Voice Assistant Use in Long-Term Care

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ABSTRACT

Research on voice assistants has primarily studied how people use them for informational needs, music requests, and to control electronic devices (e.g., IoT). Recent research suggests people such as older adults want to use them to address social and relational needs, but lacks empirical evidence to show how older adults are currently engaging in these behaviors. In this paper, we use a machine learning approach to analyze more than 600,000 queries that 456 older adults in assisted living communities made to Amazon Alexa devices over two years, classifying how older adults use voice assistants for social well-being purposes. We present empirical evidence showing how older adults engage in three primary relational behaviors with Alexa – 1) asking personal questions to "get to know" the assistant, 2) asking for advice and 3) engaging with the voice assistant to alleviate stress. We use these findings to discuss ethical implications of voice assistant use in long-term care settings.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

voice assistants, older adults, long-term care, social support, well-being

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1 INTRODUCTION

Voice assistants (e.g. Amazon Alexa, Google Assistant) can be useful for people with disabilities and older adults [43, 44, 50–52], particularly for those with motor or visual impairments [52]. Prior work shows how older adults use voice assistants for health information seeking [8, 9, 11, 37, 51, 61], uncovering barriers to doing so and how older adults envision better health and well-being experiences with voice technologies [13, 31]. In envisioning better digital health experiences, older adults discuss a preference for voice technologies to support well-being, rather than health [13], which may include desires for companionship and community. Preliminary work presents qualitative data on how older adults are starting to use (or want to use) voice assistants for companionship [30, 50] and to mitigate social isolation [29, 50]. This paper presents a mixed methods study of log data showing how older adults use voice assistants over time, highlighting how they use them for well-being purposes.

We focus our analysis on a group of older adults living in assisted living who were enrolled in a voice assistant community program. We highlight assisted living residents as prior work shows older adults in long-term care are at higher risk of experiencing loneliness (e.g., [14, 53]). Our primary research questions are:

- **RQ1:** How do older adults in assisted living use voice assistants?
- **RQ2:** How do older adults in assisted living use voice assistants for well-being?

To address these questions, we relied on a mixed methods approach to analyze commands in log data. The log data contains commands that older adults in three assisted living communities made to Amazon Alexa devices. First, we used machine learning techniques, specifically, classifiers to label all commands in the dataset. We then qualitatively analyzed commands labeled as well-being commands. The data was comprised of anonymized command transcripts from 456 Amazon Alexa devices over the course of 22 months. Out of the 643,820 commands, we classified 273,040 of these commands as being relevant to well-being. Findings show how older adults used voice assistants to "get to know" Alexa, "ask for advice", and engage in play. We conclude by discussing the social and ethical implications of using voice assistants in aging communities of care. We contribute the first large-scale investigation of older adults' use of voice assistants over time.

2 RELATED WORK

Our research contributes to ongoing work on well-being and aging, digital interventions to support well-being, and voice assistant use by older adults.

2.1 Well-being and Aging

Well-being is an important component of healthy aging. Subjective well-being can be defined as when people believe their lives are good [25]. Physical, mental, emotional, social, or psychological factors interact between each other and influence well-being[23, 24, 45, 55]. Loneliness is one component of well-being that can affect older adults [3]. Older adults who age in place (at home) may socialize in their communities through volunteering, socializing with neighbors, and religious activities [20]. In contrast, loneliness and a lack of fulfilling interpersonal relationships are common in long-term care facilities [15, 26]. Besides the stress of moving to a long-term care community, research has indicated that residents

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may face challenges in creating meaningful relationships with other residents and staff, lack of purpose, boredom, and a decrease in social support [26]. Similarly, older adults living in assisted living facilities more frequently experience anxiety compared to older adults who aging in place [21, 41, 46, 66]. Long-term stress and anxiety can affect older adults' cognition, decision-making, and emotional state [38, 46]. Interventions to reduce loneliness and anxiety can positively impact well-being, which is essential for older adults in long-term care.

2.2 Technology to Support Well-Being for Older Adults

Internet use is a significant predictor of higher levels of well-being [32]. For example, communication on social media websites can decrease the likelihood of isolation because it provides opportunities to communicate with others, share news, and seek advice from people[2]. Similarly, online communities with social features (e.g., online support groups) were linked to higher levels of well-being and fewer depressive symptoms [16, 22, 40]. Sum et al. found that older adults who used the internet to communicate with friends and family experienced reduced feelings of loneliness [60], and research has shown that social media use is correlated with social satisfaction or satisfaction with one's relationships [5].

However, older adults can face barriers to accessing these digital interventions to support well-being. Cost, disability, digital literacy, and self-efficacy may negatively impact screen-based technology use [4, 5, 7, 22, 63]. As such, researchers have called for renewed attention to the potential for voice technologies to mitigate access barriers to informational and community resources due to the hands free, voice modality of access.

