The Smart$^2$ Speaker Blocker: An Open-Source Privacy Filter for Connected Home Speakers

Chris Champion  
Xi’an Jiaotong-Liverpool University

Ilesanmi Olade  
Xi’an Jiaotong-Liverpool University

Constantinos Papangelis  
Xi’an Jiaotong-Liverpool University

Haining Liang  
Xi’an Jiaotong-Liverpool University

Charles Fleming  
Xi’an Jiaotong-Liverpool University

Abstract

The popularity and projected growth of in-home smart speaker assistants, such as Amazon’s Echo, has raised privacy concerns among consumers and privacy advocates. Notable questions regarding the collection and storage of user data by for-profit organizations include: what data is being collected and how is it being used, who has or can obtain access to such data, and how can user privacy be maintained while providing useful services. In addition to concerns regarding what the speaker manufacturer will do with your data, there are also more fundamental concerns about the security of these devices, third-party plugins, and the servers where they store recorded data.

To address these privacy and security concerns, we introduce an intermediary device to provide an additional layer of security, which we call the smart, smart speaker blocker or Smart$^2$ for short. By intelligently filtering sensitive conversations, and completely blocking this information from reaching a smart speaker’s microphone(s), the Smart$^2$ Speaker Blocker is an open-source, network-local (offline) smart device that provides users with decisive control over what data leaves their living room.

1 Introduction

Market research has shown rampant growth in the adoption of smart speakers with built-in digital assistants, such as Amazon’s Alexa or Google’s Home line of products, with more than 43 million adults in the United States owning a smart speaker as of spring 2018 [23]. A September 2018 survey estimated 57.8 million Americans own at least one smart speaker, representing 22% overall domestic growth for the sector [18].

Market newcomers, such as Facebook’s Alexa-enabled Portal devices, and the continued expansion of product portfolios with a lower cost of entry have forecast a worldwide install base of 100 million by the end of 2018, a number projected to more than double to 225 million by 2020 [7].

Along with this growth in popularity has come a growing concern about the privacy implications of these devices. Their always on nature, coupled with the fact that they stream the recorded audio to manufacturer-owned servers for voice recognition means that they potentially give these companies access to almost everything that goes on in the owners’ homes. What this data can be used for, who has access to it, and how long it is stored is often vague, and buried in a lengthy user agreement that the user consents to when they first use the device, and is subject to revision at any time. In addition, many of these devices support extended functionality via plugin modules written by third party developers, who have their own data usage and retention agreements. The end result is that who has access to recorded data and how it is used is often opaque to the end user.

Concerns regarding how data is used by legitimate parties aside, there are also concerns regarding the security of these devices. Smart speakers are typically low cost devices, and are produced by dozens of manufacturers. Based on past experience, it is likely only a matter of time before one or more of these devices are compromised, with potentially serious ramifications. For example, one recorded phone conversation with the user’s bank would provide an attacker with all the information necessary to access the user’s bank funds. Alternatively, a data breach of a large manufacturer’s servers could leak recorded conversations for millions of users, allowing the attacker to perform anything from blackmail to identity theft.

In this paper we describe a potential solution to this problem: the smart, smart speaker blocker, or Smart$^2$ for short. The Smart$^2$ works by enclosing the smart speaker’s built-in microphone in a soundproof enclosure, along with an external speaker connected to the Smart$^2$ device (see Figure 1). The Smart$^2$ has its own microphone and records audio, which it filters using speech-to-text, based on user configured parameters. Audio that does not match the filter rules is played back for the smart speaker via the external speaker. Several different filtering modes are implemented, to address a variety of security concerns. The Smart$^2$ is air-gapped (not connected to an external network), making it difficult for external attackers to compromise, with all processing done on the local device.
All software, including the speech-to-text library, is open-source and under the end user’s control, providing complete transparency.

