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An Analysis of (Non-)Use Practices and Decisions of Internet of Things

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Abstract. Recent market reports have suggested that adoption of the Internet of Things (IoT) does not always lead to long-term use. This paper aims to advance an understanding of the sociological process of the (non-)use of the IoT. To this end, we present results from a mixed-methods study that analyzed survey data from 834 IoT users in the U.S. Many of our participants treated these devices as co-actors for achieving their goals and continued to use them because they had developed a routine or because the devices influenced their social interactions and identity. Participants limited their use of a device when they did not feel in control, when the device failed to understand their intent, or when they did not understand the device’s behavior. We also found that excessive information offered by, disappointment due to, and the complexity of the devices led to their abandonment. Lastly, we discuss the implications of our results for understanding technology (non-)use and provide design recommendations.

Keywords: use · non-use · topic modeling · smart devices · Internet of Things · smart speakers · wearables · smart thermostat · smart locks

1 Introduction

A definition provided by Lazar et al. refers to smart devices as the “*devices that automatically sense data about users or their environment, assist them in automating their spaces or activities, or help the users in gaining knowledge about themselves*” [33]. These smart devices are collectively referred to as Internet-of-Things (IoT) [15]. The IoT therefore comprises a range of devices that play the roles of collector (e.g., wearables or activity trackers), an actor (e.g., smart thermostat, smart assistant), and a creator (e.g., futuristic robots) [14]. News media and researchers have suggested that both the adoption and abandonment of IoT devices is rampant. For example, researchers have found that about a third of activity tracking device owners in the United States stopped using their devices within the first six months of their purchase [34, 38]. Another consumer report on IoT adoption suggests that users think these smart devices are “gimmicky” and not very functional [8]. Specifically, users of smart speakers use a variety of voice assistants’ applications a few times, but abandon them afterwards [11]. This implies that such users face multiple barriers that either prevent them from engaging in the long-term use of IoT devices or lead to systematic limited use.

A recent movement in the HCI community advocates the study of non-use of technology along with its use. Wyatt [52] broadly clustered non-users into four categories – *resisters*, *rejectors*, the *excluded*, and the *expelled* – based on those who used a technology but abandoned it (rejectors and the expelled) and those who never used a technology (resisters and the excluded). Most related to our work is the category that Wyatt term as rejectors, who stop using a technology voluntarily, perhaps because they find it boring, expensive or if they find perfectly adequate alternative technology. Other researchers have noted that abandonment is “neither a singular moment nor a linear path” [10] and that a strict binary distinction between use and non-use can conceal more than it reveals [5]. While abandonment and the long-term use of wearables have been extensively studied (e.g., [33, 19, 37]), the same is not true in regards to other IoT devices (e.g., smart assistants, thermostats). Therefore, to fill this gap, the aim of this paper is to understand users’ motivations, preferences, and justifications for choosing to use or not use the IoT in various forms and degrees. We framed our work around the following research questions:

RQ1: Why do some users continue to use their IoT devices over the long term, while others systematically limit their use or abandon the devices completely?

RQ2: How do the reasons for using or not using differ (or not) for different types of IoT devices?

To build on the literature, disentangle monolithic perceptions of use and non-use with respect to IoT, and understand how the reasons for using different IoT devices overlap or not, we conducted a survey through Amazon Mechanical Turk (AMT), which consisted of several multiple-choice and open-ended questions aimed at understanding user practices and preferences in regard to IoT (non-)use. In the end, we collected responses from 834 participants. To analyze the open-ended survey responses, we adopted a mixed-methods approach, combining computational topic modeling [9] and qualitative reading, which helped us to identify users’ reasons for using, not using, or limiting their use of IoT devices. This paper makes two main contributions:

First, the study provides empirical evidence about user preferences that influence decisions regarding the (non-)use of heterogeneous smart devices, as opposed to related literature that investigated user preferences associated only with activity trackers or wearables. Specifically, our findings reveal user practices and experiences with IoT devices, many of which have not been reported or have been under-reported. Our participants treated these devices as collaborative actors in achieving human-defined goals, and the participants continued to use them due to their social influences, the social interaction enabled by these devices, and habit formation. Conversely, the failure to understand a device’s behavior, a device’s inability to understand the user’s intent, or the feeling of not being in control of the device led to limited or selective use, and various information concerns, disappointments, and the complexity of devices led to their abandonment.

Second, we discuss the implications of our findings for the theory of technology (non-)use. To this end, we discuss the relevance of considering “selective

users” in the design process and provide design guidelines, with the aim of better supporting use of the IoT.

2 Related Work

Many researchers believe that the effects of technologies are less a function of the technologies themselves than of how they are *used* by people [18]. Smart device users form a heterogeneous group in terms of not only their usage patterns, but also their preferences and requirements. Recent work in HCI and related areas has highlighted the importance of studying this variation in users through the lens of technology (e.g., social media, mobile phones, wearables) non-use [52, 53, 2]. Satchell and Dourish [46] further argued for examining use and non-use as aspects of a single, broader continuum, particularly as digital technologies increasingly become cultural objects. Several prior studies have identified a number of practices and motivations for technology non-use, such as Kline’s exploration of user resistance [30], and non-use practices with respect to the Internet [51], computers [48], and social media [4, 10, 27]. Examples of other studies that have specifically argued against making strict binary distinctions include a study by Schoenebeck, which examined intentional short-term breaks in the use of Twitter [47], and a study by Lampe et al., which differentiated among heavy, light, and non-users of Facebook [32].