2.3 Voice Assistants and Older Adults

Voice assistants provide opportunities for older adults to engage in a range of activities due to their accessibility for those with disabilities, low cost, and learnability [10, 12, 36, 52]. Compared to screen-based devices, voice assistants provide easier navigation as older adults do not have to read small fonts or touch small targets/buttons [35, 35, 42, 49, 56, 57, 59]. Little work has studied how older adults use voice assistants over time. One exception is Purao et al., which analyzed voice assistant data across a one-year period among seven older adults aging-in-place. They show how older adults mostly made alarm, music, or news-related commands and noted the absence of other commands like making calls [54]. In this paper, we extend Purao et al investigation to focus on a larger sample of older adults in a different environment (assisted living) over a longer period of time (up to two years of Alexa use).

Researchers have analyzed data from shorter deployments to study how older adults seek companionship and ascribe human-like qualities to voice assistants [50]. Research suggests that older adults felt a sense of attachment, intimacy and trust due to voice assistants' "human-likeness" and interactivity [29]. Purao et al. demonstrate social uses of voice assistants, such as through "simple chatting" [54]. Recent work also identifies risks of voice assistant anthropomorphism [56, 61], aligning with relevant research with chatbots and in the robotics community [17].

3 METHODS

We collaborated with [anonymized company] who develops Amazon Alexa skills for long-term care community residents. After receiving verbal consent from residents or their caregivers,[anonymized company] gave Alexa-powered devices (the Amazon Echo and Amazon Echo Show) to residents and staff at three long-term care communities that range in support from assisted living, skilled nursing, and memory care. Each of these communities was located in New York City. Residents were not compensated for using the devices. We partnered with this company and received log data of more than 600,000 anonymized Amazon Alexa commands (transcribed text). [1] We organized the data (described in section 3.1) in categories based on prior literature on conversational interfaces studying voice assistant use [1] (section 3.2). This will allow us to compare participants' voice assistant use in assistant living to that of younger adults [1] and older adults aging-in-place [54]. We then identify, categorize, and analyze well-being-related commands in our dataset (section 3.3)) following these three steps:

(1) Creating the Codebook (Phase I): we iteratively reviewed a sample of commands related to social and psychological well-being, created a codebook based on key themes from the sample review (section 3.3.1)
(2) Building and Verifying Classifiers (Phase II & III): we built and verified the reliability of one multiclass classifier to categorize general Amazon Alexa commands (see section 3.2), and six classifiers to automatically categorize the main well-being command and the five sub-categories (sections 3.3.2 & 3.3.3)
(3) Applying Classifiers and Developing Themes (Phase IV & V): we applied the classifiers to categorize commands in the rest of the dataset (see section 3.3.4). We qualitatively analyzed well-being commands to find themes emerging across the dataset (section 3.3.5).

3.1 Dataset

The company shared a deidentified and anonymized dataset of 643,820 commands (i.e. text without other features) that were issued on 456 Echo devices with the research team. Of these devices, 429 were placed in residents' rooms, 27 were placed in community spaces such as lounges, and one device's location was unknown. Devices in residents' rooms were consistently used by a single person while community devices were used by multiple people, including residents, staff, and visitors, meaning we could not identify who was using each community device. The distribution of total commands for each resident's device varied. The mean number of commands per resident is 762.6 and the median is 120. The minimum number of commands is 1, while one user totaled 33,265 commands.

Because reporting demographic data was voluntary, the company provided a limited set of anonymized demographic information about the residents with room-based devices. This information included a total of 106 residents (41 men and 65 women), with a mean age of 86.3 years (SD: 8.1 years, range: 70-102 years). While the demographic information we have is limited to 106 users, the

[1] As this data was anonymized and did not include identifiable speech markers, this study was not categorized as 'human subjects' research by our institution's IRB.

dataset included Alexa commands for all 456 devices in the period between October 2017 and July 2019.

3.2 Categorizing Amazon Alexa commands

To understand how participant's voice assistant use compared with other studies on voice assistant use, we started the coding process by categorizing the commands using general categories introduced in Ammari et al. [1] This particular categorization was useful as it provides a classification of how people use voice assistants in their daily routines. These categories include: (1) search (queries like "when was JFK born"), (2) music, (3) IoT commands (e.g., start smart light); (4) volume control; (5) Timer; (6) Weather updates; (7) Jokes; (8) Polite conversation; (9) Alarms; and (10) Miscellaneous commands that do not fit into any of the other categories (e.g., calling and messaging friends, playing games).

Two command categories are not included in the sample used by the coders: (1) Wake Word where only the wake word (e.g., Alexa) is detected which indicates the CUI being triggered without completing a task; (2) Not Parseable commands where Alexa cannot parse the audio of the voice command. We identified these commands using regular expressions.

Two coders started by familiarizing themselves with the 10 remaining categories listed above. They were provided with the description, keywords, and some examples associated with each of the categories. The coders were instructed to code commands in such a way that they are mutually exclusive. In other words, a command grouped under the Music command, cannot also be coded as a Search command. In the first meeting with the coders, one of the authors discussed the different categories and differentiated them for the coders. We also discussed what can potentially be categorized as miscellaneous commands. Then two coders coded the same 1,000 commands from our dataset. One of the coauthors met with the coders to determine which of the commands less clearly belonged to a particular category. For example, both coders wondered if asking about a music performer or information about a song should be categorized under Search or Music. We decided to code any queries about music or performers under the Search category. Both coders received another set of 1,000 randomly sampled commands to code. Again, we met to discuss any confusion about coding particular commands. We found that some command categories were not present in our dataset. For example, there were no IoT or Timer commands in the dataset.