Our evaluation of the Smart\textsuperscript{2} consists of two parts: system performance impact and a security evaluation. For the system performance impact, we measure the impact of the Smart\textsuperscript{2} on the smart speaker performance, particularly the introduction of latency by the speech-to-text engine, which we demonstrate is minimal. To evaluate the enhanced security offered by the Smart\textsuperscript{2}, we perform a two week study of the device’s performance in a real life environment and show that it substantially reduces the amount of sensitive audio data leaked, while minimally impacting the usability of the device.

2 Background and Related Work

The popularity of home voice assistants has caught the attention of many digital rights organizations and privacy advocates such as Digitalcourage, the organizing body of the Big Brother Awards in Germany [4]. The group awarded the 2018 “Consumer Protection” category winner to Amazon Alexa for Amazon’s practice of storing recorded user interactions on remote servers [11]. They were also especially critical of Amazon’s patent for “voice sniffing” algorithms that analyze background audio for trigger words in order to supply users with targeted advertising and product recommendations [13]. This functionality is in stark contrast to Amazon’s current Terms of Use for Alexa, with audio transmission only occurring upon the detection of their device’s wake word [24].

2.1 Homegrown Bugs

Privacy concerns over which data are actually being recorded and stored are not unfounded. In addition to the preeminent concern that stored user interactions (i.e. voice recordings and text transcripts) do not fall into the wrong hands, there are cases of extraneous recordings, recordings that don’t fall under the aforementioned “wake word” behavior, being sent to external servers. For example, one journalist testing an early review unit of Google’s Home Mini found the device recording and transmitting all audio to Google’s servers around-the-clock. The issue was resolved by permanently disabling the device’s touch-sensitive controls just before its official market release [2]. Other cases have seen Amazon’s Echo assistant mistaking a word for its wake word, followed by a misinterpreted “send message” command, which subsequently sent private conversations to an address book contact [14].

2.2 Legislative Uncertainty

Another area of major privacy concern lies in the unknown legislative capabilities for accessing user data. Data collected from Internet of Things (IoT) devices are more frequently surfacing as criminal evidence in court trials. In a 2017 murder case, data collected from e-mail time stamps, home security alarm logs, and a Fitbit tracker was used as evidence in charging the suspect [10]. October 2018 saw the first case in the United States of a court ordering surveillance footage from Google’s Nest smart home appliance subsidiary [6]. A transparency report from Nest labs details approximately 300 user information requests from governments and courts between June 2015 to June 2018. The report states that search warrants will first be analyzed to rule out overly broad requests and ensure the requested data pertains only to the corresponding warrant before handing over data [22]. The usage of connected device data in judicial trials has also recently extended to include smart speakers.

Shortly after Amazon’s Alexa-enabled smart devices ar-
rived on the U.S. market in 2015, an Arkansas court ordered Amazon to share recordings from a murder suspect’s Echo speaker. While Amazon initially declined to provide the court with information, the suspect eventually provided consent to use the data as evidence [12]. More recently, Amazon has again been ordered to deliver Echo recordings for use as incriminating evidence [29]. At the time of this writing, it remains unknown how Amazon will respond to the court’s demands.

2.3 Corporate Transparency

Furthermore, it remains unknown how many general requests from courts and government bodies Amazon receives for Echo devices in general. This is due to their practice of listing requests across all brand divisions as a whole when publishing transparency reports [27]. Google takes the same approach by not including per-device requests in its transparency reports, however it does include a ratio of the accounts received to the number of applicable accounts affected [28]. In contrast, Apple does not publish any data request information for its HomePod smart speaker, stating there is no effective data to release because of its implementation of local differential privacy. Instead of associating server-destined user interactions with a user’s account, differential privacy assign interactions to a random identifier [3]. Research into Apple’s implementation of differential privacy in macOS and iOS has shown a significant lack of transparency in the implementation among other shortcomings [25].

