathways through which SHEMS could impact household energy use. This is done by using quantitative metrics to illustrate the frequency at which core SHEMS constructs are discussed in the literature to date. To do so, the authors develop a conceptual model for understanding how SHEMS could deliver energy impacts and use this model to guide an analysis of the current discourse in the field around components of this model. In addition, this research extends the literature through its goals of understanding how different disciplinary perspectives influence the extent to which certain pathways to energy impacts are researched versus others.

We hope the results of this research will provoke a conversation about how to holistically advance research on SHEMS and their contribution to broader energy transitions. We aim to catalyze discussion about gaps in research that need to be addressed to better understand the ability of SHEMS to provide key energy management services and which disciplines might be poised to collectively contribute to those efforts. With these objectives in mind, this paper proceeds as follows: the remainder of section one reviews the background literature on SHEMS, with a focus towards defining the relevant technologies and their key functionalities. Section two presents the author's conceptual model and discusses the method for the review and analysis. Section three presents the results and section four concludes with a discussion regarding paths forward for this field of research.

2.1.1 Background

SHEMS represent a subset of the wider smart home, internet of things, and home energy management product industries [52]. Traditionally, home energy management technologies have been defined as technologies that "enable households to manage their energy consumption by providing information about how they use energy and/or by allowing them (or third parties) to control energy consumption in the home" [53]. In a comprehensive market study of home energy management technologies, Karlin and colleagues [54] identify two key functionalities crucial to the ability for these technologies to augment the way in which households manage energy consumption: the ability to provide control over energy use and information to the user regarding that usage. SHEMS include the portion of this technology space that have the potential to enable both information and control. Technologies typically fall into three high level categories [54]: user interfaces, such as an energy portal or load monitor; smart hardware, like smart plugs or switches, appliances or thermostats; and software platforms that provide home data analytics. As innovation has advanced, electric vehicles, home battery storage, and solar PV are increasingly considered SHEMS as well. Through these functionalities, SHEMS allow for enhanced data flows and services between households and energy service providers [55, 56].

Control functionalities refer to the capability to alter energy use through technologically enabled features and intelligence. SHEMS can provide control to homeowners or third parties through an interface (remote control) or algorithmic control strategies (scheduled automation or optimization based on previous consumption data, user preferences, and/or machine learning, i.e. rule-based control) [54]. Common examples include water heaters capable of being remotely controlled by utilities for direct load control programs and smart thermostats with their ability to learn occupant behaviors and adjust set points accordingly. Technologies with these functionalities have long enabled efficient management of energy consumption in the commercial and industrial sectors, thus the assumption their application to the residential sector would also bring about the chance to capture untapped energy savings naturally follows [57].

In addition, SHEMS offer new opportunities to provide the user in-depth information about their energy consumption and better engage them through a deeper understanding of their home. SHEMS can provide information to building occupants through interfaces such as smartphone apps, in-home displays, or displays embedded in smart appliances [13]. Effects of providing energy feedback to consumers with the goal of driving energy savings, primarily through avenues such as bill inserts or home energy reports and feedback-only devices (e.g., in-home monitors without control functionalities), has been well researched [58]. While these strategies have proven relatively successful in realizing some energy savings, they have struggled to deliver long-term, persistent energy savings or behavioral changes [14, 59, 60].

New technologies, coupled with advanced metering infrastructure, seem poised to offer the chance to build off the existing work on energy feedback and behavior-based programs generally to provide more in-depth information to users regarding energy systems (consumptions rates, as well as sources, production rates, waste, and direct and indirect personal and societal impacts). These technologies also afford the opportunity to facilitate two-way flows of communication between the user, technology, and third parties such as utilities [61, 62]. These new information streams could empower and encourage homeowners to change their behavior to align with the rhythms and needs of the wider energy system through enhancing the visibility of that system, thereby supporting more informed decisions about energy-consuming behaviors [49, 63, 64].

Spurred by these functionalities, SHEMS are expected to impact household energy consumption in numerous ways. Many stakeholders emphasize the potential to bring about household energy savings and related cost reductions both to the user and grid at large, although estimates of the magnitude of energy savings range from negative savings to over 25% depending on the product in use and their functionalities [52, 56]. Alternatively, and potentially more promising, are the load management capabilities of SHEMS [40, 65], referring to their ability to help manage, coordinate, and control the timing of when and how household end-uses consume energy [8]. Indeed, many stakeholders view SHEMS as key to unlocking “flexible demand” in the residential sector capable of matching the variable supply that accompanies increasingly present renewables [24, 66].

As these strategies diffuse into the home and increasingly intersect with everyday life, the question of agency has emerged [25]. SHEMS and their enhanced functionalities theoretically open the door to greater participation of numerous agents in the management of residential energy consumption. These agents include utilities and other third parties, residents, or the smart technologies themselves [66]. A spectrum of different visions regarding how to best to deploy these technologies to maximize their energy management potential exist. Research to date has highlighted uncertainty regarding which parties or technologies should be tasked with managing energy use in the home to access the greatest savings potential [24]. As summarized by Christensen, Gram-Hanssen, and Friis [12], “Some argue for remote control with as little active participation from residents as possible...others work with designs that aim to involve residents actively through continuous information about real-time prices” (345).

Diverse disciplinary perspectives underscore these various conceptualizations of how SHEMS will deliver the greatest energy benefits. Within the realm of energy studies, different disciplines have increasingly been shown to influence how researchers view the role of actors within the energy system in driving energy savings. Stern [67] argued that overreliance on one disciplinary perspective (ex. economic models) could lead to inaccurate conceptualizations of energy consumers and result in overlooking promising policy solutions that other disciplines (such as the behavioral sciences) might otherwise shed light on. Recently, work by Moezzi and Luztenhiser [68] and Strengers [69] has more specifically investigated the ways in which various disciplinary perspectives implicate different actors and technologies in residential energy use and lead to numerous hypotheses surrounding why they use energy and solutions to manage that use. While each perspective brings a partial truth to the table [68], such research suggests that viewing issues of home energy use from a multidisciplinary lens could help develop more robust framings of problems, understandings of the agents of change in the system, and resilient solutions moving forward [69].

Yet, to date, "smartness" in grids, technologies, and systems has often been defined in terms of technical potential and advancements that enable things to think and act for people [70]. Research in the energy sector has been continually shown to have a technical skew. Providing a historical perspective, Wilhite and colleagues [20] discuss the early dominance of device-centric approaches to demand-side management beginning in the 1980s that only started to give way to the social sciences when predominantly technical and economic solutions failed to deliver on expected potential. Supporting this analysis, Sovacool [19] found that social sciences such as psychology, sociology, and public policy made up less than 20% of the research published in energy studies journal articles between 1999 and 2013.

Recent research suggests this trend has continued as innovations in smart technologies have emerged. Darby [40] discusses two dominant narratives in the field, both centered around active technologies and passive users: the first focused on a passive user amid active technologies aimed at providing comfort and convenience, the other centered around home automation for the sake of allowing buildings to provide and receive grid services. Janda and Topuzi [71] describe narratives where smart technologies serve as the "hero" as compared to less common narratives which emphasize learning by society to overcome complex challenges. Those in favor of a more technological approach argue that energy management systems are in a better position than the user to control energy use due to their ability to alleviate uncertainty related to variables such as prices and weather and plan the appropriate response [72] and issues surrounding persistence of behavior change [73].

However, many strategies that include or rely on the user in efforts to positively affect home energy use do exist [74] and automated control strategies will likely not be sufficient to render them obsolete. Innovations in remote sensing and machine learning offer the chance to improve behavior-based demand-side management strategies [40], including more effective eco-feedback interfaces that are salient, precise, and motivating [75] and "eco-feedforward" advice and prompts for personalized actions or new routines households could assimilate into their lifestyles [76]. Pilot studies around such programs have already begun to show initial promise [77–79].

As a result, there have been a series of calls for a more holistic, integrated solution to managing energy in the home, developed by embedding technological solutions into a deep understanding of context and users [80, 81]. While the smart home has the potential to incorporate different strategies around information and controls to drive energy benefits, a better understanding of which of these strategies (either alone or integrated together) will deliver the greatest energy impacts is needed. Such integrated approaches could find a synergistic relationship between the role of the resident and their technologies [82]. Broader, ongoing changes in the energy system are creating opportunities to radically rethink the approach to demand side management, relationships between users, technologies, and energy providers [45]. As argued by a growing body of authors in the field, taking advantage of this opportunity and not repeating the historical trend of relying on purely technical or automated fixes will be necessary to meet ambitious energy transition goals.

In order to support these efforts, this research aimed to assess the dominant discourses in SHEMS research on key questions regarding their energy impacts. In particular:

1. What disciplinary perspectives have contributed to SHEMS research?

2. To what degree has the SHEMS literature focused on different types of energy-related impacts?
3. To what degree are different agents (e.g., end-user, third party, or the technologies themselves) considered to be driving the energy-related impacts of SHEMS?
4. What functionalities underlying the energy impacts of SHEMS have been the focus of research?
5. How is disciplinary perspective associated with the types of impacts, agents, and functionalities emphasized in SHEMS research?

We hypothesize that this research will show a skew towards technology-centric, controls approaches to managing energy use despite repeated calls for more interdisciplinary and user-focused energy research over the last several decades. We believe this current focus limits our understanding of SHEMS ability to deliver desired energy impacts, both to the resident and the grid.

2.2 Method

A systematic meta-review of the SHEMS literature was conducted to answer the research questions outlined above. The analysis focused on SHEMS review papers as a proxy for the state of the literature, capable of providing a landscape view of ongoing trends in and discourse dominating the research and researchers in this space. Within the last decade, a multitude of review papers have been written on the topic of SHEMS. Given the expansiveness of the field and the rapid rate at which it is growing, we sought to develop a methodology that would allow us to reasonably assess the whole state of the field spanning all disciplines. The study of review papers allowed this research to capture and assess a broad swath of the literature over a long period of time and fit our goals of understanding the dominant discourses, in terms of who is studying SHEMS and their foci. The next sections describe the search criteria used to identify relevant papers and the method of analysis.

2.2.1 Literature Search

Papers included in the review had to meet three sets of criteria:

- ***Review Paper:*** For the purpose of this research, "review paper" was defined as a paper dedicated to assessing the literature relating to the implementation of SHEMS. Thus, single study papers were excluded from the sample. If a paper included both a review and the presentation of new research, only the results of the review section were included in the analysis.

- ***SHEMS and Key Functionalities:*** Each paper had to include a discussion of SHEMS and at least one of the two key functionalities identified in the literature review above - namely information and/or control. Papers that did not discuss at least one of these functionalities were therefore excluded. While there are many strategies available to alter home energy use, this review focused specifically on those that employ SHEMS. For example, reviews that discussed information provided to users through smart phone applications would have been included but reviews that focused on other strategies, such as information provided to users on bills or home audits, were excluded. If a paper discussed both SHEMS and non-SHEMS related strategies it was included in the sample and only those strategies involving SHEMS were considered in the analysis. In addition, the criteria for SHEMS also sought to ensure papers primarily considered energy management in the residential sector. Papers that only considered other sectors (ex. commercial) were excluded. Papers that discussed multiple sectors (ex. residential and commercial) were included and only the results explicitly related to residential homes were analyzed.

- ***Focus on Energy Impacts:*** Finally, papers needed a core focus on the ability for these technologies and their functionalities to specifically manage energy consumption once installed in homes and report empirically derived results regarding the impact of SHEMS on home energy use. Since SHEMS are a subset of the broader space of smart home technologies, these criteria sought the exclude reviews that 1) discuss the broader smart home space without considering the energy savings or management potential of the technologies and 2) solely focus on topics such as security, communications protocols, and device interoperability. While these topics are certainly important for the ability of SHEMS to function optimally in the home, they are tangential to our core focus on understanding the impacts of SHEMS on energy use. In addition, the criteria to discuss empirically derived energy impacts excluded papers that only discussed hypothetical benefits of SHEMS for managing energy. If a review discussed both hypothetical and empirically supported impacts, only the findings for which empirical support was explicitly cited were coded. For the purpose of this analysis, we defined energy impacts as any outcome from the implementation of SHEMS related (directly or indirectly, positively or negatively) to how a given household consumes energy.

Keyword searches were conducted within four scholarly databases: Google Scholar, SCOPUS, Web of Science, and PsychInfo. Keywords included combinations of "home energy management", "smart home", "control", "information", "feedback", and "review". The searches were conducted in September and early October 2018, thus including papers published up until that time. The authors did not restrict the timeframe for review papers, and thus included articles from any year so long as they met the criteria. Journal articles and conference proceedings were included in the final sample, but non-peer reviewed publications, such as white papers and industry reports, were excluded in the final database even if their content otherwise met the criteria. To determine if a paper met the criteria, the abstract, title, and keywords were first reviewed. If necessary, the body of the text was also scanned.

2.2.2 General Procedure

Papers identified for inclusion were compiled in a master database for coding. Coding was performed on the "results" of each paper. If a paper had an explicitly titled "results" or "findings" section, that section was coded. However, a large majority of papers in our sample did not have such sections. In these papers, the "results" section was taken as the main body of the text, excluding the introduction, methodology, and conclusion or discussion. The rationale for this decision was supported by reviewing the final paragraph of each introduction section to confirm they outlined or otherwise set up the subsequent sections as a review and the main contribution of the paper. The authors felt the results section provided a consistent unit of analysis across each paper despite their variations in length and structure. All text, tables, and figures in the results sections were included in the analysis and coding.

Each paper in the sample was coded across four primary dimensions corresponding to the research questions, as summarized in Table 2.1. The procedure for the analysis is also visually represented in Figure 2.1. Coding procedures were conducted according to a coding guide, derived deductively from the research questions and hypotheses driving the study and a conceptual model of SHEMS developed by the authors as represented in Figure 2.2.

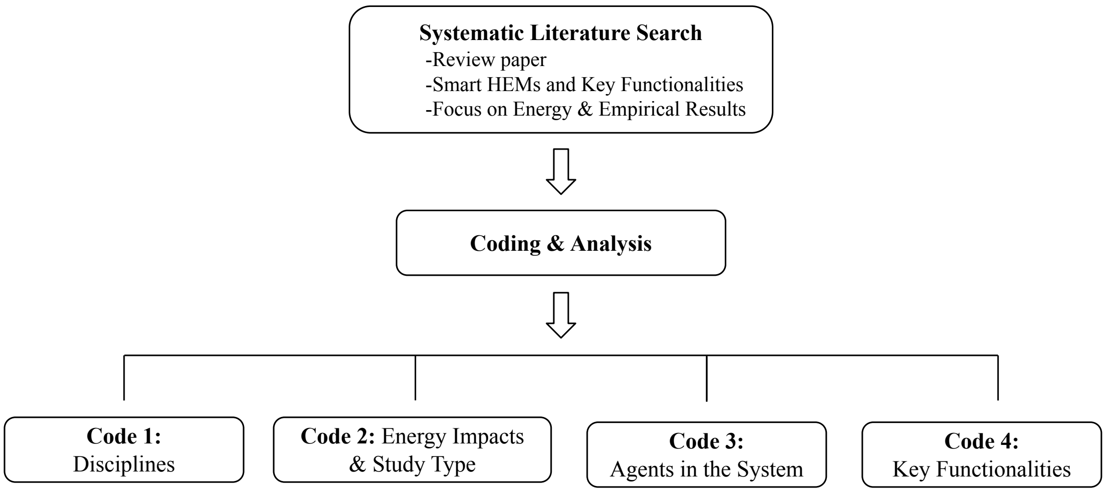

Figure 2.1: Flow diagram for search, coding, and analysis.

The authors used a quantitative approach to content analysis, recording when each paper met the criteria for a pre-established code level. Similar methodologies have been used in related studies, such as in the work of Sovacool [19]. The following subsections detail a conceptual model that organizes the coding scheme and the coding method.

2.2.3 SHEMS Conceptual Model

Figure 2.2 illustrates the authors' conceptual model of SHEMS, which was used to guide the coding scheme. The aim of such a model was to create a holistic visualization of the key components of SHEMS and potential pathways towards realizing energy impacts. The conceptual model ultimately includes three core components: agents capable of taking action in the system, SHEMS functionalities providing the ability to deliver information and control, and the resulting energy impacts driven by the relationships between the agents and SHEMS functionalities.

Within this model, three key agents exist: SHEMS technologies themselves, users, and third parties. Users and SHEMS operate within the home while third parties are primarily external to it. Within the system, any given agent could be either active or passive. Active agents are defined as those components of the system directly driving the creation of the energy impacts, such as a user making behavior changes, a smart appliance optimizing energy use, or a user or third party remotely controlling end uses through SHEMS interfaces. Alternatively, passive agents are relatively unchanging or assumed constant components of the system, such as an in-home display sitting on a counter and providing information, an individual whose behavior is assumed to remain the same, or a third party setting a dynamic pricing scheme and relying on users or SHEMS to react accordingly.

The model further incorporates the two key functionalities as identified by Ford and colleagues [83] - information and control. These functionalities are depicted by the dashed and dotted arrows within the diagram. Dotted arrows represent flows of information between agents and dashed arrows represent control actions.

Finally, the model illustrates potential energy impacts related to SHEMS. The authors hypothesized that five primary energy-related impacts could result from SHEMS: energy savings, load management, cost savings, energy education (i.e., awareness and knowledge), and specific behavior change. These impacts result from interactions between agents and functionalities.

Taken together, Figure 2.2, illustrates different pathways to achieve different energy impacts through the deployment of SHEMS. The colored arrows illustrate the diversity of pathways through which impacts could be generated based on various interactions of agents within the system via information and control functionalities. For example, the orange arrows originate between the SHEMS and user, representing a flow of information between these agents.

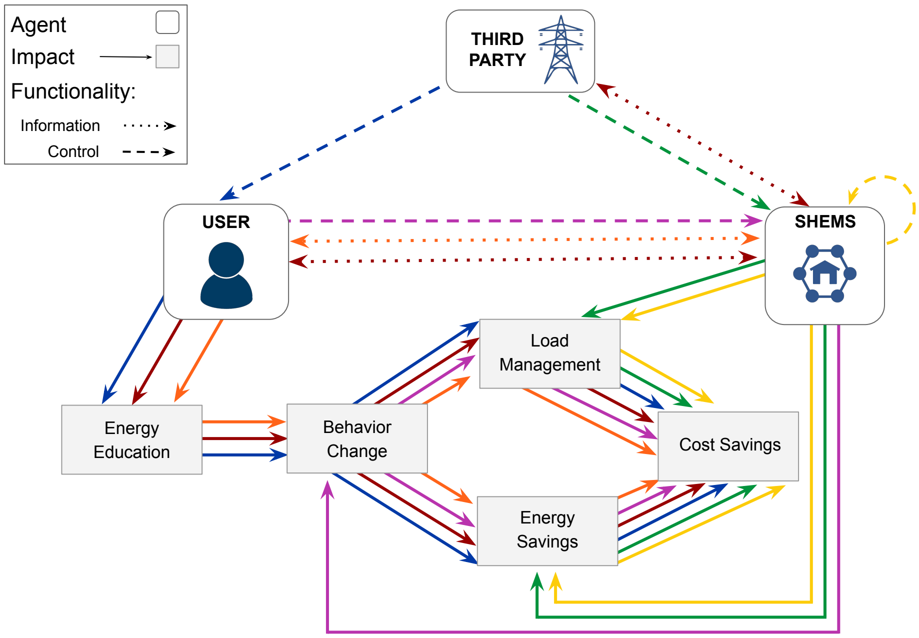

Figure 2.2: Conceptual model representing the relationships between agents, functionalities, and potential energy impacts related to SHEMS.

This information might then lead the user to better understand their energy consumption (orange arrow from the user to the energy education impact) and therefore change their behavior (orange arrow from energy education to behavior change). This behavior change might reduce peak energy use (load management), help conserve energy (energy savings), and each of these impacts could result in a reduction in the user's energy bill (cost savings). As such, the initial information passed between the user and SHEMS could result in all five of the hypothesized impacts of energy education, behavior change, load management, energy saving, and cost savings. The figure illustrates six example pathways but is not an exhaustive account of all possible pathways in order to maintain visual clarity.

2.2.4 Coding Guide and Method

The authors developed a coding guide to assess the extent to which each review paper discussed the different components of the conceptual model described above. An overview of the guide is presented in Table 2.1 and a more detailed description of the codes are provided in the following sections.

Table 2.1: Coding guide used to analyze each paper.

Research Question	**Procedure**	**Coded Constructs**
Discipline: What disciplinary perspectives have contributed to SHEMS research?	Code the department of each author *(if department not available, look to department of highest level of education) and then aggregate all authors to determine code for each paper.*	Used the classification scheme developed by Sovacool [19] which includes 20 categories of disciplinary affiliation[2]: Anthropology Business Communication Computer Science Development Economics Energy Engineering Gender Geography Hard Sciences History Law Life Sciences Philosophy Planning/Architecture Political Science Psychology Public Policy Sociology In addition, allowed for "interdisciplinary" affiliation, if 1) author had training in or belonged to two or more departments or 2) if the paper had authors from two or more separate disciplines.

[2]See Sovacool ([19], pg 4), Table 2 for a more in-depth description of which disciplines were included in each of the 20 high level categories.

Research Question	Procedure	Coded Constructs
Energy impacts: To what degree has the SHEMS literature focused on different types of energy-related impacts?	Code types of impacts for which the paper reviews empirical evidence. Each impact coded as “1” if present in the paper, “0” otherwise.	Energy Savings *Example keywords: “energy savings”, “conservation”, “energy reduction”, “energy efficiency"* Load Management *Example keywords: “load scheduling”, “direct load control”, “peak time rebates”, “load shifting”* Cost Savings *Example keywords: “reduce energy costs”, “cost savings”, “reduce total costs”* Energy Awareness and Education *Example keywords: “knew their energy use”, “using feedback to explore device usage”* Behavior Changes *Example keywords: “energy management behavior”, “change their habits”, “turn off the air conditioning”*

Research Question	Procedure	Coded Constructs
Energy Impacts *cont.*	Code type of studies in which each impact was observed. Each study type coded as "1" if present in the paper, "0" otherwise.	Field Study *Studies on real-world, or "in the wild", implementations of SHEMS, including test homes, pilot studies, and utility interventions* Modeling & Simulation *Virtual modeling of SHEMS implementations*
Agents: To what degree are different agents considered to be driving the energy-related impacts of SHEMS?	Code types of agents involved in driving energy impacts. Each agent coded as "1" if present in the paper, "0" otherwise.	SHEMS *Individual appliances (ex. smart thermostat) or entire systems (ex. smart home platform)* Users *Individuals within the home interacting/adopting the SHEMS* Third Parties *Organizations involved in deploying and/or controlling SHEMs in the home, ex. utilities or third party aggregators*

Research Question	Procedure	Coded Constructs
Agents *cont.*	Identify whether each agent holds active and/or passive roles in the system.	Active *Actors driving the creation of the energy impacts* Passive *Relatively static or unchanging actors in a system*
Functionalities: What functionalities underlying the energy impacts of SHEMS have been the focus of research?	Code type of SHEMS functionalities employed to drive energy impacts. Each high-level functionality (information, control) coded as "1" if present in the paper, "0" otherwise. Further, descriptors of that functionality (rule-based, remote control, feedback, prompts) coded as "1" if present in the paper, "0" otherwise.	Control-based *Rule-based or remote control* Information-based *Feedback, Prompts*

To begin, each paper was coded for disciplinary perspective. First, the disciplinary affiliation or training for each of the contributing authors was coded. For this, the authors referred to the methodology used by Sovacool [19] to assess the disciplines contributing to energy studies. To code the discipline of each author, the departmental affiliation stated on the publication was recorded. If no affiliation was stated, then further research was conducted to determine the discipline of the author's highest degree. If neither of these could be identified, the disciplinary code was left blank. These affiliations were then sorted into the twenty disciplinary categories established by Sovacool [19] and indicated in Table 2.1. The designation of interdisciplinary was recorded if an author either listed two or more different departmental affiliations or received a degree in two or more departments. After each author had been coded, those codes were aggregated to develop a single code for each paper. If the discipline of each author on a paper was the same then the paper was assigned that discipline. A designation of interdisciplinary was given if a paper included authors of at least two different disciplines.

Next, the main body of each paper was reviewed to identify the energy impacts resulting from empirical studies of SHEMS. Energy impacts were coded according to the guide presented in Table 2.1. While the authors primarily focused on the impacts included in the conceptual model, additional themes were allowed to emerge through coding "other" relevant themes and reviewed after completion of the coding. For each of the energy impacts identified, the authors then reviewed the text surrounding this impact to assess the methodology of the study being reviewed, agents present in the system, and the functionalities employed in realizing the energy impacts. With regards to study methodology, the authors recorded the type of study reviewed if it was explicitly stated. If it was not stated, this code was left blank. In terms of agents, consistent with the conceptual model, actors were coded as either active or passive and, in theory, a system could have more than one active and/or passive agent. Each impact was reviewed to see if was driven by information and/or control functionalities. If available, the reviewers also noted the type of information and controls employed, as noted in Table 2.1.

For the codes related to the conceptual model, coding only occurred if a given concept was explicitly mentioned in a paper (i.e., not inferred or assumed). Codes were recorded in a binary fashion, i.e. denoted as either present in the article (1) or not (0). In addition, a review article was allowed to be coded for multiple constructs under the same code, i.e. codes were not mutually exclusive. For example, a paper could discuss energy impacts related to both energy savings and behavioral changes, consider examples of SHEMS in which the end-user is both a passive and active agent, or review the results of studies using both modeling and simulation and field study approaches. For the latter example, if a review paper discussed both modeling and field studies, those codes would have each been recorded as "1" (i.e. both present in the paper). The coding was completed by the primary author, with co-authors reviewing segments to ensure accuracy and consistency.

2.3 Results

An extensive search returned 31 papers that met our criteria, including 22 journal papers and nine conference papers. All papers included in the final database were published between 2009 and 2018, as illustrated in Figure 2.3. Across this time span, data indicates a relatively consistent stream of publication of SHEMS review papers year over year, with particularly intensive publication periods in 2015 and 2016, with seven and six papers published in each of those years, respectively. These two years alone account for the publication of nearly 42% of the papers in the sample.

All 31 papers that met the criteria are listed in Table 2.2, which summarizes the high-level results of the coding analysis. These results, and their interactions, are discussed more fully

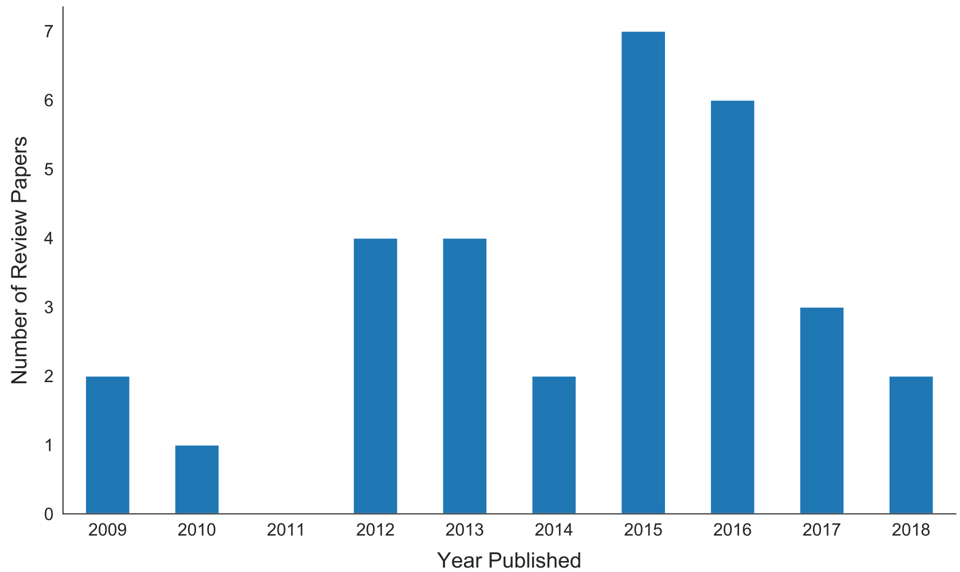

Figure 2.3: Number of SHEMs review papers published by year.

in each of the sections below.

2.3.1 Disciplinary Perspectives Contributing to SHEMS Research

To begin, each of the identified review papers was coded for disciplinary affiliation. Results of this exercise revealed four high level disciplinary categories in the sample: engineering, computer science, planning and architecture, and interdisciplinary. Together, interdisciplinary and engineering papers constituted the large majority, 81%, of the reviews in the sample, comprising 42% (n = 13) and 39% (n = 12) respectively. The remaining papers came from the planning and architecture (16%, n = 5) and computer science (3%, n =1) disciplines.

To better understand the perspectives of the interdisciplinary review papers in the sample, the disciplinary affiliations of their individual authors were analyzed. This analysis revealed a diverse array of disciplines contributing to interdisciplinary papers as represented in Figure 2.4. As with the broader sample of papers, engineering affiliations dominate the sample, representing 40% of the contributing authors. Computer scientists also represent a moderately large share of the authorship, representing 23% of the authors contributing to interdisciplinary reviews. Together, these two disciplines make up just over two-thirds, or 63% of the authors. The remaining one third of the authors, stem from a variety of disciplines including interdisciplinary (9%), hard science (8%), psychology (7%), communications (6%), and economics, energy studies, life sciences, and planning and architecture (2% each).

Figure 2.4 groups these disciplines (excluding the interdisciplinary category) into three high level categories, namely social sciences (shades of blue), technical sciences (shades of red), and traditional sciences (green). Based on these groupings we see that the technical sciences make up the large majority of authors on interdisciplinary reviews (65%) followed by the social sciences (15%), the traditional sciences (12%), and interdisciplinary (9%).

Considering the disciplinary contributions over time, the first review paper in the sample was written from the planning and architecture perspective in 2009. From 2009 through 2018, relatively flat or limited growth in the number of review papers published occurs in the computer science and planning and architecture disciplines, as illustrated in Figure 2.5 which shows the cumulative number of papers published by discipline over time. With regards to the interdisciplinary papers, the number of reviews published each year initially increases linearly from 2012 when the first review paper was published to 2014, then averages about two to three review papers per year from 2015 onward. The engineering review papers follow a similar trajectory after the first two papers are published in 2012.

Table 2.2: List of SHEMS reviews identified and the results of the coding analysis. Blank cells indicate a code was not identified in the review.