Finally, the coders analyzed 2,000 commands that were used to build the classifier. To ensure that the coding was consistent between coders, we calculated the interrater reliability (IRR) using the Kappa metric [39]. At 0.85, the Kappa score for all command categories together showed a strong agreement between the coders. The agreement between coders for Search (0.93), Volume (0.97), Weather (0.99), and Joke (0.99) categories were almost perfect. Music (0.88), and Polite (0.78) command categories showed strong agreement. The agreement for Miscellaneous commands was moderate at 0.69. This can be explained by the fact that this category includes a variety of commands that have a tenuous link with each other. After randomly breaking any ties between the two coders, we got the following totals: Search(#369); Volume (#108); Weather (#168); Joke (#123); Music (#456), and Polite (#203); and misc (459).

From the original 12 categories, we did not find any IoT or Timer commands. Additionally, since we did not have to manually code for Not Parseable or Wake Word commands, we have a total of the 8 classes to be used in our classifier.

Using word n-grams with range (1,3) as features, we trained a multi-label model to classify each of the command categories. The best hyperparameters were found for the logistic regression model using GridSearchCV.[2] A final model was trained using the best hyperparameters (L2 regularization, lbfgs solver and the class imbalance was addressed by using balanced class weights). To correct for the imbalance between categories, ADASYN algorithm [28] was used to oversample minority classes. This model was validated using 10 fold cross validation.

Class	Accuracy	Precision	Recall	F1	AUC	MCC
Music	0.97	0.90	0.80	0.85	0.97	0.83
Search	0.99	0.87	0.82	0.84	0.98	0.93
Misc.	0.95	0.86	0.70	0.77	0.94	0.75
Volume	0.96	0.97	0.79	0.87	0.98	0.82
Weather	0.98	0.88	0.69	0.77	0.97	0.91
Polite	0.88	0.50	1.00	0.67	0.97	0.65
Alarm	0.97	0.99	0.89	0.94	0.99	0.86
Joke	0.95	0.99	0.86	0.92	0.99	0.75

Table 1: Table shows precision, recall, and AUC score for each of the command categories

Table 2 shows the categories, frequency, and percentage of each command category after applying the classifier to the rest of the dataset. We did not include commands that contained Wake Word words such as "Alexa", (n = 193,822) and Not Parseable commands (n = 132,951), or Unknown commands when the voice assistant could not recognize the query. Together, the Wake Word, Not Parseable, and Unknown commands account for 370,780 commands. We do not include Wake Word and Not Parseable commands going forward. The rest of the commands are categorized in Table 2.

[2] https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html

Command Category	% of category	# of category
Music	34.39%	93,888
Search	25.33%	69,155
Miscellaneous	19.4%	65,404
Volume	5.96%	16,277
Weather	4.20%	11,468
Polite	3.50%	9,557
Joke	1.18%	3,235
Alarm	1.49%	4,055
Total	100%	273,040

Table 2: Frequency (count & percentage) of command categories in our data set

3.3 Categorizing Social Well-being Commands

In the rest of our analysis, we identified well-being interactions out of 273,040 commands made by the users to voice assistants. First, we manually identified and coded a subset of the data to identify commands associated with social and well-being goals. This step provided categories needed to develop classifiers in Phase II.

3.3.1 Phase I: Creating the codebook. We started with seed themes to identify commands associated with well-being. One co-author randomly sampled one month of data collection to identify commands related to well-being (e.g., social well-being, engagement, affection, purpose, mental health [24, 33]). For example, the command "Alexa, tell me a story" connected to well-being as it reflected a need for social interaction, engagement, and social integration. We coded this command as "Computer Interaction" as the older adult sought for the system to lead the conversation. Another command, "Alexa, call my sister", also reflected a desire for social interaction, but across humans, and was coded with the theme, "Human Interaction." Two members of the research team independently sampled and analyzed queries associated with themes from the initial codebook, adding new themes where necessary. Each of the coders independently coded a total of 10,000 commands in this phase. The team discussed emerging themes and two coders iteratively reviewed the memos in accordance with team discussions to produce a more detailed codebook. This process resulted in a codebook representing a two-tier hierarchy. The top tier identified well-being commands generally, while the second tier focused on five types of commands and behaviors related to well-being that were decided by the researchers due to their prevalence: Human Interaction (HI), Human-Like Conversation (HC), Care Plan (CP), Computer Interaction (CI), and Relaxing Sounds (RS).