An additional security vulnerability with the HomePod is its inability to differentiate between users, meaning anyone within the vicinity may request potentially sensitive information, such as personal notes and audio transcriptions of the primary user’s text messages [17]. Apple has filed a patent to implement user profiling but HomePod users, assuming they are aware of this potential for misuse, must currently choose between requiring manual authentication on their phone for every message dictation request, or accepting that anyone can access their text messages until voice profiling capabilities have been implemented [15].

How smart speaker manufacturers evaluate external data requests, how they store user data, how user Terms of Service are specified and updated, and what information is included in transparency reports are all entirely dependent upon the manufacturer and vary between each one. With software services becoming increasingly interconnected through the incorporation of third-party applications, e.g. Alexa Skills, it becomes exponentially difficult for users to maintain an overview of their personal data. As suggested by Lau et al., a legally binding set of industry standards (à la IEEE) and certifications that apply to all smart speaker and IoT device manufacturers is necessary to resolve the existing segmentation and ambiguity of company policy and legislature [21].

2.4 Speaker Vulnerability Exploitation

Corporate transparency and legislative reach are not the only domains for which security must be considered. Hardware and software vulnerabilities must also be explored as points of exploitation. Research conducted in 2017 showed the Amazon Echo’s UART connection port as a point of attack by enabling access to the device’s firmware, thereby giving root shell access to its operating system. By installing a persistent shell script that launches when the device boots and exploiting Amazon’s audio buffering application tool, raw microphone data could be streamed to the remote server of an attacker’s choosing [5]. Although this method of attack required soldering an SD-card reader to the Echo, another research group proposed using a discrete 3D-printed attachment to mitigate evidence of tampering [9]. Amazon moved the +3V input pad to the main board for its second generation of Echo devices, meaning only 2015-2016 first generation devices are vulnerable to the “wiretap” attack.

Another form of attack applies to all generations of Alexa devices and does not require physical access to the device. This method of attack, known as “skill squatting”, relies on Amazon’s natural voice recognition algorithms making misinterpretations when transcribing speech-to-text [19]. For example, a user wishing to interact with a trusted banking skill, e.g. “Capital One”, may ask Alexa to “open Capital One”. Alexa may interpret the user to have said “Capital Won”, triggering a malicious third-party skill of the same name. The malicious skill could then be used to obtain information about the user [31]. Zhang et al. demonstrate a similar form of attack by means of a malicious skill with the same name as an authentic skill, but appended with a common phrase or word, for example, “open Capital One, please” launches the malicious skill “Capital One Please” instead of the authentic “Capital One” skill [31].

Kumar et al. noted that Alexa’s speech transcription algorithms are non-deterministic by repeatedly presenting identical audio files over a reliable network connection and observing varying outcomes in the speech-to-text results [19]. Limiting speech samples to the Nationwide Speech Project (NSP) database, they identified 24 “squattable” words, i.e. semantic interpretation errors resulting from words that Alexa misinterprets both frequently and consistently [19]. The squattable words were used to identify over 30 susceptible skills available on the Alexa Skills Store but that number, limited by the study’s proof-of-concept data set, is only an initial indicator for potential current and future vulnerable skills. Using skill squatting, the group was able to successfully demonstrate phishing attacks and suggests the possibility of using malicious skills to steal a user’s log-in credentials. By applying gender and geographic predicates, they also exposed an extension of the skill squatting attack, “spear skill squatting”, thus demonstrating the ability to target specific demographics. With a precedence for political manipulation using targeted
advertisement and the growing smart speaker market, spear
skill squatting has the potential to become a new channel
of social influence [20]. Also noteworthy is the limited set
of best practices currently used on the Alexa Skill Store when
compared to other app store ecosystems, such as allowing
multiple skills to have identical names.