Ref.	**Year Pub.**	**Disc.**	**Energy Impacts**					**Agents**			**Functions**	
			Energy Sav.	Load Mngt	Cost Sav.	Behav. Cng	Energy Edu	User	Smart HEMS	Third Party	Info.	Cntrl
[84]	2009	Planning/Architecture	✓			✓	✓	Active	Passive	NA	✓	
[85]	2009	Planning/Architecture	✓		✓		✓	Active	Passive	NA	✓	
[86]	2010	Planning/Architecture	✓			✓	✓	Active	Passive	NA	✓	
[87]	2012	Engineering		✓				Active	Passive	NA		✓
[64]	2012	Planning/Architecture		✓				Passive	Active	Passive	✓	✓
[88]	2012	Engineering		✓				Passive	Active	NA		✓
[89]	2012	Interdisciplinary	✓					Passive	Active	NA		✓
[90]	2013	Engineering	✓	✓	✓	✓	✓	Both	Both	Passive	✓	✓
[91]	2013	Interdisciplinary	✓	✓	✓			Both	Active	Passive	✓	✓
[92]	2013	Interdisciplinary	✓					Passive	Active	NA		✓

[93]	2013	Interdisciplinary	✓					Active	Passive	NA	✓	
[94]	2014	Computer Science	✓		✓			Both	Both	NA	✓	✓
[95]	2014	Engineering	✓	✓	✓			Passive	Active	Passive		✓
[72]	2015	Engineering		✓	✓			NA	Active	Passive		✓
[59]	2015	Interdisciplinary	✓		✓	✓	✓	Active	Passive	Passive	✓	
[96]	2015	Interdisciplinary	✓	✓	✓			Passive	Active	Passive		✓
[97]	2015	Interdisciplinary	✓	✓	✓			Active	Both	NA	✓	✓
[98]	2015	Engineering	✓	✓	✓			Passive	Active	Passive		✓
[99]	2015	Engineering	✓	✓	✓			Active	Active	Passive	✓	✓
[100]	2015	Planning/Architecture				✓	✓	Active	Passive	NA	✓	
[101]	2016	Interdisciplinary	✓	✓	✓			Passive	Active	Passive		✓
[102]	2016	Engineering	✓					Passive	Active	Passive		✓

[103]	2016	Interdisciplinary		✓	✓			NA	Active	NA		✓
[104]	2016	Interdisciplinary	✓	✓	✓			Passive	Active	Passive		✓
[105]	2016	Engineering	✓	✓				Passive	Active	NA		✓
[106]	2016	Engineering	✓	✓	✓			Both	Active	Passive	✓	✓
[44]	2017	Engineering	✓	✓	✓			Active	Both	NA	✓	✓
[107]	2017	Interdisciplinary	✓	✓	✓			Passive	Active	Both		✓
[108]	2017	Interdisciplinary		✓				Active	Passive	Active		✓
[109]	2018	Interdisciplinary		✓	✓	✓	✓	Active	Bpth	Passive	✓	✓
[110]	2018	Engineering	✓	✓	✓			Passive	Active	NA		✓

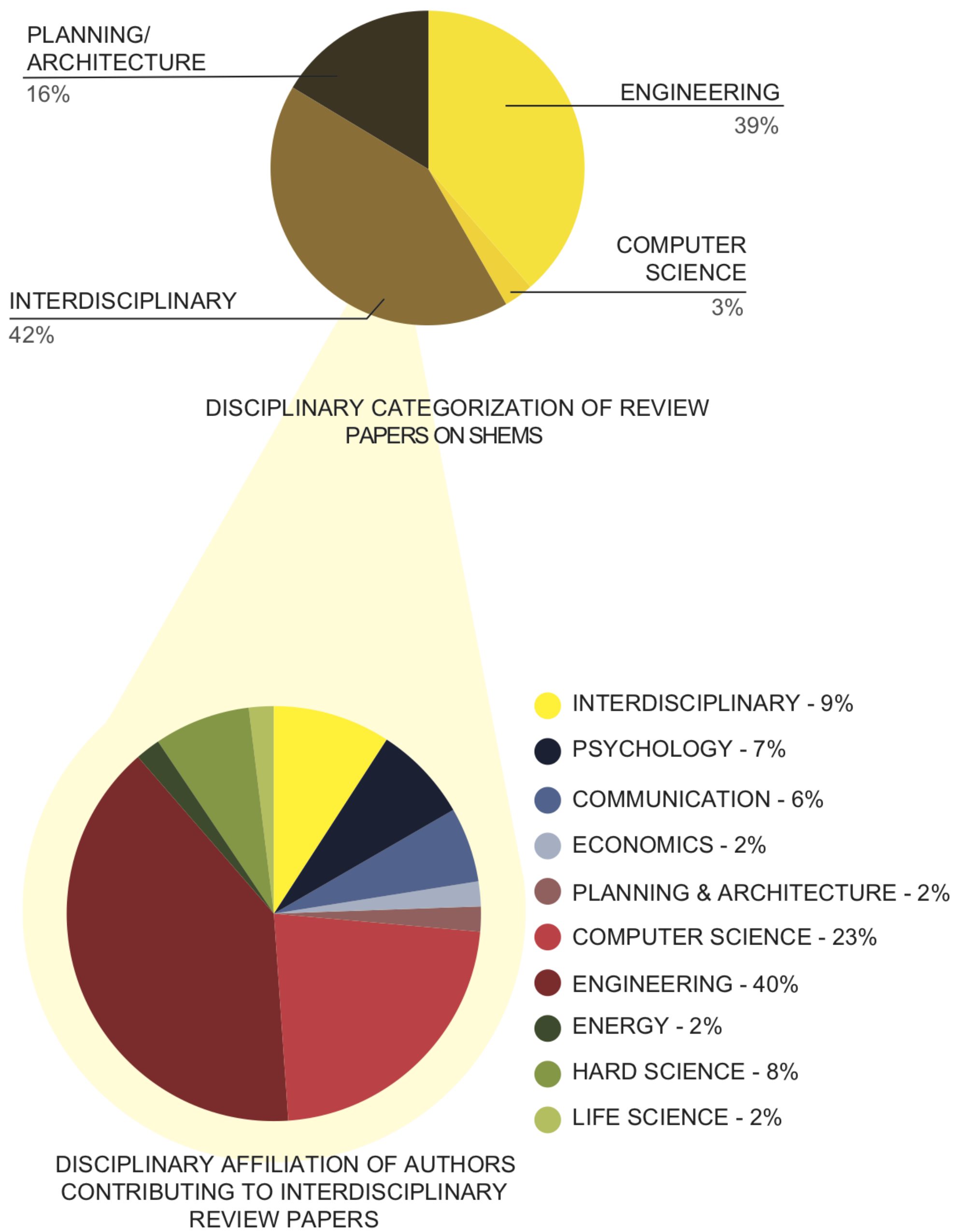

Figure 2.4: Disciplinary breakdown of SHEMS review papers in sample (top pie chart) and disciplinary breakdown of authors contributing to interdisciplinary reviews (bottom pie chart).

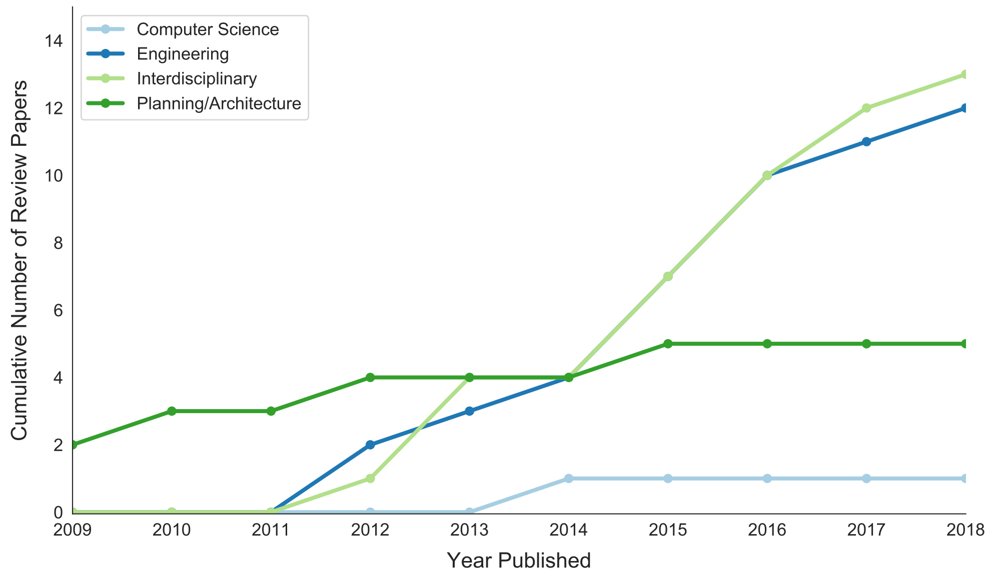

Figure 2.5: Cumulative number of review papers published by year and discipline.

2.3.2 Energy Impacts Discussed in SHEMS Literature

Within the 31 papers reviewed, each of the hypothesized impacts (energy savings, load management, cost savings, behavior change, and energy education and awareness) emerged in at least one paper, as shown in Figure 2.6. No unexpected impacts emerged.

Results reveal that the most commonly discussed impacts of SHEMS are energy savings, load management, and cost savings, appearing in roughly 74%, 68%, and 61% of the review papers, respectively. With regards to energy savings, a majority of the articles broadly discussed the ability for SHEMS, like connected appliances and in-home displays, to drive energy savings at the household level. Review papers reported a variety of energy savings results, ranging from increases in consumption, no impact on energy use, and energy savings upwards of 60%, depending on whether energy savings were referring to

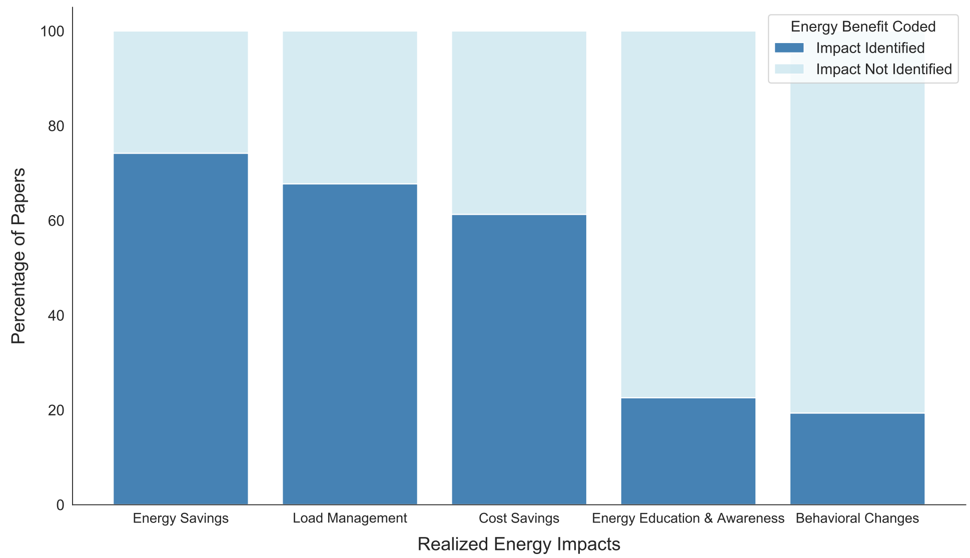

Figure 2.6: Results related to energy impacts discussed among the sample of review papers.

total household or appliance specific consumption. When discussing load management, many review papers commented on the ability for SHEMS to schedule appliance operation or optimize load curves at the level of the household. Here, reviews generally discussed shifting from on- to off-peak hours (and reduction of peak-to-average ratio), with a number of papers seeking to address solutions to rebound peaks, or periods of increased energy use after a demand response event when customers schedule loads at the same time. Although not always explicitly stated, cost reductions seemed primarily related to users of SHEMS in the form of bill reductions. Estimates of energy cost reductions ranged from 5% to 74%; although the majority fell in the 20-30% range, dependent on the rate structure, geographic location, and the technologies involved.

The least commonly discussed energy impacts were behavior change (19%) and energy education and awareness (22%). Reported actual or desired behavioral changes included conservation behaviors such as turning off appliances, in addition to general changes in household habits or lifestyles, with one paper noting end-users stated they wanted to change their behavior as a result of information obtained from SHEMS, but felt unable to do so due to lack of control. Somewhat related, the reviews that discussed educational impacts of SHEMS commented on the ability for these technologies to help users better understand their electricity use patterns or the energy-related consequences of using different end uses. For example, one paper reviewed a study in which a SHEMS device was used as a tool to explore the home and connect actions, such as opening a window, with consequences, like wasting heat.

2.3.2.1 Study Methodologies. As shown in Figure 2.7, the vast majority of energy impacts reported in the review papers were derived from either modeling and simulation experiments or field pilots. For 13% of the papers, the exact study method could not be identified for any of the SHEMS discussed, so this information was not coded. In total, over half of the review papers in the sample (55%) discussed results from modeling and simulation studies, 45% discussed the results of pilot or field studies. 13% of these papers discussed results from both kinds of studies. Looking at the connection between energy impacts and methodologies, certain energy impacts tend to be studied with one type of method over another. For example, behavior change and energy education and awareness were reported based solely on field studies. Alternatively, load management, cost savings, and energy savings tend to skew towards modeling and simulation studies, although are reported based on the results of field studies as well.

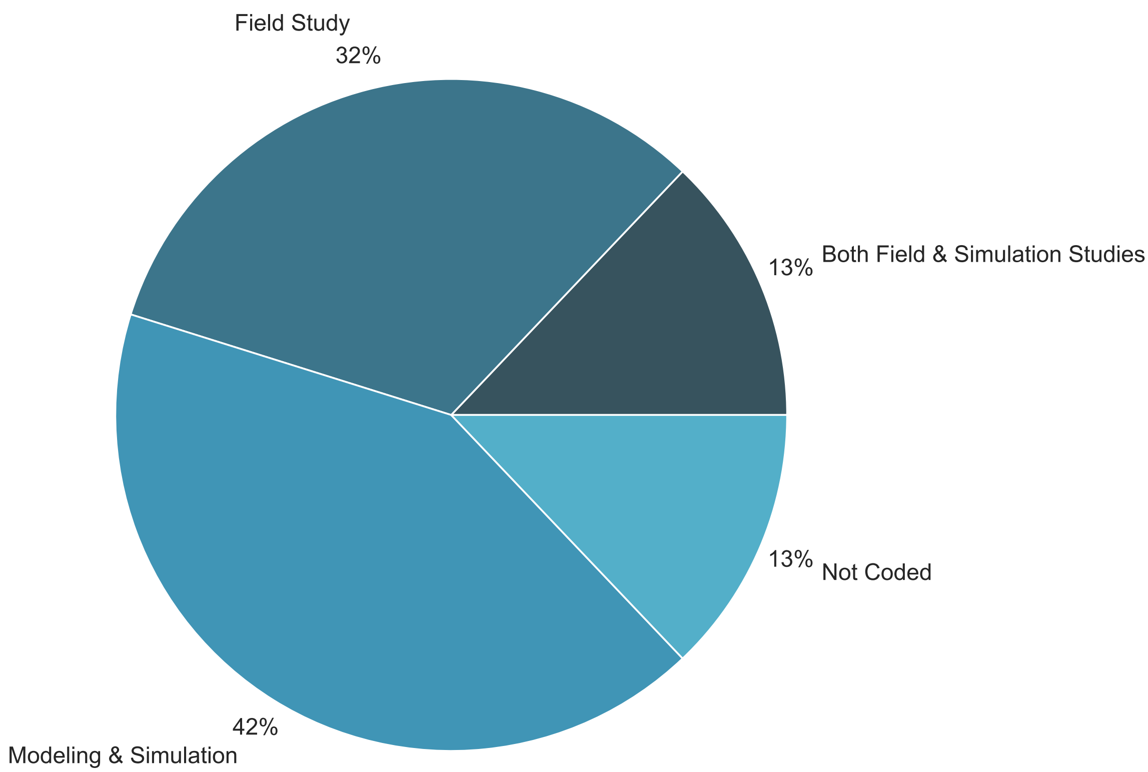

Figure 2.7: Methods used to study the energy impacts of SHEMS.

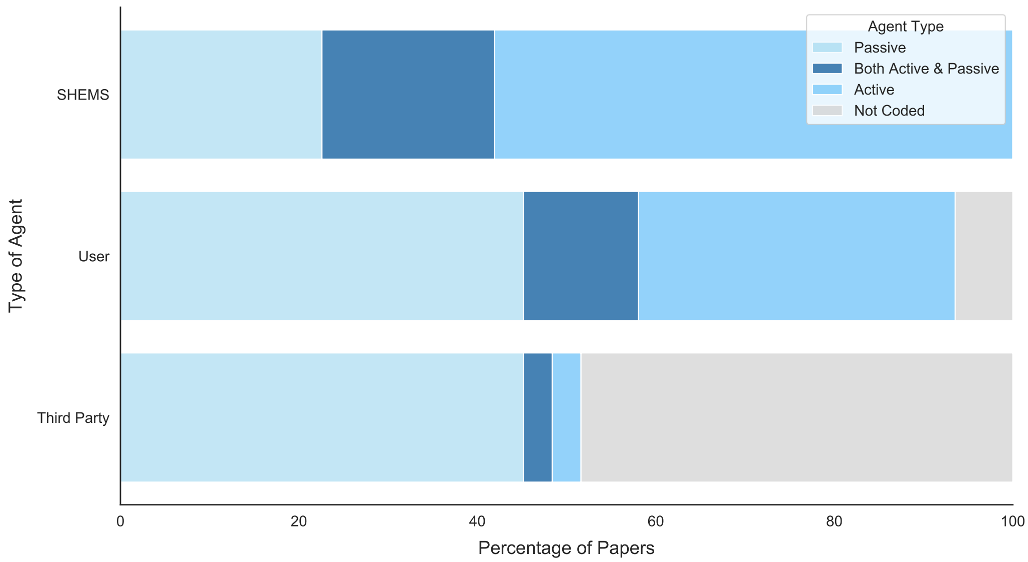

Figure 2.8: Type of agents in SHEMS systems and the ways in which they contribute to energy impacts.

2.3.3 What Agents Drive Energy Impacts

The analysis also sought to identify what agents are primarily implicated in SHEMS driving energy impacts. Given the existing literature, the authors hypothesized the dominant agents would be SHEMS, users, and third parties. As hypothesized, analysis of the review papers revealed these are the three primary agents involved in SHEMS research (no unexpected actors emerged from the review). Since discussion of SHEMS technologies was a criteria for inclusion in the research, these agents were identified in 100% of the review papers (n = 31), followed by users in roughly 94% of the papers (n = 29), and third party actors in just under 52% (n = 16).

Figure 2.8 represents the distribution of agents coded across the review papers and the extent to which they were conceptualized as active or passive components of the system. Of the three agents identified, SHEMS was the one most frequently considered an active part of the system, identified as such in 77% of all review papers. Alternatively, these technologies were seen as passive agents in about 42% of the review papers and conceptualized as both active and passive in just under 20% of the sample. The users were the next most common active agent, coded as active in just over 48% of the papers in the sample. Users were conceptualized as passive in just under 55% of the papers and identified as both active and passive components of the system in about 13% of papers. Users were not identified at all in 6% of the review papers analyzed. Finally, third parties, primarily referring to utilities or other grid-focused actors, were conceptualized as active the least often. Third parties were not mentioned in roughly 48% of the review papers analyzed and when they were mentioned, it was almost exclusively as a passive actor (48% of papers), typically a utility administering some type of dynamic rate structure. Third parties were only considered an active participant in just under 7% of the reviews, which includes papers where they were coded as both passive and active (3%) and just active (3%).

Figure 2.9 shows the correlations between energy impacts and agents as discussed in the review papers. The metric used to quantify correlation was the phi coefficient. This metric is appropriate given the binary nature of the coding data, i.e., a construct was either present (1) or not present (0) in a given review paper. The metric indicates the extent to which specific codes were likely to appear in the same review paper, such that a strong positive correlation suggests both constructs were often discussed in the same papers, while a strong negative correlation suggests that papers tended to discuss one or the other construct, but not both. To orient the reader to the figure, the top left quadrant shows the correlation between different energy impacts. The bottom left quadrant presents the correlation between energy impacts and types of actors in each paper. Lastly, the bottom right illustrates the correlation

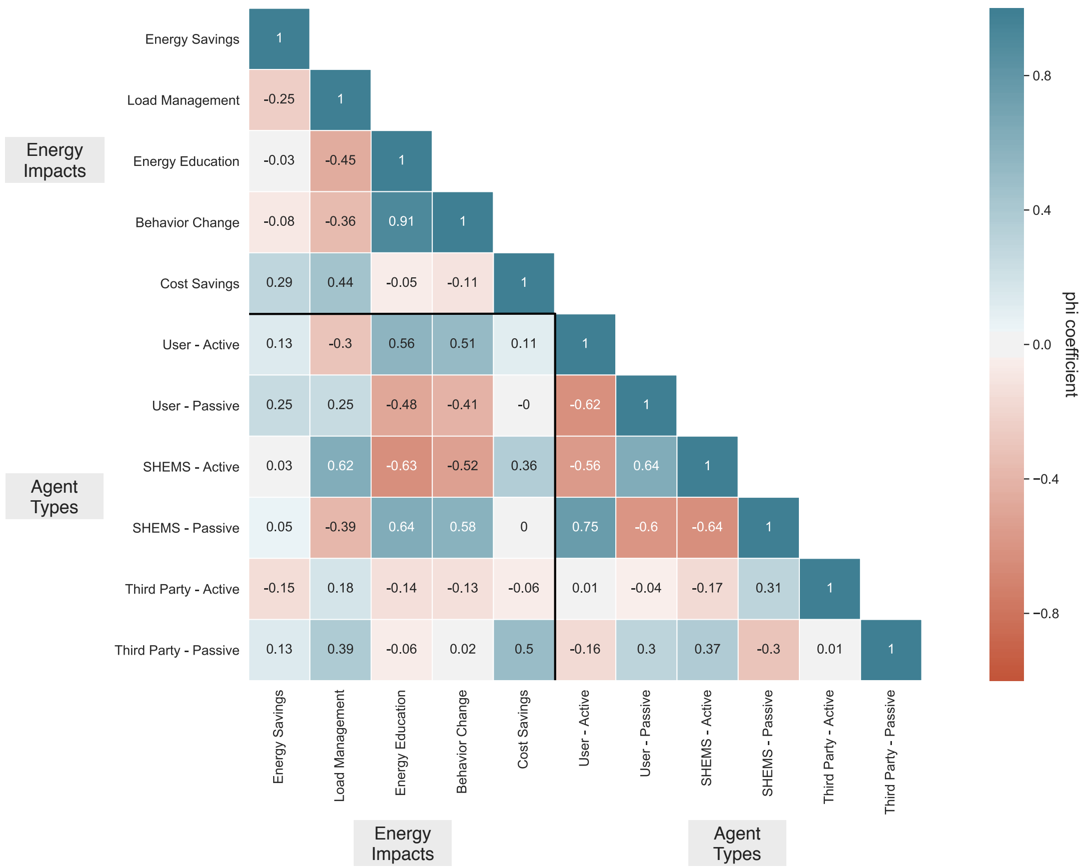

Figure 2.9: Association between energy impacts and different agents in SHEMS systems.

between different agent types. The dark blue cells indicate strong positive correlations and dark red cells indicate strong negative correlations.

From Figure 2.9, a number of observations can be made about the discourse surrounding relationships between energy impacts and the actors in SHEMS. First, considering the relationships between energy impacts, strong positive correlations emerge between behavior change and energy education and awareness (phi = 0.91), suggesting they are often discussed together. The results also suggest a moderate positive correlation between load management and cost savings (phi = 0.44). On the other hand, load management has a moderate negative correlation to energy education and awareness (phi = -0.45) and weak negative correlation with behavior change (phi = -0.36), suggesting they are not frequently considered in the same papers.

Considering the relationships between different agent types, third parties have a weak correlation with all other agents. This is intuitive since these agents are not well represented in the papers reviewed. Looking at users and SHEMS agents, however, stronger trends are observed. For example, a strong positive correlation emerged between active users and passive SHEMS (phi = 0.75) and a moderate positive relationship between passive users and active SHEMS (phi = 0.6). Conversely, moderately negative correlations exist between active SHEMS and active users (phi = -0.64), and between passive SHEMS and active SHEMS (phi = -0.64). There are moderate negative correlations between passive SHEMS and passive users (phi = -0.54) and between passive users and active users (phi = -0.55).

Finally, considering the interactions between agent types and assessed energy impacts, no strong relationships emerge across these constructs. However, there are numerous moderate relationships. The data suggest moderate negative correlations between active SHEMS and energy education and awareness (phi = -0.63) and active SHEMS and behavior change (phi = -0.52). In addition, moderate positive relationships exist between active SHEMS and load management (phi = 0.62) and active users and both behavior change (phi = 0.51) and energy education and awareness (phi = 0.56). We see roughly the same relationship between passive SHEMS and each of these same two impacts (behavior change, phi = 0.58, and energy education and awareness, phi = 0.64). Results also point to a moderate positive relationship between passive third parties and both load management (phi = 0.39) and cost savings (phi = 0.5). Finally, the results show a moderate negative relationship between passive SHEMS and load management (phi = -0.39).

2.3.4 Functionalities Underlying Energy Impacts

Each paper was additionally coded to understand whether the discourse around impacts stemmed primarily from controls and/or information-based functionalities of SHEMS. As hypothesized, control-based functionalities dominate the discussion of functionalities employed in the review papers, with 81% of the papers in the sample reporting energy impacts derived from controls-based strategies (n = 25). Alternatively, information-based strategies appeared in 48% of the review papers (n = 15). 29% of the reviews discussed both functionalities (n = 9). This breakdown is represented in Figure 2.10.

When discussing information-based strategies, the majority of the review papers broadly discussed the effects of feedback or other information from SHEMS without commenting specifically on the strategies employed. When considering the papers discussing controls-based energy impacts, the type of control (either rule or remote) employed was identified when possible. As shown in Figure 10, of the papers discussing controls, the majority (76%) commented on rule-based (algorithmic) control while only 24% discussed remote-control.

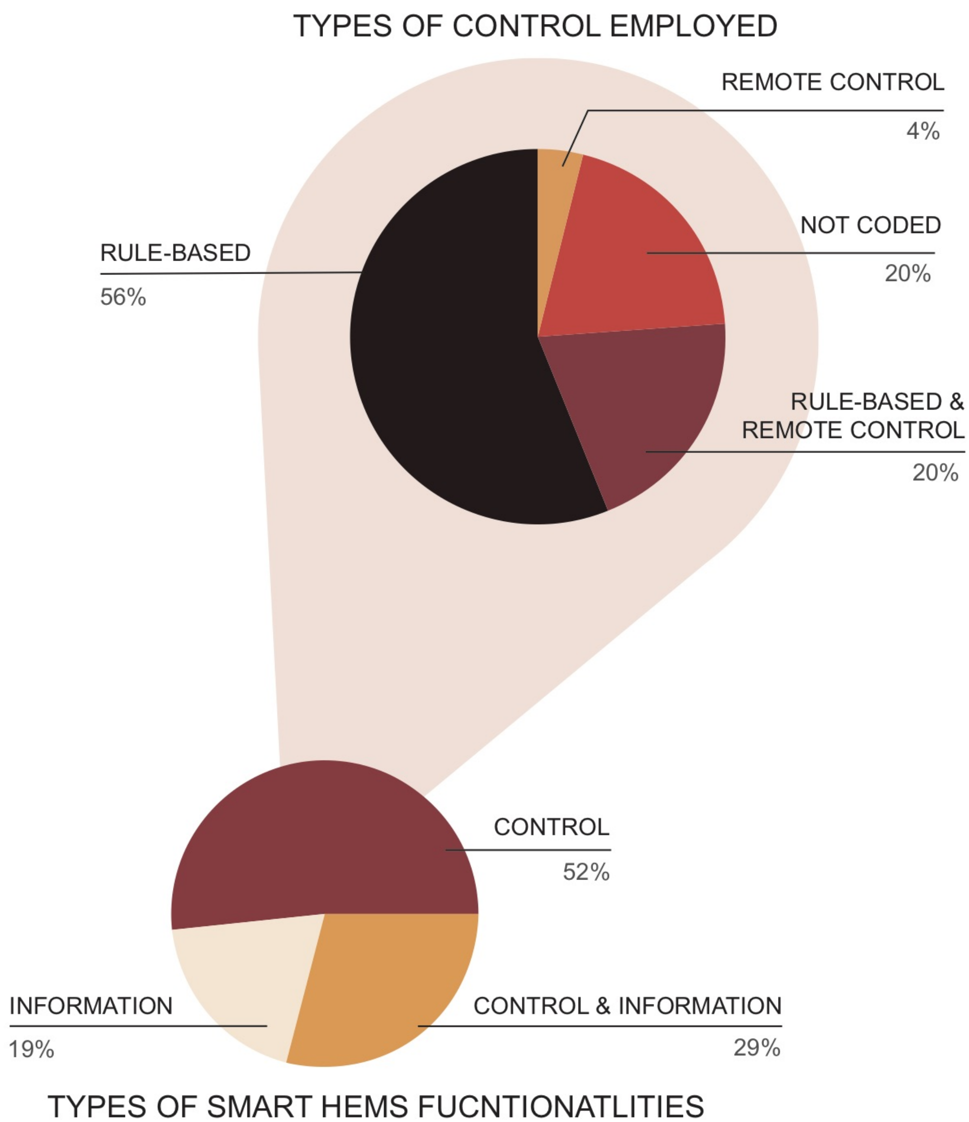

Figure 2.10: Types of SHEMS Functionalities identified in the review papers (bottom pie chart) and the types of control strategies employed (top pie chart)

20% discussed both forms of control and in 20% of the papers (n = 5), the type of control could not be distinguished.

2.3.5 SHEMS Systems by Disciplinary Perspective

Finally, Table 2.3 presents a summary of the constructs related to the conceptual model aggregated by disciplinary affiliation of the paper. Column one designates each of the four disciplines present and the number of articles within each. The resulting columns show what percentage of the total papers in that subsample discussed each of the energy impacts, agents, and functionalities related to SHEMS. Given our sample size we cannot comment on statistically significant results, but in reviewing the evidence several trends begin to emerge. Since only one paper was present from the computer science discipline, results discussed here focus on the remaining three disciplines (interdisciplinary, engineering, and planning & architecture).

With regards to the energy impacts discussed, a majority of papers in each discipline discuss energy savings, with a slightly higher percentage of interdisciplinary (77%) and engineering (75%) papers reporting impacts related to energy savings than planning and architecture (60%). Consistent with the overall results, the interdisciplinary and engineering disciplines also show a substantially lower frequency of discussing impacts related to behavior change and energy education. Only 15% of interdisciplinary and 8% of engineering papers discuss these impacts, compared to 60% and 80% of planning and architecture papers, respectively. The results show similar diversity when considering load management and cost savings. Engineering papers were the most likely to report on load management, with over 90% of them doing so, followed by interdisciplinary (69%) and planning and architecture (20%). Alternatively, interdisciplinary papers were the most likely to discuss cost savings (69%), followed closely by engineering (67%), and planning and architecture (20%).

When discussing the different agents in the system, both inter- disciplinary and engineering papers show a significant skew towards discussing active SHEMS and passive users, while this trend is reversed in the planning and architecture subgroup. In particular, all (100%) of engineering papers discussed active SHEMS, followed by 77% of interdisciplinary papers, and only 20% of planning and architecture. Alternatively, only 17% and 46% of engineering and interdisciplinary papers, respectively, discussed SHEMS in a passive light, as compared to 80% of planning and architecture reviews. When discussing users, the reverse trend emerges. Planning and architecture reviews discussed users as active in 80% of reviews and passive in only 20%. On the other hand, interdisciplinary and engineering papers considered systems in which users were active in only 46% and 33% of papers, respectively, and passive in 54% and 75% of reviews, respectively. Consistent with the high level finding of this analysis, third parties were most often considered passive components of the system across the disciplines and discussed as active in only a small minority of interdisciplinary papers.

Similar to the trends observed surrounding agents in the system, interdisciplinary and engineering papers show a distinct skew towards technical, controls-based functionalities of SHEMS. 100% and 85% of engineering and interdisciplinary papers discussed controls functionalities, respectively. On the other hand, only about a third of the papers in each of these disciplines discussed information-based functionalities of SHEMS. The reverse trend emerges in the planning and architecture field, with all papers (100%) discussing information-based functionalities and a minority (20%) discussing controls. Table 3. Summary of dominant trends in SHEMS discourse by disciplinary perspective. Note, under the "Agents" column, "A" signifies "Active" and "P" signifies "Passive".