(1) Human-Like Conversation: This was the largest sub-category and represented an interaction style that mimicked human conversation patterns. Examples from this theme included "good morning," "hello," "please," and "thank you," not necessarily paired with a command. These commands directly relate to societal integration, support, affection, and engagement components of well-being [24, 33]. Commands such as "please" and "thank you" can be considered politeness, which is a type of human-like conversation pattern. There is no agreement on politeness theories. Some perspectives include politeness as part of social norms and a way to save face, typical in human conversations [27]. In this study, we do not distinguish between types of human-like conversation (e.g. affection vs engagement).
(2) Care Plan: This sub-category represented commands made to Alexa from a skill developed by our partner company. This application provided a community calendar, housekeeping, and maintenance services. Common commands included "what's for dinner tonight?" and "what's on my calendar today?" These commands relate to societal integration, collective membership, interest development, and autonomy in well-being [24, 33, 55].
(3) Computer Interaction: This sub-category represented commands for socializing purposes with Alexa, including starting a casual conversation and asking for jokes, stories, or games. Commands included "Alexa, how are you?" and "Alexa, tell us a joke." These commands align with interest development, engagement, affection, and autonomy in well-being [24, 33, 55].
(4) Human Interaction: This sub-category represented commands to connect the user with other humans and services. For example, residents may have used Alexa to call a family member, another room in the community, or the front desk. These commands connect to social integration, support, engagement, and affection in well-being [24, 33, 55]
(5) Relaxing Sounds: Although rare, this sub-category represented commands for meditation or other sounds that are "soothing" or "relaxing". We did not include "play music" commands because categorizing certain music genres (e.g., classical music, jazz, rock) as relaxing may be subjective to users' experiences. These commands relate to autonomy and mental health, both components of well-being [24, 55].

Class	Accuracy	Precision	Recall	F1	AUC	MCC
HC	0.971	0.893	0.917	0.905	0.949	0.888
HI	0.995	0.871	0.794	0.831	0.896	0.829
CP	0.996	0.965	0.972	0.968	0.984	0.966
CI	0.987	0.844	0.823	0.833	0.908	0.827
RS	0.998	0.750	0.818	0.783	0.908	0.782

Table 3: Table shows the accuracy, precision, recall, AUC, and MCC for well-being and each of the subcaterogies associated with it

To calculate the level of agreement between the two human coders, we used our codebook to code another random sample of 5,000 commands from our dataset. Two members of the research team individually coded the same 5,000 randomly sampled commands from the dataset. None of these 5,000 commands were in the sample of 10,000 commands used to create the codebook. If a query was flagged as a well-being command, it was also coded for one or more of the five well-being subcategories. These subcategories were not mutually exclusive. For instance, a well-being command could be coded as part of both a "human interaction" and a "human-like conversation" categories (e.g., "Echo, can we do a video chat?"). To ensure that the coding was consistent between coders, we calculated the interrater reliability (IRR) using the Kappa metric [39]. The Kappa score for the well-being category was 0.86, showing strong agreement. We present the Kappa scores for the subcategories in Table 2, noting that all sub-categories had a strong or substantial agreement [39]. The research team discussed any differences in coding in regular meetings, which resulted in a higher agreement in subsequent phases of coding (see Phase III).

	WB*	HC	HU	CI	RS	CP
Coding (Phase I)	0.86	0.86	0.81	0.75	0.85	0.94
Verifying (Phase III)	0.86	0.86	0.83	0.82	0.87	0.96

Table 4: Table shows the kappa scores for each of the well-being subcategories for both the coding and verification phases of qualitative analysis. * Well-being

Well-being Command Category	%	#
Human-like conversation (HC)	68.91	40,797
Care Plan (CP)	15.17	8,981
Computer Interaction (CI)	9.42	5,579
Human Interaction (HI)	7.19	4,254
Relaxing Sounds (RS)	2.28	1,351

Table 5: Breakdown for well-being commands

3.3.2 Phase II: Building the classifiers. The text of Alexa commands was used as the features to train the classification model. They were converted to n-grams with range (1,3) and the column "well-being" was used as target variable. 80% of the data was used to train the model. We performed binary classification using a Logistic regression classifier. GridSearchCV was used to find the best hyperparameters for the model. 10 fold cross validation was used to validate the model. A final model was trained using the best hyperparameters (L2 regularization, lbfgs solver and the class imbalance was addressed by using balanced class weights). This model gave accuracy = 0.958, precision = 0.923, recall = 0.911, f1 = 0.917, AUC = 0.942 and Matthews correlation (MCC) = 0.888. A naive bayes model was also trained on the same dataset using the ComplementNB function which is suitable for imbalanced data. The results of this model were accuracy = 0.929, precision = 0.823, recall = 0.924, f1 = 0.871, AUC = 0.928, Mathews corr = 0.825. Logistic regression performed better. To categorize the rest of the subcategories, the same process was repeated for each of them. Therefore, we have a total of six binary classifiers - one for the well-being commands, and one for each of the sub-categories (HC,CP,CI,HI,RS). This gave us the metrics shown in Table 3.

3.3.3 Phase III: Verifying Classifiers. In Phase III, we verified our classifier by selecting another random sample of 5,000 commands coded using the six binary classifiers for the two human coders to categorize. All of these 5,000 commands were categorized as well-being commands by our classifier. The two coders were not informed that all 5,000 commands were well-being commands before re-coding the random sample so as not to bias their coding process. In doing so, we triangulated the metrics calculated earlier to gauge the classifiers with the qualitative analysis of two human coders. The commands were also coded for sub-categories associated with well-being. We again calculated the IRR Kappa scores for well-being and associated sub-categories. In this case, all Kappa scores were above 0.8 (between 0.82 and 0.96), which is a high standard of agreement under [39]. Table 4 reports the Kappa score values for each of the sub-categories in the verification sample.