Lazar et al. reported that 80% of devices that were purchased by the participants for use in their study were abandoned after two weeks [33]. Shih et al. provided 26 undergraduate students with activity trackers, and 75% of them stopped using the device within the first four weeks [49]. Other researchers have observed that people abandon a device when there is a misfit between the device and the participant’s self-conception, when the data collected by the device are not useful, and when too much effort is required to use the device [33, 43]. Lazar et al. found that when users evaluate the data provided by wearable devices as irrelevant and not actionable, the devices become frustrating or time-consuming and ultimately not worth the time investment [33]. However, these findings are based on devices that were provided to the participants after their recruitment for the study. This must have affected their choices, preferences, and (non-)use decisions.

Other studies focused on participants who adopted health-related tracking devices of their own volition, and identified several reasons behind their abandonment. For example, Clawson et al. investigated the rationale for why people abandon health-tracking technologies, by analyzing 1,600 advertisements for the resale of such technologies posted on Craigslist, an online marketplace [16]. They argue that in many cases, abandonment did not necessarily reflect individuals’ dissatisfaction with the technology; that is, people may have been selling their devices because they achieved their goals or their life circumstances changed. Through a survey of 193 participants, Epstein et al. found that the cost of collecting, the cost of sharing the data, discomfort with the information revealed, data quality concerns, the lack of something new to learn, and changes in life cir-

cumstances led to the abandonment of self-tracking devices [19]. Harrison et al. identified poor device accuracy and aesthetics as reasons for abandonment, and discussed implications and workarounds to help overcome barriers to long-term use [28]. Rantakari et al. presented a study on people’s preferences with respect to wearable devices, based on an online survey of 84 participants [43]. The findings show that 27% of the participants stopped using their devices within a month for one or many of the reasons listed above. However, in contrast, the highest-rated features of these devices were found to be their comfort and long battery lifetime. Patel and Ann O’Kane while examining technology use and non-use in the context of the gym use, showed that fitness informatics adopters pursued varied practices related to distraction, the appropriation of technology into their routines, and information needs [41].

Finally, another set of studies has focused on understanding the reasons underlying the long-term use of wearables [22, 37, 29]. For example, Frtiz et al. [22] indicated that long-term (between 3 and 54 months) users rely on activity trackers to motivate them to achieve a consistent level of activity. Similar findings emerged in a longitudinal study on the use of activity trackers, conducted with 34 patients recovering from myocardial infarctions [37]. Only a few studies discuss the challenges [54] or smart voice assistants [35], and they do not specifically discuss users’ (non-)use practices and decisions.

Overall, previous research has primarily examined the (non-)use practices of social media and wearables. Furthermore, prior work has mostly examined these practices in regard to a particular device, rather than comparing how these practices vary across different devices. To fill these gaps, this study contributes to an understanding of the reasons that influence individuals’ decisions to use or not use the IoT, and of how the reasons for using different devices overlap, if at all.

3 Methodology

We conducted an online survey with 834 IoT users from the U.S. in order to understand their reasons and preferences for (not-)using IoT devices. The data were collected between November 2017 and January 2018. The study was approved by our Institutional Review Board (IRB).

3.1 Survey Design and Data Collection

To identify people who had previously used IoT devices and the kinds of devices they had used, and to determine the reliability of users’ experiences, the participants first completed a one-minute screener survey. The selection of participants who had adopted device(s) of their own volition helped us to identify the exact reasons for continued use, and benefits that faded away with time. In the screener survey, every participant was shown five scenarios to identify devices they had past experience with:

Scenario 1: A device for self-**security** purposes that collects your personal data (e.g., location) to be shared with trusted friends and family in case of emergency.

Scenario 2: A device that can be used during activities to collect your personal data (e.g., heart rate) or to keep track of or improve your **health and well-being**.

Scenario 3: A device that can be used to collect data (e.g., number of steps taken during the day) for personal **informatics/logging** purposes.

Scenario 4: A device that is part of your **connected and automated home** to notify you about the conditions of the objects to which the device is connected (e.g., for opening the garage or the main doors of your house), or to remotely control objects (e.g., lights, thermostats)?

These scenarios were designed to help participants gain a clear understanding of a situations in which a smart devices are used and thereby to remind them of their own devices. Four scenarios were selected (purposeful sampling [40]) to reveal variations and patterns in the challenges and dynamics of using IoT in day-to-day living. This increased the capability of generalizing our results to other devices. Based on the responses to the screener survey, each of the participants answered questions in the main survey with respect to only one of the above-mentioned scenarios. In connection with each scenario, two types of questions were presented to the participants.

The first category consisted of factual questions that included Likert scale questions and yes-or-no questions. Some of these were developed based on the most relevant factors, identified in prior research [33, 39, 50, 16, 22, 37] that examined people’s attitudes and experiences toward using or not using tracking devices and wearables. For instance, to determine their level of *relatedness with the device*, we asked participants when they started using the device. We also asked them how *important* the task was that device helped them fulfill, and to what *extent* the device helped them to *achieve their purpose*. The survey also included question on whether they had any *privacy concerns* about using these devices, and how *relevant privacy* was to the way they used a device. The answers to Likert-scale questions were based on a five-point scale; for instance, with respect to the importance of the task, the scale ranged from 5 = “Extremely Important” to 1 = “Not Important At All.”