Table 2.3: Summary of dominant trends in SHEMS discourse by disciplinary perspective. Note, under the "Agents" column, "A" signifies "Active" and "P" signifies "Passive".

Discipline	**Energy Impacts**					**Agents**			**Functionalities**	
	Energy Sav.	Load Mngt	Cost Sav.	Behav. Cng	Energy Edu	User	Smart HEMS	Third Party	Info.	Cntrl
Interdisciplinary (N=13)	77%	69%	69%	15%	15%	A: 77% P: 46%	A: 46% P: 54%	A: 15% P: 54%	38%	85%
Engineering (N=12)	75%	92%	67%	8%	8%	A: 100% P: 17%	A: 33% P: 75%	A: 0% P: 58%	33%	100%
Planning & Architecture (N=5)	60%	20%	20%	60%	80%	A: 20% P: 80%	A: 20% P: 80%	A: 0% P: 20%	100%	20%
Computer Science (N=1)	100%	0%	100%	0%	0%	A: 100% P: 100%	A: 100% P: 100%	A: 0% P: 0%	100%	100%

2.4 Discussion & Conclusion

This research sought to conduct a systematic, interdisciplinary assessment of the SHEMS literature in terms of the dominant discourses surrounding their potential to impact household energy use. It analyzed 31 review papers written on this topic since 2009, stemming from engineering, computer science, planning and architecture disciplines and interdisciplinary research collaborations. These reviews had a heavy reliance on modeling and simulation methods, especially when estimating potential energy savings and load management. Review papers tended to focus exclusively on either user-centered, information-based solutions or techno-centric, controls-focused solutions to managing home energy use, with the latter being much more prevalent. Relatedly, energy savings, load management, and cost savings impacts received the most attention, with a minority of papers focusing on energy education and behavior change impacts. As a result of limited integration, few of the numerous potential pathways for SHEMS to impact household energy use, articulated in the conceptual model presented in Figure 2.2, have received frequent attention in the literature. The following sections reflect on these key findings among others, consider the limitations of the present study, and draw out key considerations for future work. In particular we look at the need for more holistic solutions to home energy management, the role of the social sciences and interdisciplinary research moving forward, and implications of the reliance on modeling and simulation studies in research.

2.4.1 Advancing SHEMS: A Holistic Path Forward

Taken as a whole, the findings of this review point to the need for more holistic approaches to understanding the role of SHEMS in driving energy benefits in the residential sector and tradeoffs between different approaches to doing so. Results show a skew towards technology centric, control-based solutions to managing home energy use and this bias manifests in several ways. First, the analysis indicates a dominant focus on SHEMS as the core and active agent within the system. While users still appear in nearly all papers, they are more frequently considered as passive actors. One unexpected finding from this review was that third party actors were not identified in over half of the review papers and when they were discussed it was almost exclusively in a passive role through the use of dynamic pricing structures. Further, the results indicate that active users and active SHEMS were rarely discussed in the same papers. While this finding may be less surprising in single study papers taking predominantly one or two views of the system, our study reviewed review papers, which typically seek to cover wider swaths of the literature.

The second way this bias manifests is through a reliance on controls approaches to managing energy use as opposed to information-based ones. Although 29% of the review papers did consider both information and controls-based functionalities, these papers mainly discussed them as two separate solutions to managing energy use, not integrated into one program. A further 52% of papers focused on control-based solutions only, with no mention of information-based opportunities surrounding SHEMS. The limited number of papers discussing behavior-based energy impacts logically flows from this finding - if the technology is primarily charged with controlling energy use why does the user need to change?

Revisiting the model presented in Section 2.2, Figure 2.2 we can see the ways in which this bias conceptually limits the potential SHEMS-related pathways towards energy impacts. Figure 2.11 presents an illustration of the modified conceptual model excluding third party actors and their associated pathways to energy impacts and Figure 2.12 shows the same model excluding the user and related pathways. The ways in which this limits the potential opportunities to enact change in the system is immediately apparent. For example, without

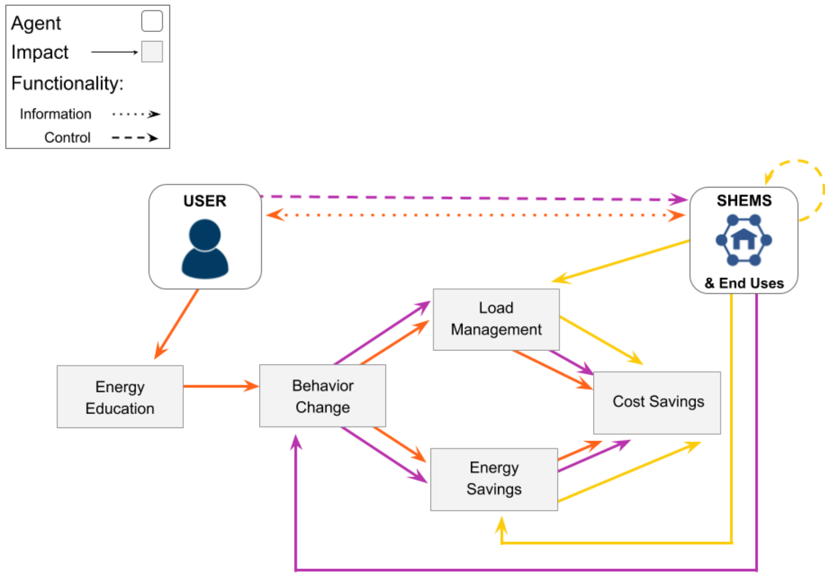

Figure 2.11: Representation of the SHEMS conceptual model excluding third party agents and related pathways to impact.

the user, impacts around energy education and behavior change disappear, which also limits the potential pathways towards achieving load management, energy savings, and cost savings. Without the third parties, the system loses its connection to the external grid and also reduces pathways to energy savings and load management.

While it may turn out to be true that the greatest potential impacts lie in the technical functionalities of SHEMS, there is no way of knowing this is true unless all potential pathways are investigated. History has shown that policy approaches relying on technical potential will only go so far towards delivering energy benefits if the underlying assumptions regarding the role of actors, such as users, are incorrect. Perhaps the best example of this relates to innovations in manual, programmable, and smart thermostats. While programmable thermostats were expected to provide significantly greater energy savings than their manual counterparts, and initially received an ENERGYSTAR label designation, ENERGYSTAR

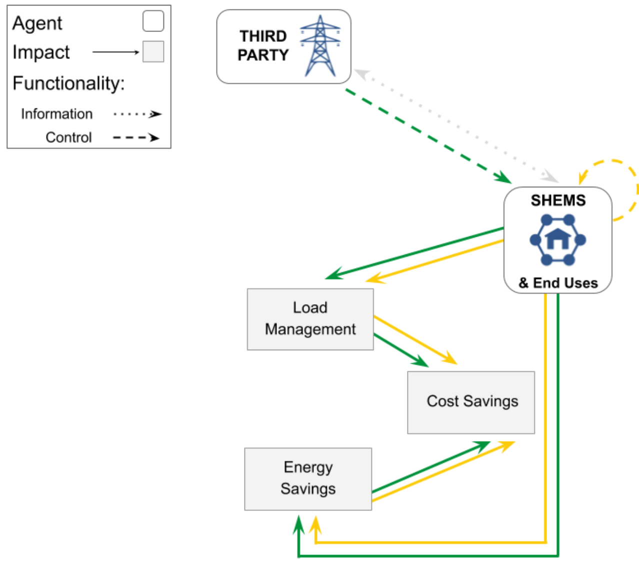

Figure 2.12: Representation of the SHEMS conceptual model excluding user agents and related pathways to impact.

removed its label from the product in 2009 when these savings were not realized [111]. Research has suggested that this gap, between expected and realized savings, was likely related to the fact that estimates of savings potential often underestimated the degree to which individuals already manually manage heating and cooling loads in their home [49]. For example, Malinick and colleagues [111] evaluate how energy savings projections around these programmable thermostats relied on the assumptions that users programmed their thermostats and let them run. Sintov and colleagues [112] recently found users who pre-program their thermostats are just as likely as those who did not to adjust their thermostat on any given day. Such assumptions likely contributed significantly to lower than expected energy savings and ultimately the removal of the ENERYSTAR designation [111]. It is hypothesized that similar assumptions often underlie the reasons research and development pilots, broadly speaking, often do not live up to expectations [71].

The results of our research suggest that, despite such evidence, SHEMS research has continued to make similar assumptions regarding the passive role of customers. This is supported by recent work by Larsen and colleagues [66], who conducted an analysis of the role of smart technologies in district heating systems in Denmark. The study found that smart home technologies appeared to have been developed with the aim of removing uncertainties surrounding unpredictable human behavior through strategies such as automated controls. The authors argued that this ignores both the ability for these technologies to serve as disruptive forces, reconfiguring household dynamics, and for users to override or subvert controls if motivated to do so. Yet, there is no evidence to suggest that new innovations in automated technologies will be exempt from issues surrounding human behavior that previous technologies, like programmable thermostats, have dealt with. Research has consistently shown that users prefer some level of control over their environments and will take actions to regain it where possible [113]. Indeed, some research suggests that energy savings potential around thermostats could be greatest when both users and technologies are involved in the process of creating heating and cooling schedules [79].

In addition to these findings about the user-technology relationship, our findings regarding third parties also feel disengaged from current developments in the industry. In our sample, when third parties were considered, it was primarily to institute dynamic pricing schemes that active SHEMS would then use to optimize or schedule demand accordingly [95, 104, 107]. Very few articles discuss the role of programs like direct load control or other utility-run demand response programs. These findings seem disconnected from visions of the future that highlight utilities or other third parties as using smart technologies to unlock new opportunities to manage energy use, afford greater penetration of renewables, and provide grid services to support the energy transition more broadly. In the review by

Sovacool [19], he notes "...some critiques suggest that a large gap exists between what energy policy researchers think is important, and what business persons, utility commissioners, and policymakers actually think and do."

Our findings here suggest that this could also be the case within the realm of SHEMS research and policy. Yet third party actors such as utilities seem uniquely placed in the energy system in terms of their connections to a wide array of stakeholders, including industry players in emerging technologies, policymakers at the local, regional, and federal levels, and customers across sectors, to help deploy new innovations. Indeed many such actors are currently in the process of conducting field pilots to test out these technologies. Past research from the field of socio-technical transitions has long pointed to the key role of intermediary or middle actors with such connections to help move systems towards more sustainable states [114, 115] and this should be further investigated in future SHEMS research.

Taken together, these findings suggest that future exploration of SHEMS should explicitly investigate the potential for multiple active agents to contribute towards the generation of energy benefits and acknowledge that these agents interact within a system, constantly evolving based on interactions, and potentially in unexpected ways. The results of this analysis seem to primarily fall on only a few components of our conceptual model and thus we encourage future work on SHEMS to dive deeper into a more holistic understanding of the relationships represented in Figures 2, 11, and 12. To do so will involve critically examining underlying assumptions regarding which components of the system are truly passive and reconsidering how functionalities of SHEMS regarding information and control can holistically be leveraged together.

2.4.2 Role of the Social Sciences and Interdisciplinarity in SHEMS Research

A crucial component of successfully challenging assumptions and taking a more holistic approach to the successful deployment of SHEMS to deliver energy benefits will be the increased participation of more disciplines in SHEMS research. Results of this study reveal a significant underrepresentation of the social sciences in SHEMS work. An extensive search identified no review papers strictly from a social science perspective, and only 15% of authors contributing to interdisciplinary papers had affiliations within the social sciences. This finding is consistent with Sovacool [19] who argued social sciences are vastly underrepresented in contemporary energy research, broadly speaking. In recent years, the literature has seen increasing research contributions in the smart home or SHEMS space by social scientists, including the work of authors such as Strengers and colleagues [8,83,84] and Hargreaves and colleagues [62, 116, 117]. This research has brought to light important critical perspectives on whether new innovations in the smart home space actually address energy-related challenges in the residential sector [49] and how future research regarding SHEMS functionalities like information can be reframed to engage a wider range of actors and develop new solutions to address energy transitions [62].

While we believe more contributions such as these will be key to the future success of SHEMS, further research in this space should not focus solely on increasing the presence of social sciences alone, but on integrating these perspectives with more technical ones. Surprisingly, the results of the current analysis suggest an impressive amount of interdisciplinary collaboration in this field to date. Roughly 40% of the review papers in the sample came from interdisciplinary collaborations. Compared to the results of Sovacool [19], who finds that less than one in four papers on energy studies reported interdisciplinary affiliations, the findings of this research suggest greater levels of interdisciplinary collaboration occur on the topic of SHEMS relative to energy studies generally. However, even the interdisciplinary perspectives here were significantly skewed towards technical collaborations (e.g., engineering and computer science). Perhaps as a result, this research revealed largely similar trends across the interdisciplinary and engineering disciplines, with a slightly more pronounced technical, controls-focused skew within the engineering papers.

There is clearly more interdisciplinary work to do on this topic with richer collaborations between disciplines. Managing home energy use will only become more complex as a wider variety of technologies are introduced into the home where they will interact with user behaviors and household practices. Developing robust solutions will require bringing together and integrating a variety of perspectives, in particular greater contribution from the social sciences. Future work should investigate how best to facilitate these cross-disciplinary collaborations, perhaps through the development or expansion of transdisciplinary theories or frameworks such as the conceptual model presented here. An example of such potential frameworks, the development and use of Energy Cultures Framework [118, 119] has proven a valuable tool to help communicate across disciplinary boundaries and bring together diverse perspectives on issues of energy use. To our knowledge, this framework has not yet been widely applied to the SHEMS space.

To date, the dominant policy framing around energy efficiency programs in the residential sector has been to focus on or incentivize either technical, widget-based programs such as more efficient products or home audits, or behavior-based approaches [120]. As research in the realm of SHEMS continues to evolve, more unifying, integrated frameworks surrounding home energy management will be needed to bring together all the pieces of the puzzle. In theory, both information-based strategies and technical controls approaches seek to increase the way in which energy use is controlled. Although these strategies often strive to achieve the same goal, they are often researched through different perspectives. Future programs seeking to manage energy use would benefit from one unified framework from which to analyze trade-offs between these two SHEMS functionalities

2.4.3 Role of Modeling & Simulation in Contributing to Our Understanding of SHEMS

Findings of this review confirm existing arguments in the literature, such as those by Darby [40] that much of the information that exists about the potential impacts of smart technologies on home energy management stems primarily from modeling and simulation studies as opposed to real-world pilots and programs. We find a particular skew in how methods are applied to understand different energy impacts. In particular, estimates of the potential of these technologies to spur broader behavior change or educate users on their connection to the energy system are derived solely from field studies in this sample versus the energy impacts of load management, energy and cost savings, which are studied using both modeling and field studies, with a skew towards modeling and simulation.

On one hand, this finding is unsurprising. Such simulations have long supported decision-making in the energy industry, and they hold advantages in being able to generalize findings to multiple building cases, climate zones, and grid networks. It can be expensive and impractical to do many field pilots and, further, many innovations on the grid side are still in development or hypothetical. In these situations, modeling and simulation can serve as a practical way to explore the realms of possibilities with regards to solutions to address grid challenges, yet few robust field pilots exist to support the extent to which modeled impacts hold true “in the wild".

On the other hand, this is problematic in that many modeling and simulation programs don't capture people in particularly realistic ways, as most simulations are defined predominantly through a technical lens with simplistic representations of the human component of the system [41, 121]. For example, studies in our review reference users through preferences defined by hot water, thermostat, and other appliance set point boundaries [87, 89, 90, 107], with little to no mention of broader psychological or sociological considerations. Alternatively, they frequently consider users as passive agents who do not actively control the appliances managed by the SHEMS, but rather state their preferences and expect these to be met by the technology. This assumption is often unrealistic, and it is a significant departure from how these appliances are controlled today.

While there is growing recognition of this fact, the misrepresentation and simplistic consideration of behavior can lead to inaccurate assessments of energy impacts [122], inherently limiting the capacity for such models to holistically explore promising program opportunities [41, 43] or comment on the potentially negative implications of the deployment of SHEMS. The growing field of computational social science (using tools such as agent-based modeling; [123] affords an exciting chance to enhance these modeling efforts while real-world deployments come online. Such simulation tools both provide the opportunity to create virtual worlds [124] and have been cited as promising opportunities to better understand the dynamics of the emerging smart grid [125, 126]. Such models present ways to more realistically explore possible future scenarios for the grid and identify which interventions to fully develop and roll out before investing in costly pilot or field trials. They could prove potentially powerful tools to help develop and test integrated frameworks, such as those called for in Section 4.2. Further, future modeling efforts should seek to work closely with new field pilots as a way to investigate how impacts of smaller field studies could be scaled. Increased partnerships between academia and industry could prove particularly fruitful. Such collaborations would offer insights to draw on experiences on the ground that might not otherwise be published in peer-reviewed venues, provide rich sources of data with which to validate and calibrate models, and work towards addressing the lack of field studies published in the literature.

2.4.4 Limitations

While the results presented here offer some potentially important findings for the SHEMS literature, they should be considered within the context of several limitations to the methodology. The main goal of this review was to study the dominant discourse around the energy impacts of SHEMS rather than the phenomenon itself. As such, the findings do not add to the body of evidentiary work on the energy impacts of SHEMS and underlying mechanisms.

The meta-review method, of reviewing review papers, offers advantages with regard to achieving the study's goal. Specifically, it enabled a survey of the breadth of literature in a growing and expansive field. However, this approach also has several drawbacks. First, summaries of primary studies within a review limit the amount of detail available and therefore prevent a deeper, more nuanced analysis of the details of SHEMS pathways to delivering energy impacts. The meta-review method also relies on the accurate interpretation of primary studies by review authors. Further, given the lag in research process between conducting and publishing primary research and then that research being incorporated into a review article, the perspectives in these review articles is likely missing the most recent research even though the most recent review in this article was from 2018.

In addition, the authors are aware of seminal review papers on the topic of energy feedback from social science perspectives [14, 75, 127]. These reviews present information crucial to advancing the use of SHEMS via information functionalities, but they did not surface in the literature search for this research, likely because they do not focus on SHEMS (Darby [127] and Karlin and colleagues [14] review studies of energy feedback largely pre-dating SHEMS with control functionalities; Sanguinetti and colleagues [75] focuses on eco-feedback more broadly). This perhaps points to the need for a social science review to take stock of the insights specifically from these perspectives. Although we hope to encourage more interdisciplinary and less siloed work, such a resource would prove a formative reference for the more technical disciplines as they seek to integrate with the work of other disciplines in this field.

Finally, while the analysis here offers an initial glimpse at the disciplines predominantly contributing to SHEMS research, we would like to acknowledge the challenges around assessing disciplinary affiliation. For example, while the departmental affiliation listed on a publication provides a snapshot of an author's perspective, it does not, for example, reveal when scholars have trained across multiple disciplines in their career. Few explicitly interdisciplinary departments or institutes exist at this time, thus it is possible this analysis underestimates the extent to which certain disciplines contribute to SHEMS research.

2.4.5 Conclusion

As the energy system transitions towards a cleaner, more efficient energy future increasingly defined by distributed energy resources, we believe it is imperative that an understanding of the potential contribution of SHEMS is approached from an interdisciplinary, socio-technical perspective. Such an approach will enhance both academic and industry ability to comprehensively assess the pathways towards achieving desired energy benefits and the implications of these innovations for the energy system and the people it supports. The scale of the challenges ahead in transitioning the energy system are too large to impose artificial constraints on the system when seeking solutions. While automation and controls technologies present new, largely unexplored opportunities to rethink the ways in which energy is managed in the home, they are only one piece of the puzzle. As has been argued by many others in this field, we would be remiss not to equally consider the human side of the equation and find ways to holistically bridge the gap. This research provides evidence that, despite calls for greater integration of disciplinary perspectives on this issue, the gap has not yet been bridged. The energy industry stands in a moment of disruption, where the status quo is being challenged. While this brings uncertainty, it also presents an opportunity to reconsider and reframe the ways in which energy policy and related programs are designed and new technologies are deployed.

2.5 Acknowledgments

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Chapter 3

Agency and automation in smart home energy systems: An interdisciplinary taxonomy

Claire McIlvennie, Christopher Koliba, & Marco Pritoni

Target Journal: Energy Policy

Abstract

Issues of agency and control are central to how smart home energy management systems (SHEMS) will contribute to low carbon transitions. These technologies have begun to break down the divide between the generation of energy and the customers who use it, raising questions of agency and who, or what, should manage energy use in the future. Despite their centrality, there has been limited investigation to date on how to holistically define SHEMS-enabled controls and how assumptions about SHEMS deployment shift agency in energy systems. To support investigation of these questions, this research draws on theoretical and empirical evidence across disciplines to develop an interdisciplinary taxonomy of control for SHEMS-enabled strategies. The taxonomy highlights two dimensions of control,

(automation and agency). It defines control types as a function of the level of automation used and the relationships between core actors within smart home energy systems. The taxonomy identifies four simplified control types and illustrates how dominant framings of SHEMS-enabled control shift agency away from residents towards technologies and third parties. The discussion reflects on policy and program design implications of this finding, and argues this taxonomy offers a powerful tool to prevent narrow exploration of only one control scenario, acknowledge the diversity of solutions that exist to manage home energy use, and enable the balancing of both grid-related and individual needs.

3.1 Introduction

Issues of agency and control are central to visions of future energy systems. In the United States, ambitious federal and state decarbonization objectives are projected to spur rapid deployment of renewable energy and electrification of the building and transportation sectors [1]. This will lead to increases in variable generation of and demand for electricity [4, 9], emphasizing the role of demand-side management strategies to support grid operators as they seek to ensure the system remains reliable and affordable, among other objectives [1]. Demand-side strategies such as load flexibility, i.e. the ability to alter the amount or timing of energy use [8], seem poised to deliver significant system benefits including reduced costs, enhanced reliability, and reductions in greenhouse gas emissions [4, 5].

Through advances in smart home energy management systems (SHEMS) like smart appliances, electric vehicles, storage, and analytics platforms, the residential sector is expected to evolve from a relatively passive entity in the energy system towards a more active participant in the balancing and choreography of supply and demand [2, 5, 48, 50]. New technologies offer more granular information on buildings and how their occupants use energy and automation of operations to more dynamically and precisely manage energy use [83]. They further provide opportunities to aggregate appliances in the home through distributed energy management systems to serve as "virtual power plants" managed by third parties outside the home and providing the grid with flexible generation and demand reductions as needed [5].

Much of the conversation to date about this transition has been driven by grid operators, planners, and policymakers at the system level white less attention has focused on impacts at the household level [28], including how technologies with enhanced information-based and technical functionalities will affect control over energy use within homes and the roles envisioned for residents [26]. Empirical evidence not only shows that residents respond to automation differently based on which appliance is being controlled and how [26], but also that use of smart home technologies to control space heating can lead residents to feel loss of control despite the system's objectives to enhance it [17]. Even among experts, conceptualizations about the role of control in the smart grid differ, and at times conflict, regarding who will hold control in future systems [31].

As SHEMS break down the historical divide between the generation of energy and the customers who use it [128], major questions of agency arise [25,26]. As noted by [129], "the essence of the 'smart' transformation is a transfer of agency from householders to an array of technologies and structural elements that contribute to the production of energy services" (52). While residents have traditionally had the most direct agency, or ability to control, energy use within their home, the diffusion of SHEMS has the potential to redistribute agency across actors such as residents, grid operators, utilities, and even technologies themselves [26].

As policies increasingly look to advance visions of the future energy systems with rapidly increasing amounts of energy flexibly managed through technical automation of home devices [2], it remains unclear what level of public support exists for this vision [26]. Explorations of future smart grid visions among various stakeholders highlight support for energy systems to enhance energy democracy in and community ownership of energy systems as opposed to centralized control by industry and government [130] and recent reviews of pilot programs in Europe have highlighted broad-based support for renewable energy does not necessarily apply to demand flexibility efforts [26]. Affective influences such as control, uncertainty and trust are significant determinants of innovative technology rejection [30] and people are more likely to participate in automated demand-side management efforts if they align with their values, fit within current daily schedules, and are transparent about how and why energy use is being managed [26].

If control-based solutions are to be deployed rapidly at scale to achieve decarbonization objectives [2], deep considerations of how control is defined and who possesses the agency to wield it are imperative. There have been calls for greater clarity regarding how control will be operationalized, who should govern it, how we define it, what roles diverse actors will play in these systems, and ultimately if SHEMS will (or won't) contribute to the transition towards a low carbon future [17, 26, 40, 131–133]. Such transformations warrant consideration of questions around how actors in the smart home energy system will experience and/or operationalize enhanced control and what configurations of automation and agency among different actors and technologies will be most successful at balancing the needs of the grid and the individuals it seeks to serve.

To address these calls, this research developed an interdisciplinary taxonomy of control in smart home energy systems. The taxonomy draws upon theoretical concepts and empirical evidence across disciplines to enhance an understanding of how SHEMS-enabled strategies implicate issues of control over energy use and to visualize these dynamics for researchers and practitioners as they consider future demand flexibility policies and programs. The taxonomy represents the first attempt to integrate interdisciplinary understandings of control via SHEMS under one umbrella, responding to repeated calls for more interdisciplinary work in the realm of smart technologies and demand-side management [18, 23, 42, 134].

Through the lens of agency, the taxonomy illustrates how implementation of SHEMS distributes control over energy between actors in and beyond the home depending on how actors employ different functionalities of the technologies. The taxonomy offers a holistic view of control, equally acknowledging contributions of both information-based and technical considerations and explicitly recognizing that "smart" energy systems require consideration of smartness embedded in both people and technologies [22, 130]. It views control as relational in nature, embodied not just in functionalities of SHEMS but in the relationships between actors within energy systems as well. The taxonomy explicitly incorporates third parties external to the home as recognized actors within such systems and users of SHEMS, building off findings of previous research acknowledging these actors have been frequently omitted from research on SHEMS [18]. Considering third parties as users reveals where shifts of agency implicitly occur when deploying SHEMS, exposing dynamics often assumed but not acknowledged or critically reflected on in policy and practice. As a whole, the taxonomy offers an important decision support tool which can be used to investigate deployments of SHEMS through a critical lens, fending off bias towards narrow exploration of one control type, acknowledging the diversity of solutions that exist to manage home energy use, and helping deploy programs in a way that meets both grid-related objectives in addition to those of residents in the home.

The paper proceeds as follows: Section 3.2 covers foundational literature on SHEMS, control, and agency. Section 3.3 proposes the taxonomy, identifying four smart home control types and reviewing illustrative real-world examples. Section 3.4 offers a discussion of systematic design considerations, limitations, and future work and Section 3.5 concludes.

3.2 Background

3.2.1 Defining SHEMS and the smart home energy system

The smart home encompasses a complex system of diverse actors, technologies, and their relationships. In their review of the literature, Sovacool and Del Rio [133] identify three core attributes of such homes:

1. Enabling greater control and functionality via monitoring and sensor interfaces
2. Being networked or layered to connect technical features to optimize delivery of key services (ex. via digital information systems and non-digital infrastructure) and
3. Empowering, enabling, or facilitating behavior change of users.

Smart homes enable these attributes through actions by users or, when permitted, by the technologies themselves [135] and include user interfaces like smartphone applications, smart hardware like smart appliances or thermostats, and software platforms, such as those that provide data analytics [83]. In the context of demand-side-management, they also often include consideration of electric vehicles, smart panels, energy storage, and/or residential solar systems [2, 5].

[18] utilize a conceptual model of smart home energy systems in their systematic assessment of the SHEMS literature that highlights two key functionalities of SHEMS: the ability to provide greater information on and control over energy use in the home and identifies three

core actors: users of SHEMS, third parties, and SHEMS themselves. The following sections discuss these functionalities, actors, and anticipated applications of SHEMS.

3.2.2 SHEMS Functionalities

Two functionalities of SHEMS drive their expected capacity to control energy use: greater flows of information between actors in the system and technical control [83].

Information-based functionalities relate to the ability of these technologies to provide data regarding energy consumption to a user within or external to the home. In the realm of home energy use, this information could include both raw data (kWhs consumed) and analyzed data (energy consumption trends). Types of information fall into two subcategories: feedback and feedforward [83]. Feedback provides users information on their behavior to either reinforce existing behaviors or suggest behavior change. Feedforward information offers targeted or timed prompts for behavioral suggestions to the user with the objective of encouraging them to manage energy use more actively.

Control-based functionalities similarly fall into two categories: remote and algorithmic control. With remote control, users of SHEMS control appliances and other end uses through smart interfaces. This offers an extension of informational control, giving the user additional opportunities to act upon information provided by the SHEMS. With algorithmic control, SHEMS schedule or automate operations of devices according to preferences provided by users of the system, such as what thermostat set points they find comfortable. Algorithmic control optimizes the operation of home appliances based on historical data through algorithms that use mechanisms like machine learning to predict future states or actions [54].

Together these functionalities provide SHEMS with their "smarts". However, differing perspectives exist on what smartness achieves and how human and non-human actors contribute to making a home "smart". Definitions of SHEMS frequently discuss "users" but previous research has identified a need for further clarity on who are "users" and what their role is in the system [40].

3.2.3 SHEMS Users

Two dominant "users" of SHEMS have been identified in the literature: residents of homes and actors external to the home, called third parties. The literature on SHEMS frequently focuses on residents as the primary "users" of SHEMS [26]. This can include an individual or groups of individuals within residential buildings who interact with each other, technologies, and external parties in ways that influence energy consumption. Despite opportunities to actively engage residents, previous research has argued many visions of smart homes view them as "passive" actors in efforts to manage energy [18, 132, 136].

Although less frequently considered as such, third parties are equally "users" of SHEMS [54]. Traditionally, utility service providers represent the primary third party actor in smart home energy systems, but the diffusion of SHEMS has introduced new market actors, including aggregators who contract with utilities or energy markets to provide grid resources [132]. In their systematic assessment of SHEMS literature, [18] highlighted that SHEMS research frequently omits consideration of these third party actors and studies that do include them often view them as passive actors in efforts to deliver energy-related benefits. These findings come despite the fact that much of the current motivation for the use of SHEMS to support demand flexibility and decarbonization initiatives focuses on their use by system planners and grid operators, particularly as aggregated and controlled by software like Distributed Energy Resource Management Systems (DERMS) [5]. Third party actors seem uniquely poised to deploy SHEMS to maximize energy use and customer benefit [54] due to their connections to a wide array of stakeholders and the fact that many are currently in the process of conducting field pilots to test these technologies [18].

3.2.4 SHEMS' Objectives

Darby [40] offers two common conceptualizations of the use of SHEMS in the home. The first highlights SHEMS as an opportunity to offer services that respond to the needs of residents. The second focuses on the home's connection to the energy system and interaction with the grid to provide services like demand flexibility. While both conceptualizations consider provision of service, each differs with regards to who those services benefit: the first providing services to residents and the second providing services to third parties and the grid.

Through their use, SHEMS could offer a variety of benefits to residents, including finer control over end use appliances and providing enhanced benefits around comfort, simplicity, entertainment, health, security, and convenience [17, 46, 137]. While saving energy, and the related costs, are recognized as potential benefits, they are not always the primary ones [52]. However, SHEMS may also offer drawbacks, including lack of energy savings, inconvenience, and discomfort through increased temperatures, need for technical literacy, and finding workarounds to subvert automated features to achieve resident-objectives [17]. Research has highlighted that residents also perceive certain risks associated with the use of SHEMS, such as the loss of control or privacy [17, 46].