Even though great progress in the development of voice
processing and machine learning algorithms used in personal
voice assistants has been made, as technology progresses,
new possibilities of interacting with AI assistants will emerge,
extending the types of data being exchanged and increasing
the importance of data security. A recently submitted patent
from Amazon details a feature that could determine some
of the physical characteristics or emotional states of a user
and react accordingly. For example, if a user is recognized
as having a sore throat, Alexa might recommend a particular
brand of cough medicine and order it. The patent mentions
the detection of health conditions: having a cold, thyroid is-
issues, sleepiness and emotional states including happiness, joy,
anger, sorrow, sadness, fear, disgust, boredom, and stress [16].
With Amazon’s acquisition of online pharmacy PillPack, Inc.
in June 2018, there are inherit benefits to the convenience of
supplying customers with medicine and pharmaceuticals [8].
However, due to the considerable value of medical informa-
tion, even when compared to other highly sensitive data such
as credit card and social security information [1], there is
equally an inherit risk in handling such valuable data securely,
responsibly, and transparently.

The segmented set of rules and policies between device
manufacturers, an incomplete set of best practices for third-
party applications/skills, uncertain legislature, and the future
potential for data harvesting all exhibit the current deficit
surrounding data privacy and smart speakers.

3 The Smart\(^2\) Speaker Blocker

3.1 Threat Model

Before discussing the design of Smart\(^2\), we first want to spec-
ify the threat model we are attempting to protect against. Our
goal is to protect against sensitive audio data leakage, either
to the device manufacturer or a malicious external third party.
We assume that either the device, the manufacturer’s server,
or both may be compromised or that they, either intentionally
or unintentionally, may not work as advertised. As such, our
goal is to physically prevent audio data we deem sensitive
from ever reaching the microphone of the smart speaker and
entering the unsafe environment. However, once audio data
does reach the smart speaker microphone, Smart\(^2\) provides
no protection, nor do we provide any protection for any data
stored on manufacturer servers. We also provide no protection
against insider threats who have physical access to the Smart\(^2\)
and may easily disable it.

3.2 Design

The Smart\(^2\) is an intermediary that sits between the end user
and the smart speaker, providing user-configured filtering to
prevent sensitive audio from being recorded by the smart
speaker. It does this by enclosing the smart speaker micro-
phone in soundproof material, along with an external speaker
that is connected to the Smart\(^2\). The Smart\(^2\) has its own ex-
ternal microphone that it uses to record environmental audio.
This audio is fed into a speech-to-text engine in chunks, where
each chunk is separated by a pause, indicating a phrase. The
speech-to-text engine converts this phrase to text, and passes
it to the filtering engine. The filtering engine uses a series
of user-specified keywords and actions to decide whether to
pass the phrase along to the smart speaker, drop the phrase,
or take other action. In order to handle different use cases, the
Smart\(^2\) has several actions that it can take which are discussed
in Section 3.3.

The Smart\(^2\) is based on open-source software and non-
proprietary/off-the-shelf hardware. The main hardware com-
ponents consist of a mini-ITX PC running Linux Ubuntu LTS
18.04, an external microphone for speech input, and a speaker
for speech output to the smart speaker. A Python 3 virtual
environment was then created to run Smart\(^2\)’s speech recog-
nition software, facilitated by the SpeechRecognition Python
library. This library was chosen for its ease of integration and
support of both online and offline speech recognition engines.
To improve security the Smart\(^2\) is an air-gapped device, so
we used an offline speech recognition engine developed by
researchers at Carnegie Mellon University to ensure that in-
teractions with the device remain local. CMU’s CMUSphinx,
an open source, Hidden Markov Model (HMM) based speech
recognition system, was determined to be the most viable
solution due to its offline nature [26].

3.3 Operation

The Smart\(^2\) can be configured by the user by using pat-
tern/action pairs. A pattern can simply be a keyword, such as
"password", or for more sophisticated users it can include reg-
ular expressions. In addition, some actions can take additional
parameters. The current set of actions includes:

- **Phrase filter** - The phrase filter action drops the current
  phrase. This action is intended to be used in cases where
  the current phrase may have some sensitive information,
  but we don’t expect the information to extend past the
  current phrase. For example, we may use the pattern
  "password" with the phrase filter action, because we
  want to filter cases where the user says things like "My
  password is XXX", but we don’t believe more sensitive
  information will be discussed after this phrase.