The second category consisted of questions that were aimed at exploring experiences with IoT devices and the reasons for using them (completely or partially) or abandoning them. To this end, we adapted the method proposed by [42], who used a survey to elicit stories about issues related to computer security. The participants were asked to share a story about how and why they systematically limited/restricted their use, stopped using a smart device, or still used their device regularly. We emphasized at the outset of the main survey that detailed responses to the open-ended questions would help with our analysis. While we did not specify how much detail was required, we informed participants about the possibility of earning an extra bonus for detailed responses, in addition to the standard compensation for finishing the survey. Lastly, to avoid

Education Level (in %)	Annual Income (in %)	Race/Ethnicity (in %)
No High School, 0.4 (10.9)	<\$15K, 2.9 (11.6)	White, 60 (72.4)
High School, 6.1 (28.8)	\$15K - \$34K, 25.8 (20.5)	African American, 15 (12.6)
Associate’s, 37.7 (10)	\$35k - \$74K, 41.3 (29.4)	Hispanic or Latino, 12 (16.3, of any race)
Bachelors, 42 (48.7)	\$75K - \$149, 24.5 (26.2)	Pacific Islander, 7 (0.2)
Professional, 11.9 (1.5)	\$150K - \$199K, 3.7 (6.2)	Asian, 4 (4.8)
No answer, 1.8	>\$200K, 0.2 (6.1)	Native American, 2 (0.9)
	No answer, 1.6	

Table 1. Additional Demographic Breakdown of the 834 Participants. The numbers in parentheses Show the U.S. average, based on data from the 2015 Census.

priming the participants’ responses in any way, we deliberately did not explain the terms “systematic limited use,” “continued use,” or “stopped use” throughout the study. Towards the end of the survey, we also collected the respondents’ demographics, such as gender, age, and annual income.

3.2 Pilot Study

To assess the comprehensibility of these questions, we piloted the survey protocol with 20 graduate students in October 2017. The pilot results suggested that the students understood the questions, although most of them did not understand which devices qualified as smart devices or as part of the IoT. For instance, many of them asked if laptops are considered part of Internet of Things, as they support Internet connectivity and are capable of collecting personal information. We then revised the survey based on the feedback from the pilot study to include the definition of the IoT mentioned in the previous section.

3.3 Participants

The participants recruited through AMT had completed at least 1,000 tasks, with an approval rate of above 95%. Our survey was completed by 900 AMT workers from the U.S. We then checked each response to make sure it was meaningful. This led to the removal of 66 participants, and responses of 834 participants were included in our analysis. The average age of the participants was 36.47 years (min: 18, max: 74), which is very close to the US average of 37.9. Of the participants, 56.5% were female, 42.9% were male, and 0.6 percent declined to report their gender. Table 1 summarizes additional demographic information of our participants, along with corresponding US national averages.

We note our participants do not represent the entire population of IoT users. But, our study adds substantial knowledge to the existing literature as our sample composed of a large number of non-technical respondents who had adopted different types of smart devices voluntarily. We also note that all the devices that our participants listed for Scenarios 2 and 3 were identical. Therefore, we combined the respondents’ answers for these two scenarios for the purposes of the analysis. The different types of devices that the participants owned for each

of the scenario are listed below. The numbers in brackets represent the number of people who are continuing to use their device/ who have limited use of their device/ who have abandoned their device with respect to respective scenario.

Security (81/55/119): Security cameras, smart locks, baby monitors, GPS trackers

Health and well-being, informatics/logging (85/68/113): Activity trackers, smart watches, heart-rate monitors

Connected home (88/106/128): Smart thermostats, smart blinds, smart doorbells, smart locks, smoke alarm detectors, door sensors, smart speakers, smart plugs, smart light-sensing systems.

3.4 Content Analysis

While statistical information regarding responses to the yes-or-no and Likert scale questions is provided below, this paper primarily focuses on an analysis of the open-ended responses. This is driven by the aim to identify practices of, and reasons for, (not-)using the devices to various degrees. On an average each participant wrote around 175 words (total of approx. 1,50,000 words). Therefore, motivated by advocacy in recent work [26, 12, 13, 6, 7] for combining topic modeling [9] and qualitative reading to analyze free-text survey questions, this study used the Latent Dirichlet allocation (LDA) model [43], the most commonly used topic model in HCI and related communities, along with close inductive qualitative reading, to identify the underlying themes and label “topics” identified by the model.

Specifically, LDA is an unsupervised computational approach in which documents (in context of our study, the responses to open-ended questions) are represented as random mixtures of latent topics, where each “topic” is characterized by a distribution of words [9] that summarizes the main themes in the documents. A lexical word may occur in several topics with a different probability, however, with a different set of neighboring words in each topic. Therefore, LDA is based on automatic detection of the likelihood of term co-occurrence. Before identifying topics, each survey response was preprocessed to remove stop-words, such as prepositions and conjunctions. Since we wanted to identify reasons for, and practices of using or not using devices, we did not remove common pronouns (e.g., *I, it*) and a few determiners (e.g., possessives, demonstratives, quantifiers). As LDA is an approximating algorithm, we followed the approach proposed by Baumer et al. [7] to find stable topics and generated 10 independent topic modeling solutions, each consisting of 5 topics. The number of topics was chosen after manually increasing the number of topics from 2 to 30. We then manually examined each topic and the top 100 words most likely to occur across the solutions and excluded topics that exhibited more than a 50% variation in word distribution across solutions. This enabled us to identify topics that were distributions of identical words with small variations resulting from random initializations. The upper bound for the number of topics and the threshold for variation in word distribution per topic were chosen based on the limits suggested in the literature on topic modeling (e.g., [26, 9]).