Third parties expect SHEMS will achieve numerous objectives established by and promoted via enhanced energy efficiency [138] and decarbonization [2] requirements. These include helping to align demand with renewable energy supply, reducing overall energy use and greenhouse gas emissions, enhancing grid reliability and resilience, and reducing costs of grid operation, thereby supporting affordable electric service [5, 9, 139–141]. SHEMS and their ability to unlock demand flexibility are increasingly seen as critical to supporting the regulatory paradigm of "least cost integrated resource planning" as utilities plan to rely on managed charging of resources like space and water heating and electric vehicles to avoid costly infrastructure upgrades and energy use during times when carbon intensive fuels are more likely to supply energy [142].

3.2.5 Conceptualizing control in the smart home

Regardless of who the "user" represents, the concept of control is central to visions of how SHEMS will operate in homes. Many stakeholders assume control of energy use will stem from automated features [21, 116, 132]. Previous research has suggested investigations of SHEMS to date have skewed towards techno-centric solutions without fully integrating information-based solutions or insights from the social sciences [18, 42]. Yet SHEMS may also mediate control over energy through shaping human behavior via information-based mechanisms that encourage residents to change resource use [17, 143]. Use of information-base mechanisms may also mediate acceptance and effectiveness of technology-enabled control [26, 144]. Discussions of how control should be operationalized often center around these two perspectives [83, 133].

3.2.5.1 Technical Control

Technical control involves the physical ability to use or program technologies [116] using sensors, controls, or computer software to automate and optimize processes and operations within buildings [138]. The “smartest” homes are often considered those defined by automation that remove technical control opportunities from the resident and place them in the hands of SHEMS. Sovacool and Del Rio [133] reflect this in their “spectrum of smartness in smart home technologies” which ranges from the analog home with no SHEMS through several levels of increasing automation to “sentient” systems which meet all needs of the home through automation without user assistance.

Engineering, building automation, and controls literature root such concepts in control theory which examines how to achieve desired outcomes in technical systems. SHEMS provide the opportunity to develop such control systems within residential homes in a way that was not previously feasible. [14] highlights control characteristics of SHEMS specifically, including the controlling source (who controls energy use), control type (remotely by users and/or according to rules or algorithms), and control intelligence (the “smart” mechanism that controls energy use). With the diffusion of SHEMS into homes, many practitioners and policymakers argue for the use of SHEMS to control energy through automated support invisible to the resident [145] through networked systems and, often, in exchange for an incentive [2]. This type of control is often referred to as “direct control” in that technology itself shifts energy use [16].

3.2.5.2 User-enabled Control

While technical solutions offer one avenue through which SHEMS enable greater control, user centered solutions have also been mentioned as powerful opportunities to achieve desired energy-related outcomes. SHEMS enable these control opportunities through the provision, analysis, and visualization of information and the related impacts on energy-dependent behaviors [133,143]. Information feedback systems have their roots in traditional control theory, which served as the foundation for the field of cybernetics [13]. Cybernetics sought to integrate humans into technical control systems, particularly through understanding how information could be manipulated or communicated in dynamic systems for the purpose of better controlling those systems. The field of psychology has also identified information as a critical precursor of control, with some theorists identifying the concept of "informational control" even if information alone does not always lead to more actual or perceived control [146]. McCalley and colleagues [147] further discuss the potential role for SHEMS to increase control in the home, noting, "The system would offer much more information, and thus control" (2).

Work on persuasive technologies [148, 149] explores computing technologies as new social actors, where information provided by the technologies seeks to shape or reinforce behaviors through social cues that provoke specific responses from their users [149]. While enhanced automation often seeks to exclude users from decisions, the provision of information seeks to enhance control by humans themselves, keeping the human "in the loop". Significant research exists within the social sciences and field of human-computer interaction (HCI) that seeks to understand how to present information to achieve desired goals [75] and a long history of research on energy use has shown the extent to which social influence and feedback can generate and manage change [58, 60, 150, 151]. In SHEMS research, these efforts are often referred to as enabling "indirect control" in that the technology sends information to users to change behavior and manage energy use [16].

In addition to the ability for users to physically control energy use, the importance of perceived control has been highlighted [116, 132, 146, 152–154]. Perceived control denotes a person's beliefs around how much control is available to them. Skinner [146] notes that many theorists suggest perceived control beliefs more strongly predict behavior than actual control. This concept is reflected in commonly used theories like the Theory of Planned Behavior [152], which shows perceived control both as a precursor of intention to perform a behavior and a direct antecedent of performing the behavior. This has also been highlighted in research on SHEMS, specifically [116] suggesting informational capabilities of SHEMS may play a role both in enabling greater control over energy use and increasing feelings of being in control, even when some of that control has been shifted to automated functionalities. Alternatively, deployment of SHEMS risks making residents feel less in control if programs are not properly designed [17] and recent work underscores that residents may desire differing levels of information and transparency around automated actions based on how technical control (automation) is being deployed in their home to maintain feeling of being in control [26, 154].

3.2.5.3 A spectrum of control

Although technical and user-enabled control are often viewed as dichotomous, in reality they are not mutually exclusive [53]. Sovacool and Del Rio [133] criticize the presentation of these two paths as overly dichotomous, highlighting a "paradox" of control in smart home literature to date where SHEMS promote notions of enhanced control while, at times, removing control from certain actors in the system (residents) and transferring it to others (technologies, third parties). This concern is consistent with early research on smart homes from the field of building automation and HCI. McCaulley and colleagues [147], acknowledging a need to balance control by technical and user components of the system, concluded home computer systems that control energy use must provide users some level of control through appropriate feedback and opportunities for goal setting. There is a long history of research across disciplines seeking to delineate different levels of automation which balance control by technologies and their users (see [155] for a detailed review) and past research on building automation has cautioned against over-reliance on full automation to achieve desired energy and sustainability related outcomes [82, 113, 156].

More nuanced control opportunities that blend technical and user control offer another way to consider SHEMS-based control. Effective control solutions will likely require a combination of the two dominant pathways, as explored by [26, 144, 156]. Karjalainen [156] identify three levels of control when discussing management of thermostats: no automation (humans do everything), automation that offers humans a set of action options, and automation that decides everything and circumvents the human. The second of these levels encompasses a range of opportunities for integrating user and technology-centric control. For example, one option would involve automation identifying a set of action choices and then narrowing the options for the human to select from. Alternatively, the automation could execute its preferred solution and then inform the human of its actions and the results if asked. Similarly, after reviewing 15 case studies, Adams and colleagues [26] highlight similar levels of automation: low automation involving manual behavior change or programming of devices by residents; medium automation with resident opt-in or opt-out of technical decisions; and high automation where the resident can either restrict or interrupt parameters of automation (ex. Thermal comfort preferences) or cannot override automated settings. In their study, Karjalainen [156] found a majority of interviewees preferred middle levels of automation along this spectrum and initial empirical evidence suggests these types of control systems may also be more effective at delivering on energy-related objectives [79]. Diamond and colleagues [144] and Heatherly and colleagues [154] further highlight that information-based functionalities of SHEMS that help augment the transparency of automation and control actions taken by technologies likely play critical roles building trust around and increasing resident acceptance of various degrees of automation.

Together, investigations of control have led to many questions regarding roles of various actors within these systems related to an interrogation of “who” (or what) should be given control of SHEMS in order to deliver on energy-related goals. Viewing such questions through the lens of agency provides a useful way to explore these considerations.

3.2.6 Agency and smart home energy systems

Theories of agency have not yet been robustly applied to the realm of SHEMS although scholars increasingly reference how SHEMS and the programs they are deployed within influence dynamics of agency and who may control the valuation of the energy services they offer [17, 26, 27, 29, 42, 129]. Definitions of agency differ, but agency broadly concerns the ability for actors, individual or collective, to intentionally influence their own functioning [157] and the outcomes of processes within their environment [158]. Agency emerges as agents self-regulate and adapt in relation to norms or to achieve goals specific to their environment [157]. Agents set intentions and develop plans on how to realize them, influenced by the capacity to anticipate outcomes of actions in relation to achieving those objectives and examining the success of different strategies retrospectively [159]. Agents sense and perceive information from and characteristics of their environment [157].

Constructs of control typically center the individual as agent since personal control or agency often leads to the most direct experiences of control. However, agents could include any individuals or groups who exert control through various means to achieve desired ends [146], such as public actors at local or national scales [160] or non-human actors (ex. technologies). Previous literature has conceptualized different dimensions of agency, including a spectrum between personal and collective agency [158, 159, 161]. Personal agency emphasizes an individual agent's choice to influence their own functioning and events within their environment [159]. On the other hand, collective agency considers how individuals are aggregated and contribute to broader change [159, 161].

While actors other than the self can hold agency in a system, not all actors are necessarily agents. Actors constitute individuals, organizations, and/or networks involved in decision-making processes and agents represent a subset of those actors who specifically have the ability to influence or prescribe the behavior of the system under consideration [160]. Understanding which actors within a system who exert agency often requires answering "*who* governs for *whom* and *how* and to *what effect*" (87) [160] and considering whether actors share agency in a system or if it operates such that when certain actors gain agency others lose it.

Such considerations point towards examining the embodiment of agency within individual entities and within relationships between actors in a system, as highlighted by agency theory [162] and the principal-agent problem [163]. These theories offer a model of social relationships involving delegation of authority and issues of control in complex systems which result from information asymmetries between two parties: 'principals', entities who have delegated authority of control over a specific system, and 'agents', entities to whom control has been delegated [162]. Within relationships between entities, these actions of control involve the agent identifying and providing services to the principal and the principal guiding or correcting agent actions to better achieve a goal.

Once agency relationships have been established, problems of control emerge for several reasons, often discussed as the "principal-agent (PA) problem". These include that the interests of agents and principals differ or that information asymmetries exist between these entities, such that agents have more information about their own actions than the principals do [162]. Further, an agent's actions might lead to costs for principals, incentives for action for the agent and principal may not align, or principals may find it impossible or challenging to constrain actions of the agent to align with their objectives [163]. Agency theory ultimately helps identify and understand mechanisms to mitigate these issues of control. Strategies include identifying specific types of agents to delegate control to, monitoring agent actions, and utilizing sanctions or incentives to encourage optimal behavior [162].

The lens of the PA problem has previously been used to evaluate energy efficiency programs [163] and similarly offers an informative lens through which to consider SHEMS and their anticipated use to manage the timing of energy use in homes. In efforts to manage energy use, the utility has historically been the principal, delegating control of energy to the residents who act as agents [163]. Viewed through the PA problem, inefficient energy use on the part of residential agents arises for various reasons, including that the resident does not have adequate information regarding the performance of different appliances in the home (and therefore does not understand the extent of inefficient use) or the broader energy system dynamics within which residents operate, such as how demand for electricity aligns with sources of renewable supply. As the principal, a utility or third party may not have full information on the amount or activities underlying residential home energy demand, appliance characteristics, or the flexibility of schedules, limiting their knowledge of where to save or how to best shift energy use. PA problems arise due to misalignment of goals, i.e residents may not want to shift use of appliances to reduce or alter the timing of energy use due to perceived or actual discomfort or inconvenience. Further, issues of monitoring and enforcement arise, such that even with perfect information, utilities cannot require a resident to adopt specific technologies or certain energy use behaviors [163].

Diffusion of SHEMS into homes begins to challenge these existing PA dynamics. Whereas residents have historically held direct agency over their own energy consumption, SHEMS present as new potential agents in the system and/or vehicles for third parties, like utilities, to become agents themselves. As new potential agents in the system, SHEMS provide opportunities to reduce information asymmetries between residents and third parties by providing residents with better information about household energy usage, prompts related to broader energy system needs, and more salient incentives to align behavior. Third parties, as principals, receive better information on resident energy use, areas for potential for savings, and actual behavior to inform programs or monitor actions or SHEMS or residents. Technical controls further offer the ability to bypass residents as agents and directly control end uses in ways that align with their objectives. Although the PA problem has not yet been used to understand control dynamics in SHEMS work, work at the intersection of demand flexibility and energy justice [27] acknowledges that equitable outcomes of those programs involve, in part, consideration of who has the ability to economize (the individual self or an external "other") and control the capacity to shift energy use in time. Similarly, research by Larsen and colleagues [17] conceptualizes control via smart home technologies as "reconfigur(ing) who (agency) performs [everyday practices] and when (temporality) they do so." (14)

3.2.7 Summary

This review leads to several conclusions. Control represents a nuanced concept, defined equally by user-centric (information-based) and technical considerations. The introduction of SHEMS into the home expands potential agents of control over energy use beyond just the resident, offering opportunities to address issues of control over energy use that emerge in relationships between actors through informational and technical avenues. This highlights a need for a clear framework for holistically considering such issues in order to assess how they balance needs and achieve objectives of different actors in the smart home system.

Seeking to provide that framework, this research builds upon conceptual models introduced by [18, 164–166] to offer a taxonomy of SHEMS-enabled control to support scenario analyses of deployment structures. Scenario analysis offers opportunities to explore a range of program designs to help decision makers consider pathways they might otherwise bypass and challenge existing mindsets [167] about what will or won't work to achieve a certain objective. Such analyses will prove critically important for SHEMS research. McIlvennie and colleagues [18] highlight how SHEMS research is biased along disciplinary lines with regards to the extent to which they investigate how information- and controls-based functionalities may impact energy use in various ways. SHEMS research has been found to be predominantly conducted within technical disciplines and largely explores technical pathways to achieving energy-related benefits. Recent research has continued to argue that social science perspectives are not yet integrated into visions of smart energy systems [42] and research on human-building interactions [23]. Such bias risks leaving less technical or socio-technical pathways unexplored in pilots and programs. While technical functionalities may hold the greatest potential for unlocking grid-related benefits in some or all situations, the industry cannot know that for sure unless all opportunities are explored [18]. It will also be critical to explore how best to deploy information-based and technical-functionalities in tandem to ensure broad public acceptance of and participation in efforts to manage energy use [22, 144, 154].

3.3 Taxonomy of Control in the Smart Home

The taxonomy builds upon three core components: a conceptual model of the smart home energy system (Section 3.1), and two dimensions (3.2) representing agency of actors and levels of automation.

3.3.1 Conceptual Model

Figure 3.1 illustrates the conceptual model underpinning this taxonomy (adapted from work by [18, 164–166]), including three types of actors, each of whom have the potential to be agents in the system: residents, third parties, and SHEMS. Within this system, SHEMS could be a platform linked to one or many end use appliances providing services to residents and third parties. Agent actions are influenced by different factors and objectives. A resident's action may be motivated by the desire to achieve certain services, such as comfort, their willingness to engage with SHEMS, or flexibility in completing activities at specific times. Third parties might be motivated by providing affordable, reliable, or low carbon energy to their customers depending on the regulatory environment. SHEMS differ in they do not inherently optimize behavior to achieve their own goals but operate with regards to the preferences set by principal actors.

Flows of information and technical functionalities of the SHEMS link the three actors, illustrated by the arrows between them. These represent means of enabling control over energy and the basis for agency relationships between actors. Residents and third parties interact with SHEMS through interfaces (such as smartphone applications, distributed energy management systems, or on the appliances themselves).

The model includes end use appliances in the home. Residents or SHEMS exert direct con-

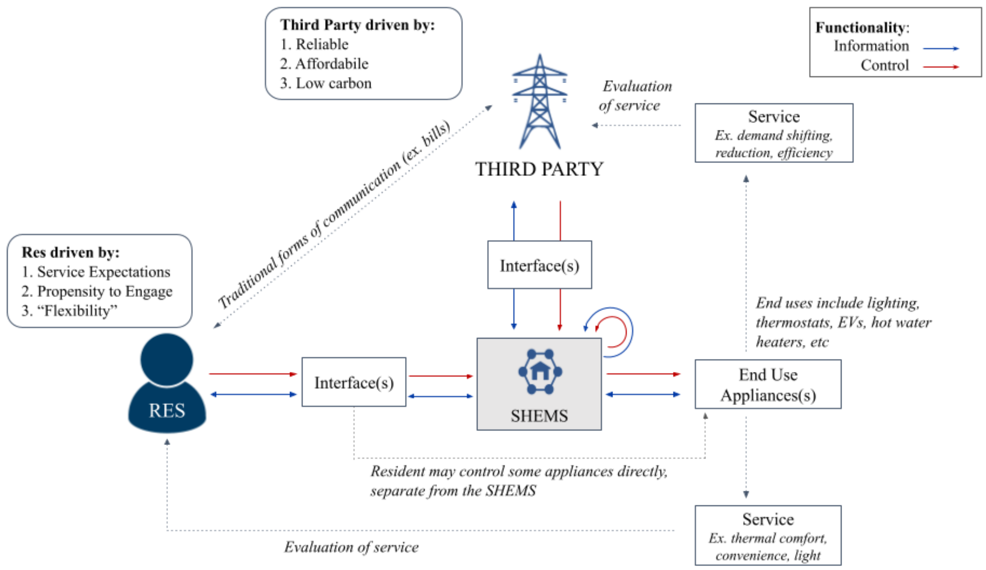

Figure 3.1: Conceptual model of smart home energy systems

trol over these end uses to achieve various services, such as load flexibility, energy savings, or enhanced comfort. Appliances could be heterogeneously controlled such that residents have direct control over certain devices, SHEMS automatically controls the operation of others, while a third party remotely controls end uses enrolled in demand-management programs. Alternatively, all appliances might be controlled by a SHEMS as a centralized system as opposed to appliances with "smarts" embedded within them. Operation of end use appliances produces services which the residents, third parties, and/or SHEMS evaluate compared to service expectations or needs.

3.3.2 Dimensions of Smart Home Control

Two core dimensions provide the foundation of the taxonomy: the first relating to the level of automation and the second to agency, illustrated in Figure 3.2.

Following [26, 138, 156], dimension one of the taxonomy represents levels of automation (xaxis, Figure 3.2). Specifically, we adopt the spectrum used by Adams and colleagues [26] where levels of automation range from low to high. For the low levels of automation, solutions require manual action by and seek to augment the agency of users through information-based and remote control functionalities of the SHEMS. Alternatively, high levels of automation rely on fully automated systems with minimal to no user input or ability to intervene. Users provide basic programming for SHEMS and consent to automation, and then allow automation to make decisions regarding operation of end use appliances. In between these two ends of the spectrum, medium level automation solutions enable control through a combination of provision of information to users and technical automation by the SHEMS.

The second dimension focuses on agency (y-axis, Figure 3.2), ranging from individual to system-level. Individual agency emphasizes agency of residents within the home to control energy-related end-uses, prioritizing needs of and delivering services as desired by residents. System-level agency emphasizes agency of third parties, focusing on achieving the needs of the grid. In the middle lies a space where residents and third parties share agency to varying degrees and potentially with SHEMS. Any of the three actors could operate as agents within the system who hold primary control over end uses depending on the SHEMS-enabled solutions employed and the delegation of control established. Agency could be enhanced or inhibited based on the availability of information or automation available via the SHEMS.

3.3.3 Types of Control in Smart Home Energy Systems

Figure 3.3 combines dimensions of smart home control with the conceptual model, identifying four types of smart home control defined by different configurations of automation and

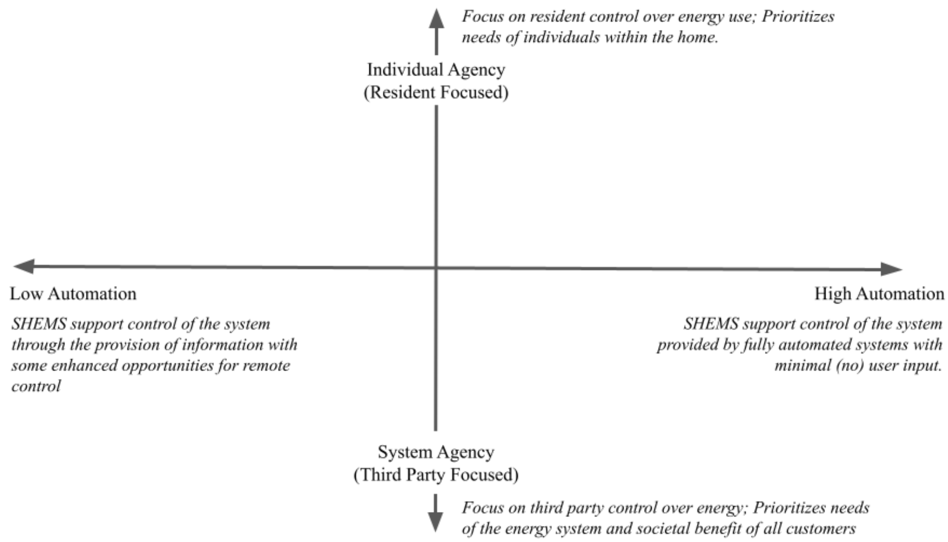

Figure 3.2: Taxonomy of control to support scenario analyses, highlighting core dimensions of SHEMS-enabled control

agency. A simplified version of the conceptual model illustrates the representative control pathway for the quadrant, as shown by the presence or absence of different control arrows and the agency levels of different actors as shown by shades of green. We consider the two types of control on the left side of the y-axis (smart residents and smart grid residents) as user-centric control and to the right side as technology-centric control. The following sections describe the characteristics of each quadrant and provide illustrative case studies of control configurations.

3.3.3.1 Quadrant One: Smart Residents

The top left quadrant (Q1) represents Smart Resident control. Residents are the primary agents and users of SHEMS, exerting manual or remote control over end uses to achieve energy-related objectives and prioritizing needs identified by residents. SHEMS have moderate agency and third party actors have the most limited agency to enact changes in

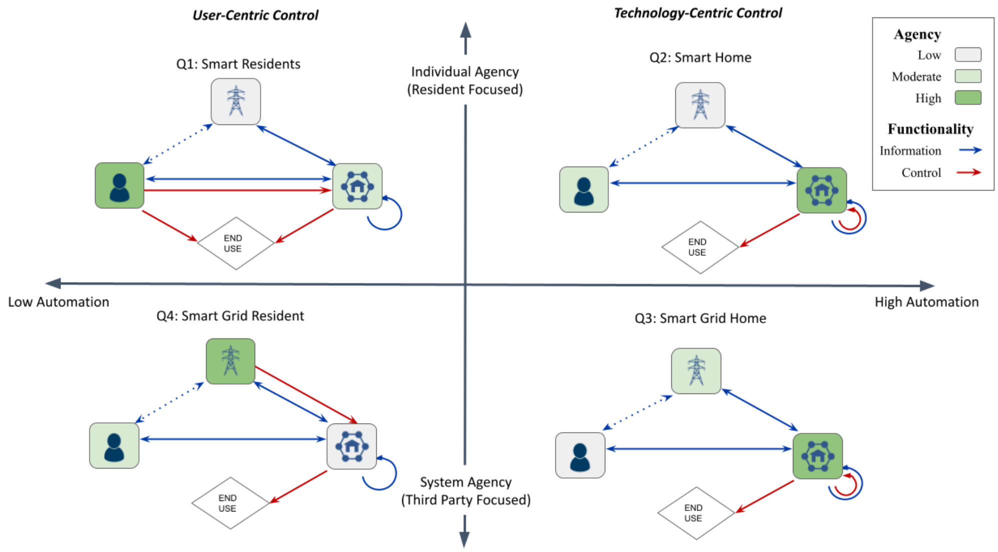

Figure 3.3: Taxonomy of control in smart home energy systems

energy use. Efforts to better control energy focus on augmenting the agency of residents by employing SHEMS to provide them with greater information on home energy use and/or suggest strategies to manage it. Energy impacts largely depend on resident behavior change or manual programming of devices. Automation, through remote control of end use devices, operates as an extension of information, enabling residents to shift behavior or appliance operation more easily via the SHEMS. Third party actors may attempt to influence energy while still delegating control to the residents by providing the resident with information related to energy system needs via the SHEMS (ex. dynamic rates, notifications, persuasive messaging).

The program offered by OhmConnect, called Behavior-based Demand Response (DR) [168–170], offers an example of Smart Resident control. A software platform is the SHEMS actor, managed by a third party. Residents of the home interact with the platform through an interface (e.g. phone application, web dashboard). The program utilizes primarily information-based functionalities of the SHEMS to allow residents to participate in wholesale energy markets in California. The program provides payments to incentivize residents to reduce energy use during specific hours of the day when the grid is stressed and engages residents via incentives and gamification strategies. Depending on appliances within a home, some remote control opportunities are available to automate responses to events (ex. smart thermostats).

With OhmConnect, flows of information go from the third party to the resident via the SHEMS, while the SHEMS also takes in information from the home. OhmConnect then aggregates information on household demand reductions to bid into the energy market. Evaluations of the program indicate the potential for demand reductions of 12-14% for behavior-based changes in energy usage, and up to 25% for more automated, remote control events, compared to control groups [169]. One program evaluation identified per-household impacts of roughly 0.51 kW, with aggregate impacts of a typical summer event upwards of 1 MW over roughly 2,142 households [170]. Considerations highlighted by the program include that behavioral demand reductions vary by user characteristics, such as house-specific loads, and outdoor temperature [170] and persistent engagement matter for overall impact. Resident engagement falls slightly over the course of events, with a larger demand response effect size experienced early on [168]. This could impact the persistence of energy savings, which requires either new behavior formation, adoption of more efficient technologies, or ongoing engagement of residents with the SHEMS to maintain benefits. Impact evaluations for the program have found that although OhmConnect delivers significant DR resources, the impacts of purely behavioral actions tend to be lower overall with greater variability than DR from automated devices participating in the program, which tended to produce more reliable effects [170].

3.3.3.2 Quadrant Two: Smart Home

The second quadrant represents Smart Home control, where residents shift from agents of control to principals, delegating control to automated functionalities of SHEMS, the primary agents within the system. SHEMS optimally operate end use devices within given parameters for services residents require, such as comfort and cost savings. This can include technical automation that involves the resident, for example notifying them of a decision and providing an opportunity to opt-out, and systems where the SHEMS makes decisions autonomously. Information functionalities primarily allow SHEMS to sense information from the home to inform optimization procedures and, secondarily, to communicate decisions of the SHEMS and related outcomes to residents. At the extreme, this type of smart home control enables fully automated or sentient systems without interaction with the resident, as represented in the diagram by the fact the only control pathways (red arrows) appear between the SHEMS and end uses. Achieving energy-related outcomes in this quadrant requires residents to allow the SHEMS to operate independently, without overriding settings executed by the SHEMS.

A common Smart Home solution involves Smart Thermostats, which have been widely deployed through off-the-shelf consumer adoption and utility energy efficiency programs. As the SHEMS in the system, smart thermostats offer residents opportunities to monitor and adjust a home's temperature, whether at home or away, through an interface (ex. phone app) [171]. The thermostats provide information on energy usage to residents to show home performance over time. Technically, the products can include algorithms capable of learning resident occupancy schedules to operate heating and cooling systems to save energy and features such as geo-fencing that establish virtual boundaries around the house, triggering rule-based actions when residents enter or leave the area [171]. The primary role of residents is to install and provide preferences to the SHEMS while third parties can provide incentives for adoption and installation support. Evaluations of smart thermostats [172] have shown the ability to deliver 3-10% electric and 1-6% gas savings per household. Evaluations further suggest energy savings vary by time of day and season. One pilot found that smart thermostats delivered the greatest savings in the early afternoon (1-4pm) on summer days, with less savings in the late afternoon (4-8pm) [172].

3.3.3.3 Quadrant Three: Smart Grid Home

The third control type, Smart Grid Homes, operates under a scenario of high system agency that materializes through partial or full automation of household appliances by the SHEMS. Agency prioritizes service requirements of third parties who act as principals within the system, delegating control to the SHEMS. SHEMS serve as the primary agents with residents in the home having the lowest levels of agency over home energy use. Control stems from SHEMS optimizing energy use according to parameters provided by the third party actors (i.e. algorithmic control), potentially with some involvement of those third parties in evaluating actions taken. Information-based functionalities of SHEMS allow it to sense information on the home and/or communicate with third parties or residents. Residents receive energy optimized to achieve societally-set objectives such as least-cost or environmentally sound energy use. Residents might provide preferred operating bounds to the SHEMS and could override actions of the SHEMS in some cases, but SHEMS give higher weight to third party needs. Expected energy benefits rely on residents remaining absent from the system.

The pilot Retail Automated Transactive Energy System (RATES) by the California utility

Southern California Edison (SCE) [173] sought to implement a "retail decentralized energy market", connecting residents, distribution operators and load serving entities (utilities), and wholesale markets. The primary SHEMS in the pilot was a software platform that transmitted market price signals to appliance-specific optimization agents in order to schedule home energy usage at hourly intervals. Agents considered forward market prices, weather forecasts, and customer preferences to set schedules for and adjust energy usage for heating and cooling systems, pool pumps, battery storage, EV charging, and electric water heating (depending on the appliances owned by the residents). Residents could also remotely control appliances requiring customer input, including electric dryers, clothes washers, and dishwashers. The program aimed to provide customer bill stability via "subscription transactive tariffs", offering fixed monthly costs based on granular estimated energy usage. Customer bills remain stable assuming residents keep energy usage roughly the same as their "subscribed" hourly demand.

Residents interacted with the SHEMS through a two-way voice interface (using systems like Amazon Alexa) to set preferences for the operation of appliances. For fully controlled appliances, residents set preferred setpoints (for example by saying "Set my AC comfort to medium") and for manually controlled appliances could ask about optimal runtimes (ex. "What is a good time to run the dishwasher?") [173]. The pilot evaluation noted that due to the simple interface, residents would not need to see (or understand) the technical details of the platform, and that "participation in RATES is much easier when agents hide the complexity of RATES from the customer" [173](11), highlighting the aim of the program to rely on technical functionalities and information flows between then SHEMS and third parties to enhance control. The pilot was implemented in 100 homes within SCE service territory. The evaluation focused on customer bill impact and did not report implications for load management, resident engagement, or satisfaction with the system. Results showed the platform could reduce energy bills in some months compared to traditional pricing but not others and would require further analysis to understand the impact of issues like the number of flexible loads in the home or presence of solar net-metered systems on savings.

3.3.3.4 Quadrant Four: Smart Grid Residents

The final control type describes Smart Grid Residents. As with Smart Residents, low levels of automation are involved with controlling energy use, but here the "user" of the SHEMS is primarily the third party. Third parties seek to move from principals, delegating control to residents, to agents themselves directly controlling home energy use guided by information from the SHEMS and via remote control functionalities of SHEMS. Third parties persuade residents to delegate control to them often in exchange for financial incentives or penalties (ex. higher peak rates in exchange for lower rates during "off peak" periods). Such programs frequently involve appliances like thermostats, heat pumps, and/or EVs. Primary agency resides with the third parties, with the residents holding the lowest levels of agency. Information functionalities of SHEMS flow data from the home to the third parties to inform their decision making on program design, incentives, and evaluation of impacts. They might also inform residents of event days or actions taken by third parties. Along the y-axis, programs that sit closer to the origin may use the SHEMS to ask residents to "opt in" to control events, and as programs move towards the axis extremes, this may shift to resident opt-out structures, or in their most extreme structure, programs may not offer residents the ability to override. Supporting residents' perception of control within a given solution will likely increase chances of achieving desired energy-related impacts by minimizing overrides or event opt-outs.

Smart Thermostat DR programs are similar to Smart Homes, but a third party operates as the primary agent instead of the SHEMS. Residents who own smart thermostats (the SHEMS) enroll in their local utility DR program, generally for a financial incentive like a one-time payment for enrollment [174] or based on actual performance in events. The utility chooses events given expected system needs (ex. Peak demand on a summer day). Events typically involve a "pre-cooling" phase where thermostat setpoints reduce to cool the home and then a setpoint increase to reduce demand during peak event hours (generally leading to a warming of the home). For example, within the Eco+ program, a smart thermostat DR program with the manufacturer Ecobee [174,175], the thermostat determines the pre-cooling phase based on analyzing historical thermal energy use and chooses optimal operation based on a particular home. Evaluation of data from over 23,000 such DR events in 6,000 homes attempted to evaluate energy impacts and resident interactions with the program [174]. They found residents overrode event schedules set by the thermostats in 6.3 - 28.8% of events, with an average override rate of 12.9%, compared to an average probability of overriding a thermostat schedule on non-event days of 9.9%. Households that were not frequent users of overrides, overrode their thermostat significantly more often during DR events.

