U.S. Smart Thermostat Adopters through the Lens of Diffusion of Innovation Theory

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Abstract
The goal of this study was to characterize smart thermostat (ST) adopters in the U.S. through the lens of the Diffusion of Innovation (DoI) theory. STs serve as a key medium in smart and connected communities (S&CC), enabling remote control of heating, ventilation, and air-conditioning systems, which typically account for half of the total energy use in residential buildings. Accordingly, U.S. utilities have promoted the adoption of STs – providing rebate programs since 2013 – due to their potential for demand response. Leveraging the Donate Your Data program by ecobee (a Canadian ST vensor), this study analyzed more than 44,500 user-submitted metadata entries, including housing, HVAC, and ST adoption characteristics to examine how user attributes vary. Using DoI-based adopter categories, ST adopters were categorized into two groups—innovators and early adopters—and compared their respective characteristics. Key takeaways from this study highlight that early adopters were more likely to reside in smaller homes with fewer occupants and utilize simpler thermostat configurations compared to innovators. However, many of the observed differences were subtle, indicating a steady, rather than transformative, progression in user profiles in adoption matures. These findings deepen our understanding of adoption trajectories and offer actionable insights for designing targeted incentive programs and user-centric technologies. Such strategies can further accelerate the adoption of energy-efficient systems in residential settings and suppor the broader realization of S&CC.
Keywords
Smart thermostat, diffusion of innovation, housing and demographic characteristics, smart and connected communities

1. INTRODUCTION

Realizing smart and connected communities (S&CC) is a promising pathway toward achieving a net-zero or even positive-energy society by streamlining the control and management of energy supply and demand. Buildings—one of the main contributors to the total energy use (27.6% in 2023 in the U.S. [1])—must undergo a transformation to enable various stakeholders, including owners, facility managers, and engineers, to manage energy-intensive appliances and systems systematically.

A key technology facilitating this transition is the smart thermostat (ST). Typically integrated with heating, ventilation, and air-conditioning (HVAC) systems in residential buildings [2], STs collect and transmit operational data to cloud servers and enable remote control via application programming interfaces. Given that HVAC systems account for nearly handle half of the total energy usage in residential buildings [3], STs have the potential to support demand response (DR) strategies by creating significant dispatchable loads that help intelligently balance energy supply and demand. Due to this DR potential through STs, utilities in the U.S. promote their adoption through rebate programs. These programs often offset upfront costs to encourage wider deployment of STs within their service territories and provide compensation to ST owners who permit utility-initiated DR interventions (e.g., adjusting the thermostat setpoint during peak hours), thereby recognizing their contribution to peak load management. According to Salt River Project (a utility based in Phoenix, Arizona, USA) their smart thermostat rebate program reduced peak demand by over 200 MW during the summer of 2023 through nine DR events [4].

To further support this transition to S&CC, this study aims to analyze the housing, HVAC, and ST adoption characteristics of ST adopters through the lens of the Diffusion of Innovation (DoI) theory. The DoI theory explains how new technologies or products spread through a population and categorizes adopters into distinct five groups (Figure 1) [5]. Building on this framework, this study identified two key adopter types—innovators: risk-takers who adopt technologies early with minimal hesitation; and early adopters: opinion leaders who often impact broader uptake—using metadata collected through the Donate Your Data (DYD) program, organized by ecobee (a

Canadian ST vendor). Based on the 2020 Residential Energy Consumption Survey (RECS) data gathered by the U.S. Energy Information Administration, smart thermostats' adoption rate was 10.8%. In other words, as of March, 2022 when the 2020 RECS data was collected, only the innovator and early adopter categories had been reached in the U.S. Consequently, the research questions guiding this study are as follows:

- Do ST early adopters exhibit different housing, HVAC, and ST adoption characteristics compared to ST innovators in the U.S.?
- Who should be prioritized in future ST rebate programs in the U.S.?