As noted by Baumer et al. [7], algorithmic approaches such as topic modeling complement rather than replace the methods of grounded theory [23]. Therefore, while topic modeling provided empirical evidence in terms of the words that were most likely to occur in a topic, inductive analysis helped us to identify the links between these words, and their contexts, to understand the reasons for device use, limited use, and abandonment in our survey responses. Previous research (e.g., [26, 12, 6]) has also suggested that the top words within these topics can be considered equivalent to the “codes” that are otherwise assigned by human researchers using open coding [23]. However, identification of such codes or topics computationally neglects the syntactic and semantic knowledge of human coders. Therefore, the responses categorized within each topic (based on the topic’s proportion, which indicated the topic’s relevance in the response) were then carefully read to include the linguistic and contextual knowledge of the human coders use to identify the reasons for (non-)use.

Qualitative reading served three purposes. First, even though proportions of topics within each response differed substantially, the qualitative reading of all the responses ensured that each response was associated only with the topic that was present in the highest proportion. For example, the percentages of Topic 1 (the most frequently occurring topic) and Topic 2 (the second most frequently occurring topic) were 92% and 8%, respectively. A qualitative reading of this response corroborated that it belonged only to Topic 1. Second, through an inductive reading of the responses and the top 20 words of each topic as identified by LDA, relationships between codes or words emerged. These relationships were then used as the labels or themes of the corresponding LDA topics. Finally, qualitative analysis enabled a detailed and fine-grained analysis to identify sub-topics within each of the topics that emerged with LDA.

Overall, our process was analogous to open coding, which fractures the data into categories (top words within each topic in context of our analysis), and then axial coding, which puts the data back together by making connections between these categories (the labels of the topics in context of our analysis) [23]. Depending on the participants’ current status of use, limited use, or non-use of their devices, they gave their reasons for either continuing, limiting, or abandoning use. Also, our purpose was to identify separately the underlying reasons for use, limited use, and non-use. Therefore, we applied the above-mentioned procedure thrice; once on the textual corpus to determine reasons for use, next to determine reasons for limited use, and finally explanations for non-use. This process was also analogous to qualitative coding, where codes for reasons for use, limited use, and non-use would be developed separately.

In the next section, we discuss the stable topics that were identified, their underlying theme(s) (obtained by establishing connections between top words by reading the responses within each topic), the breakdown of each topic’s applicability to the different scenarios or categories of IoT devices, and the highest-ranking responses (based on the percentages of the corresponding topic in the responses) for every scenario.

Factor	Number of Current Users, Limited Users, Non-Users per Likert-Scale value
Duration	<6 months: 77, 67, and 93; 6 months - 1 year: 64, 58, and 97; 1-2 years: 58, 42, 72 , >2 years: 55, 51, and 98
Relevance of Privacy to Current State of Use	Extremely Important: 10, 39, 18; Very Important: 22, 20, 31; Neither Important or Unimportant: 117, 73, 177; Slightly Important: 40, 42, 71; Not Important: 65, 44, 73
Importance of Task for which Device was Adopted	Extremely Important: 78, 66, 41; Very Important: 75; 53, 35; Neither Important or Unimportant: 31, 31, 36; Slightly Important: 41, 36, 170; Not Important: 29, 32, 78
Extent to which Device Fulfills the Task	Extremely Helpful: 76, 41, 76; Very Helpful: 79, 31, 68; Neither Helpful or Unhelpful: 44, 49, 26; Slightly Helpful: 22, 66, 44; Not Helpful: 33, 31, 146

Table 2. Distribution of Responses to Multiple-Choice Questions for Different Categories of (Non-)Users

4 Findings

Our analysis revealed that the IoT users developed various technology-oriented individual, collaborative, and social practices that affected their decisions to use or not use IoT devices in various forms and to various degrees. It also revealed not only that several participants used same types of devices in multiple scenarios, but also that their reasons for (not-)using different devices overlapped in many cases. Statistical information relevant to the multiple-choice questions is provided in Table 2.

4.1 Why Did the Participants Use Devices?

Topic modeling and qualitative analysis identified the following three stable topics associated with the reasons for continued use. These topics, along with the highest-ranking response corresponding to each device, are as follows:

Topic: Collaborative Support

Top 20 words: *monitor, together, track, other, senses, helps, itself, him, allow, does, me, her, supports, manages, us, it, ensures, partner, benefit, our*

This topic refers to the collaborative relationships that people develop with their devices to achieve their own goals, and the collaborative activities that these devices enable. The topic was found to be in the highest proportion in the responses of 72 current users. These 72 responses comprised 27, 19, and 26 responses to the scenarios of *security, health and informatics, and connected home*, respectively.

Over the past decade, several researchers in the HCI and CSCW communities have studied the collaborative practices that emerge from the use of personal trackers [17, 20, 44]. Atzori et al. recently pointed out that, with the IoT, many more objects and spaces have entered the realm of connectivity, thereby making

possible cooperation among these devices to accomplish a particular task [3]. In contrast, our findings suggest that these devices are not currently perceived as objects cooperating with one another to complete a task; rather, devices act like, and are treated as, collaborative actors that work with or for users to achieve a human-defined goal. Participants' responses suggest that when their collaborative experience(s) with the device is/(are) positive and successful, the result is continued use. For example, participants wrote: *Smart sock for monitoring heart rate and oxygen levels of my kid during sleep helps me achieve so much. The device is like my extension as it allows me to constantly track the vitals when I cant be with my kid and other things that I could not do myself* (P325, Security), and *It [activity tracker] helps me like a partner in reaching the goals faster by tracking my steps by ensuring that I know how much I have walked. It does the tracking, I do the walking* (P123, Health and Informatics).