The analysis concluded the energy impacts of these overrides depended on when residents overrode events and how many residents in an event did so. In evaluating one event, results indicated the 27% of homes that overrode their thermostats nearly canceled out the DR benefit of the entire event group due to when overrides occurred and the energy use required to return homes to desired setpoints, highlighting the need to consider strategies to mitigate or anticipate overrides. The authors emphasized the importance of behavioral considerations, noting "the present study also showed that going through several DR events 'teaches' occupants to let events proceed until the end", hypothesizing that actual loss of comfort was not as severe as anticipated and over time residents better understood and adapted to programs [174]. This suggests the need for efforts to mitigate overrides particularly in early phases of program enrollment to allow such adaptations and learnings to occur.

3.4 Discussion

Table 3.1 summarizes the characteristics of the four control types and details of the real-world examples described. Although not a representative sample, and therefore not generalizable, the comparison begins to identify key considerations for understanding control. As a tool, the taxonomy offers a powerful opportunity to engage different stakeholders (such as policy makers, industry, and communities) in conversation around the design of future SHEMS-based programs and the risks that programs designed from a purely techno-centric vision of control may be exposed to. The following sections discuss core observations associated with these risks and make recommendations for how to address them moving forward. We also discuss limitations of the existing work and areas for future study.

3.4.1 Many Types of SHEMS-based Control Remove Agency over Energy Use From Residents

Despite considering types of control over energy use within the home, the taxonomy identifies residents as primary agents in only one of four scenarios and secondary agents in one of four scenarios. Residents operate with the least agency in half the control types. This vision of control reveals numerous issues for deep consideration as these efforts move forward. For example, if the dominant approach to managing energy is one that removes agency from residents in managing their own energy use, what is the role of the resident

Table 3.1: SHEMS-enabled control types and design considerations

Quadrant	Q1: Smart Resident	Q2: Smart Home	Q3: Smart Grid Home	Q4: Smart Grid Resident
Agency Primary (Secondary) Agent	Resident (SHEMS)	SHEMS (Resident)	SHEMS (Third Party)	Third Party (SHEMS)
Level of Automation	Low to Medium	Medium to High	Medium to High	Low to Medium
Focus of Control	User-Centric	Technology-Centric	Technology-Centric	User-Centric
Case Study	Behavior-based Demand Response	Smart Thermostat - *no demand response*	Retail Automated Transactive Energy System (RATES)	Smart Thermostat - *demand response*
<u>Characteristics of Control System Highlighted in Case Studies</u>				
Goals	Set by resident, operationalized by resident	Set by resident, operationalized by SHEMS	Set by third party, operationalized by SHEMS	Set by third party, operationalized by third party via SHEMS
Information Sensing				
SHEMS	Electricity monitor senses total household energy use (historical, real-time); appliance-specific energy use (historical, real-time)	Heating/cooling energy use, occupancy patterns, comfort preferences (setpoints), weather, determines (in some cases) appliance operation schedule	Forward market prices from wholesale market, weather forecasts, resident preferences, appliance energy use (historical, real time); Sets optimal operating schedules (limited appliances)	SHEMS provides raw and/or analyzed information to third party to inform action
Resident		From SHEMS, historical	From SHEMS, optimal operating times for running	SHEMS may provide third parties

	Home energy use data from SHEMS, evaluates service from appliances based on behavior changes, can set goals/notifications to receive specific information	heating/cooling energy use, SHEMS may inform resident of prospective decisions re: setpoints and/or impacts of historical decisions	appliances; Otherwise absent	menu of decision options, potential impacts, and/or evaluation of service in retrospect to inform resident action
Third Party	Home energy use data from SHEMS, used to influence pricing and/or messaging to resident	N/A	From SHEMS receives information on home energy use needs and transactions; Third parties also exchange information on energy use purchases and pricing	From SHEMS receives home energy use data uses to inform pricing and control actions
Control Actions	Manual by resident Remote Control *initiated by resident taken by SHEMS for select smart appliances* (*if owned*)	Remote Control - *initiated by residents taken by SHEMS* Rule-based Control - *initiated and taken by SHEMS*	Remote Control - *initiated by third parties taken by SHEMS* Rule-based Control - *initiated and taken by SHEMS*	Remote Control - *initiated by third party taken by SHEMS*
Considerations				
Energy Impacts	12-14% potential behavior-based, 25% controls based reductions; 0.51 kW reduction per household avg.	3-10% electric, 1-6% gas savings, vary by time of day	Not included in evaluation	0.52 kW [60]
Principal-Agent Problem Solutions	Reduces information asymmetries; Enhances some direct control opportunities	Shifting agency from resident to SHEMS - enhancing direct information on and control/monitoring of system	Shifts PA relationship to SHEMS - third party, greater information and monitoring	Seeks to exclude resident as agent, provides third party with direct control, information, monitoring
End Uses Implicated	Possible to impact any end use appliances in the home	Thermostat (heating/cooling system)	Heating/cooling system, pool pump, battery storage, EV, electric water heating; Electric dryer, clothes washer, dishwasher	Thermostat (heating/cooling)

Other Considerations	Evidence shows resident engagement with SHEMS decreases over time Delivers non-energy benefits including shifts in opinion of utility, knowledge of home energy use, spillover to additional energy efficient actions	Savings potential dependent on resident not interfering with SHEMS and with SHEMS correctly sensing/analyzing system characteristics	Complex information sharing / communication architecture Control of certain appliances requires persistent resident interaction despite program aim to limit resident participation in control	Small segment of households overriding event can nearly cancel out benefit of entire cohort or limit savings achieved v. potential predicted

in participating in and helping develop visions of what those approaches look like? Very likely, residents have had little to no voice to date in shaping dominant policy visions, such as those illustrated in emerging policies and planning efforts like the Department of Energy's Building Decarbonization Blueprint [2].

Whereas this taxonomy has focused on how agency exists in efforts to directly control agency, it does not capture how agency is more broadly embedded in equitable processes where those most impacted by energy-related programs and technologies are given a seat at the decision-making table. Such considerations are captured in efforts to advance recognition and procedural justice [176] and have been highlighted as a gap in work on smart grid visions generally [130] and demand flexibility specifically [37, 177]. The taxonomy presented here offers a promising starting point for those conversations, offering a way to reveal these tensions to policymakers driving these visions and engage with residents on how they might react to or value different types of control that SHEMS offer them. Such conversations could reveal where novel technologies might fit into residents current lives and support achieving their own goals alongside those of grid operators or highlight friction points that programs may need to address in order to achieve wide-spread participation and estimated energy reductions.

3.4.2 There is Risk in Underestimating Resident Involvement in SHEMS-based Control Systems

Where most SHEMS-based control opportunities showcase visions of residents with less agency, a robust and growing body of empirical evidence suggests that residents are rarely as absent from systems using automated functionalities as expected. In fact, evidence has long suggested that residents often use technologies in innovative and unexpected ways [178, 179] or find workarounds to subvert smart automation and achieve their own desired goals [17]. Research also shows residents more actively managing energy use than predicted [112] and that residents are already working to shift energy-related activities in the home to balance a variety of issues like need, cost, and availability of renewable energy [26]. In this taxonomy, the agency of residents emerges in the case studies for the two most technical control types (Smart Home and Smart Grid Home) in two ways. First, within RATES (Smart Grid Home), the program design explicitly recognizes some limitations of technical control such that for certain appliances (ex.dishwashers), automatic scheduling will always need the support of resident actions. Second, within Smart Thermostat DR (Smart Home), unintended resident intervention (overriding of SHEMS settings) leads to suboptimal outcomes.

While many dominant policy visions of SHEMS-enabled control may assume that providing technologies or utilities with direct control over energy use are less risky pathways to capture societal grid benefits via managing energy use, they fail to account for the risk associated with underestimating the propensity for people to be active within highly automated or technical systems. These risks, related to the social dimensions of how people experience and react to control systems that do not meet their needs (ex. [154]), pose threats to program effectiveness at best and rejection of SHEMS-based demand flexibility programs at worst, thereby posing a major threat to achieving decarbonization objectives in a timely fashion or at all.

The risk surrounding human intervention in the system depends on the extent to which program designers and policymakers plan for and understand it. Mental models or visions of the smart home energy system that exclude resident actors from the start are likely at high risk of suffering negative consequences of underestimating the human element. Current program design and evaluation frameworks do not yet account for this risk and regulators often rely on cost-benefit analyses to assess whether a program is worth pursuing. Those assessments rely on considerations such as energy savings and costs that can be quantified and monetized [180], and do not capture how different program design elements or equity related considerations might influence the impact or effectiveness of technology deployment [181]. Future work is necessary to consider how issues such as community engagement, technology design, and customer support in the technology adoption process could be integrated within or considered alongside more traditional cost-benefit analyses to allow for more accurate screening of whether programs will be successfully adopted and achieve estimated energy-related impacts.

Underestimating or devaluing agency or intelligence of residents fails to open the door to conversations around how we build upon, not ignore or subvert, "social smartness" that already exists within homes [22, 130] or similarly investigating what collaborative opportunities might exist between technologies embedded in the built environment and residents to better understand and manage energy use [23, 50]. Just as this taxonomy can serve as a discussion tool with communities to integrate their voices in the design of SHEMS-based control systems, it can also serve as a discussion tool with the utility industry, policymakers, and regulators to highlight the importance of resident agency and discuss opportunities for programs to more actively consider their roles.

3.4.3 Explicitly Acknowledging Third Parties as Users of SHEMS Helps Reveal These Risk Points

Within the taxonomy, third parties appear as critical, active components of the system with primary agency in one control type and secondary agency in another. This aligns with dominant policy framings associated with demand flexibility and decarbonization initiatives and highlights the need for research on SHEMS to explicitly consider third parties as core actors in these systems, a gap previously identified in the literature [**?**]. Without doing so, it is not possible expose the assumptions or the associated risks discussed above.

Although the model in this taxonomy represents one third party, the RATES case study (Smart Grid Home) showcases the potential complexity of third party actors, including software or product manufacturers, local utilities, and wholesale market participants, and the ways in which SHEMS transmit information among third parties in addition to between third parties and residents. While important for functional program design related to delivering grid services (ex. information sharing architecture), questions remain regarding whether this complexity matters from the resident perspective - i.e. do they perceive differentiated third parties or just the primary one providing them the solution, and, how does this complexity impact control within resident-third party relationships? Similarly, further work is needed to explore the role of policymakers as third parties in helping define dominant narratives around visions of control of the embedded energy system future [17].

3.4.4 Effective Programs Must Recognize the Complexity and Temporal Aspects of Control

In deploying demand-side management programs, little attention is often played to the support residents need to learn about and feel comfortable with new and potentially disruptive technologies, even if they are designed to operate in the background. Recent reviews of smart technology case studies have highlighted that the most successful efforts to flexibly manage energy 1) provide residents defined roles in the system 2) eventually become 'invisible' to residents when they understand that role and 3) are built upon meaningful goals from the residents' perspective [26]. Yet to date the expected role of residents in these systems remains unclear [17, 26] as discussions of the use of SHEMS to achieve demand flexibility continues to be primarily considered from the technology-based, system perspective [28] which fail to directly engage with these considerations.

For example, the four real-world examples highlight the complexity of controlling household appliances and the diversity of control types that may be required to optimize energy service delivery. The cases highlight the full spectrum of potential "smart" control - ranging from control over one end use (Smart Thermostat in Smart Home and Smart Grid Resident), to several (Smart Grid Home with RATES) to all (Smart Resident with Behavior-based DR reaching any end use residents manually interact with). The examples also highlight different types of control might be required to manage different appliances, like rule-based control via SHEMS for some (ex. battery storage), remote-control via resident interaction for others (ex. dishwasher), or manual resident control. This begs the question of whether all end use appliances within the home need to be controlled with energy use in mind and the extent to which programs seeking to do so will need to blend different control types identified within this taxonomy (and the complexity of program design required to do so).

This raises questions around the temporal nature of control (not yet captured by this taxonomy), and the potential impact of a more user-centric control type early in the program that emphasizes the resident as they learn and evolves towards a more technology-centric design in the long run. For example, in the Smart Thermostat DR example, evaluation of the program suggests learning by residents as events proceed may lead them to adjust expected discomfort versus reality, adapting actions (ex. reduced overrides) in beneficial ways. Although this taxonomy identifies four simplified control types in each quadrant of the axes, future efforts would benefit from envisioning what "middle ground" control types would look like - such as one operating at the origin of our axes which balances both individual and system needs with various levels of automation. Might there be a future where residents could opt in or out of different levels of automation for specific appliances in their home depending on their needs, thereby helping increase buy-in of automation and eventually graduating to more automated solutions based on their comfort?

Findings from [144] and [26]) show that in all types of automation, information-based considerations likely to play an important role in gaining the trust and buy-in of residents whose home they operate in. Review of the case studies also highlights the centrality of information-functionalities in all control scenarios, underscoring the need to include information-based considerations in definitions of control. Within each control type, information serves as a core link in the relationships between agents (or principals and agents to whom they delegate control), whether seeking to address issues such as information gaps or asymmetries (Smart Residents), improve monitoring of energy use by the SHEMS (Smart Home or Smart Grid Resident), or enforcement of control decisions (Smart Grid Home) related to enhancing control. This highlights the importance of elevating information-based and user-centric considerations to equal technical ones in matters of control and evaluating who (or what) receives information in the system and how this influences control dynamics over time. Heatherly and colleagues [154] similarly find information-based transparency by smart technologies around the rationale for automated decisions helps increase user acceptance and decrease negative reactance to the system. What information is necessary may depend on the type of automation being deployed and appliances being controlled.

What this taxonomy does not yet capture is the extent to which the ability to control or flexibly operate specific appliances is embedded within the activities, routines, and rhythms of daily life in which they are used [17, 182]. For example, in their review of smart technology programs, Adams and colleagues [26] conclude that "there is no one simple hierarchy of energy loads that are more or less amenable to automated controls" and that this depends on a suite of contextual factors.

3.5 Conclusion

As SHEMS become more prevalent in homes, issues of control will be central to understanding their contribution to energy system transitions. To further that understanding, this research introduces a taxonomy of control in the smart home, drawing on interdisciplinary concepts of control, automation, and agency to offer a taxonomy of control to support scenario analyses of what "control" means and how it is employed. The taxonomy identifies four control types that range from user-centric to technology-centric and highlight how control is embodied in functionalities of technologies and the ways in which they influence, support, and/or shift agency-based relationships between residents, third parties, and SHEMS. The comparison of control types and real-world examples showcase initial considerations around resident and third party agency and the complexity of control that become evident through the use of the scenario analysis tool.

While a promising start, the taxonomy presented here is ripe for further refinement, as Section 3.4 began to highlight. While this taxonomy represents a relatively simple and static representation of such smart home control systems (both a strength and limitation) future research could seek to dive deeper into details of issues such as information flows, temporal aspects of the evolution of control, greater complexity of actors both within and external to the home, or even building types (ex. single versus multifamily or commercial systems), to further explore control dynamics. The application of the lens of agency and related understanding that control is relational in nature offers a major contribution of this work and deserves further attention and exploration in future research as well. Previous work [130] has identified the relational nature of control in smart home systems, discussing it as an emergent outcome of relationships between users, technologies, and everyday life, although these concepts have received little exploration in SHEMS research to date [183]. This taxonomy extends those concepts beyond the boundaries of the home to include relationships with broader energy system actors. Such conceptualizations of control deserve further exploration and particularly consideration of what theories of human behavior coupled with models and simulation tools might be necessary to capture the relational aspects of control as research seeks to estimate potential benefits from smart home control systems and how such framings can enhance understandings of equity-related implications of the deployment of SHEMS.

Previous work [138] has highlighted that smart solutions aimed to better control energy use require a careful balancing of technologies and humans where each maximizes or enhances energy saving opportunities. This underscores the need to find the “right” degree of automated control for the right situations, acknowledging that many humans already hold a certain level of intelligence related to how they operate their homes and this human intelligence can be hard to replicate or replace with artificial intelligence [156]. Moving forward, the question is not only what the right type of control or level of automation is but the right type of control for which households or grid contexts and end uses at what time. While a highly automated version of the smart home might successfully drive energy benefits in some scenarios, focusing on these scenarios alone may limit the overall potential of the system to meet sustainability related objectives. This taxonomy will prove a powerful tool to help fend off bias towards narrow exploration of one control scenario, acknowledge the diversity of solutions that exist to manage home energy use, and help deploy an array of programs in a way that meets sustainability and grid- related objectives in addition to those of residents in the home.

Chapter 4

Recognizing (in)equity in demand flexibility initiatives: An interdisciplinary approach

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Abstract

Two emerging areas of focus in the clean energy transition are demand flexibility and energy justice. Demand flexibility will serve a critical role in aligning demand for energy with increasingly intermittent renewable energy resources and helping reduce costly and carbon intensive peaks. Electric customers, particularly those in the residential sector, are expected to play a central role in producing flexible demand yet impacts on those customers remain uncertain, particularly for low income or otherwise disadvantaged communities. Limited research exists to identify which customers would be most negatively impacted by demand flexibility initiatives and what public policy could do to support those populations. The

present research seeks to address this gap through a quantitative assessment of American Time Use Survey data [184] and the Residential Energy Consumption Survey [185]. We investigate the predictive ability of energy justice indicators to determine temporal patterns of household activities and technology adoption of key technologies for demand flexibility. Results show that socio-economic justice indicators related to income, race, employment, education, disability, housing type and tenure, and age significantly correlate with activity patterns and technology access in ways that, we argue, could have implications for these customers' ability to realize benefits associated with demand flexibility programs. We make recommendations for how policymakers and grid operators can better recognize and understand these barriers to access and mitigate them not only through more granular distributional equity analyses and simulation efforts but also through community engagement.

4.1 Introduction

Driven by factors such as public policy and social movements, the energy system is currently undergoing a significant transition. Alongside traditional energy planning objectives such as affordability and reliability, new objectives to equitably decarbonize the energy system have begun to emerge [33, 186]. Achieving emerging goals will require an evolution of the tools, frameworks, and perspectives guiding system operators and policymakers. This will be particularly true as smart technologies are increasingly deployed to more granularly control energy use in the residential sector, raising significant questions around who has the agency and capacity to participate in and receive benefits from innovative technologies and the programs that utilize them [26, 129].

Energy equity and justice seek to ensure the energy transition centers the voices of the communities previously marginalized by the energy system [32, 187]. These initiatives recognize which communities have or will face disproportionate impacts from the energy system and develop targeted strategies to mitigate those inequities. Despite emergence in state and federal policy initiatives, a robust application of an equity lens has been limited in many areas of grid planning to date including integrated resource and distribution system planning in addition to demand-side management efforts [188]. This is particularly true in the realm of demand flexibility and the application of smart technologies to help manage grid operations [28]. Demand flexibility, or the ability to alter the amount or timing of energy use [8], is increasingly seen as a critical pathway to balance the expected deployment of intermittent renewables like wind and solar and rising demand associated with electrification of the buildings and transportation sectors, core strategies to achieve decarbonization goals [1].

As a result, demand flexibility is a central component of grid planning and policy initiatives. The Department of Energy [2] recently released the National Blueprint for Decarbonizing the Building Sector. One strategic objective calls for a transformation of the grid edge and a tripling of demand flexibility potential by 2050 vs. 2020. Similarly, in 2023, the California Energy Commission established a goal of procuring seven Gigawatts of flexible load resources - equivalent to the amount of electricity capable of powering seven million homes - by 2030 to support transitioning to 100% clean energy [10]. As demand flexibility efforts emerge, grid operation and related programs will increasingly intersect with everyday life in novel ways [25]. Grid operators and policymakers see the residential sector as a particularly promising source of flexible energy demand, with some studies estimating upwards of 50% of potentially flexible energy use resides in this sector [9].

Visions of the future grid expect the diffusion of smart home energy management technologies (SHEMS) will help capture this potential. These technologies offer enhanced functionalities to support more fine grained control over energy use in homes through the collection, monitoring, and sharing of information between actors in the system (ex. residents, third parties) [15, 54, 83]. For example, to achieve a tripling of demand flexibility by 2050, The Department of Energy [2] envisions that in 2050, over 75% of lighting and heating and cooling systems in residential homes and businesses will be able to support networked, flexible control of energy use and that over 90% of these customers will be offered some form of incentive for flexible control of their space and water conditioning technologies. At the grid level, recent modeling [4] has illustrated the ability for such programs to provide numerous societal and grid-related benefits. Such benefits amount to an estimated 8% reduction in carbon emissions and 9-10% cost savings for grid system operation in 2050. This equals savings of upwards of $10 billion in costs that would otherwise largely be passed to customers through electric rates.

While potential for net positive benefits at the grid level seem clear, the impact at the customer level remains uncertain, particularly for low income or otherwise disadvantaged communities [27, 28]. Analysis at the customer scale has received surprisingly little critical assessment given the scale of new technology deployment meeting these objectives will require and the highly ambitious changes in the way energy is managed and controlled within homes they consider. To date, much of the conversation around, and motivation for, demand flexibility has occurred at the system level [28, 189] and there has been limited study at the intersection of energy justice and demand flexibility [28, 36]. This is despite an increasing number of states enacting environmental justice laws and centering equity in climate and energy policies [33]. Yet Yule-Bennet and Sunderland [28] argue "*Which* kilowatts flexibility schemes extract and *how* they are extracted is socially important" (71), highlighting that as grid operators seek to shift energy use (kWh) in time and space, the customers contributing this energy shift and the way in which they do so matters. Without careful attention to understand which customers are and aren't capable of shifting energy use in time, such programs risk imposing high electric rates on already vulnerable customers with inelastic energy use. However, current program approaches and regulatory frameworks do not yet robustly recognize this [28]. For example, the DOE Building Decarbonization Roadmap [2] highlights equity and affordability as core goals of building decarbonization, but offers only broad characterization of disadvantaged communities with no specific commentary or analysis recognizing equity concerns for strategic initiatives related to demand flexibility.

Ultimately, at the intersection of demand flexibility and energy justice, there is a noticeable gap in work seeking to understand which communities do or do not have the capacity to engage with these programs grounded in an understanding how people currently experience and interact with the energy systems on a temporal basis [37] and their access to enabling technologies [27]. Such issues ultimately impact customers capacity to have agency in their participation in this transition. Achieving decarbonization objectives requires urgent, sustained efforts to deploy clean energy technologies and related programs and policies [1]. This suggests there is a narrow window to embed principles of equity and justice in current efforts to significantly scale demand flexibility policies and programs [28]. The present research seeks to support that effort and address gaps in the literature by assessing residential demand flexibility initiatives through a recognition justice lens, one of few studies to do so. We take a recognition justice approach as it represents a critical starting point to assess the social and technical contexts within which these programs will be situated and the inequities that currently exist [190]. As a result, this perspective provides a necessary foundation from which to advance consideration of other principles of energy justice as relates to demand flexibility initiatives. To do so, we draw on literature from the fields of energy and environmental justice to provide a holistic perspective on existing inequities and the potential to perpetuate them without intentional program design. This assessment is supported by quantitative evaluation of two publicly available datasets, the American Time Use Survey [184] and Residential Energy Consumption Survey [185], analyzing how socio-economic indicators of social vulnerability ("justice indicators") in emerging policy predict temporal patterns of activities at home and technology adoption patterns. Evaluating the findings offers insights on the social and technical structures demand flexibility programs will operate within and critical areas of focus for equity and justice work in this area over the coming decade.

The remainder of this paper proceeds as follows: Section 4.2 reviews the literature on energy and environmental justice, demand flexibility, and their intersection. Section 4.3 describes the quantitative approach to evaluating justice implications of demand flexibility and Sections 4.4 and 4.5 review the results and discuss implications for future research and policy.

4.2 Literature Review

4.2.1 Energy and Environmental Justice

After reviewing literature by community-based organizations, practitioners, social scientists, and law, the Initiative for Energy Justice (IEJ) [187] defines energy justice as "the goal of achieving equity in both social and economic participation in the energy system, while also remediating social, economic, and health burdens on those historically harmed by the energy system." The IEJ further states that "Energy justice explicitly centers the concerns of marginalized communities and aims to make energy more accessible, affordable, clean, and democratically managed for all communities." [187] Building off foundational work in the environmental and climate justice spheres, the field of energy equity and justice work has emerged over the last two decades to advance these objectives [32, 187].

Energy equity and justice are unique in grid planning in that they represent both an objective in and of themselves and also a lens through which to analyze and evaluate policies designed to achieve other grid objectives (ex. decarbonization) [188]. For example, as an objective energy equity strives for equitable representation and recognition of diverse communities cultural values and ways of interacting with the energy system [176]. As a lens of analysis, this perspective helps understand and address where misrepresentation is occurring and the related injustices that stem from these through identifying issues of concern, understanding who is disproportionately impacted by those issues, and how to remediate them [32, 176]. The work in the field is often organized around three or four core tents [32, 187, 191, 192]:

- Recognition justice, focusing on who is impacted or recognized by, has the capacity to exert agency in, or is particularly vulnerable within the energy system;
- Procedural justice, considering processes to remediate inequities, question who holds decision making power, and what mechanisms exist to keep them accountable;
- Distributive justice, focused on equitable distribution of outcomes, centering analysis of where injustices occur among communities identified as most likely to be impacted by programs and policies; and
- Restorative justice, considering pathways to remediate past and present harms.

An energy justice perspective requires recognizing the socio-technical nature of the energy system, looking beyond the techno-centric lens often taken in the field [32]. This means founding equity-focused assessments in a holistic, whole systems understanding of how issues such as technologies and infrastructures, user practices, and policy frameworks intertwine [32, 193].

The previous decade in particular has shown significant growth in scholarship regarding energy justice [181]. This research has emerged across a variety of areas in field of energy studies touching on issues of both energy supply and demand. Similar growth in consideration of equity and justice has emerged in the policy realm in the United States [33]. In 2021, the Biden Administration initiated "Justice40" via Executive Order 14008 [34]. This initiative seeks to direct 40% of the investments in climate and energy towards disadvantaged communities. At the state level, as of 2022, nearly half of states in the US had taken some action to advance energy and environmental equity through avenues such as legislation, executive orders, or Public Utility Commission activity [33].

However, as energy justice related inquiries have emerged, so to have gaps in research and practice, particularly around the consideration of a recognition justice lens. In a comprehensive review of the academic literature, Jenkins and colleagues [181] found that less than 40% of research papers considered recognition justice in their conceptual framing. Similarly, state-level policy has tended to emphasize distributive and procedural dimensions of energy equity over recognition or restorative ones [33], despite recognizing disadvantaged communities as being a core (the most common) focus of equity-related policy actions.

Despite this, initial efforts to translate energy justice principles to modeling and assessment frameworks highlight recognition justice as a foundational first step towards viewing policy and programs through a justice lens [38]. As noted by McDermott and colleagues [190] in the environmental justice field, "To uncover the origins of injustice it is necessary to understand the political processes and distributive outcomes in their social context" (419). They further argue that a full definition of equity, considering all dimensions of equity and justice, is imperative for the development of effective policies and planning efforts. Although considerations of equitable distribution of the benefits and costs of a program are crucial to understand, they provide an incomplete understanding of the injustices potentially occurring and their origins [190, 194]. Such considerations are the focus of a recognition justice lens, which we explore in more detail in the next section.

4.2.1.1 Recognition Justice

Although various definitions of recognition justice exist, the common focus centers around the "who" of equity and justice. These considerations highlight which communities are rendered invisible or misrepresented in mainstream policies or discourses [32] alongside "institutionalised patterns of cultural value" that prevent certain individuals or groups from fully participating "as peers in social life" (246) [176]. In applied policy realms, when considerations of recognition justice are explored they are often tightly tied to distributive considerations, focusing on "who is impacted" by inequitable distributions of benefits or costs [32, 191]. The Energy Equity Project highlights that “recognition justice is sometimes referred to as ‘structural’, indicating that factors such as identity and demographics which are largely beyond a household’s or community’s immediate control play a role in determining the distributional outcomes they experience.” (32) In quantitative assessments and policy analysis, this is often applied through the increasingly common best practice of identifying disadvantaged communities via mapping tools and overlaying indicators of vulnerability geospatially to identify populations of interest [195] or correlating specific outcome variables (i.e. technology adoption trends) by socio-economic demographics. In seeking to advance the limited quantitative assessments of (in)justices, the Energy Equity Project framework [191] establishes four categories of recognition justice metrics, including indicators of historical disinvestment (historical discrimination and disenfranchisement, such as redlining or investment disparities), identity (including demographic, socio-economic indicators of vulnerability, access, and burdens), energy security (ex. power outage duration and shutoff policies), and affordability (ex. rate structure, limits to energy burden). Sovacool and colleagues [35] similarly identify demographic inequity as one of four primary justice concerns in the electric power grid.

While this approach offers a practical way to integrate the "who" of equity into applied policy and program development, it fails to engage with a deeper understanding of recognition justice which seek to understand the social structures that determine context for (in)equities [32, 190, 194]. For example, McDermott and colleagues [190] argue recognition justice looks beyond outcomes and processes that develop during program implentation towards inequities present before a program or policy is designed, i.e. "what kind of inequity is present at the starting point?" (419) This perspective seeks to understand where nonrecognition (ex. rendering certain individuals or communities invisible) or domination or valuation of certain cultural perspectives result in inequitable status quo, recognizing that inequitable outcomes or patterns occur for a reason [194].

Along these lines, Lamonaca & Batel [176] propose four dimensions of recognition justice in their exploration of smart housing projects:

- Agency, foregrounding issues of control, voice and decision-making power, and capabilities to access resources such as time and information necessary to assert agency

- Interpersonal treatment, considering issues of respect and dignity, including feeling heard
- Trust in relationships, a critical foundation for empowerment, and
- Place attachment, considering people-place attachments around places like home and community

Lamonaca & Batel [176] assert a recognition justice lens particularly emphasizes issues of agency, needs, practices, and flexibility, bringing to light "those less tangible, symbolic, and affective dimensions...of people's relations with the eco-social systems where they live" (245). Aligned with energy justice more broadly, this speaks to the need to ground equity-based assessments in both a social and technical (material) understanding of the status quo to first identify who experiences existing inequities and the socio-technical contexts for why. From this understanding, inclusive and just policy pathways can be developed to accurately redress historical inequities and build towards a more equitable energy future.

Given the focus on agency and control, such a perspective will be critical in understanding how smart technologies may or may not support more equitable energy outcomes since such technologies inherently seek to change the way in which energy is managed in homes, and often, who is managing that energy use. Lamonaca & Batel [176] argue that "dismissing this tenet of energy justice might result in the failure of projects and efforts towards greening the energy system in an inclusive and just way" (245) noting that "recognition justice is often considered absent or assumed in empirical investigations in the Global North; that is, it is not analysed based on individuals' and communities' lived experiences of recognition (in)justice." (244). Building on this work, we seek to bring a recognition justice lens to an understanding of smart technologies as enablers of demand flexibility in the residential sector. We first review the literature on demand flexibility and then the extent to which it has been assessed through an equity lens.