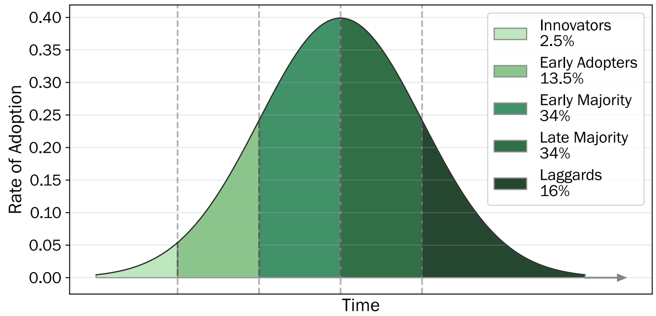

Figure 1. Adopter categories defined by the diffusion of innovation (DoI) theory

2. LITERATURE REVIEW

Understanding ST adopters' characteristics has been a steady interest across various stakeholders. Previous studies have employed mixed-methods approaches to explore both personal (e.g., innovativeness, tehno-coolness) and technology attributes (e.g., upfront costs, functionality, energy usage) impacting the adoption of STs. Specifically, Mamonov and Koufaris [6], [7] demonstrated that techno-coolness—a construct that encompasses the perception that a ST makes a home look modern and futuristic, is enjoyable to use, and enhances the user's technological image—was a key predictor of ST adoption intention. Tu, Faure [8] showed that ST adopters valued cost saving potential, remote control capabilities, energy use displays, and expert recommendations. Additionally, adopter characteristics such as innovativeness and environmental identity reinforced the acceptance of STs' technical features and environmentally beneficial attributes. When ST customer reviews were analyzed, it was revealed that customers primarily focused on usability aspects and expressed interest in remote-control functionalities [9, 10].

However, no prior research has investigated how the housing, HVAC, and ST adoption characteristics of ST adopters evolve over time. Understanding these shifts is critical, since it helps identify how market penetration progresses across different household types, building vintages, and system configurations. Such insights can inform the design of more inclusive and adaptive technologies, guide utility rebate strategies, and ensure that energy-efficiency interventions are responsive to the changing needs and constraints of residential users.

3. METHODOLOGY

Figure 2 illustrates the methodological framework of this research and more details are present in the following subsections. The author used Python and its libraries (e.g., pandas) to clean, process, and analyze data.

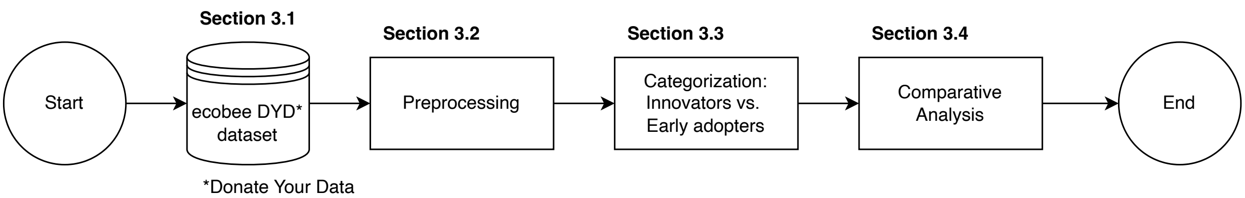

Figure 2. The analysis framework of this study

3.1. ecobee Donate Your Data: Metadata

The metadata collected through the ecobee DYD program were voluntarily provided by ecobee ST users. This study accessed the DYD cloud server through a research partnership with ecobee. The metadata were downloaded on April 3rd in 2024 and included a total of 239,931 data points, with device identifier serving as the primary key. These data points encompassed the following variables (numerical variables are indicated in italic):

- Device information: Device identifier (uniquely assigned to ecobee thermostats), model, user ID, *number of remote sensors* (multiple remote sensors—measuring air temperature and motion—can be connected to an ecobee thermostat), and initial connection timestamp.
- Home characteristics: Location (country, province/state, and city), *floor area*, *number of floors*, *building age*, and *number of occupants*.
- HVAC information: *Number of cool stages*, *number of heat stages*, presence of a heat pump, and whether the heat source is electric.

3.2. Preprocessing

The metadata, which included global participant data primarily derived from user-inputted information, required preprocessing prior to analysis. The following steps were undertaken:

1. Excluding non-US data using country, state (province), and city information.
2. Excluding invalid entries – e.g., missing location data or zero values for square footage, building age, number of floors, and number of occupants.
3. Estimating building construction years utilizing the 'initial connection timestamp' variable and categorizing them into nine groups: (1) before 1950, (2) 1950-1959, (3) 1960-1969, (4) 1970-1979, (5) 1980-1989, (6) 1990-1999, (7) 2000-2009, (8) 2010-2015, (9) 2016-2020.
4. Aggregating housing, location, ST, and HVAC data for users with multiple ST devices.
5. Identifying the climate zone that each user was operating their ST(s).