Thirty participants also mentioned that the ability to asynchronously collaborate with family members through a device for various activities (e.g., maintaining music or to-do lists, sharing calendars) and/or the ability to provide temporary access to others by configuring different access levels also contributed to their continued use. For example, participants observed: *My Google home brings so much benefit to me. Me and my husband make our common to-do list on Google home, when I go to shopping I know what my husband has added remotely. Same is true for calendar access and so many other things* (P712, Connected Home), and *When my mother visits I can give her partial access to Nest so that it learns her whereabouts and preferences but at the same time she can not change any settings. This saves me lot of time and energy to manually accommodate my mother's preferences* (P801, Connected Home).

Topic: Social Interaction and Influence

Top 20 words: *us, friend, together, people, like, fun, they, other, feel, family, group, flaunt, I, challenge, argue, enjoy, know, affect, personal, someone*

This topic was found to be in highest proportion in 91 responses – 31, 25, 35 survey responses with respect to the scenarios of *security, health and informatics*, and *connected home* respectively. Goffman [24] discusses how people tend to create impressions of themselves that are publicly visible. Forty eight responses suggested that people continue to use the IoT because it influences the way they are viewed or perceived by others. For example, participants responded *I flaunt my automated security systems and smart door locks each time friends, family or someone else come over. They feel I am rich, and I like that* (P756, Security), and *All of my friends have smart assistant. If I stop using mine they will feel I am not able to keep up with the changing times* (P345, Connected Home).

For 17 other participants, even though these devices became a source of contention with their significant others due to their having different preferences, they continued to use them for their utility. For example, P589 explained: *Sometimes I have argued with my husband over setting the boundaries of geofencing that I can set for the GPS tracker of my kid. However, the potential of knowing where our daughter is, reduces anxiety for us, and hence I continue using it despite a constant difference of opinions* (Security).

Fifteen participants indicated that the increased interactions that some of these devices enabled with their strong and weak social ties motivated their continued use. Strong social ties consist of blood ties, as well as friendship ties that are equivalent to family ties, and weak ties consist of affiliations such as friends of friends or friends of family [31, 36, 25]. Through participation in online groups that were supported by various activity trackers, people not only communicated with their strong ties, but also extended their links through recommendations and transitively created weak ties. For example, P843 wrote: *I do not see my family and friends that often. But through the Fitbit groups I can keep track of who is doing what from health point of view. If someone who desperately need to work out fails to do so, I can remind them about it* (Health and informatics).

Finally, while their devices motivated many of the participants to achieve their goals through reminders and notifications, for 11 participants these devices provided a platform whereby they competed with people in their network of close or weak ties. For example, community groups within Fitbit,¹ enabled them to discuss with, track the progress of, or compete with other people in the group. For example, P834 further explained, *In other cases when my friends are doing physical activities, the competition and challenge makes me workout even more to achieve my own goal* (Health and informatics).

Therefore, even though the focus of the study was on individuals' (non-)use of IoT, this topic illustrates that IoT devices have a greater social impact that extends beyond one-to-one relationships, and these relationships in turn influence an individual's use of these devices.

Topic: Developed Routine

Top 20 words: *goal, me, habit, use, do, I, my, long, always, time, reach, achieve, able, target, money, convenience, routine, myself, it, continue, help*

Previous work has reported that people try to integrate a wearable device into their life only when the device is not obtrusive or uncomfortable [33]. Responses for this topic were often from people who had been using a device for more than a year and had developed a routine for using it. A total of 91 responses – 23, 41, 27 responses related to the scenarios of *security, health and informatics*, and *connected home* respectively – were categorized under this topic.

In contrast to previous work, the analysis of these responses indicated that the underlying reasons related to habit formation can be quite varied and include factors such as the associated economic benefit users get from enrolling in rewards programs offered by various device manufacturers and their partners (e.g., the Rush Hour program for the Nest thermostat, the incentive program for Fitbit Health) (21 responses), convenience (11 responses), a higher probability of achieving goals with the help of the device (23 responses), intentional use arising from the fact that it was already purchased or was received as a gift (20 responses), and development of a compulsive habit of unconsciously using the device (16 responses). Interestingly, all these reasons were prevalent in responses to all three scenarios.

¹ Fitbit Community Groups: <https://blog.fitbit.com/fitbit-community-announcement/>

Examples reflecting these factors include this by P842: *During my initial use of the device I lost 30 lbs because I was able to log my food intake via the Fitbit app. I can see the difference in my lifestyle when I do not use it, so I will continue to use it till I reach my goal, and afterwards to maintain my healthy routine. I have now found myself wearing the Fitbit just absent mindedly too, it has become such a habit* (Health and informatics), this by P391 *The convenience of the device [smart lock] made me used to it. I don't have to carry my keys all the time. Now I use it always and can not do without it* (Connected Home), and these by P219 and P97 *I am enrolled in Rush Hour program of Nest so now I just use it habitually* (Security) and *I had bought [GPS tracker] for my kids a long time ago. Now my kid is in a habit of wearing it. So without me reminding him, he always wears it* (Security).