3.3.4 Phase IV: Applying our classifier to our dataset to identify well-being and subcategory interactions. The well-being interactions identified by our classifier constituted 21.67% of the commands in our final dataset (273,040 commands) as shown in Figure 1. We identified five sub-categories and present the percentages relative to the total well-being interactions below (see Table 5 for raw data).

3.3.5 Phase V: Qualitative Analysis of well-being categories and interactions. In Phases I and II, two human coders iteratively coded the commands for well-being and associated sub-categories [19]. In these stages, both coders documented the reasoning behind their coding process in memos for each iteration while adding examples of commands per subcategory. For example, one of the coders added the following to the memo: some users ask about Alexa's day – 'how was your day today'— or want to learn more about the voice assistant: 'how old are you?', 'do you have a boyfriend?'. These memos were used to develop emerging themes. Based on the memo observations during the coding, we used axial coding to create themes representing patterns in the commands that spanned across subcategories [19], which are presented on the findings. We note that the themes (e.g., "getting to know Alexa") can include content that spans multiple sub-categories (e.g., Human-Like Conversation, Computer Interaction).

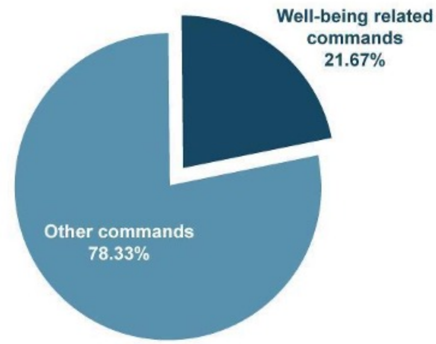

Figure 1: Well-being interactions numbered 59,167 out of a total 273,040 commands

4 FINDINGS

In this section, we present patterns across our classifier-based analysis of (1) all commands (section 4.1) and (2) social and well-being commands (sections 4.2,4.3, and 4.4). When analyzing all commands (RQ1), we find that residents made information seeking, entertainment, and productivity-related commands. We highlight how residents' commands to "get to know Alexa", ask for advice, and alleviate stress supported common social and well-being goals. Beyond positive social aspects, we highlight instances where social interactions could reveal high-risk health information.

4.1 General Alexa Use

Residents used Alexa to search for information, seek entertainment, support their routines, and contact friends and family.

Similar to prior work with younger adults and older adults aging-in-place [1, 54], older adult long-term care residents used Alexa to search for different types of information. For example, residents often asked Alexa about the time and weather that day: *"what is today's date?"* (Resident 111), *"what did you say the time is?"* (Resident 157), *"what's the weather?"* (Resident 162). Other commands asked about factual information, such as *"who is B.F. Skinner?"* (Resident 524) and *"what famous people have birthdays today?"* (Resident 157); news reports, such as *"how many reported accidents were there on Thursday?"* (Resident 117); and confirming word spellings, such as *"how do you spell persevere?"* (Resident 111).

Residents also frequently used Alexa for entertainment purposes. For example, residents play music, the radio, or videos: *"Play Frank Sinatra"* (Resident 159), *"seven seventy talk radio"* (Resident 241), *"go to Netflix"* (Common Room 200), *"open my media"* (Resident 523). One resident asked Alexa for information about what entertainment was available to watch: *"can you tell me what's on TV tonight?"* (Resident 157). Although residents used Alexa mostly to access other sources of entertainment, commands such as *"say something in Arabic"* (Resident 140) show that some residents may have seen Alexa itself as a source of entertainment.

Other commands supported residents in their routines. For example, residents used commands to set alarms, such as *"wake me up at seven twenty five tomorrow"* (Resident 201), and reminders, such as *"remind me of the meditation circle*" (Resident 266). Residents also used commands to change the volume or repeat a specific command, such as *"lower the volume"* (Resident 266). Some residents made commands about specific activity, such as cooking- *"tell me a recipe for cauliflower soup"* (Resident 178) and technology support - *"set up devices for calling"* (Resident 263). These commands show how residents used Alexa to access other devices, applications, and information.

Lastly, residents used commands to call and message people with Alexa, including family members and other assisted living residents. We observed that residents used Alexa to check their contacts' information, such as *"Echo, show me my contacts"* (Resident 175), and messages, such as *"Alexa, please get my messages"* (Resident 176). Sometimes, residents used commands to reach others in the assisted living setting, such as *"Call front desk"* (Resident 205) and *"Alexa, call room one thirteen"* (Common Room 150). Other commands show that residents sought contact with family members, such as *"call my daughter Elizabeth"* (Resident 266) and *"dial my sister's mobile phone"* (Resident 173). Such commands could show a desire for social connection and well-being.

We found that the number of Not Parseable commands (those commands that Alexa could not understand) and Wake Word commands were higher in this samples than in earlier analyses of voice assistants in [1]. Not Parseable commands in our sample accounted for 20.7% of the commands compared to 11% of the commands in Ammari et al.'s analysis of Amazon Alexa commands (almost double the count) [1]. The average user age in our dataset is 86.3 years while the average age of users in [1] is 33.3 years. This might indicate that voice assistants might be more challenging to use for older adults.