The 'initial connection timestamp' variable represents the initial connection of the thermostat to ecobee's server. This timestamp served as a proxy for installation time, allowing the identification of when metadata was submitted by users. During the WiFi setup process, ecobee users were prompted to provide metadata. The fourth step was conducted to account for users who installed multiple STs within their homes. Different aggregation methods were applied depending on the nature of each variable, as outlined in Table 1. Decimal values resulting from aggregation were rounded as needed. The fifth step aimed to assess whether climate zones influenced the adoption of STs. State and city information were used to assign each home to an International Energy Conservation Code (IECC) climate zone.

Table 1. Aggregation methods used for different variables

Method	Variable
Mean	Floor area, number of floors, age, number of occupants, number of cool stages, number of heat stages, electric-based heat source, heat pump
Sum	Number of remote sensors
Min	Initial connection timestamp
Count	Device identifier

After all these preprocessing steps, a total of 58,669 data points remained, restructured with user ID serving as the primary key. This restructuring allowed for user-level analysis by consolidating data from multiple devices and eliminating redundancies across records.

3.3. ST Adopter Categorization

According to 2015 and 2020 RECS data, ST adoption rates increased from 3.6% (203 homes out of 5,689) to 10.8% (1,990 homes out of 18,496). Even though these rates did not perfectly align with the innovator and early adopter proportions defined by the DoI theory, this study employed them as reference benchmarks to distinguish innovators from early adopters within the ecobee DYD metadata, given the comprehensiveness and reliability of the RECS data. Specifically, the author used the RECS data collection periods—2015 (Sep/2014 to Apr/2016) and 2020 (Jul/2021 to Mar/2022)—to guide this categorization. The author removed the data points that did not fall within these two categories, resulting in a total of 44,593 observations included in this analysis—3,757 classified as innovators and 40,584 as early adopters. This filtered dataset allowed for a focused comparison between the two adopter groups based on the DoI framework.