- **Timed filter** - The timed filter takes an additional dura-
tion parameter, and does not transmit audio for a fixed
duration after detecting the pattern. This is intended to filter more sensitive discussions that may extend beyond the current phrase. For example, the pattern may be set to "girlfriend" and the duration to 10 minutes, because we do not want sensitive personal discussions transmitted to the smart speaker, and we expect that this will be part of a discussion. The duration of this filter may be extended if other timed filter patterns are detected, and the duration is the time to wait after the last occurrence of the pattern.

- **Pattern deletion filter** - The pattern deletion filter deletes the pattern from the phrase, and transmits it to the smart speaker. It does this by removing the pattern from the phrase text, and using a text-to-speech engine to play back the modified text.

In addition to pattern matching, the Smart\(^2\) has several other modes that are activated by keywords or other triggers. These are:

- **Privacy mode** - This mode is activated by keyword, and does not transmit any data to the smart speaker until it is turned off. While this mode replicates the physical "Mute" button on most smart speakers, for many smart speakers it is not clear if the mute button is a hardware mute button, meaning no electrical signals are sent from the microphone to the device, or a software mute, meaning the software ignores the input from the microphone. In many cases it is strongly suspected that the button is a software button, in which case the software may intentionally or through programming errors continue to transmit. Software mute buttons are also vulnerable to exploits which can render them inoperable. Privacy mode guarantees (to the extent that Smart\(^2\) is bug-free) that sound cannot be recorded by the smart speaker.

- **Strict hotword mode** - In this mode only audio that is prefixed by the hotword for the smart speaker is passed through. All other audio is blocked. This completely prevents the smart speaker from inadvertently listening to any conversation that is not a specific command.

- **Loudness mode** - Loudness mode uses a decibel estimator to estimate the loudness of the speaker’s voice. This mode is an example of a more general emotion detection filter, where the user can filter based on their current mood. Loudness mode is designed to detect arguments or disagreements, which the user is unlikely to want transmitted to the smart speaker. This mode was inspired by a recent Amazon patent which detects the mood of smart speaker users [16].

- **Text-to-speech mode** - This mode is activated by keyword, and uses text-to-speech to mask the identity of the speaker, providing an extra layer of anonymity.

4 **Performance Evaluation**

Our analysis of the Smart\(^2\) system is broken into two parts. The first part is system performance impact, meaning the impact of the Smart\(^2\) system on the performance of the smart speaker. The second part attempts to address the increased security offered by the Smart\(^2\). The actual security gain, meaning the decrease in sensitive material leaked to the smart speaker, is a function of the individual user configuration, as well as many other factors, and is nearly impossible to measure. Instead we try to quantify how the Smart\(^2\) system changes user perception of smart speaker security, which is an important metric for smart speaker adoption.
4.1 System Performance Impact

To evaluate the impact of the Smart\textsuperscript{2} on smart speaker performance, we consider the latency introduced to the smart speaker responses due to the Smart\textsuperscript{2} and the increases in the smart speaker error rate due to the additional speech-to-text layer.

4.1.1 Experimental Setup

The hardware used for our tests consists of a mini-ITX PC with an i7 7500u CPU, 8Gb of memory, and a 128Gb SSD drive running Linux Ubuntu LTS 18.04, an external microphone for speech input, and a speaker for speech output to the smart speaker. The system was developed in Python 3, using the SpeechRecognition package and the CMUSphinx library with the CMUDict dictionary for US English for speech recognition. Text-to-speech was done using the PyTTSX3 library, an offline library. The smart speaker used was the Amazon Echo Dot, Generation 2. All tests were done in a large, empty room, with minimal background noise.