4.2.2 Demand flexibility: Definition & Enabling Pathways

Demand flexibility broadly considers the ability to alter the amount or timing of energy use over a variety of timescales [8, 27]. Often depending on the disciplinary perspective, this focuses on how rhythms of energy demand, derived from working patterns, social practices or culture, and use of household appliances, can be changed to align with system needs. Policies and programs seeking to encourage flexible demand, work over timescales ranging from multiple years, seasons, or hours, to second-to-second. These programs have a variety of objectives, including energy conservation or electrification, moving use towards periods of abundant renewables and away from costly and carbon-intensive peak periods, or curtailing use and regulating frequency during emergency situations [8, 189, 196].

Demand flexibility can be conceptualized through a variety of socio-technical pathways, including technology-led or activity-centric approaches [27, 41, 197], and hybrid combinations of the two [198]. These pathways are often coupled with dynamic pricing schemes to encourage customers to consume energy during low-price periods and avoid high-price times of the day [189]. The pathways are largely expected to be facilitated via functionalities of emerging smart home energy management technologies, which have more granular opportunities to communicate with customers about load flexibility needs and automate load shifting on their behalf [83]. Such technologies also offer improved ability to measure and monitor the effectiveness of programs and operation of the energy system as a whole [16, 27].

With technology-led approaches, demand flexibility programs rely primarily on the automated functionalities of smart devices to alter energy use patterns [197]. These programs assume technologies can alter energy use in buildings behind the scenes, without significantly impacting the activities of people or their level of service. Appliances are typically categorized by their controllability when designing programs and estimating flexibility potential. Highly controllable loads include those where service can be interrupted or changed without inconvenience to the resident [196] including thermal loads (space and water heating; cooling and refrigeration), electric vehicles and batteries, and mobile electronics [189]. Moderately controllable loads include wet appliances like washing machines or dishwashers, and limited to uncontrollable loads are those where operation is particularly important to the customer, like lighting, television, and cooking appliances [189, 196].

Activity-led (sometimes referred to as behavior-based) programs rely on people changing their behavior or the timing of activities during the day [41, 197]. These types of programs require more active participation of people, whether driven by price signals or information-based signals from smart technologies. Examples include manually changing set points on thermostats or other thermal appliances, changing cooking or meal times, or reading a book instead of watching TV [197]. The past decade has seen growing research focused on understanding temporal aspects of energy demand and some emerging consensus around what activities occur during peak periods of energy use. These include meal-related actions, entertainment (such as TV or gaming) and socializing-related activities [27, 199–201].

Conceptually, the ability to change the timing of energy use could be impacted by a variety of factors. These include duration of activities, how they are sequenced or synchronized in time (with each other or other people), and how frequently they occur [177, 202]. Flexibility is also influenced by geography, institutional arrangements, norms (ex. cultural conventions, mealtimes, holidays), public infrastructure, and bodily needs (ex. hunger, sleep, thermal comfort) [177]. From this perspective, Libertson [177] argues "generating demand response flexibility entails the ability to interrupt and decouple activities from time and space" (7) (or at least their energy use). This decoupling could be considered on multiple scales, including for various people, practices, or societies [202] based on the socio-temporal configuration and contexts within which people operate. Initial studies show activities as significant predictors of weekday demand and when household evening peak demands occur [199, 203] and potential flexibility seems highly dependent on internal household variation and synchronization of activities [204].

Each of these two pathways is expected to be coupled with various pricing schemes to help incentivize energy use shift, and compensate those customers who are able to do so. These rate structures include time of use or real-time pricing, which offers varying rates throughout the day according to wholesale market prices. Critical peak pricing or rebates typically offer a lower base rate for electricity during off peak periods and a particularly high rate or reward during peak periods on special event days to promote reductions in usage [189]. These rates can be offered both as whole home electric rates or as appliance-specific offerings.

Although often considered separate pathways, demand flexibility initiatives ultimately need to consider both social (activity-based) and technical (technology-based) aspects of programs as they are deployed. Technology-focused initiatives are likely subject to social constraints [197] and social pathways may similarly be impacted by or improved due to presence of technologies. Holistic consideration of the two can highlight uncertainties for programs and policies [22, 189, 198].

4.2.2.1 Demand flexibility: Potential Impacts

Given the potential interaction with daily lives and home infrastructures, there has been surprisingly limited study of the impacts to residential customers from demand flexibility programs. Recent research by Yule-Bennet & Sunderland [28]) delineates between possible direct and indirect benefits residential customers could experience. Indirect benefits, related to societal benefits, occur when demand flexibility helps reduce operating costs, price volatility, and emissions for the grid (i.e. reduced rates for all customers, societal benefits of mitigating impacts of climate change). Alternatively, direct benefits experienced by customers could be either financial or non-financial. Financial benefits include being paid in exchange for flexible energy use either through bill rebates or savings by using during lower cost, off peak times. Non-financial benefits could include those to health, comfort, security, or agency and autonomy - i.e. riding out outages for longer periods of time, using smart technologies to anticipate and serve needs, and connecting communities who can pool resources to access financial benefits at scale.

However, to have agency in these systems and access the potential benefits they offer requires a certain level of capacity to engage in the programs or respond to price signals, and questions remain regarding who has that capacity and how it is enabled (i.e. technically or socially). There is growing recognition that capacity to be flexible may not be equitably distributed across customers, and electricity use itself may not be inherently flexible [27, 36, 177]. Barriers to participation include those that are 1) technology-based, i.e. not having the right infrastructure and limited upfront capital or control to change that, including access to internet and smart meters, 2) psychological-based, including lack of trust in service providers or being particularly risk averse and unwilling or able to absorb price risk, and

3) skills or knowledge-based, such as being aware of innovative rates offerings or levels of digital literacy and comfort with smart technologies [28, 36]. Risks of negative financial or non-financial impacts exist if customers are unable to either enroll voluntarily in a program to benefit financially or shift consumption if a program becomes the default. Equity and justice lenses provide insight into how to develop better understandings of such issues.

4.2.3 A Recognition Justice Framing for Demand Flexibility

There is currently a limited but growing body of research at the intersection of demand flexibility and energy justice [28]. Most academic research to date has been rooted in a theory of "flexibility justice" introduced by Powells and Fell [27] who call for a deep understanding of the justice implications of flexibility as it becomes more prevalent. Powells and Fell [27] conceptualize the ability to shift, or be flexible in, energy usage as a form of capital, defining capital broadly to include "social and cultural forms of value which are linked to tangible benefits or advantages." (57). They argue smart energy systems support valuation of flexibility. Consistent with the literature on demand flexibility, the authors highlight that flexibility can be derived from technology- or socially-driven pathways and economized or controlled by different parties, ranging from the individual to an external "other" [27, 177]. Since individuals may have more or less ability to be flexible in energy use, combinations of these dimensions lead to a range of different impacts.

Paralleling trends in broader energy justice work, much of the focus of this body of research is the uneven distribution of flexibility capital and how this may lead to inequitable distribution of benefits and burdens associated with impacts of demand flexibility programs [27, 37]. This research has primarily focused on low income or disadvantaged communities (broadly defined) and the financial impacts associated with bill savings or increases and month-to-month bill volatility. On this front, Calver and Simcock [36] note that "whilst [time-of-use] tariffs have the hypothetical potential for positive justice outcomes via reductions in energy bills for vulnerable households, empirical evidence thus far demonstrate that the picture is complex and that there are significant risks of injustice" (17). While some evidence exists that a transition to more dynamic rates could reduce bills for both the average residential and disadvantaged customer, investigations have also shown shifts in rates could increase bill volatility [205]. This could be felt disproportionately for some (low income) customers more than others and disproportionately impact certain customer segments (ex. elderly, disabled), financially and non-financially (ex. predicted health outcomes; [206]). Recent investigation of the California Flex Alert program showed that high income, high energy users were more likely to respond to requests to reduce load vs. low income, low energy users) [207].

Despite initial evidence of inequitable distribution across populations, there has been less attention to a recognition justice framing of these programs focused on which communities may have less capacity to engage in these programs and the related consequences [177]. Some initial studies have sought to evaluate the relationship between socio-economic characteristics with activities and technology adoption patterns critical for demand flexibility. Olawale and colleagues [200] found that personal factors (gender, age, time spent alone), job or social status (labor force status, income, ownership farm/business), family dynamics (presence of household children, number children, number people living in the household, household type), education level, and cultural tendencies (race and ethnicity) significantly predict duration of demand flexibility-related activities and when they occur. Similarly, Barsanti and colleagues [208] find age, employment status, and household size are important predictors for time-based patterns of washing and laundry use. Related to technologies, Xu & Chen [209] explore the relationship of income to technology adoption and find discrepancies in access to and use of smart technologies. Although they highlight correlations of income with other marginalized identities, they do not explicitly investigate them.

Generally, there has been a lack of exploration of recognition justice issues inherent in demand flexibility despite initial work on flexibility capital identifying the need for further exploration of "how to recognise and include those most at risk of disadvantage in designing progressive energy service provisions" as a key focus of future work [27]. This is concerning, given the critical foundation a recognition justice perspective offers on inequities present in status quo systems and how effective policy and planning to can achieve both decarbarbonization and equity related objectives. The smart home energy management literature and related considerations of demand flexibility have skewed towards technical disciplines investigating controls-based pathways for managing energy use [18]. Yet a deep application of an energy justice perspective, and recognition justice in particular, points towards need to understand both material and social contexts for this work [32, 176, 181]. Given the limited window to proactively embed equity in the foundation of demand flexibility initiatives, this research seeks to fill this gap and advance understanding of who demand flexibility programs and policies should explicitly recognize in their design and implementation to ensure programs seeking to advance equitable outcomes actually do so.

4.2.4 Research Objectives & Questions

Ultimately this research sought to answer the following research question:

1. How might social aspects of daily life and technology access influence the capacity for communities to participate in, and thus benefit from or be burdened by, demand flexibility initiatives?

We do so through analyzing how socio-economic indicators used to identify disadvantaged communities in emerging public policies predict how people spend their time at home and their adoption of technologies that enable participation in demand flexibility initiatives. Together, these two considerations provide insight to considerations for both social (ex. time-use) and technical pathways to enable equitable demand flexibility. In reviewing the results, we reflect on next steps for policy to support these populations as demand flexibility becomes a central component of energy planning efforts.

This research makes several contributions. We add to the limited body of research quantitatively applying a recognition justice lens to demand flexibility initiatives. We do so guided by an interdisciplinary (socio-technical) lens and through quantitative assessment. Although use of ATUS data has become more prevalent in building modeling and simulation studies, it has not yet been applied to advance understanding of equity and justice related implications related to capacity to engage in time shifting of energy use. This work also draws upon newly released data from the RECS, which has not yet been robustly analyzed.

4.3 Methods

This section describes the approach to the analysis, each of the two datasets analyzed, how justice indicators were selected, and the methods of analysis used to analyze each dataset.

4.3.1 Data Sources

4.3.1.1 American Time Use Survey (ATUS)

The ATUS [184] is an annual activity-based survey conducted by the Census Bureau and sponsored by the Bureau of Labor Statistics. Annually surveying roughly 8,000-

12,000 Americans on how they spend one 24-hour period (4:00am-4:00am), the ATUS collects data on the time Americans spend doing different activities. The survey includes information on the types of activities conducted, their start and stop time, and whether activities are coordinated with other members of a household. The ATUS also data offers socio-economic information about participants, including income, race, employment status, education, household characteristics, and geography.

This research analyzed data from the 2022 ATUS, the most recently available survey year (N = 8136). The original sample was filtered to exclude survey responses from holidays as non-typical activity patterns (N = 137). The limited occurrence of responses with missing activity data were also excluded, leaving a final sample of 7603 individual survey respondents. Of this final sample, 52% surveys were taken on weekdays and 48% on weekends.

It is worth noting the COVID-19 pandemic is known to have had a significant influence on daily activity patterns. Recent work has explored how household occupancy specifically [210] and travel behaviors more broadly [211] were impacted by COVID-19 using the ATUS survey. These studies showed that during 2020-2021 in particular, American's spent less time out of the home and traveling [211]. In particular, duration of activities occurring at home tended to increase in 2020, then slightly decline in the years following [211]. While the duration of some household activities remain elevated from their pre-pandemic levels and some household activities continue to occur more frequently (ex. eating and drinking at home, washing and grooming, and leisure-related), many trends are trending back towards pre-pandemic levels [210]. Along these lines, in their analysis of daily household and travel patterns, Shi and colleagues [211] identified the same types of daily activity patterns, with the exception of the emergence of a work from home pattern not see pre-COVID. The findings from this study should be interpreted with the understanding that activity patterns may continue to shift as we emerge from the end of the pandemic.

4.3.1.1 Residential Energy Consumption Survey (RECS)

The RECS is conducted typically every three years by the United States Energy Information Administration [185]. The most recently released data were collected in 2020 via web and mail from 18,496 households. The survey is designed to be nationally representative of occupied housing units and provides data on building stock, ownership and use of home appliances, fuel use, participation in energy assistance programs, and socio-demographics. For the purpose of this analysis, we used the microdata files from 2020 with the provided weighting factors.

4.3.2 Identifying Justice-Focused Populations

While existing policy tools consider a range of indicators to identify justice-focused populations[1], this work focuses on socio-economic indicators given their availability in the ATUS and RECS datasets. Thus, a first step in answering the research questions was determining which socio-economic indicators to include in the analyses. Federal and state energy, climate, and environmental justice policies and screening tools were reviewed to identify which indicators are most commonly used to identify justice-focused populations. We began with the socio-economic indicators of vulnerability included in the tool developed by Popovitch and colleagues [195] for use by the Department of Energy. Next, state-level definitions of justice-focused populations and related tools were compared to those indicators.

[1]Terminology used to identify and discuss populations in equity assessments varies and includes terms such as disadvantaged communities, environmental justice populations, and frontline & impacted communities. Here we broadly use the term "justice-focused populations" to encompass each of these groups.

The database of state environmental justice laws compiled and maintained by a consortium of academic institutions [212] was used to facilitate this search. We identified 22 states that either have statutorily defined definitions to identify justice-focused populations and/or state-specific mapping tools. While some states include criteria outside of those identified by Popovich and colleagues [195], they either fell outside the realm of socio-economic indicators or were not identified by a critical mass of states to warrant inclusion in the analysis. Based on this search, eight indicators were selected for inclusion. Of note

- Race and ethnicity was not included in the tool by Popvich and colleagues [195] who note they "do not include race in our definition of disadvantage since its inclusion could potentially limit the use of our tool by federal agencies." (3) However, in reviewing state definitions and tools, it is one of the most common indicators considered so was included here.

- The RECS does not collect information on respondent disability status. It does collect information on respondents with medical devices in the home. Although not an exact proxy, this variable was considered for the RECS data.

- While consideration of linguistic isolation (typically through the Census variable "limited English proficiency") was one of the most commonly considered indicators across state and federal tools, there was no appropriate proxy for it in the indicators collected by either the RECS or ATUS, thus was not included in this analysis.

- Indicators for housing burden, uninsured, unhoused, and single parents were excluded given lack of data and/or consideration in state policy.

The raw data from the ATUS and RECS were transformed into binary indicators so that survey participants who met a specific criteria (ex. are renters, qualify as having low income) could be evaluated relative to respondents who do not meet those criteria (ex. do not rent, do not qualify as having low income). This is consistent with how programs might structure eligibility to provide extra support to a justice-focused population (ex. someone considered having low income based on their annual household income being less than 200% of the Federal Poverty Level (FPL) may qualify for a special electric rate or increased incentive amounts).

Table 4.1 provides a description of the indicators selected, their prevalence in state and federal tools and definitions, and compares the prevalence of these populations in each of the survey samples to the US population as a whole[2]. Low income thresholds were identified based on 200% or less of the 2022 FPL considering household size and location [213]. Table 4.2 shows how the categorical income data provided by ATUS and RECS were mapped onto the FPL thresholds. This methodology likely overestimates the number of survey respondents with a household income at or below 200% of the FPL. Table 4.1 suggests this is the case in the RECS data, but suggests that it provides a reasonable approximation of the percentage of individuals meeting this criteria in the ATUS compared to the US overall.

4.3.3 ATUS Analysis Procedure - Latent Class Analysis

To investigate whether indicators of justice-focused populations predicted patterns of daily activity, the ATUS data was analyzed using latent class analysis (LCA). LCA is a model-based clustering method to identify population segments within a larger dataset [214, 215]. LCA offers a way to identify subgroups, called “latent classes”, not otherwise

[2]Data on the US population was collected from a variety of American Census Bureau sources for 2022 https://www.census.gov/. The ATUS survey asks if people have a disability that prevents them from working, which likely accounts for the under representation of this population in the data. Additionally, RECS was fielded in 2020 during the initial wave of the COVID-19 pandemic, possibly leading to the over representation of unemployed individuals compared to the national average.

Table 4.1: Descriptive information on indicators assessed to identify justice-focused populations. Note: percentages in ATUS and RECS columns indicate the percentage of the unweighted (ATUS) and weighted (RECS) prevalence of individuals in the sample meeting justice criteria

Indicator	**Coding Scheme**	**ATUS**	**RECS**	**National Average**	**Prevalence in State/Federal Definitions** (out of 23)
Low Income	1 - Not low income 2 - Low income (see **Table 2** for thresholds)	28%	36%	27%	91%
Race & Ethnicity	1 - White identifying only 2 - Non-white identifying (BIPOC; incl. individuals identifying as more than one race including white)	19%	19%	25%	96%
Age 65+	1 - Aged 64 or younger 2 - Aged 65+	32%	32%	17%	43%
No GED	1 - High school degree or higher 2 - No GED	8%	5%	11%	39%
Has a disability (ATUS only)	1 - Does not identify as having a disability 2 - Identifies as having a disability	4%	*NA*	13%	30%
Has Medical Devices at Home (RECS only)	1 - Does not have medical devices at home (RECS) 2 - Identifies having medical devices at home (RECS)	*NA*	14%	Not available	*NA*
Unemployed	1 - Employed or otherwise not in the labor force 2 - Unemployed	1%	13%	3.8%	39%
Lives in a Mobile Home	1 - Does not live in a mobile home 2 - Lives in a mobile home	3%	6%	6%	17%
Renter	1 - Owns home or other living arrangement 2 - Renter	25%	32%	35%	17%

Table 4.2: Low income threshold by family size and location.

State	**Number of Household Members**										
	1	2	3	4	5	6	7	8	9	10	11
Lower 48	$29,999	$39,999	$49,999	$59,999	$74,999	$74,999	$99,999	$99,999	$99,999	$149,999	$149,999
Alaska	$34,999	$49,999	$59,999	$74,999	$99,999	$99,999	$149,999	$149,999	$149,999	$149,999	$149,999
Hawaii	$34,999	$49,999	$59,999	$74,999	$79,999	$99,999	$99,999	$149,999	$149,999	$149,999	$149,999

observable or measurable within complex, multidimensional datasets [215]. Cluster analysis generally has gained increasing popularity to investigate temporal patterns of activities and energy use [216–219]. Although LCA is a common clustering method in the behavioral or health sciences, previous efforts to assess patterns of energy-related activities often rely on traditional clustering methods such as k-means or k-mode and other hierarchical clustering methods.

LCA has a number of advantages over traditional clustering methods such as k-means including 1) probability-based instead of distance-based classification, which allows for estimating misclassification error rates, 2) support for determining the appropriate number of classes for the model via diagnostic and model fit criteria, and 3) the ability to include socio-demographic covariates directly in the model instead of conducting a secondary analysis [214]. Although application to energy-related studies has been limited to date, Barsanti and colleagues [208] highlighted model-based clustering as an area for future exploration with regards to clustering activity data to inform demand flexibility initiatives.

We implement LCA utilizing the poLCA [220, 221] package in R on unweighted ATUS activity sequences. ATUS includes three major biases: 1) oversampling of weekend days, 2) oversampling of specific demographic groups, and 3) response rates of specific demographic groups [222]. ATUS provides a weighting factor to be applied to data on durations of activities to allow for representative statements regarding American time use on specific activities broadly, but it is not possible to apply this for activity sequence data. Thus, we cannot generalize the findings to the population as a whole.

4.3.3.1 Modeling Approach & Selection Criteria

Figure 4.1 offers a visual representation of the latent class model with covariates estimated. The LCA includes two components - the measurement and the structural models. The measurement model assesses latent classes according to observed indicators (i.e. what activities occur at each time point of the sequence) and the structural model evaluates the relationships between the latent classes and explanatory variables (i.e. indicators of justice-focus populations) [223]. In addition to the eight indicators previously discussed, the structural model included five additional indicators: sex (1 = Male, 2: Female), age (continuous 15-85; topcoded), number of children (continuous, 0-99), the season (1 = shoulder season (March-May, Sept-Nov), 2 = peak load season), and day of the week (1 = weekend, 2 = weekday) of the survey day.

We first estimate the latent class measurement model without covariates to determine the appropriate number of classes for the model. Initially, a one-class model is calculated and then iteratively class size is increased by one. Each n-class model was estimated with 1000 random starting values to ensure the global maxima had been identified. Once an appropriate measurement model had been selected, that model was re-estimated inclusive of the structural model. This approach accounts for classification error in the model [223] and has been argued to provide the best estimates of the relationship of covariates to latent classes compared to other approaches [220]. When estimating, we confirmed via model diagnostics that inclusion of the structural model did not significantly alter the measurement model.

Best practices for model selection involve several steps, including review of model fit indices and diagnostic criteria as well as consideration of theoretical grounding and interpretability

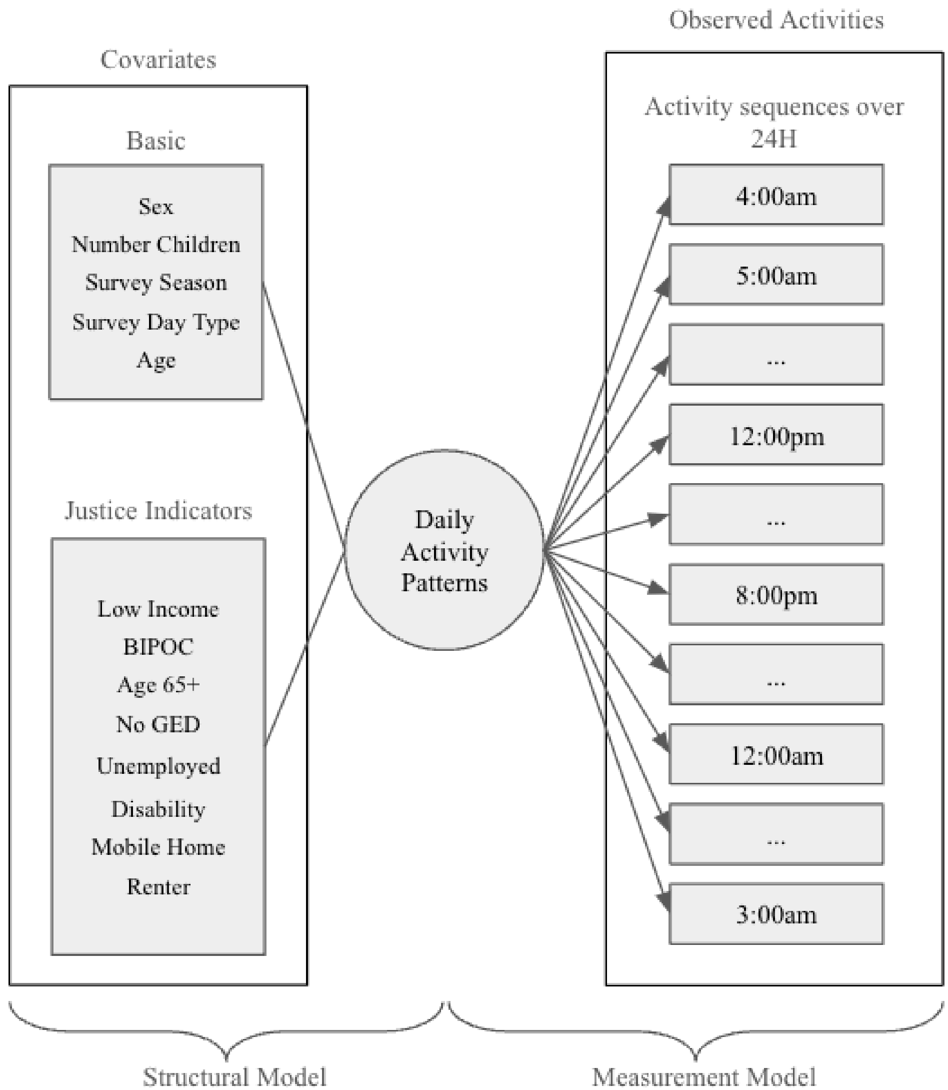

Figure 4.1: LCA Model Structure

[224]. We considered several model diagnostic and fit criteria, including the Bayesian Information Criteria (BIC), sample size adjusted-BIC (aBIC), Akaike Information Criterion (AIC), in addition to Bayes Factor (BF), estimated using the BIC approximation [225]. These information criteria balance fitting the model to the sample data while maintaining generalizability [224], penalizing complexity to avoid overfitting [225]l. The objective is to find a model that minimizes information criteria often assessed via scree plots to identify inflection points where adding classes to the model produces diminishing improvements [225]. BIC in particular has been highlighted as a reliable method for identifying the correct number of classes [224].

BF provides a relative fit indices, comparing a model with n classes to a model with n+1 classes. A BF of 3-10 indicating moderate support for the n-class model compared to the n+1-class model and BF greater than 10 suggests strong support for the smaller model [225]. Consistent with best practices [226], we also compared model entropy, smallest class identified, and average latent class posterior probability (ALCPP) to assess class separation and definition accuracy. In LCA, posterior probabilities are the probability a given person in the sample is a member of each of the identified latent classes. While LCA does not offer definitive prediction of membership in a class, the predicted class is based on the class for which their posterior probability is greatest.

4.3.3.2 Data Formatting Considerations for LCA

ATUS data were structured for the LCA to balance model complexity (i.e. number of activity categories and time series granularity) and LCA assumptions of local independence.

Activity Categorization. The ATUS includes three tiers of pre-established activity categories: 17 Tier I codes, over 100 Tier 2 codes, and over 400 Tier 3 codes. The ATUS also collects information on where the activities occurred, distinguishing between 26 different locations. We employed a simplified categorization scheme based on activity location, frequency in the sample, and energy-intensity to focus on activities occurring within the home (or likely to occur within the home) given the focus on residential demand flexibility programs and with the goal of minimizing model complexity. Activity selection was also informed by activities previously investigated in studies of temporal patterns of energy-related activities (ex. [199, 200]). Table 4.3 provides an overview of the activities considered and Figure 4.2 shows the aggregate prevalence of these activities in the survey population at 1-minute time intervals for weekends and weekdays, separately.

Time Series Granularity. Previous studies investigating activity time use have considered a variety of time intervals, as granular as 15 minute intervals [219]. However, more granular time intervals require a more complex model and risks greater covariation of model indicators given durations of activities. A core assumption of LCA is that of local independence - i.e. that any covariation between model indicators (observed variables) is explained by the latent variable [215]. Sinha and colleauges [227] therefore discuss the need to be transparent about covariation of indicators and recommend a threshold of 0.5 (moderate correlation) between any two indicators.

Table 4.3 shows the average distributions of the unweighted length (minutes) for each of the nine activity categories. Activity categories have mean durations between 30 and 248 minutes. In reviewing activity sequences aggregated at the 1 minute, 15 minute, 30 minute, and 60 minute interval, broad activity patterns are similar at each time interval. There is relatively minor loss of information with regards to washing and grooming and laundry activities at the 60 minute aggregation, although this makes sense given their shorter duration, on average. We further investigated correlation between model activity

Table 4.3: ATUS Activity Categorization

Location	ATUS Activity Code(s)	Activity	Description	Mean Duration of Activities (minutes)
Location Not Collected	0101**	Sleeping	Sleeping or sleeplessness	248 (std: 123)
	0201**	Washing & Grooming	Showering, bathing, brushing teeth, getting dressed, washing hands/face, etc	30 (24)
Home	0201**	Housework	Laundry, interior cleaning, miscellaneous housework tasks (ex. sewing, putting away groceries)	62 (67)
	0206** & 03**** & 04****	Caring for Others	Care of children, adults, and/or pets including bathing, preparing meals, etc	31 (45)
	11**** & 0202**	Eating & Drinking	Preparing, eating, and cleaning up after meals	31 (26)
	12****	Socializing, Relaxing, & Leisure	Relaxing, watching tv or movies, reading, socializing with others, computer games, arts and crafts or other hobbies, writing for personal interest,	107 (96)
	05****	Working from Home	Activities associated with primary or secondary jobs conducted at home	146 (118)
	All activities reported at home	Home - Other	All other activities occuring at home, ex. exercising/sports, religious activities, education-related, interior and exterior household maintenance, gardening, etc	56 (73)
Not Home	*All activities reported outside the home*	Not Home	All activities coded as occurring outside the home	53 (85)

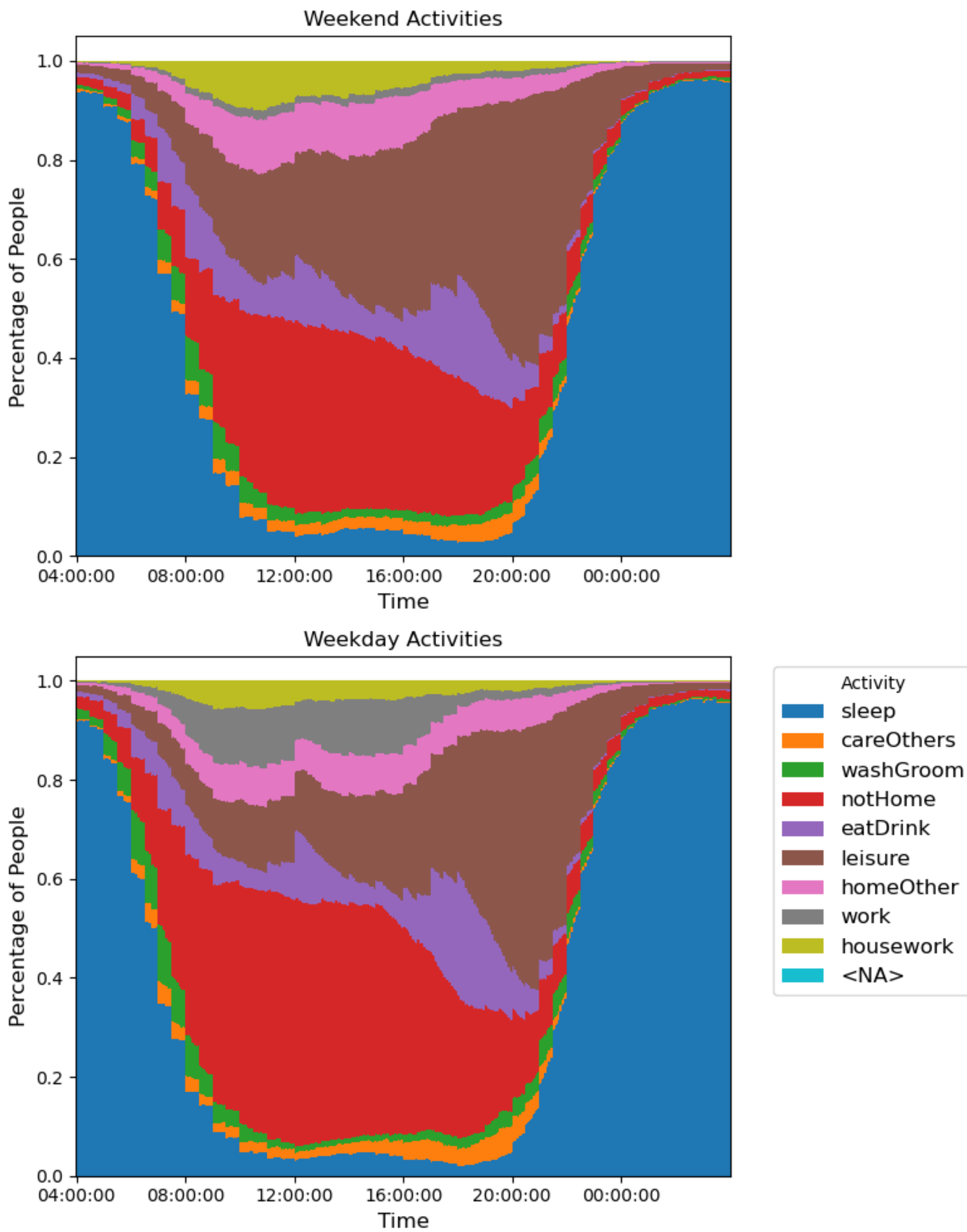

Figure 4.2: Frequency of activities at the 1m interval on weekends and weekdays in the sample

indicators when sampled at the 60 minute time interval by calculating Cramer's V. Results show moderate correlation between some adjacent time periods, particularly overnight due to duration's of sleeping activities, but otherwise indicate weak to moderate covariation during the daytime and other time periods. Ultimately, we proceeded with the 60 minute time intervals as best balancing granularity, information, and assumption of local independence.