3.4. Comparative Analysis

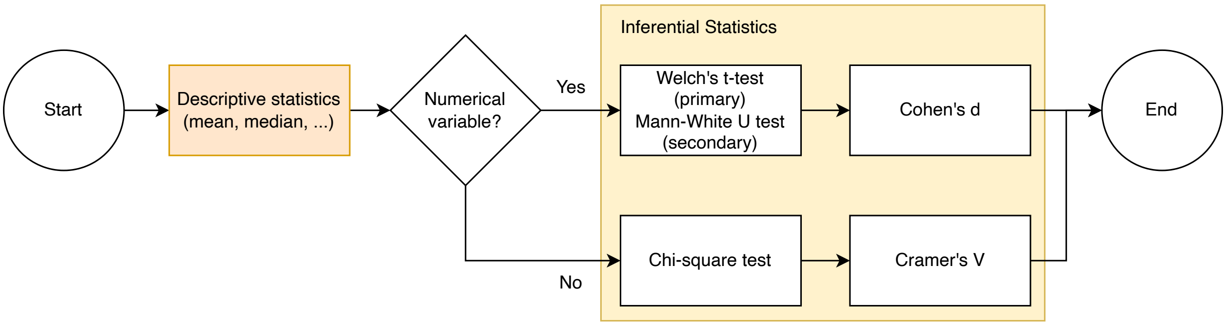

Figure 3. Two-stage analytical framework in this study

This comparative analysis approach examined differences between innovators and early adopters of ecobee STs through a two-stage analytical framework (Figure 3). The analysis began with comprehensive descriptive analysis to characterize each adopter group, using means, standard deviations, and medians for numerical variables and frequency distributions for categorical variables to establish baseline group profiles. Following descriptive characterization, inferential statistical analysis was conducted leveraging the Central Limit Theorem (CLT) [11], using Welch's t-test as the primary method for numerical variable comparisons, which robustly handles unequal variances without requiring normality assumptions given the large sample sizes [12]—benefiting from CLT. To ensure analytical robustness, Mann-Whitney U tests [13] were also performed as non-parametric comparisons for all numerical variables, enabling verification that parametric and non-parametric approaches yielded consistent results. For each numerical comparison, Cohen's d effect sizes [14] were calculated to assess practical significance beyond statistical significance, along with 95% confidence intervals for mean differences to quantify the magnitude and precision of group differences (Please refer to Table 2 for its interpretation guideline). Categorical variables were analyzed using Chi-square tests of independence [15] with Cramér's V effect sizes [16] to measure association strength between adopter groups and categorical characteristics. This comprehensive comparative analysis framework—combining descriptive profiling with dual-testing statistical approaches (parametric with non-parametric verification) and effect size reporting—ensures both statistical rigor and practical interpretability while leveraging substantial sample sizes to detect meaningful differences between innovation adoption groups (Please see Table 2 for its interpretation guideline).

Table 2. Interpretation guidelines for Cohen's d and Cramér's V [14]

Cohen's d	Cramér's V	Intepretation
< 0.2	< 0.1	Negligible
0.2 – 0.5	0.1 – 0.3	Small
0.5 – 0.8	0.3 – 0.5	Medium
0.8 – 1.0	0.5 – 0.7	Large
> 1.0	> 0.7	Very large

4. RESULTS

Table 3 (next page) synthesizes the results from numerical variables in this study and the details are the following:

Housing characteristics showed the most significant differences. Floor area, number of floors, and number of occupants were all statistically different between groups, with ST early adopters tending to occupy smaller homes with fewer occupants. Specifically, mean floor area decreased from 2,657.03 ft² (innovators) to 2,495.37 ft² (early adopters), supported by a large sample size ($p < 0.001$) and negligible-small effect size (Cohen's $d = 0.146$). As illustrated in Figure 4, the distribution of square footage revealed a noticeable shift: while 38.5% of innovators lived in homes larger than 2,500 ft², this dropped to 32.8% among early adopters. Meanwhile, representation among homes with 1,500–2,000 ft² and 2,000–2,500 ft² increased, suggesting broader uptake among households with mid-sized homes. Similarly, the number of occupants dropped from 3.27 to 2.83 (Cohen's $d = 0.135$). The proportion of one- and two-person households rose from 10.5% and 33.0% among innovators to 15.8% and 34.5% among early adopters, respectively. This result reinforced the trend toward adoption by smaller households.

Table 3. Comparison of housing, HVAC, and ST adoption characteristics between innovators and early adopters (numerical variables)

Variable	Group	Mean	Median	Std*	Welch's t-test		Mann-Whitney U test		Cohen's d
					t-statistics	P value	U statistics	P value	
Housing Characteristics									
Floor area	Innovator	2,657.03	2,500	1,093.7	8.64	$7.39e^{-18}$	84,745,798	$1.96e^{-23}$	$1.46e^{-1}$
	Early adopter	2495.37	2,500	1097.3					
Number of floors	Innovator	2.00	2.00	0.78	6.19	$6.66e^{-10}$	80,979,252	$1.37e^{-11}$	$1.02e^{-1}$
	Early adopter	1.92	2.00	0.82					
Number of occupants	Innovator	3.27	3.00	10.00	2.65	$8.04e^{-3}$	83,068,111	$6.44e^{-21}$	$1.35e^{-1}$
	Early adopter	2.83	2.00	1.44					
HVAC Characteristics									
Number of cool stages	Innovator	1.01	1.00	0.38	2.21	$2.72e^{-2}$	77,271,093	$1.63e^{-2}$	$4.07e^{-2}$
	Early adopter	1.01	1.00	0.35					
Number of heat stages	Innovator	1.10	1.00	0.38	4.86	$1.20e^{-6}$	78,538,343	$1.61e^{-7}$	$8.83e^{-2}$
	Early adopter	1.06	1.00	0.35					
Electric heat source	Innovator	$2.56e^{-2}$	0.00	0.16	9.62	$1.12e^{-21}$	78,128,721	$1.21e^{-21}$	0.47
	Early adopter	$7.39e^{-4}$	0.00	$2.71e^{-2}$					
Heat pump	Innovator	$1.75e^{-1}$	0.00	$3.80e^{-1}$	–6.32	$2.85e^{-10}$	73,090,314	$3.86e^{-2}$	$2.91e^{-2}$
	Early adopter	$2.16e^{-1}$	0.00	$4.11e^{-1}$					
ST Adoption characteristics									
Number of STs	Innovator	1.27	1.00	0.84	2.07	$3.86e^{-2}$	77,023,551	0.12	$4.30e^{-2}$
	Early adopter	1.24	1.00	0.66					
Number of remote sensors	Innovator	2.33	2.00	2.18	11.60	$1.18e^{-30}$	84,463,640	$3.83e^{-29}$	0.22
	Early adopter	1.91	1.00	1.91					