4.2 Why Did the Participants Limit Their Use of Devices?

For the corpus consisting of participants' reasons for limited use, two stable topics emerged. The reasons related to restricting the duration of use, engaging in occasional use, or using only specific application(s) on a device.

Topic: Understanding and Controlling the Capabilities of a Device

Top 20 words: *not, ability, allow, let, help, can, do, change, becomes, useful, modify, I, unable, my, understand, myself, adapt, need, decide, itself*

This topic consisted of 55, 34, and 52 responses to the scenarios for *security, health and informatics, and connected home*.

The responses indicated that a vague understanding of a device's capabilities not only reduced use, but also constrained participants in terms of their ability to successfully control or predict the capabilities of the device. For example, with respect to a GPS tracker, P100 said: *I find it tough to trust trackers for my children or pets. It's useful sometimes, but if connectivity is poor I do not know if it tries to send emergency notifications to me. Its unclear to me how soon after loosing connectivity it tries to connect back* (Security), and fuelled by the fear of smart assistant listening in a private space, P643 explained: *We are not sure if it really listens our conversation all the time or not. But to be on a safer side we always keep it on a mute mode. So the need of physically tapping it to unmute the device before giving any command has reduced our use* (Connected Home).

Furthermore, participants' also limited their use of a device due to doubts or disappointment in regard to its learnability and automatic adaptability. For instance, participants were disappointed with smart speakers, because the speakers could not base their responses on previous user interactions, and the users had to state their commands in a specific style (e.g., using simple words, not concatenating commands). For example, P710 said, *It [smart assistant] has a hard time adapting to my accent and the way I give commands. I am not even sure if the device is trying to learn it or not. Therefore, the only time smart assistant is useful is when I am next to it and I have 10 minutes to spare for a simple command* (Connected Home). Similarly, in the case of smart thermostats, not being able to precisely identify how and whether factors such as anomalous and manual temperature changes or occupancy levels in the room influenced

the thermostat’s learning led participants to not trust or use more sophisticated functionalities such as Auto-Schedule, Airwave, or Auto-Away. Similar concerns were reported with respect to wearables as well. For example, P329 wrote, *Without knowing the relevant parameters it is difficult to believe various scores such as cardio fitness score that it [activity tracker] generates for me. For example, I do not wear it all the time so that means score can be incorrect. So the device is good to count number of steps, but nothing fancy* (Health and Informatics).

Overall, such experiences led users to blame themselves for not being technically adept; for employing an economy of interaction, such as limiting the words used while giving a command to a smart speaker; for avoiding the complex capabilities of devices such as thermostats, wearables, or speakers; or for using only features that they understood and believed the device could perform successfully.

Topic: Devices’ Inability to Understand Users’ Intents and Contexts

Top 20 words: *understand, know, not, prefer, believe, kid, unclear, result, it, feel, difficult, try, want, tell, his, think, hard, my, aware, child*

This topic consisted of 34 responses to the scenario for *health and informatics* and 54 responses to the scenario for *connected home*. The analysis revealed that factors such as a device’s inability to understand a user’s changing behavior and contexts, and dissonance between the user’s expectations and the pragmatics of a device, led users to stop using or relying on certain features of devices. For example, with respect to smart speakers, P334 said, *I feel it does not understand my context. If me and my wife start talking in middle of placing an order, it will start saying: sorry I don’t understand that. As it can not learn that I always order after discussing with my wife, I do not use purchasing functionality anymore* (Connected Home), and with respect to activity trackers, P20 said *If I am walking or biking on a bumpy trail, I know I will get extra steps. Sometimes when I am walking too slow and arms are not moving fast enough, I know I will get a few steps less in my logs. So most of the times when I go for a bumpy trail I don’t trust on the logs* (Health and Informatics).

Twenty of the participants specifically reduced their smart speaker use around children because of fears about the speakers’ impact on children’s social development skills, and their use of smart assistants for fear they might play inappropriate content when children were around. P210 said, *I have reduced the use of Google home in front of my children. There is no way I can make it understand that kids are around. I fear it might one day misinterpret me and start playing explicit content* (Connected Home). Along similar lines, P186 explained, *I do not want my children to feel everything is achievable by just giving a command. We reduced our use because our 6 year old used to get irritated when not being understood by the speaker, which is not acceptable to us* (Connected Home).

4.3 Why Did the Participants Stop Using Devices?

For the corpus comprising participants’ reasons for non-use, the three following stable topics emerged:

Topic: Disappointment

Top 20 words: *never, lost, nervous, nothing, stress, goal, not, purpose, motivation, sad, me, work, fail, worry, achieve, myself, made, don't, it, help*

The negative emotions seen in this topic's top words (e.g., *sad, stress, nervous*) as seen in this topic's top words, and the subsequent reading of 128 responses that had this topic in the highest proportion suggest that disappointment is the primary reason for cessation of use. Even though feelings of disappointment were evident in the 60, 22, and 56 responses corresponding to the scenarios for *security, health and informatics*, and *connected home*, respectively, the reasons of the let down for each category of devices were different.

In regards to devices associated with the scenarios of *security* and *connected home*, users felt disappointed when the devices failed to serve any purpose. P440 explained: *The lock would only work if it had good Internet connectivity. The worry of it failing to secure the home and fulfilling its purpose due to any reason made me stop using it* (Security). Forty participants also perceived these devices as trivial and banal, which gradually led to their abandonment. For example, P333 said: *My google home was fun in the beginning. But there is not much you can do with it, like a phone has so much purpose. It is mere waste of time* (Connected Home).