4.3.4 RECS Analysis Procedure - Technology Adoption Trends

The RECS data was used to assess access to demand flexibility facilitating infrastructure and technology adoption by justice-focus populations based on the eight indicators in addition to prevalence of electricity use across important end uses. We considered two categories of data:

Facilitating conditions consider data about conditions necessary to participate in demand flexibility initiatives. We assess:

1. Prevalence of electricity usage for large thermal loads of interest to demand flexibility programs (space heating and cooling, water heating)
2. Access to internet and
3. Adoption of smart meters

Controllable technologies include adoption of key technologies for participating in demand flexibility programs. In particular, we consider:

1. Adoption of programmable and smart thermostats
2. Ownership and use of smart speakers (ex. Amazon Alexa) to control any device in the home including temperature, lighting, television, and other devices

3. Use of heat pumps in those households heating or cooling with electricity (this included both centrally ducted and ductless mini split heat pumps) and
4. Electric vehicle ownership

The analysis compared these data across the representative national average and indicators to identify justice-focused populations. We followed the EIA guidelines [228] for acceptable RSE and sample size inclusion. We calculated 95% confidence intervals for each mean using the provided sampling weights and the survey and dplyr packages in R following EIA guidance.

4.4 Results

Analysis of the ATUS and RECS data suggest indicators of justice-focus populations ("justice indicators") significantly predict how people spend their time and technology adoption levels for critical demand flexibility technologies. The LCA identifies five distinct activity patterns in the ATUS sample and illustrates that people who have low incomes, identify as BIPOC, are age 65 and older, do not have a GED, and identify as having a disability are significantly more likely to engage in daily activity patterns that diverge from stereotypical work patterns. Similarly, the assessment of RECS data illustrates significant disparities in technology adoption across justice indicators particularly for thermostats and smart speakers. Disparities also exist in internet and smart meter access and use of electricity for core thermal loads.

Table 4.4: LCA model fit statistics and diagnostic criteria

	Diagnotic Criteria					*Model Fit Criteria*				
	Num. Parameter	Smallest Class %	DF	ALCPP	Entropy	Log Likelihood	BIC	aBIC	AIC	Bayes Factor
1	192	1.00	7411	1.00	1.00	-234442	470599	470181	469267	0
2	385	0.47	7218	0.98	0.93	-216090	435620	434782	432950	0
3	578	0.09	7025	0.98	0.96	-206544	418253	416994	414244	0
4	771	0.08	6832	0.97	0.95	-200533	407956	406276	402608	0
5	964	0.08	6639	0.95	0.93	-195845	400305	398206	393619	0
6	1157	0.08	6446	0.95	0.93	-193421	397182	394662	389157	0
7	1350	0.08	6253	0.95	0.93	-191160	394383	391443	385019	0
8	1543	0.08	6060	0.94	0.93	-189076	391940	388580	381237	0
9	1736	0.06	5867	0.94	0.93	-187247	390008	386227	377966	0
10	1929	0.03	5674	0.94	0.93	-185684	388606	384405	375226	-

* DF = Degrees of Freedom, ALCPP = Avg. Latent Class Posterior Probability

4.4.1 Indicators of Daily Activity Patterns

Latent class models with 1 to 10 classes were fit. Table 4.4 summarizes the model fit indices and diagnostic criteria for each model. All model fit criteria appear to favor larger class models, as information criteria do not reach a minimum but instead decrease with each additional class. Similarly, BF consistently shows a preference for *n+1* class model.

Figure 4.3 compares the information criteria for each of the models in a scree plot, which reveals inflection points at the two, three, and five-class models. Entropy, ALCPP, and smallest class size all suggest each of these models offer a well separated model which defines each of the classes well. Beyond 5 classes information criteria show diminishing information gained as the number of classes increase. The two, three, and five-class models were examined, ultimately selecting the five class model as it includes the classes identified in the two- and three-class models and the smallest class was adequately sized. The additional classes in the five class model were reasonable to interpret and consistent with previous findings in the literature [211, 219]. Once identified, the 5 class model was

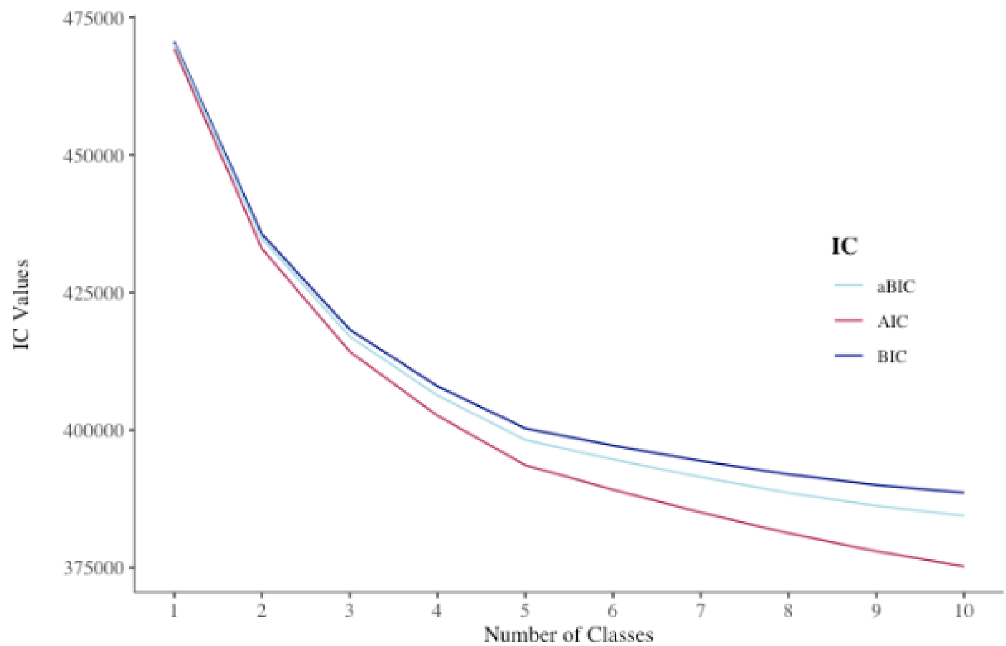

Figure 4.3: Scree plot comparing BIC, AIC, and a-BIC for latent class models with 1-10 classes

re-estimated including the chosen covariates.

4.4.1.1 Model Interpretation - Five Daily Activity Patterns

Figure 4.4 illustrates the daily activity patterns that represent each of the 5 classes, showing the probability of engaging in different types of activities throughout the day based on item response probabilities. Figure 4.5 shows activity sequences for each respondent, based on their predicted class.

Of the five classes identified, three describe daily activity patterns of people who are largely at home. The Home Discretionary Day[3] class is defined by largely being home and engaging in socializing, relaxing, and leisure-related activities. Individuals in this class typically go out in the mid morning or early afternoon if at all, are not engaged in taking care of others,

[3]For this class, we adopt the name used by [211] to describe a similar class identified in their cluster analysis of ATUS data and COVID-19 impacts on activities.

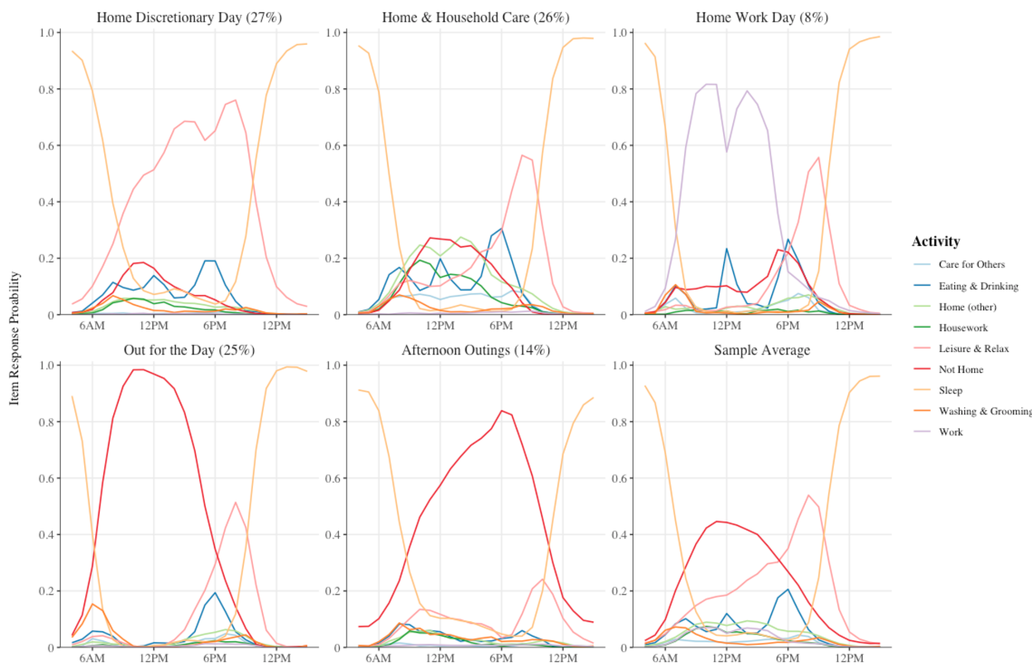

Figure 4.4: Five daily activity patterns identified by the LCA plus the ATUS sample average for comparison (y-axis for this plot is the percent of respondents doing each activity). Parentheses indicate the percent of the sample predicted to have each pattern for the five classes.

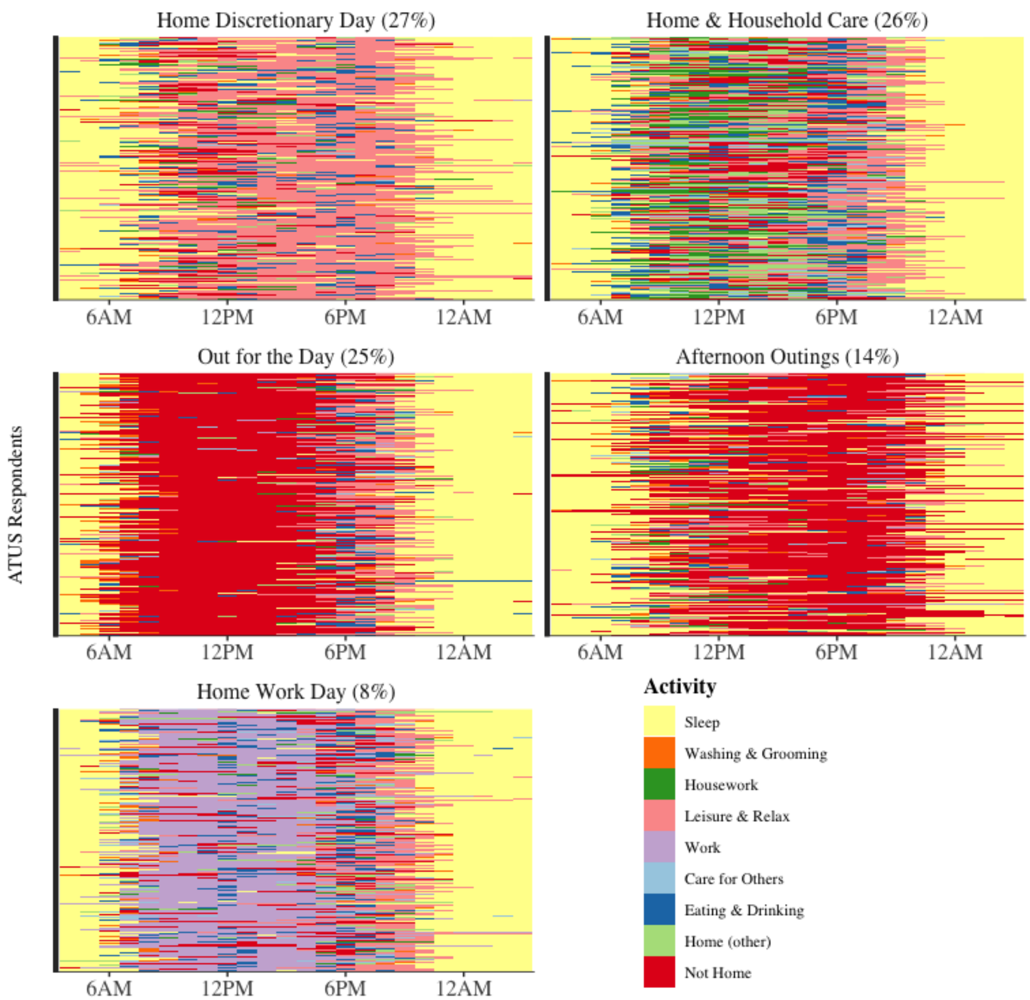

Figure 4.5: Actual activity sequences of ATUS respondents by predicted class

and wake slightly later than the other classes. Home & Household Care is characterized by largely being home and engaging in a diverse mix of activities throughout the day, including housework, care for others, and other household activities. If they go out, individuals in this class typically go out in the late morning or early afternoon. The Home Work Day class is defined by individuals working from home most of the day. When not working, they otherwise engage in similar activities to Home & Household Care with the exception of being most likely to go out in the evening hours if they go out at all. Together, these three classes account for roughly 61% of the ATUS sample.

The remaining two classes are predominantly defined by individuals who spend most of their day out of the home. Out for the Day is primarily identified based on leaving home early in the morning and remaining away from home until the evening period. This class includes the earliest waking time in the morning and highest prevalence of washing and grooming in the mornings (peaking around 6am). Similar to Out for the Day, Afternoon Outings is defined by the tendency to be outside the home, but shifted later towards the afternoon and evening period. The probability of leaving home increases throughout the day, peaking around 6:00-7:00 pm.

Despite the defining differences, across the classes a number of commonalities emerge in daily activity patterns, including relatively similar eating and drinking patterns for the home-based classes, predominantly morning washing and grooming activities, and similar sleeping schedules with some variation in waking and bedtimes.

Table 4.5 illustrates activity item response probabilities for each of the classes during the 9:00am to 9:00pm period. While the carbon intensity and peak (highest) periods of electricity use may vary by geography and season of the year, these hours of the day are often those of interest to grid operators. For example, in regions of the United States with high penetrations of renewable supply such as California, electricity is likely to have the lowest carbon intensity during the morning and early afternoon hours (ex. 9am-4pm) while electricity from renewables such as solar may be particularly abundant [229]. Alternatively, in the late afternoon and evening as demand rises and solar resources become more scarce, the carbon intensity of the electric grid increases as more carbon-intensive resources (e.g. natural gas, oil peaking plants) are used to meet demand. In this scenario, demand flexibility programs would seek to encourage residents to shift energy-intensive activities toward low emissions and less costly low demand periods earlier in the day and away from carbon intensive, peak demand late afternoon and evening hours.

Reviewing each of the daily activity profiles through this lens, reveals a number of insights. Three of the classes are likely to be home during the entirety of this period: Home & Household Care, Home Discretionary Day, and Home Work Day. In theory, individuals following these activity patterns could have greater capacity to be flexible in their energy use, shifting energy-intensive activities to align with times beneficial to the grid (i.e. mornings or early afternoons). However, two of the classes are predominantly doing one kind of activity throughout most time periods (i.e. either working from home or engaging broadly in relaxing, leisure, or socializing activities) which may limit flexibility as well. Similarly, if individuals are primarily at home but without enabling technologies to support participation in flexing energy use, this may lead to burdens associated with high cost periods of electricity pricing, either in terms of needing to manually shift activities or face higher bills. Alternatively, the Out for the Day class is unlikely to be home during the morning and early afternoon period. This suggests they are not likely to be at home engaged in energy-intensive activities during this time, although returning home at the beginning of peak energy and carbon intensive periods could mean they experience constraints on their capacity to be flexible in energy use. Last, The Afternoon Outings class is very likely to be out of the home during the entire period - suggesting they are unlikely to be using much home energy during this period, but also potentially unable to economize or benefit from program participation.

For the four classes predicted to be home during the peak period, results generally confirm previous literature that leisure, entertainment, and eating and drinking-related activities are particularly common during this period, although to varying degrees across classes. This suggests that the activity patterns revealed by the system average do capture some common activity patterns, although not necessarily the dominant activities that precede or follow them. For all four classes, meal-related activities peak around 5pm-7pm consistently but leisure-related activities vary - dominating the whole period for Home Discretionary Day and increasing in likelihood throughout the period for the other three classes. This period also shows a peak in activities associated with care for others for three of the classes (Out for the Day, Home Work Day, and Home & Household Care), although prevalence of care activities is minimal across all classes generally. For these three classes in particular, we see the 5-7pm period generally characterized by a mix of possible activities - often no one activity exceeding a probability of greater than 50% of occurring. Broadly, activities associated with washing and grooming and housework (ex. laundry) are limited during this period.

4.4.1.3 Justice Indicators Effect on Daily Activities

Table 4.6 summarizes the effects of justice indicators on daily activity pattern class membership using odds ratios. Table 4.6 shows the odds ratios which are significant at $p < 0.05$

Table 4.5: Item response probabilities for activities occurring from 9:00am-9:00pm by each class

	Hours of Interest												
	9AM	10AM	11AM	12PM	1PM	2PM	3PM	4PM	5PM	6PM	7PM	8PM	9PM
Home Discretionary Day													
sleep	0.237	0.129	0.085	0.072	0.078	0.092	0.083	0.062	0.050	0.038	0.049	0.117	0.278
washGroom	0.053	0.036	0.025	0.015	0.014	0.008	0.012	0.012	0.010	0.012	0.020	0.017	0.025
housework	0.049	0.058	0.055	0.039	0.045	0.029	0.027	0.022	0.018	0.017	0.009	0.007	0.004
work	0.001	0.004	0.005	0.002	0.002	0.005	0.003	0.003	0.004	0.003	0.001	0.002	0.002
leisure	0.359	0.445	0.494	0.514	0.574	0.658	0.685	0.683	0.618	0.652	0.745	0.760	0.645
notHome	0.140	0.181	0.185	0.165	0.123	0.099	0.082	0.067	0.068	0.052	0.033	0.020	0.011
eatDrink	0.096	0.087	0.096	0.139	0.106	0.059	0.062	0.105	0.191	0.190	0.105	0.047	0.013
careOthers	0.006	0.003	0.003	0.004	0.004	0.003	0.004	0.006	0.007	0.009	0.010	0.004	0.003
homeOther	0.058	0.057	0.052	0.052	0.053	0.046	0.041	0.040	0.035	0.027	0.027	0.026	0.018
Home & Household Care													
sleep	0.084	0.022	0.014	0.017	0.025	0.035	0.027	0.019	0.012	0.012	0.019	0.070	0.234
washGroom	0.060	0.045	0.025	0.015	0.010	0.011	0.009	0.014	0.020	0.021	0.023	0.034	0.035
housework	0.165	0.193	0.180	0.132	0.143	0.140	0.127	0.102	0.062	0.043	0.033	0.030	0.025
work	0.006	0.005	0.003	0.005	0.004	0.005	0.006	0.009	0.009	0.010	0.009	0.011	0.013
leisure	0.121	0.112	0.100	0.102	0.126	0.140	0.167	0.223	0.236	0.297	0.439	0.565	0.548
notHome	0.159	0.219	0.272	0.268	0.265	0.240	0.244	0.212	0.179	0.131	0.095	0.043	0.010
eatDrink	0.132	0.086	0.101	0.198	0.126	0.088	0.088	0.136	0.280	0.306	0.193	0.077	0.029
careOthers	0.067	0.073	0.067	0.054	0.064	0.068	0.073	0.074	0.062	0.064	0.085	0.079	0.034
homeOther	0.205	0.247	0.237	0.208	0.238	0.275	0.258	0.213	0.141	0.116	0.104	0.092	0.074
Out for the Day													
sleep	0.004	0.000	0.001	0.007	0.008	0.018	0.025	0.024	0.020	0.020	0.040	0.118	0.353
washGroom	0.029	0.004	0.002	0.000	0.003	0.000	0.006	0.009	0.018	0.021	0.029	0.037	0.044
housework	0.002	0.000	0.001	0.001	0.002	0.006	0.010	0.016	0.019	0.024	0.019	0.020	0.015
work	0.003	0.002	0.001	0.000	0.002	0.004	0.005	0.007	0.013	0.013	0.012	0.011	0.011
leisure	0.016	0.004	0.001	0.002	0.007	0.027	0.062	0.134	0.202	0.294	0.423	0.514	0.425
notHome	0.926	0.984	0.984	0.969	0.953	0.917	0.833	0.698	0.500	0.348	0.237	0.143	0.067
eatDrink	0.008	0.002	0.005	0.016	0.016	0.014	0.021	0.055	0.150	0.194	0.127	0.055	0.027
careOthers	0.002	0.001	0.001	0.001	0.001	0.003	0.009	0.019	0.030	0.032	0.048	0.043	0.018
homeOther	0.010	0.002	0.004	0.004	0.009	0.011	0.028	0.038	0.047	0.054	0.063	0.058	0.040
Afternoon Outings													
sleep	0.268	0.156	0.113	0.103	0.103	0.094	0.089	0.075	0.062	0.047	0.040	0.040	0.071
washGroom	0.063	0.068	0.045	0.047	0.044	0.034	0.026	0.033	0.037	0.021	0.022	0.022	0.028
housework	0.058	0.051	0.050	0.043	0.034	0.030	0.017	0.010	0.011	0.004	0.008	0.011	0.009
work	0.007	0.009	0.010	0.008	0.007	0.007	0.007	0.009	0.007	0.008	0.009	0.009	0.011
leisure	0.101	0.135	0.131	0.117	0.103	0.098	0.085	0.084	0.069	0.034	0.045	0.118	0.208
notHome	0.356	0.462	0.524	0.575	0.633	0.677	0.716	0.741	0.775	0.839	0.824	0.720	0.608
eatDrink	0.081	0.056	0.059	0.055	0.038	0.022	0.027	0.021	0.023	0.032	0.036	0.059	0.041
careOthers	0.012	0.006	0.007	0.005	0.007	0.007	0.005	0.003	0.002	0.005	0.005	0.010	0.009
homeOther	0.054	0.057	0.060	0.045	0.031	0.033	0.026	0.025	0.016	0.011	0.012	0.011	0.016
Home Work Day													
sleep	0.026	0.011	0.007	0.013	0.006	0.013	0.013	0.010	0.011	0.008	0.013	0.035	0.154
washGroom	0.011	0.006	0.007	0.006	0.002	0.001	0.006	0.010	0.008	0.010	0.011	0.016	0.047
housework	0.016	0.014	0.011	0.013	0.004	0.003	0.014	0.016	0.019	0.011	0.016	0.010	0.013
work	0.783	0.817	0.816	0.577	0.730	0.793	0.746	0.652	0.358	0.152	0.122	0.090	0.061
leisure	0.018	0.014	0.014	0.027	0.029	0.032	0.040	0.094	0.158	0.220	0.328	0.506	0.557
notHome	0.092	0.101	0.099	0.102	0.082	0.080	0.108	0.136	0.230	0.221	0.182	0.108	0.058
eatDrink	0.019	0.020	0.024	0.234	0.108	0.039	0.036	0.023	0.130	0.268	0.192	0.104	0.040
careOthers	0.006	0.005	0.008	0.005	0.010	0.011	0.020	0.029	0.042	0.052	0.075	0.061	0.015
homeOther	0.028	0.013	0.013	0.024	0.030	0.027	0.018	0.031	0.043	0.058	0.061	0.070	0.055

Table 4.6: Odds Ratios Illustrating the Relationship Between Covariates and Class Membership

	Basic					Justice Inidcators							
	Sex	Num. Children	Season	Day Type	Age	Low Income	BIPOC	65+	No GED	Disability	Unemploy	Mobile Home	Renter
Out for the Day (reference)													
Afternoon Outings		0.82**		0.23**	0.98**	1.38**	1.57**	2.15**					
Home Work Day				2.24**		0.43**	1.45**		0.15**				
Home Discretionary Day		0.76**	1.27**	0.16**	1.01*	1.62**	1.57**	5.94**	1.81**	15.55**	2.48**		
Home & Household Care	1.87**	1.18**		0.21**		1.25*		3.58**		5.03**			0.69**

[a] Significance values denoted as * < 0.05, and ** < 0.001

and *0.001* levels, highlighting odds ratios greater than one. When odds ratios are greater than 1, this indicates that an increase in 1 in the covariate indicator suggests an individual is more likely to be in another class than the reference class. For example, the odds rations comparing Home Discretionary Day to a reference class of Out for the Day suggests that people who have low incomes are 1.62X as likely to be in Home Discretionary Day that Out for the Day compared to individuals who do not qualify as having low incomes. Significant odds ratios less than one are also shown in gray.

Effects are summarized using Out for the Day as the reference class chosen since it represents a dominant "stereotypical" activity pattern. Out for the day is similar to what a stereotypical workday is considered to be (e.g. waking early, exiting the home for the majority of the day, and then returning home in the evening to prepare and consume meals, care for others, and relax). Full results of the LCA structural model are available in the Appendix.

Compared to a stereotypical work day ("Out for the Day") the results show that numerous justice indicators significantly predict daily activity patterns. Low income, BIPOC, individuals age 65 and older, those who do not have a GED, have a disability, and are unemployed are all more likely to be in Home Discretionary Day than Out for the Day compared to individuals who don't meet justice criteria. This is particularly pronounced for those 65 and older, have a disability, and are unemployed who are 5.94, 15.55, 2.48 times more likely to be in Home Discretionary Day than Out for the Day. Individuals who have low incomes, are 65 and older, and have a disability were also significantly more likely to be in Home & Household Care as compared to those who didn't meet those criteria, suggesting those populations are generally more likely to be engaging in activities at home during the day.

Results further show that individuals with low income, are BIPOC, and are 65 and older are 1.38, 1.57, and 2.15 times more likely to be in the Afternoon Outings class compared to individuals who do not have low income, are white, and are younger than 65. If these populations do spend a day outside the house, it is shifted later compared to a stereotypical day. We generally see low predictive power for living in a mobile home, unemployment, and renting in this reference case.

Although not shown here, the full results also show that many individuals meeting justice thresholds are significantly less likely to be in Home Work Day in reference to all other classes compared to individuals not meeting justice criteria. These results also highlight that women are more likely to be in Home & Household Care than all other classes and the likelihood of being in Home & Household care increases as the number of children in the home increases.

4.4.2 Indicators of Demand Flexibility Readiness & Load Control Technology Adoption

Figures 4.6 and 4.7 illustrate access to enabling conditions and adoption of key control technologies for demand flexibility across justice and non-justice focus populations. The data indicate a number of disparities.

With regards to the use of electricity for major thermal loads, individuals living in mobile homes are significantly more likely to use electricity for space and water heating compared to the national average, with over 75% of mobile homes using electricity for water heating compared to a national average of 47%. Disparities in electric water heating use also exist for individuals who are unemployed, rent, and have low incomes. Use of electricity for space heating is great amongst BIPOC individuals, those with medical devices in their homes, individuals who have low incomes, and who are unemployed compared to the national average and, significantly compared to individuals who do not meet these criteria. In terms of space cooling, individuals who are BIPOC, do not have a GED, are unemployed, rent, and have low income have less access to space cooling than individuals not meeting those criteria.

In terms of enabling conditions to participate in demand flexibility programs, disparities also exist in access to the internet and smart meters. Access is particularly low for individuals without a GED, with less than 75% of this population having access to either internet or smart meters, compared to a national average of 93% and 89% respectively. Individuals who are 65 and older, have low incomes, live in mobile homes, rent, and are unemployed are also significantly less likely to have internet and smart meter access than the national average and significantly less likely to have access compared to individuals not meeting those criteria. Access to smart meters in BIPOC individuals is also significantly less than among white individuals.

Considering adoption of key technologies needed to support demand flexibility, the data again show significant disparities in adoption between people who do and do not meet identified justice criteria. With regards to thermostats, adoption of both programmable and smart thermostats in most justice-populations significantly lags behind both the national average and individuals not meeting those criteria. Adoption of thermostats in populations

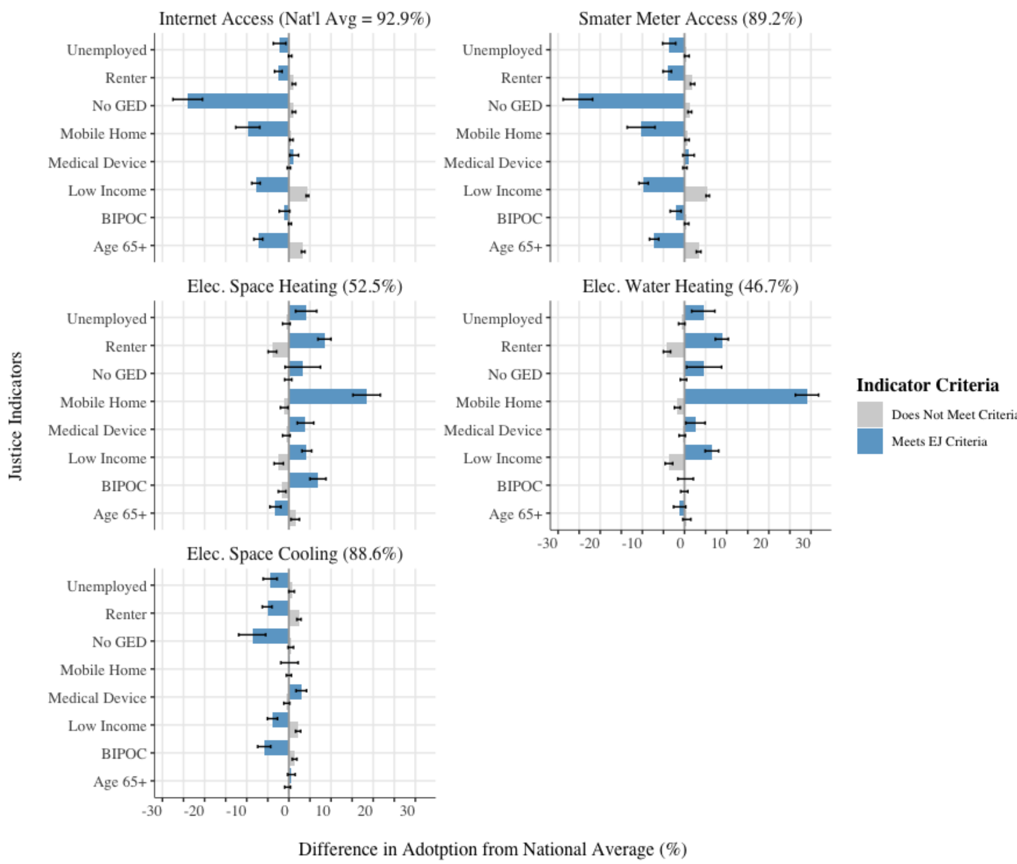

Figure 4.6: Comparison of access to demand flexibility facilitating conditions across justice and non-justice focus populations based on divergence from national average adoption levels.Percentage in the subtitle parentheses shows the national adoption level and bars indicate percentage points above or below the national average.