Note: Variables with a 'small' effect are shown in blue texts, while those with a 'negligible' effect are shown in black.

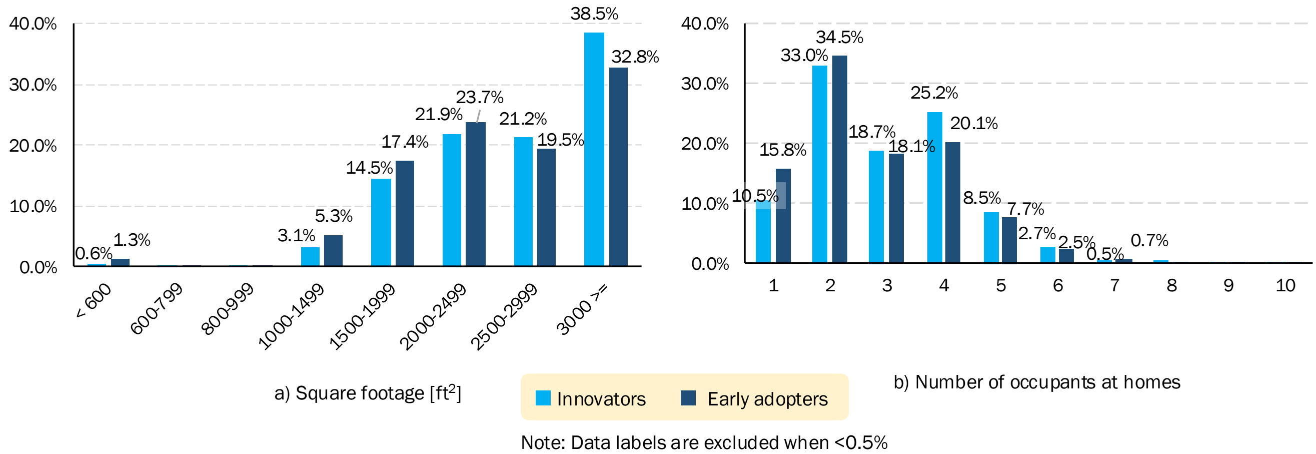

Figure 4. Distribution of household square footage and number of occupants among ST adopters

HVAC characteristics were largely consistent between groups. While the number of cooling stages remained nearly identical, a slight but statistically significant reduction in heating stages was observed (Cohen's d = 0.088). One key difference was the reduction in electric heat source usage from 2.56% to 0.07% (Cohen's d = 0.47), suggesting increased selectivity for energy-efficient systems among early adopters. Additionally, heat pump adoption increased from 17.5% to 21.6%, albeit with a negligible effect (Cohen's d = 0.029).

ST adoption characteristics also exhibited minor differences. The number of STs per household was slightly lower for early adopters (mean: 1.24 vs. 1.27). Subfigure (a) in Figure 5 shows that the majority of users in both groups installed only one smart thermostat, with 81.2% of innovators and 82.2% of early adopters reporting single-device installations. This indicates that single-thermostat setups remained the norm throughout both adoption phases, likely reflecting standard residential HVAC zoning practices. In contrast, the number of remote sensors dropped more substantially (2.33 to 1.91), with a small effect size (Cohen's d = 0.22). While innovators were more likely to install multiple remote sensors—24.3% had three or more sensors—early adopters demonstrated a notable reduction in sensor count, with only 15.0% using three or more. Additionally, the proportion of users with zero or one sensor increased among early adopters (from 25.9% to 27.1% for zero sensors; 20.0% to 27.1% for one sensor). This suggests a shift toward simpler or more cost-conscious installations.