4.1.2 Latency

The Smart\textsuperscript{2} system by necessity introduces some latency into smart speaker interactions, simply because it must play back audio. This is somewhat mitigated by the fact that most smart speaker commands are generally quite short, for example querying about the weather or time. In addition to the playback time, additional latency is introduced by the speech-to-text (STT) engine and for some modes, the text-to-speech (TTS) engine. Because the playback time is fixed, and always equal to the length of the phrase spoken, we focus our measurements on the processing overhead introduced.

We evaluated Smart\textsuperscript{2}’s processing overhead by running a controlled experiment using four separate speech recordings as input data for the system. Each test was timed using the system’s current time at the end of the capture audio procedure. Each test was repeated ten times and the results averaged. The tests were conducted by the system as follows:

1. Initialize microphone for audio input
2. Capture ambient background noise and adjust the microphone accordingly (SpeechRecognition)
3. Play recording
4. Capture audio data
5. Retrieve system time
6. Transcribe speech to text (CMUSphinx)
7. Evaluate text transcript via the filter engine
8. Write elapsed time, evaluation results, and transcription to file output

| Input                          | Action | Min | Max  | Avg (1/10) |
|-------------------------------|--------|-----|------|------------|
| “How’s the weather today?”    | FWD    | 740 | 836  | 811        |
| “Bank account password.”       | BLOCK  | 712 | 832  | 801        |
| “What’s 10 x 3?”               | FWD    | 696 | 795  | 752        |
| “Play Pachelbel Canon in D.”   | FWD    | 823 | 907  | 850        |

The process was repeated ten times for each recording. Performance testing results are documented in Table I, showing the minimum, maximum, and average processing time in milliseconds. Testing the system indicated the Smart\textsuperscript{2} adds approximately 800 milliseconds of overhead to convert speech to text and apply the filtering rules. The vast majority of this time is used by the speech-to-text library, with the filtering process taking an almost undetectable amount of time due to the efficiency of the Python regex library and the small text size. We additionally repeated these tests including the time to convert the output text to audio using the text-to-speech library, but found that the additional overhead introduced by this step was negligible.

4.1.3 Accuracy

The error rate of the speech-to-text library is determined by the size of the dictionary, the complexity of the model, and various other parameters. The Sphinx4 library has reported error rates as low as 3.9%, for small dictionary sizes [26]. As the Smart\textsuperscript{2} only needs to recognize keywords, rather than completely accurately transcribe everything heard, the dictionary size can be relatively small, as compared to more general speech-to-text dictionaries used by devices like smart speakers. This allows us to maintain high accuracy, with respect to the keywords, while using a less complex model. In comparison, server-based speech-to-text services, like those used by smart speakers, typically achieve around 5% error rates for general speech [30]. While we did not attempt a comprehensive evaluation of the accuracy of the Sphinx 4 speech-to-text engine for our application, as part of our security evaluation in section 4.2 we found a less than 2% error rate in transcription of keywords. This is a prototype system, and we feel that as such this is sufficient evidence to show that an offline speech-to-text engine is accurate enough to provide substantial security, and that a commercial implementation could increase this security by refining the speech-to-text algorithm.

4.1.4 Usability

To assess usability we setup the Smart\textsuperscript{2} in two home environments where the home owners regularly used a smart speaker. Both users evaluated the Smart\textsuperscript{2} for a week, then provided feedback regarding the usability of the device. Both users reported that neither they nor their family members noticed any
substantial decrease in the usability of their smart speakers. While they did notice the increased delay, they felt that given the existing delay in replies from the smart speaker, that the small increase did not significantly affect their usage. They did not notice any instances of inaccurate filtering.