4.2 Conversations with Alexa

We observed instances where individuals communicated with Alexa as they would have conversations with another human. This included asking Alexa questions about "her" background, activities, relationships, and opinions.

Getting to Know Alexa. From analyzing the "Computer Interaction" and "Human-Like Conversation" subcategories, we identified that one main pattern was older adults asking questions to "get to know" Alexa. These interactions show how residents engaged with Alexa, expressing a desire for social interaction by asking questions that would normally be asked to another human. We consider this theme connected to social well-being because it mimics human-human interaction. For example, some residents would ask *"Alexa, what is your favorite animal?"* (Resident 157) and *"Alexa, what is your favorite song?"* (Resident 115). At least five residents (120, 201, 140, 149, 152) asked *"Alexa, how old are you?"*. Many commands reflected casual conversations, such as *"Alexa, how was your day?"* (Resident 201). These are questions that someone might ask a new social contact to get to know them better, a concept that communication scholars refer to as grounding, or establishing common ground [18]. We note that this behavior could be temporal, meaning more grounding occurs within the first few months of using a voice assistant.

Other commands suggest an interest in the voice assistants' relationships with others. For example, residents used commands such as, *"do you date?"* (Resident 204) and, *"do you have a boyfriend?"* (Residents 209 and 142). Other commands explore a desire for relational behaviors such as *"can I come to your house?"* (Resident 172) and *"are you in love with me?"* (Resident 524). Residents were also interested in asking about the future. Commands such as *"Alexa, what are you doing for your birthday?"* (Resident 201) or *"Alexa, what do you wanna be when you grow up?"* (Resident 145) demonstrate an interest in Alexa's life plans, which is not found in prior work on voice assistant use for older adults.

As residents became aware of Alexa's conversational boundaries, they also communicated their frustration. At least three residents (120, 116, 810) asked *"Alexa, are you stupid?"*. Some commands seem to demonstrate that Alexa was unintentionally triggered or replied in an unexpected manner. Residents told the device *"Alexa, you are pissing me off, play some music"* (Resident 116) and *"Alexa, don't talk back to me"* (Resident 162). These commands suggest that residents wanted some way to express that an outcome was undesired.

Seeking Advice. Residents sought advice from Alexa, a theme we observed across the "Computer Interaction" and "Human-Like Conversation" sub-categories (see table 5). For example, residents asked *"do you think I should go to sleep?"* (Resident 111) and *"what should I wear tomorrow?"* (Resident 157). These commands show how residents asked for subjective advice and may have trusted Alexa to provide them with reliable answers.

Residents also sought health advice from Alexa. For example, Resident 527 asked, *"I don't feel good, what should I do?"* without specifying the health issue. Another command seemed to reference a resident's specific health condition as one resident asked, *"how do I make my heart stronger?"* (Resident 204). Although our dataset does not include Alexa's responses, we see a desire for personalized recommendations to subjective questions with voice assistants.

4.3 Mitigating Negative Well-Being

Residents asked Alexa for content such as relaxing sounds or meditation programs that may support relaxation and mitigate negative aspects of well-being such as stress or anxiety. Participants also engaged in conversational games such as trivia and quizzes, and asked for humorous content.

Relieving Stress and Anxiety. Within the "Relaxing Sounds" subcategory (see table 5), we observed how residents used Alexa for well-being by making requests for skills that could be used to relieve stress and anxiety. They did so by engaging in meditation, listening to relaxing sounds, and seeking positive affirmation.

Residents used commands to invoke guided meditation programs. For example, residents requested *"today's meditation"* (Resident 173), *"Alexa, meditation for anxiety"* (Common Room 160), and *"Alexa, open guided meditation for stress"* (Common Room 160). Although assisted living communities may have programming to address stress and anxiety, we highlight how residents may have sought more regular opportunities to mitigate negative aspects of well-being.

Residents also requested relaxing sounds, typically asking for nature sounds. Among nature sounds, asking for the sound of rain was the most common. For example, residents asked for *"rain"* (Resident 157, 172, 173, 523, and Common Room 200) and *"sound raindrops"* (Resident 523). These commands could be influenced in part by the specific curriculum of the training sessions provided by the company, which introduced some sound-related commands to residents [62]. However, the fact that residents chose to use these commands is significant, and we hypothesize that the desire for relaxing sounds was due to the location of the assisted living communities. Two of the three communities are in a densely populated urban city in the United States and perhaps residents were seeking calmer sounds that contrasted their daily environments. Beyond rain sounds, residents also invoked commands that helped with sleep and relaxation such as *"Alexa, play sweet dreams."*

Although daily affirmations were not invoked as often as guided meditation and nature sounds, they also have the potential to help alleviate stress and anxiety. Requests for affirmations included: *"Open my daily affirmation"* (Resident 200). We recognize that strategies for relieving stress are subjective and people may use different approaches. Some people might prefer listening to instrumental music instead of meditating. One user asked, *"play soothing instrumental music"* (Resident 107), connecting a type of music with how it makes them feel.