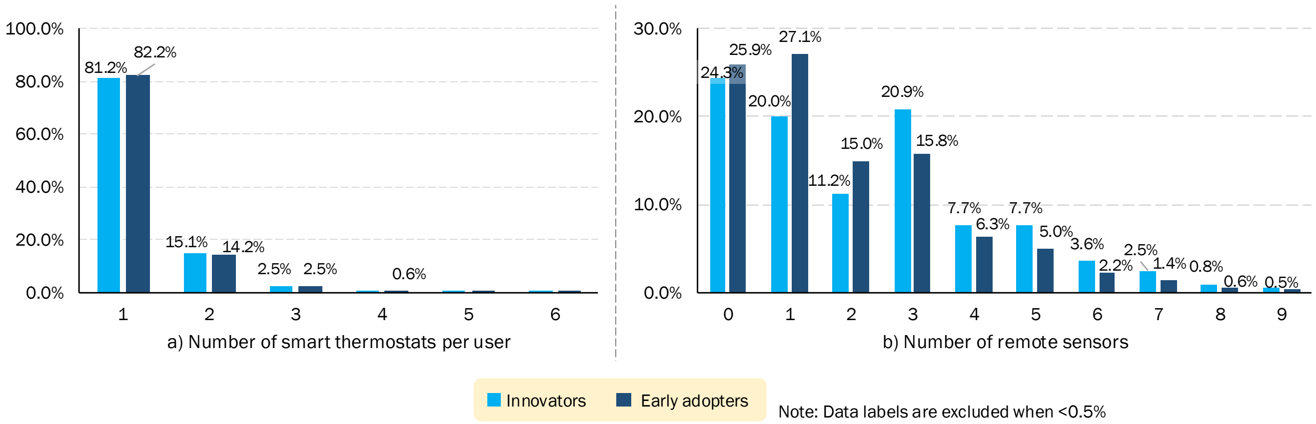

Figure 5. Distribution of the number of ecobee STs and remote sensors per user among innovators and early adopters.

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Table 4. Comparison of housing characteristics between innovators and early adopters (categorical variables)

Variable	Number of categories	Degrees of freedom	Chi-square test		Cramér's V
			Chi-square statistics	P value	
Building type	9	8	106.57	$1.93e^{-19}$	$4.90e^{-2}$
Climate zone	8	7	40.11	$1.20e^{-6}$	$3.01e^{-2}$
Year built	9	8	607.60	$5.43e^{-126}$	0.12

Note: Variables with a 'small' effect are in blue, while those with a 'negligible' effect are in black.

Table 4 presents the results of Chi-square tests evaluating differences in categorical housing variables—building type, climate zone, and year built—between smart thermostat innovators and early adopters. These tests assessed whether the distribution of these variables significantly differed between the two groups.

- **Building type** showed a significant difference with a negligible effect size. This difference might be partially explained by the lower average floor area among early adopters, as smaller homes were more often associated with housing types like townhouses, apartments, or other compact dwellings, as shown in Figure 6.

- **Climate zone** also differed significantly between groups, though the effect size was negligible. This suggests that while statistically different, the distribution across climate zones was relatively similar between innovators and early adopters (Figure 6).
- **Year built** displayed the strongest distinction, with a very large Chi-square statistic and the largest effect size in the table, which was on the higher end of the 'small' effect range. As shown in Figure 6, early adopters were more likely to live in older homes, particularly those built before 1950 (41.5% vs. 25.9%), suggesting that smart thermostat adoption has expanded into less energy-efficient, older housing stock over time.