Devices belonging to *health and informatics* were abandoned as they demotivated the users through reminders about their failures or unattained goals. P208 explained, *The device keeping track of my activities did not help me achieve my goal rather it made me sad. Earlier the reminders used to trigger me to work. But then I started to become nervous of them coming and then it caused stress and sadness that my group members are getting fit but I am not. It started demotivating me by reminding me about my failures and then slowly I lost the motivation to use it* (Health and Informatics).

Topic: Information Concerns

Top 20 words: *much, privacy, many, too, distract, information, excessive, private, share, not, data, does, me, alter, allow, my, need, monitor, lot, disturb*

A total of 115 responses, comprising 24, 39, and 52 survey answers to the scenarios for *security, health and informatics*, and *connected home*, respectively, listed information concern(s) as the reason for abandonment.

Thirty-nine of these responses indicated that too much information annoyed the participants, distracting them from focusing on the task at hand or other important daily activities, and sometimes even affected their productivity. For example, one respondent remarked, *Every time getting a notification when something was ordered through my smart assistant or if somebody called my kid was annoying. I also think it was constantly collecting my information* (P250, Connected Home); another said, *It [activity tracker] used to distract me multiple times in a day while being at work or with family* (P1, Health and Informatics).

Thirty-seven responses suggested that not trusting the ways sensors worked rendered the devices less useful for participants. Participants explained, *I am not sure if the sensor was capable enough to save my energy cost* (P499, Connected

Home), and *The fact that device gives better results on dominant wrist made me skeptical of its overall accuracy* (P222, Health and Informatics).

Another 17 participants mentioned the inability to customize information or learning behavior of a device as their reason for abandoning these devices. For example, P66 said, *The smart lock that I had did not allow me to customize my schedule. Also, as my schedule was getting stored on the Internet, there were high chances of it getting leaked* (Security).

Furthermore, the analysis of the respondents' answers to multiple-choice questions revealed that 301 (36.09%) of our participants reported privacy issues to be relevant to their decision to forgo use. A total of 140 (46.5%) of the participants reported privacy issues to be *extremely important* or *very important* to the way they used a device. However, only 22 participants highlighted data ownership and misuse of data by device manufacturers as the sole reason for abandonment. For example, P56 explained, *I am not sure how my location data and my temperature preferences are being used by Nest. They might be misusing the data by selling it for certain benefits* (Connected Home). Overall, even though privacy concerns of IoT are well documented (e.g., [39]) and many participants mentioned it being relevant to the decision of use, only few (22) of the participants in our study mentioned privacy as the sole reason for abandonment.

Topic: Overload of Features and Devices

Top 20 words: *money, cost, upgrade, maintain, it, much, like, looks, hate, annoy, feature, many, high, extra, difficult, dependent, less, function, not, manage*

The scenarios for *security, health and informatics*, and *connected home* drew 35, 52, and 30 responses on this topic, respectively.

In addition to issues over device aesthetics, comfort, and high frequency of maintenance, as found by other studies (e.g.,[49, 33]), the participants in our study also stopped using a device because it became too complicated to use due to an overload of features or because the cost of maintaining or owning it was too high. For example, one respondent said, *I stopped using the iWatch because I really didn't need all the extra features. Phone functions in a similar fashion, but is much less obtrusive, and I almost always have my phone on me anyway* (P811, Health and Informatics); another observed, *The security device that we installed was difficult to maintain and I started to hate it after a while. It's costs so much money to maintain such high end devices* (P111, Security).

Twenty out of 117 responses also attributed abandoning the devices to negative consequences related to productivity and an overdependence on technology. Participants explained, *At some point I realized I am constantly using or checking one device or another. It kept me from doing other important tasks. So I got rid of my activity tracker as I was constantly checking my activity stats* (P542, Health and Informatics), and *I realized it was getting ridiculous that even for a simple task like switching on a light I was giving commands. I did not want to be so dependent on technology* (P777, Connected Home).

5 Discussion and Design Implications

The goal of this study was to identify reasons and practices that lead to the (non-) use of a variety of IoT devices adopted voluntarily by the participants. Previous research (e.g., [49, 33]) has explored use or non-use only with respect to wearables such as activity trackers. To the author’s best knowledge, this is the first study to empirically investigate reasons for the use, limited use, or abandonment of various IoT devices that are used for *security, health and informatics/logging, and connected home*. This section discusses our contribution to the literature on the (non-)use of technology and associated design implications for the future of the IoT.

Value of Considering Selective Users

In the past, HCI researchers have argued that the role of non-users is important and valuable in designing successful technologies (e.g., [52, 46]). Our findings provide empirical evidence for the existence of *selective users*, who limit or restrict the use of their devices of their own volition. This highlights the value of further refining the categories of (non-)users, resisters, rejecters, the excluded, and the expelled [52] to include *selective users*. The participants who had limited their use of IoT devices either felt a lack of control while using them or did not understand devices’ behavior. Therefore, disenfranchisement for a user can arise not only from technical and economic constraints [46], but also from conceptual barriers, such as limited knowledge of a device’s capabilities and questions about what it means to take a particular action when the device is sensing. This calls for transparent designs that make a device’s capabilities, functionalities, and processes easily observable and understood by users. Furthermore, a device’s autonomy can add to its convenience for some users, but for others it can prove to be a barrier to continued use. For the latter group of users, devices that exercised a high level of control scored low on perceived ease of use and usefulness.