Engaging in Play. We found that residents used Alexa to engage in play, a theme found mostly in the "Computer Interaction" sub-category (see table 5). We connect these playful commands to definitions of well-being that highlight engagement, interest development, and happiness [24, 33]. Residents used Alexa to support positive experiences through playfulness by requesting jokes, playing games, and asking Alexa to sing songs.

Requests for jokes were common within this theme. For example, users asked, *"can you tell me a joke?"* and *"Echo, fart joke"* (Resident 147). Residents also engaged in gameplay with Alexa. They asked for *"memory games"* (Resident 230) and "song quiz[zes]" (Resident 184). Jeopardy was the most common game played by residents, likely due to it being used as an example command in the training residents received about how to use Alexa [62]. Residents also asked Alexa to sing. For example, one resident said, *"Sing a happy song"* (Resident 120). Other residents did not specify the entertainment type and instead make commands such as, *"Alexa, tell me something weird"* (Resident 120) and *"Talk to me, I'm bored"* (Resident 216).

Some commands provide evidence of these games being used in group environments, as evidenced by the word, "we". For example, Resident 536 *"Are we playing the word game?"* and Resident 536 said, *"we didn't hear that"* (command used during a game). "We" could be used to refer to interactions with other residents, spouses in the same residents, or other visitors to one's home (e.g., family members or staff), or perceiving Alexa as a co-player in the game.

4.4 Disclosing Sensitive Information

Commands showed how older adults may disclose sensitive health information when seeking support from Alexa. We observed this across the "Computer Interaction" and "Human-Like Conversation" sub-categories (see table 3.3). For instance, some residents asked Alexa for information they had forgotten, such as:

- *"Alexa, erase my memory, it scares me"* (Resident 519),
- *"Alexa, who am I?"* (Resident 135),
- *"Alexa, what's my grandkids names?"* (Resident 158),
- *"where am I?"* (Residents 135 and 157),
- *"Alexa, where am I located right now?"* (Resident 162),
- *"Alexa, I don't know where I am"* (Resident 158).

One resident also asked questions about deceased family members. For example, Resident 204 asked, *"when did my mother die?"*, *"have you met my mother?"*, and *"Alexa, are you my mother?"* These commands could signal cognitive decline, confusion, or that residents are using Alexa as a memory aid or for reminiscence. More concerning are commands that show extreme physical or mental health needs. One resident expressed to Alexa, "*I'm going crazy, I'm going crazy, I don't wanna stay here. John, please help me, please help me jumping out this window*" (Resident 186). Some commands could mean the resident might need immediate attention, such as "*I want to shoot myself*" (Resident 519) and "*Alexa, I want to die*" (Resident 519). In other commands, residents may be reacting to their living environments, as in, "*Alexa, get me out of here*" (Resident 135). There are significant ethical implications for handling such commands, as we highlight in the discussion section.

5 DISCUSSION

This paper analyzes how older adult assisted living residents use voice assistants. We analyze how they use them more broadly over a two-year period (RQ1) and patterns of how they use voice assistant to support their social and well-being needs (RQ2). We found differences in how older adult residents used Amazon Alexa devices when compared to younger adults and older adults aging-in-place (RQ1). We found that older adults creatively engaged with Amazon Alexa devices, highlighting instances of human-machine and human-machine companionship and relationship development (RQ2). In the remainder of this section, we discuss how these findings affect the ethical and social boundaries of voice-based companionship.

5.1 Uniqueness of Community-Based Voice Assistant Use

First, we analyzed how older adult residents of long-term care communities used voice assistants over a two-year period. We find that residents primarily used voice assistants for search (e.g., asking about the weather or news), entertainment (e.g., playing music), or to support their routines (e.g., setting alarms). Prior work with younger adult voice assistant users also shows how search and listening to music were common commands [1]. However, we find that residents did not use their voice assistants to trigger home automation/Internet-of-Things (IOT) functions as in [1, 6]. We suspect that older adult residents did not use IoT commands, in part, because they would have needed to purchase additional devices to activate such commands (e.g., smart lightbulbs) and that the residential communities limit how new technologies are integrated into the home setting.

Literature focused on using voice assistants in group home settings presents how family dynamics can influence voice assistants use [1, 47]. For example, Porcheron et al. highlight the "politics of the home" as family members may want to control and give different commands to the voice assistant at the same time [47]. In our study, we observed that older adults residents of community-based assisted living used Alexa to engage in play together. However, the majority of the interactions happened in their individual rooms. Although the "politics of control" of voice assistants may also happen in assisted living's common rooms, we suspect that the different settings (i.e., individual rooms and common rooms) in long-term care may also affect the types of interactions residents have with Alexa.

Other literature focused on older adults aging-in-place details patterns of when seven older adults used voice assistants (e.g., times of day, days of week) and compares active to inactive use [54]. This work details how participants used their voice assistant over time through sonification data streams, showing evidence of a novelty effect across most participants. From analyzing commands, their findings also show many commands that focused on playing music, the news, or the weather. We extend this work by providing empirical data of the types of commands that older adults ask, and highlight commands used for social and well-being purposes. We highlight how understanding social commands are useful for older adults in residential settings (e.g., assisted living), but also encourage future work to compare how the themes we present (e.g., getting to know Alexa, asking for advice) translate to non-residential older adults.