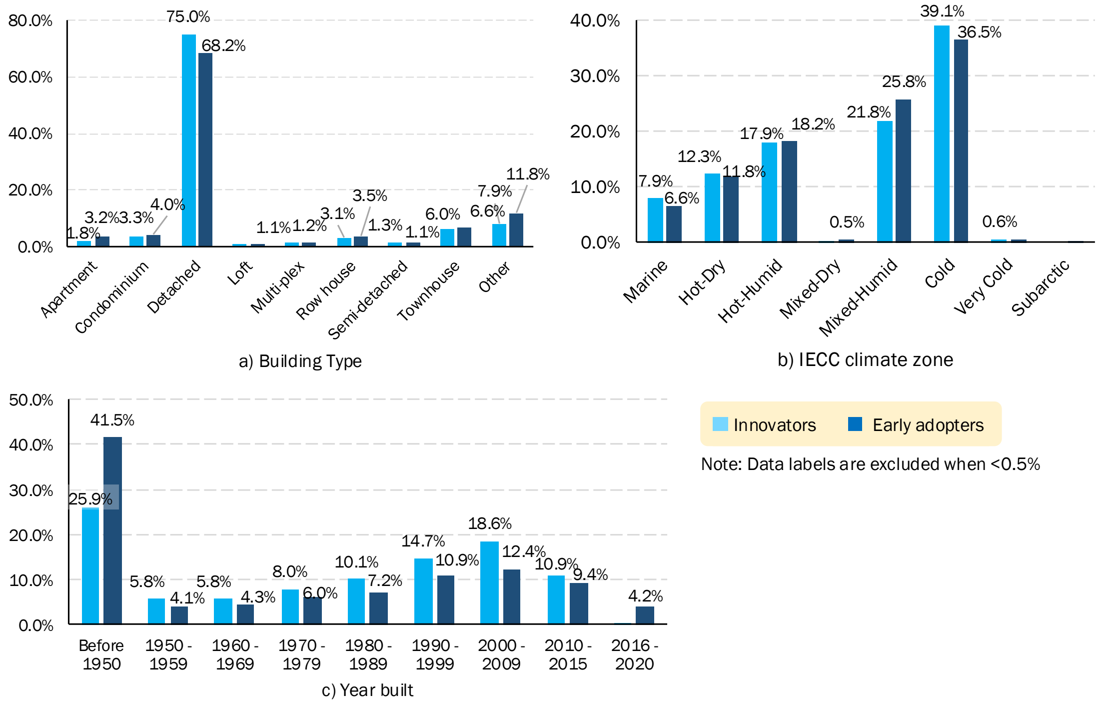

Figure 6. Distributions of housing characteristics – building type, climate zone, and year built – by ST adopter category

Overall, the analysis reveals that early adopters of smart thermostats differed meaningfully from innovators across several housing, HVAC, and ST adoption characteristics. Early adopters tended to live in smaller homes with fewer occupants, more varied building types, and a higher likelihood of residing in older housing stock—especially homes built before 1950. While both groups were concentrated in cold climate zones, early adopters also showed a modest expansion into other regions. HVAC configurations remained largely consistent, though early adopters had slightly higher heat pump adoption and fewer electric heat sources. Smart thermostat setups became simpler over time, with early adopters installing fewer remote sensors per device. These patterns suggest a shift from early, high-investment users to a broader, more diverse user base driven by affordability, retrofit needs, and increasing market accessibility.

6. CONCLUSION

This study contributes to the growing literature on S&CC by examining the evolving characteristics of ST adopters through the lens of the DoI theory. By categorizing users into innovators and early adopters, the analysis revealed meaningful variations in housing, HVAC, and ST adoption characteristics over time. The findings of this study underscore the value of applying DoI theory to uncover behavioral and contextual differences among adopter groups, offering important implications for designing incentive/rebate programs targeting early adopters and early majority, informing energy policy interventions that support the adoption of STs, or developing new STs tailored for building types that have shown lower adoption rates.

Despite its contributions, this study has several limitations. First, the analysis was limited to ecobee users, a subset of the broader ST adopter population, and may not fully reflect the diversity of all ST users. Second, the ecobee DYD metadata lacked detailed techno-economic information—such as household income or energy use—that could further clarify adoption motivations and constraints and only contained ST adopter data. Third, ecobee DYD metadata were manually provided by users, which may introduce inconsistencies or inaccurate entries due to variations in user input quality, effort, or understanding of the requested information.

Future research could address these gaps by integrating additional data sources to triangulate behavioral patterns and enhance the reliability of findings. Additionally, conducting complementary surveys or interviews with a more representative sample of ST users could provide richer contextual and motivational insights, particularly regarding techno-economic constraints, user satisfaction, and long-term engagement with ST technologies.

Nevertheless, this research offers a novel perspective by linking large-scale behavioral metadata with DoI theory, providing new insights into how ST adoption is diffusing across the residential building sector and highlighting emerging opportunities for promoting energy-efficient technologies at scale.

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