In order to cater to the different needs and preferences of users, future IoT devices need to balance end-user control with automation to match each user’s preferred degree of interaction. Such a hybrid approach would enable users to decide if they want to opt out of “intelligent features” or willingly relinquish (some) control to avail themselves of a more automated version of a feature or device. Some devices and manufacturers (e.g., “mute button” on a smart speaker gives users control over whether the device can actively listen for the wake command) Further, we do not recommend abandoning autonomous devices; instead, we believe that devices with autonomy should aim to increase users’ understanding of how their systems learn and makes decisions. For example, devices can visualize and point out (un)successful actions, making users aware of the unforeseen outcomes that may result from their decisions.

Devices that Integrate into Daily Activities

Previous research has noted that *lagging resistance*, a sense of wanting to quit but not deciding to do so just yet, to be the most prevalent phenomenon amongst users [4]. The responses of our participants, however, suggested that

they make well-reasoned and lucid decisions to forgo the use of devices or to systematically limit their use of certain functionalities.

The non-users of IoT devices within this work resonate with the *rejectors* [52], as they first used the devices of their own volition, but did not continue to do so. Several previous studies (e.g., [33]) have suggested that an established routine is essential for people to not reject the technology. The participants in our study who regularly used their devices indicated economic incentives associated with a device’s use, convenience, or a device’s emotional relevance in their life as their reasons for routine use. Participants who used devices other than wearables, such as smart thermostats or plugs, also developed a habit of use because the devices did not have to be deliberately used or worn. In other words, a device’s ability to work independently after installation to achieve human-defined goals led to its becoming an integral part of its owner’s life. This suggests that users are more likely to continue using devices that are minimally obtrusive, do not require extra work, and fit easily into their daily routine.

The designers of future IoT devices should examine ways in which devices can blend into users’ existing routines without adding to users’ workloads or responsibilities, or can work independently to achieve human-defined goal(s). In other words, future designs need to integrate more context sensing capabilities so that devices do “not force users to adapt” [1] and support continuous, yet unobtrusive engagement.

Devices’ Enabling Social Interaction and Support

Previous research has pointed out the influence of network structure – consisting of strong social ties, such as friends and family, and weak social ties, such as friends of friends – on the adoption of technology. However, our findings draw attention to the influence networks of strong and weak ties have on the continued use of IoT devices. Our results further resonate with Self Determination Theory and Social Comparison Theory. While the former emphasizes the innate role of social relatedness (the will to interact and connect with others) in self-motivation [45], the latter suggests that people alter their behavior based on how others perceive them [21]. For the participants in the study, the ways they were evaluated or viewed by others and the ability to connect with their network of strong or weak ties affected their decisions on whether or not to continue use.

We recommend leveraging the inclination of users to connect with others as an opportunity to help users develop suitable conceptual or mental models as they incorporate new smart devices into their daily lives. In other words, new IoT devices can support online platforms or topic-specific groups where users can discuss the challenges and benefits of using such devices. A few devices, such as Fitbit and Nest Thermostat, already provide online and public troubleshooting communities, but we believe the ability to connect with friends through private groups will enable users to learn from the experiences of others (strong ties) and collaboratively understand how a new device operates. Such groups can also promote reflection on one’s failures and help users to develop strategies that accommodate the changing nature of their preferences and needs.

6 Limitations and Future Work

This research involves some limitations that should be addressed in subsequent studies. First, this study analyzed only self-reported data from the participants' past recollections of (non)-use. This may be inaccurate to varying degrees. Therefore, further work may expand on finding hidden motivations by evaluating actual usage logs for different types of IoT devices. Usage logs would also enable dynamic analysis, which can uncover other nuanced patterns pertaining to how use and non-use change with time. Second, our participants were all U.S. IoT users, and the Amazon Mechanical Turk population is not entirely representative of U.S. residents in general (as seen in Table 1). One advantage of such a population is that our sample was composed of a large number of non-technical respondents who had adopted different types of smart devices voluntarily, which is an improvement over other studies of the users of smart devices. However, since there is a large number of non-U.S. IoT users, our results may address only part of the phenomenon. Therefore, future studies might investigate how users of different backgrounds use or abandon IoT devices. Finally, in the course of this study, we also found that many of these devices were co-owned by members of a family. Therefore, another promising direction for future work could be to explore how people make decisions about (non-)use in a shared context.

7 Conclusions

In this paper, we have explored the key preferences and practices that affect decisions about whether or not to use IoT devices, through an empirical study of 834 users who had previously and voluntarily adopted various types of IoT devices. To analyze the data, we adopted a mixed-method approach consisting of topic modeling and the inductive qualitative analysis of responses under each topic. We found that the possibility of treating IoT devices as co-actors, the social influences of these devices, and habit formation led to the continued use of IoT devices. However, if the devices disappointed the users, demotivated them with negative notifications, distracted them from important activities, or were too complex, the participants abandoned them. While we discuss several design implications of our findings, we also advocate including the category of *selective users*, who intentionally use devices only to a limited extent, in the taxonomy of non-users. The participants of our study limited their use of IoT devices specifically when they felt a lack of control over the devices, when the devices failed to understand their intent, or when they did not understand the device's behavior. These findings have implications for the design of future IoT devices, which need to meet the needs of users more closely, thereby enabling long-term use.

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