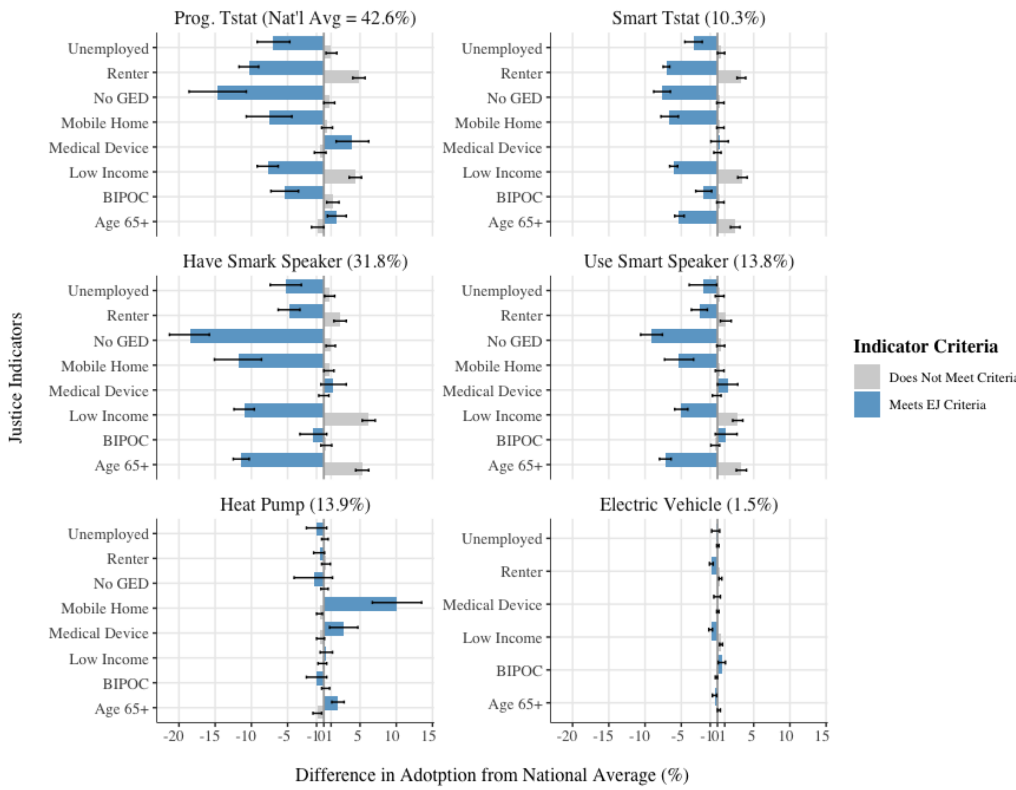

Figure 4.7: Comparison of mean access to enabling controllable technologies across justice and non-justice focus populations based on divergence from the national adoption levels. Percentage in the subtitle parentheses shows the national adoption level and bars indicate percentage points above or below the national average. Prog. Tstat = Programmable thermostat; Smart Tstat = Smart thermostat

meeting justice criteria often lags behind the national average between 5-15% and 2-7% for programmable and smart thermostats, respectively. The exceptions are individuals with medical devices in their homes and, for programmable thermostats, individuals age 65 and older. This is noticeable given the context that nationally only 53% of the population has adopted thermostats capable of providing some automated control features. This suggests that among individuals meeting justice criteria, over 50% either have a manual thermostat or no thermostat access at all.

With regards to smart speaker adoption and use, data also show disparities among populations who do and do not meet justice criteria, particularly among individuals who have low incomes, live in mobile homes, are 65 and older, do not have a GED, are unemployed (for ownership), and rent. Disparities in ownership lag behind the national average between 2-12% and even more so behind individuals not meeting justice criteria. Slightly smaller disparities appear to exist regarding use of smart speakers to control devices among populations who own them but are still prevalent.

Adoption of electric vehicles is still in the early stages in much of the United States, yet here we also see disparities in ownership, particularly among individuals who have low incomes, rent, and are 65 and older. A larger share of BIPOC individuals own electric vehicles than white individuals. Note, data for populations living in mobile homes and who have medical devices at home were excluded from this calculation given the small sample size.

Heat pump use showed the least disparities of the data assessed, although noticeably more people living in mobile homes, who are 65 and older, and rent use heat pumps compared to the national average and populations who do not meet these criteria.

4.4.3 Summary

Table 4.7 provides a high level summary of the relationships between social and technical capacities to participating in demand flexibility programs highlighted by this analysis. When reviewing results of the analysis holistically, we can begin to see which communities may face challenges in their capacity to fully engage in demand flexibility initiatives, whether due to current social, technical, or socio-technical realities. For example, individuals who live in mobile homes, rent, or are unemployed appeared to experience primarily technical divergences from the broader population, suggesting demand flexibility initiatives for these communities could primarily focus on closing technology access gaps to advance equitable outcomes. Alternatively, and of particular note, reviewing these considerations together raise concerns that several of the populations identified by justice criteria, particularly those with low incomes, who are 65 and older, and do not have a GED may face compounding social and technical constraints to their capacity to engage in and benefit from demand flexibility programs. These populations are more likely to be home, engaging in activities that are generally considered "uncontrollable", and using electricity for core thermal loads during potentially high price, peak periods of energy use. They similarly face lower access to facilitating contexts and adoption of controllable technologies to support shifting energy use using automation during high price periods, meaning the burden of changing activities may fall on them to maintain affordable electricity bills. The analysis suggests that viewing capacity through a purely technical lens would miss social vulnerabilities these communities may face and their potential interaction with technical ones. This suggests that without intentional program design, these populations may be particularly at risk of experiencing financial and non-financial impacts from demand flexibility initiatives if they are unable to either voluntarily enroll in programs or are forced to participate without adequate support.

Table 4.7: Comparison of social and technical considerations for individual capacity to engage in demand flexibility in the home

Justice Indicator	**Social (Activity-based) Considerations**	**Technical (Technology Access) Considerations**	
	Daily Activity Patterns (reference class: Out for the Day)	**Facilitating Conditions**	**Load Control Technology**
Low Income	1.62X more likely than individuals without low incomes to be in Home Discretionary Day 1.25X more likely to be in Home & Household Care; 1.38X more likely to be in Afternoon Outings	Greater use of electricity for space & water heating Less access to internet and smart meters	Significantly less access to programmable and smart thermostats Significantly lower adoption and use of smart speakers Significantly less ownership of EVs
Age 65+	2.15X more likely to be in Afternoon Outings than individuals younger than 65 5.94X more likely to be in Home Discretionary Day 3.58X more likely to be in Home & Household Care;	Greater use of electricity for space heating Less access to internet and smart meters	Significantly less access to programmable and smart thermostats Significantly lower adoption and use of smart speakers Significantly less ownership of EVs More use of heat pumps
Disability (ATUS only)	15.55X more likely than individuals without a disability to be in Home Discretionary Day 5.03X more likely to be in Home & Household Care		
No GED	1.81X more likely than someone with at least a GED to be in Home Discretionary Day	Slightly greater use of electricity for water heating Significantly lower access to internet and smart meters	Significantly less access to programmable and smart thermostats Significantly lower adoption and use of smart speakers
BIPOC	1.57X more likely than white individuals to be in Afternoon Outings 2.15X more likely to be in Home Discretionary Day 3.58X more likely to be in Home & Household Care;	Greater use of electricity for space heating Less access to smart meters	Significantly less access to programmable and smart thermostats Greater ownership of EVs

Medical Devices (RECS only)		Greater use of electricity for space heating, slightly more use for water heating	More likely to have a programmable thermostat
Unemployed	2.48X more likely than people who are not unemployed to be in Home Discretionary Day	Greater use of electricity for space & water heating Less access to internet and smart meters	Significantly less access to programmable and smart thermostats Significantly lower adoption of smart speakers
Mobile Home	*No Significant predictors*	Much greater use of electricity for space & water heating Less access to internet and smart meters	Significantly less access to programmable and smart thermostats Significantly lower adoption and use of smart speakers, Greater use of heat pumps
Renter	*No Significant predictors greater than 1*	Greater use of electricity for space & water heating Less access to internet and smart meters	Significantly less access to programmable and smart thermostats Significantly lower adoption and use of smart speakers, Significantly less ownership of EVs

4.5 Discussion

Results of this research identifies several key considerations about who should be intentionally recognized as we seek to design equity-focused demand flexibility initiatives and how that recognition might be associated with social and technical capacities to shift timing of energy use in the home. Data on daily activity patterns and access to technologies that enable participation in demand flexibility programs show significant disparities across indicators of income, race, education, employment, housing tenure and type, and disability but that the extent to which these populations face socio-technical disparities in this capacity differs across them. Holistic consideration of both social and technical factors highlight that individuals who have low incomes, are 65 or older, have a disability, and do not have a GED could be particularly vulnerable to experiencing negative impacts of demand flexibility initiatives. This is based on their likelihood to be at home during the day and without enabling technologies to support their participation in these programs. We reflect on the significance of these findings in the discussion below and consider next steps for policy and research related to community engagement and distributive impact analysis to further understand the potential for demand flexibility to either mitigate or exacerbate status quo inequities.

4.5.1 Policy and Programs Need a Nuanced Understanding of Customers and the Social Context They Operate In

As previously highlighted, results show that core justice indicators used to identify disadvantaged communities in public policy significantly predict both 1) how people spend their time and 2) their level of access to critical technologies related to demand flexibility initiatives. These predictors begin to reveal where status quo inequities exist across a diverse array of communities, the starting point within which future demand flexibility initiatives will be embedded. This includes and also extends beyond consideration of income, an indicator often discussed in equity-related policy and program discussions. While current energy equity policy framings predominantly seek to advance affordability, these findings challenge whether that framing adequately recognizes who currently experiences inequities in the system and underscores the need to take an expansive and socio-technical lens when designing programs to recognize and remediate past and present injustices through innovative programs and policies.

Previous research has highlighted failures of industry and government policies to accurately reflect the diversity and intersectionality of customer experience in the energy system broadly [30, 181] and smart automation pilots and programs specifically [26, 176]. The failure to recognize and account for the diversity of lived experiences significantly risks customer support for these types of programs. Empirical evidence has shown failure to recognize current realities of how communities engage with the energy system could have implications for the adoption of smart technologies [30] and acceptance of and participation in programs seeking to more granularly manage demand. In their recent evaluation of programs seeking to offer smart energy services in social housing units, Lamonaca and Batel [176] reveal that programs failing to acknowledge and account for agency of residents in managing their own homes can lead them to experience anger, detachment, disappointment, fear, and distrust towards the programs and related technologes, ultimately resulting in a lower sense of ownership in and disinterest towards smart technologies.

The data analyzed here suggest that, at minimum, policies and programs should consider how to best offer targeted support for closing technology access gaps and begin to investigate how dynamic rates with high-price periods during the peak hours intersect with specific populations who are likely to be home during these periods and understand why they structure their days as they currently do. The recognition of these socio-technical differences in daily practices and their connection to material infrastructures across a plurality of communities must be built into the foundation of the tools and modeling frameworks used to screen, approve, and evaluate innovative programs and policies. This is critically important given the prevalence of modeling and simulation studies informing our current understanding of how demand flexibility initiatives will be deployed and their potential impacts on disadvantaged communities.

Spurlock and colleagues [38] highlight the importance of recognizing who might be most impacted and the need to meaningfully engage them to inform modeling efforts. While datasets like the ATUS and RECS are increasingly common inputs to building simulations [230] given calls for more accurate representation of building occupants and end uses [7,23], they often rely either on simplistic demographic representations or focus on indicators which have been shown to drive energy use at peak periods, which may or may not be aligned with equity and justice related experiences and outcomes. Similarly, assessments of bill impacts often focus on low income customers or group disadvantaged communities together which may not provide the nuance of actually representing diverse realities and potential futures given varying disparities in technology access or time scheduling.

At the same time, regulatory screening and evaluation models must be updated to include considerations of social context, both the current realities of communities programs will operate within and how they might shift them. Cost-benefit analyses are one of the predominant mechanisms to ensure the benefits of rate-payer funded investments in new technologies outweigh their costs [180, 181]. Various tests exist to consider costs and benefits from different stakeholder perspectives (ex. utilities, customers, and society more broadly) [180], often relying on information about energy reductions or financial impacts which can be easily quantified and monetized [180, 181]. While useful to understand certain program aspects, these assessments do not currently include considerations of often less tangible socio-cultural considerations required of a recognition justice perspective and to robustly understand how "risky" various program designs are from a customer acceptance and adoption perspective. Complementary tools such as distributive equity analysis [231] which explicitly represent equity-focused communities in their foundation or social impact assessments [181] will be necessary to capture these considerations, and should be weighted equally with consideration of cost-benefit assessments when deciding whether a program and policy is appropriate for different communities. Without doing so, demand flexibility initiatives risk reinforcing, not remediating, existing inequities unless intentionally deployed, supporting previous arguments of this nature [36]. While this effort offers initial insights on datasets and methods that could help identify who might be most vulnerable to experiencing negative impacts, it underscores the need for continued future study in this realm.

4.5.2 Meaningful Engagement Will Be Critical To Further Explore and Understand These Impacts

In addition, results of this effort emphasize the need for meaningful participation of communities around how demand flexibility programs are deployed across different customer segments, another gap identified in energy justice efforts generally [42] and with regards to demand flexibility specifically [37]. Particularly given the limited window that exists to embed equity in demand flexibility if the rapid deployment needed to achieve decarb objectives is realized. As highlighted by Spurlock and colleagues [38] in their Equitable

Deep Decarbonization Framework, recognizing who might be impacted is a critical first step in estimating the potential distribution of impacts of clean energy policies and programs across populations. We argue it is also important to establish appropriately granular pathways to evaluate their success. Recognizing who might be most impacted directly informs an understanding of who priority communities are in order to design targeted and meaningful engagement efforts to ensure the lived experiences of these communities are accurately understood. While data such as the ATUS and RECS offer opportunities to assess at a high level where and how disparities may exist, they should be considered in parallel with meaningful opportunities for communities to shape understanding of the experiences that stem from disparities in routines or technology access. Meaningful engagement helps ensure this understanding is embedded within program design considerations and metrics designed to support modeling and assessment efforts from the beginning [38]. While traditional metrics of kW reductions and bill impacts are a starting point, there are likely more diverse and robust ways to quantify and understand what impacts of demand flexibility initiatives are felt as either burdens or benefits and communities should be involved in identifying what these metrics are.

In this analysis, the potential for technology access to lead to inequitable program outcomes seems relatively clear - the majority of justice-focused populations investigated face disparities in access to both facilitating and enabling technologies to support participation in demand flex initiatives compared to both the national average and populations who do not meet justice-related criteria. However, signals related to social considerations around timing of activities and rhythms of daily life are less obvious, highlighting the potential for either benefits or burdens to result from efforts to shift energy use. This signals a critical area for greater attention to community input, whether through informal or targeted engagement opportunities for communities to learn about and shape future programs.Such engagement will likely require regulators and utilities to show up in communities, or engage with community-based partners to do so, to first listen to and understand diverse experiences in the energy system today and then collaborate over strategies to develop sustainable futures. Meaningful engagement opportunities will also be necessary to better understand the intersectional impacts of justice indicators on cumulative burdens related to shifting energy use and other energy insecurities [195].

4.5.3 Limitations

While this study offers insights on how publicly available datasets could be used to recognize who might be most vulnerable to impacts of demand flexibility and how they might be vulnerable, several limitations are worth noting. This research analyzes time use and technology access from a national perspective. While this is informative, equity and justice-related work is most impactful when tailored to the specific context and communities that programs and policies seek to serve. Similar analyses should be replicated with more granular data at a variety of geographic scales (ex. regional, state, or local) to best understand what indicators and/or metrics are most relevant for specific communities and geographies and ensure meaningful engagement is tailored to those contexts. With regards to the activity data analyzed, ATUS offers insight into data for one survey day for one participant, but does not speak to how stable or variable daily activity patterns are over time for given populations, capture multi-person household dynamics with regards to structuring of time or technology use, or indicate the extent to which households are engaging in various activities simultaneously. All these dynamics are hypothesized to impact social capacity to be flexible in energy use, and they warrant future investigating. With regards to RECS data, we have only analyzed a sample of data related to technology access which this survey offers; further analysis of data related to energy use behaviors, costs, and vulnerabilities that this dataset offers, would likely help build a more complete picture of who might be impacted, either positively or negatively, by demand flexibility initiatives. Further, indicators of social and technical constraints will be most meaningful when analyzed in coordination with actual energy use data [199], which highlights a core consideration for future demand flexibility programs and pilots as they consider what data to collect in order to evaluate program impact.

Last, as noted in the Section 4.3.1.1, the COVID-19 pandemic greatly impacted American activity patterns. As the country continues to emerge from this time, it is possible less time will be spent in the home. This could either impact the number of individuals engaging in the types of activity sequences identified in this work or mean that time spend out of the home becomes more likely with certain patterns identified (i.e. "Home & Household Care") which could influence exposure to high price periods or ability to shift energy-related activities. Future work in this space should continue to assess these dynamics.

4.6 Conclusion

A limited window of time exists to embed principles of equity and justice within demand flexibility initiatives. Recognizing the populations who may be most likely to experience negative impacts from those initiatives is a critical first step in that process. This research has sought to quantitatively advance these efforts, exposing the extent to which individuals with marginalized identities may already face challenges to shift energy use in time given social and technical constraints. Without intentional efforts to close these technology access gaps and acknowledge differences in patterns of daily life, we suggest demand flexibility initiatives could exacerbate, not mitigate, existing inequities in the energy system.

4.7 Appendix

	Basic					*Justice Inidcators*							
	Sex	Num. Children	Season	Day Type	Age	Low Income	BIPOC	65+	No GED	Disability	Unemploy	Mobile Home	Renter
Home Discretionary Day (reference)													
Home & Household Care	1.98**	1.55**		1.29**		0.77**	0.65**	0.60**	0.42**	0.32**			0.58**
Out for the Day		1.31**	0.78**	6.14**	0.99*	0.62**	0.64**	0.17**	0.55**	0.06**	0.40**		
Afternoon Outings	1.24*			1.42**	0.97**			0.36**	0.42**	0.14**			
Home Work Day		1.26**		13.76**		0.27**		0.12**	0.08**	0.04**			
Home & Household Care (reference)													
Out for the Day	0.53**	0.85**		4.76**		0.80*		0.28**		0.20**			1.45**
Afternoon Outings	0.63**	0.69**			0.97**		1.54**	0.60**		0.43*			1.61**
Home Work Day	0.63**	0.81**		10.66**		0.35**	1.42*	0.19**	0.19**	0.12*			1.62**
Home Discretionary Day	0.50**	0.65**		0.77**		1.30**	1.53**	1.66**	2.36**	3.09**			1.71**
Out for the Day (reference)													
Afternoon Outings		0.82**		0.23**	0.98**	1.38**	1.57**	2.15**					
Home Work Day				2.24**		0.43**	1.45**		0.15**				
Home Discretionary Day		0.76**	1.27**	0.16**	1.01*	1.62**	1.57**	5.94**	1.81**	15.55**	2.48**		
Home & Household Care	1.87**	1.18**		0.21**		1.25*		3.58**		5.03**			0.69**
Afternoon Outings (reference)													
Home Work Day		1.17*		9.68**	1.02**	0.32**		0.32**	0.19**			0.18*	
Home Discretionary Day	0.81*			0.70**	1.03**			2.77**	2.40**	7.13**			
Home & Household Care	1.60**	1.45**			1.03**		0.65**	1.66**		2.31*			0.62**
Out for the Day		1.22**		4.32**	1.02**	0.73**	0.64**	0.47**					
Home Work Day (reference)													
Home Discretionary Day		0.80**		0.07**		3.74**		8.54**	12.35**	26.69**		5.55*	
Home & Household Care	1.59**	1.23**		0.09**		2.87**	0.70*	5.14**	5.24**	8.64**		4.36*	0.62**
Out for the Day				0.45**		2.31**	0.69**		6.81**				
Afternoon Outings		0.85*		0.10**	0.98**	3.17**		3.09**	5.15**			5.70*	

[a] Significance values denoted as * < 0.05, and ** < 0.001

Figure 4.8: Full results of the LCA structural model, illustrating significant odds ratios for basic and equity indicator covariates with all classes as the reference.

CHAPTER 5

CONCLUSION

Taken together, the body of research presented in this dissertation provides a critical assessment of how academic research and current policy understand, investigate, and seek to deploy smart home energy management technologies (SHEMS) to achieve ambitious decarbonization objectives equitably in the United States and beyond. The research critically analyzed how dominant narratives in research and practice envision the role of people in smart energy transitions and assessed implications of these narratives for agency in advancing more equitable energy futures. The results offer new conceptual frameworks to help think through and evaluate the impacts of policies seeking to promote SHEMS and related demand flexibility initiatives. In this concluding chapter, I summarize the findings across these three studies and outline four recommendations and areas for future work for academia, industry, and policymakers.

5.1 Energy Systems in Transition: Equitable Decarbnonization in the Smart Home

The energy system stands at a critical moment in its evolution. Emerging grid planning objectives seek to achieve unprecedented levels of decarbonization to avoid the worst impacts of climate change in a way that centers the voices and needs of society's most historically marginalized communities. The Department of Energy [2] recently released a blueprint for building decarbonization which seeks to achieve a 65% reduction in greenhouse gas emissions by 2035 and 90% by 2050 (compared to 2005). At the same time, over 20 states have adopted policies striving for 100% renewable energy or zero-greenhouse gas emissions for their power sector or even their whole economy [3]. Similarly, the previous decade has shown significant growth in scholarship and policy focus on energy justice [32,33], focused on how to achieve equitable economic and social participation for all during this energy transition [187]. Nearly half of states in the United States have taken some action to advance energy and environmental equity [33], often intertwined with steps to advance decarbonization.

Existing visions among grid operators and policymakers of how to achieve decarbonization objectives view ambitious deployment of innovative and smart technologies throughout the grid as core to success [5]. These technologies offer enticing opportunities to deliver more granular data on, and control over, the way energy is used in homes and businesses, creating the potential to manage the grid more efficiently and affordably. As electricity supply becomes increasingly renewable and the building and transportation sectors are electrified, a paradigm shift is occurring in grid planning and operation [1]. Planning must now consider how much energy is being consumed, at what times, in what ways, and where, in coordination with an understanding of how intermittent and distributed resources like wind and solar supply that demand.

Smart technologies and programs designed around them to flexibly manage energy use offer a pathway to bridge this gap. This includes residential homes, where deployment of smart home energy management technologies to monitor and manage home energy use is understood to have significant potential to provide flexible energy services to the grid [9]. For this pathway to be successful at achieving decarbonization, rapid and widespread adoption of new technologies, alongside the emergence of new ways of interacting with and managing energy use, will be necessary.

Many policymakers believe this shift, if approached intentionally, could support more equitable energy systems through increasing affordability of electricity and access to the benefits of innovative technology [2,5]. However, the use of smart technologies, particularly in homes, has been largely understood from the system perspective [28] and there has been a lack of interrogation of how the deployment of smart technologies in the home will shift agency over energy use between people, technologies, and the grid operators and policymakers supporting the deployment of those technologies. Questions worthy of serious engagement include:

- Who should be tasked with managing energy use in the home and for what purposes;
- How is control over energy use defined and how will the introduction of smart technologies in the home shift who has it;
- Who has (or does not have) the capacity to engage in efforts to manage energy use and how is that recognized in policy striving to advance a more equitable energy future;
- How do we define smartness and how might that privilege certain perspectives and solutions above others

Answering these questions will require a holistic and interdisciplinary approach from academics, practitioners, and policymakers alike. Given the rapid scale of change required to achieve decarbonization goals, it is imperative we understand both the technical and social aspects of these questions. Failure to engage with them in this way could at best prevent social acceptance of decarbonization pathways including the adoption and use of smart technologies and at worst perpetuate or exacerbate existing inequities.

5.2 Current Practice & Policy Recommendations

A holistic understanding of smart home energy management systems will be necessary to successfully achieve equitable decarbonization. Findings from Chapter 2 of this dissertation show this is not yet the dominant approach. There have long been calls for more holistic understanding of energy use and strategies to manage demand [20]. Different disciplines bring unique perspectives to the table, each offering an understanding of a critical portion of the whole picture. However, previous study has historically shown a techno-centric bias of traditional demand-side management initiatives and policy in the energy system [19] with social science and technical approaches often advanced in parallel or at odds with each other.

Key findings from Chapter 2 show SHEMS-related research has continued this paradigm, generally skewing towards investigation by technical disciplines and focusing on automation-based approaches to managing energy use in the home. Studies have emphasized the ability for technologies themselves to actively manage energy use, at the expense of considering residents themselves and third parties like utilities. Third parties in particular appear either as passive actors or not at all, a vision drastically divorced from practice. Consistent with the state of the literature when this work was completed, equity and justice considerations had not emerged within core SHEMS work nor were they explicitly built into the lens of analysis by myself and co-authors.

Although published four years ago, evidence continues to emerge to support these findings. Reviews of SHEMS research [15, 16, 232] continue to show the same basic understanding of smart home energy management systems and emphasize focus on control functionalities to manage energy use. A similar, techno-centric bias also appears in research around demand flexibility initiatives more broadly [7]. Calls for enhanced interdisciplinary approaches to understanding visions of smart energy systems and the role of humans in them continue [23, 42, 233], although these calls come from increasingly larger collaboratives of interdisciplinary scholars and now include a focus on equitably implementing smart technologies into future buildings and energy programs. While interdisciplinary perspectives continue to gain broader traction in academic work, Robison and colleagues [42] assert that "the social nature of smart energy systems is not currently reflected in mainstream agendas" (2).

As a consequence of this, research and practice continue to be guided by incomplete models of the core actors and change agents, their relationships, and roles in the energy system. Conceptual models used throughout this dissertation demonstrate the unintended yet important outcomes of this. In Chapter 2, use of the novel conceptual model of SHEMS shows that when residents or third parties are removed from consideration, potential pathways to support achieving decarbonization disappear without investigation. By contrast, in Chapter 3 use of interdisciplinary understandings of control and explicit consideration of multiple actors as possible change agents expose dynamics often assumed but not acknowledged or critically reflected on in policy and practice - namely how smart technologies shift agency away from residents. Similarly, findings from Chapter 4 show that an understanding of capacities to engage in demand flexibility programs rooted in both social and technical disciplines shows a more complex illustration of where status quo inequities exist than a technical perspective alone.

As a starting point, these incomplete understandings of the system mask where risk lies in developing and advancing programs, whether overestimating decarbonization potential, misunderstanding status quo inequities from which to build more equitable energy futures, or disregarding promising pathways for change altogether. Conceptual frameworks offer the foundation for research methods, data sources and models, and program screening approaches. This suggests that errors in our understanding of the system that originate from the beginning permeate throughout the research and development, program implementation, and evaluation chain.

While the energy system is a highly technical system it is not solely technical in nature. A technical understanding of smartness will likely fall short of achieving both equity and decarbonization objectives. Thus our definition of “smartness” must also extend beyond technical intelligence to understand, acknowledge, and build upon a diverse plurality of social intelligences as well. The scale of challenges that lay ahead to meet decarbonization goals equitably is too large to impose artificial constraints on the system. While automation and controls technologies present new, largely unexplored opportunities to rethink the ways in which energy is managed in the home, they are only one piece of the puzzle. Policymakers and industry must also recognize and respect the people for whom the energy system is designed to serve as co-creators of solutions to decarbonization that build upon innovative technologies.

To support this, I provide the following four recommendations:

1. **All SHEMS deployments must be understood in their social context. This is necessary both to design effective programs and achieve equitable outcomes.**

Although many investigations of SHEMS have focused on understanding either social or technical perspectives on their use, often via siloed investigations of information-based or automation-based functionalities, this must shift. Shifting this perspective will require equal participation and valuation of technical and social sciences in building a holistic picture of how SHEMS can help people and the energy system better manage energy use in the future. This is not only critical for understanding effective technology deployment from a decarbonization perspective, but it is also a necessary foundation for deeply applying an energy justice lens.

Resident intervention in a technical system is only unpredictable to the extent you don't anticipate that customer will intervene and why. The social sciences have provided robust evidence that this will be the case in systems that people don't understand, that don't meet their needs, or that remove their control (perceived or otherwise). Even in fully automated systems, there is a role for the social sciences in understanding how to craft those systems to meet customer needs and prevent them from interfering with systems (likely through trust building, information sharing, and program designs that evolve over time) .

Understanding SHEMS through an equity and justice lens will also require this perspective. As noted by McDermott and colleagues [190] in the environmental justice field, "To uncover the origins of injustice it is necessary to understand the political processes and distributive outcomes in their social context" (419). Thus, we cannot understand the full context for existing inequities nor prevent their perpetuation without a socio-technical understanding of these systems and how they interweave user practices, material infrastructures, and policy framings in a whole systems approach [181].

2. **There must be greater collaboration across academic and applied fields.** This will ensure conceptual models of SHEMS align with real world applications of and contexts for these technologies while supporting the diffusion of interdisciplinary perspectives from academia into policy making and practice. Regulators and policymakers are key change agents in these systems and research must see them as such, already tasked with balancing trade-offs to support individual, community, and societal wellbeing. These collaborations will further ensure more timely communication across research and practice and support the diffusion of interdisciplinary tools, frameworks, and data sources into this realm. Utilities, regulators, and other industry actors are on the frontlines of applied research offering critical opportunities to collect a diverse array of data and metrics spanning social and technical perspectives around SHEMS. Regulators in particular have a critical role to play in determining how utility-programs are screened, approved, and evaluated in ways to advance our collective understanding of the impact of SHEMS in the wild.

3. **Accounting for socio-technical aspects of SHEMS in program development and evaluation will likely require significant organizational change in regulatory and utility industry sectors.** These sectors typically rely on engineering and economic expertise and screening tools such as cost-benefit analysis to assess whether certain emerging technologies and the policies or programs to deploy them will be effective. Integrating process related, social considerations such as whether communities have appropriately recognized and been supported in the design and development of those programs represent issues not easily monetized and quantified. Developing complementary screening tools or revising approaches to cost-benefit analysis will require methods, metrics, and data sets which social scientists and communities can bring

to the table. Whether through embedding professionals with the skill sets within regulatory bodies and utilities directly or through collaboration with academics or consultants, this will require fundamental change in the approach to understanding risk, both social and technical in nature.

4. **Getting this work right takes time, policy timelines must account for this.** The energy industry stands in a moment of disruption, where the status quo is being challenged. While this brings uncertainty, it also presents an opportunity to reconsider and reframe the ways in which energy policy and related programs are designed and new technologies are deployed. Although a narrow policy window exists to embed deep equity in decarbonized systems and related smart technology-based solutions, the industry does not have the time to get it wrong. We must move intentionally from the start. That means building in the appropriate time on the frontlines of research and development for a deep recognition perspective with an understanding that programs grounded in community and understood holistically in their social and technical contexts will roll out more smoothly and be more likely to succeed in achieving both equity-focused and decarbonization objectives in a sustainable fashion.

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