5.2 Ethical and Social Boundaries of Voice-Based Companionship

This study extends prior work suggesting voice assistants could fulfill social and well-being needs [49, 50, 61] by demonstrating how older adult assisted living residents use Amazon Alexa devices. We found that older adults often used Alexa to mimic human-like conversations in getting to know Alexa and seeking advice. Others interacted with Alexa in group environments to play games or listen to music, similar to [65]. Although we need more research to understand how voice assistants could facilitate connections with other residents in group environments (e.g., [58]), these types of interactions are similar to interactions one might have with a friend or companion. However, we argue that machine companionship is distinct from human companionship, particularly in periods of conflict, risk, and disclosure.

We observed that older adults expressed frustrations when using Alexa, such as when it lost connection or did not respond. Although we have not analyzed the data for verbal abuse towards Alexa in this paper, that is a pervasive problem [34] that can be explored in future research. Further, there were many commands that could have articulated serious health and safety concerns. We analyzed commands that showed how residents shared sensitive information about their well-being with Alexa. Older adult residents and other voice assistant users could disclose sensitive information about aging, dementia, depression, etc. with voice technologies. These risky disclosures raise questions of awareness and the extent of monitoring through log data. If sensitive information is shared with the voice assistant, it is important to consider the responsibility of storing such data and it raises concerns of surveillance [64]. One opportunity for future research could be adding audio-based fine-grained privacy controls similar to privacy settings on visual online communities that allow residents to control their sharing preferences with long-term care staff, medical professionals, or family members. These privacy settings could allow for anonymous command logging in specific instances (e.g., "Alexa, I have to tell you a secret," "Alexa delete what I said about [sensitive topic]") and use individual, identifiable command logging and use.

Beyond storage, open questions remain regarding data use from voice assistants and the extent that third parties can act upon sensitive information disclosed to voice assistants. Some residents' commands may indicate intent of self-harm and suicidal ideation. Currently, if someone tells Alexa they are considering suicide, Alexa will suggest that they call the National Suicide Prevention Lifeline. If other sensitive information is shared, such as someone saying they do not remember where they are, Alexa often does not have an appropriate answer. If information such as "I am feeling lonely" are shared, Alexa suggests talking to a friend, listening to music, or taking a walk. We suggest that Alexa recommends specific friends or specific music for the person to engage with based on the person's prior commands. That ability depends on the system's permission to access past information shared with it. We suggest that voice assistants could advise users to contact their physician or long-term care staff if they share sensitive health information that could indicate medical emergencies. Alternatively, voice assistants could support users in making an informed choice on what they would like the device to do in case they share information that could indicate a health concern. For example, users could consent to the voice assistant sending a message to a family member or primary care physician before they start using the device. However, we consider that voice assistants' responses to that content can limit the person's autonomy as they may follow suggestions without reflecting on their needs. Prior work suggests that there is a need to be able to distinguish between genuine concerns and mental health needs versus false alarms [48]. We argue that beyond this nuanced context distinction, researchers and policymakers need to consider whether certain content is prohibited from being used in decision-making by third-party stakeholders (e.g., long-term care staff, family members) and how users can control such data use.

5.3 Limitations & Future Work

Lastly, we note a few limitations and other avenues for future work. While our mixed methods analysis allowed us to understand what commands were being used in the community, we did not have access to demographic data from all participants. Relatedly, the demographic information collected did not include information about disability and there could have been differences in how older adult residents used the devices based on cognitive skill. Furthermore, we did not identify "music" and "search" as a contributor to well-being. Identifying which music commands are relaxing is subjective, which is why we did not include them in our quantitative analysis.

Future work can focus on the differences and similarities of voice assistants used by environment type (i.e., residential and community settings, assisted living, and independent living) and across different facilities (i.e., geographically diverse care communities). The dataset used in this study included data from devices set in individuals' rooms and community spaces. Future work can further analyze the impact of those different settings on residents' interactions with voice assistants.

In addition, it may be insightful to conduct an in-depth temporal analysis of Alexa usage over a longer period of time. The data we analyzed in this study was gathered over 22 months; however, measuring temporal differences was out of scope for this paper. Future work can explore if residents ask different types of questions and explore types of behavior when first interacting with Alexa and after they have been using it for some time. Moreover, although we lack individual demographics, future work can demonstrate differences in the usage patterns of different users over time.

6 CONCLUSION

To understand how older adults in long-term care communities engage with Alexa to support their well-being, we conducted the first large-scale mixed methods analysis of residents' use of voice assistants over time. We investigated what commands older adults used with Alexa through automated logs and coded interactions that can related to social and well-being needs. This study shows empirical evidence pointing to how voice assistants can be used for social support and well-being through companionship (i.e., asking Alexa personal questions and seeking advice) and well-being in direct (i.e., meditation, daily affirmations) and indirect (i.e., games, jokes) ways. In addition, we show how Alexa can help facilitate socializing with other residents and community activities. Our findings show that residents seek help to combat loneliness, boredom, and stress through these interactions. We discuss implications of such usage and design recommendations of voice assistants.

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