4.2 Security Assessment

In order to evaluate the security protection offered by the Smart², we devised a real world test scenario. Our test configuration, shown in Figure 4.1, consisted of the Smart² and a separate computer with two microphones. One microphone was used to record output from the Smart² and the other to record the raw, unfiltered audio. Our test configuration was setup in an open office space shared by six students, all of whom were told about the nature of the test. We then choose a set of keywords that we expected to be commonly used in our test environment, for example “computer”, “exam”, and similar terms. The Smart² was configured to filter these keywords using a variety of filter actions. Both the raw audio and filtered audio were recorded and transcribed using the online Google speech-to-text API, which is the same speech-to-text engine used by Google Home smart speakers, and saved to time stamped log files. The Smart² was also configured to log its transcription of intercepted phrases.

At the end of two weeks we compared the two transcripts. In the transcript for the unfiltered audio there were 947 occurrences of the keywords, while in the filtered transcript there were only 15 occurrences, a 98% reduction. By cross-referencing the time stamps on the errors with the Smart² log file, we determined that these 15 occurrences were due to errors by the Sphinx 4 speech-to-text engine. While this is a limited test of the system, we feel that it offers strong evidence that the Smart² system has the potential to significantly reduce audio data leakage.

5 Discussion and Future Work

Smart speakers pose an enormous potential privacy risk to consumers, a risk that they currently have little way to mitigate. In this paper we present the Smart² system, which leverages the same machine learning algorithms that endanger user privacy to offer transparent, open-source protection for users of smart speakers that is completely under their control. We then demonstrate that the device offers significant privacy enhancement, filtering 98% of sensitive audio in our test, while at the same time minimally impacting the performance of the smart speaker.

While the Smart² is a complete system as presented, we feel there is substantial work remaining to be done. For example improving the accuracy of the offline speech-to-text library or implementing emotion detection based filtering and other filtering modes that are not strictly keyword based. We also feel that approach of using machine learning to develop systems that protect or enhance the security of end user systems and devices is a promising technique that has not been broadly explored either commercially or in the research literature.

References

[1] Health data is wealth: Why hackers targeted Singapore, September 2018. https://healthcareasiamagazine.com/sites/default/files/healthcareasiamagazine/print/HCA_BODY-%2012-13.pdf [Online; accessed November 15, 2018].

[2] AndriodPolice. Google is permanently nerfing all Home Minis because mine spied on everything I said 24/7, 2018. https://www.androidpolice.com/2017/10/10/google-nerfing-home-minis-mine-spied-everything-said-247/#2 [Online; accessed December 3, 2018].
[3] Apple. Approach to privacy, 2018. https://www.apple.com/privacy/approach-to-privacy/ [Online; accessed January 3, 2019].

[4] Big Brother Awards. Watching the watchmen worldwide, 2018. http://www.bigbrotherawards.org/ [Online; accessed November 7, 2018].

[5] Mike Barnes. Alexa, are you listening?, 2017. https://labs.mwrinfosecurity.com/blog/alexa-are-you-listening [Online; accessed October 15, 2018].

[6] Thomas Brewster. Smart home surveillance: Governments tell Google’s Nest to hand over data 300 times, 2018. https://www.forbes.com/sites/thomasbrewster/2018/10/13/smart-home-surveillance-governments-tell-googles-nest-to-hand-over-data-300-times/#2b7aa83e2cfa [Online; accessed December 18, 2018].

[7] Canalys. Smart speaker installed base to hit 100 million by end of 2018, 2018. https://www.canalys.com/newsroom/smart-speaker-installed-base-to-hit-100-million-by-end-of-2018 [Online; accessed November 11, 2018].

[8] Joe Ciolli. Amazon’s $1 billion purchase of PillPack wiped out 15 times that from pharmacy stocks — and it shows the outsize effect the juggernaut can have on an industry, 2018. https://www.businessinsider.sg/amazon-pharmacy-pillpack-acquisition-merger-showing-outsized-impact-2018-6/?r=US&IR=T [Online; accessed November 25, 2018].

[9] Ike Clinton, Lance Cook, and Shankar Banik. A survey of various methods for analyzing the Amazon Echo, 2016. https://vanderpot.com/Clinton_Cook_Paper.pdf [Online; accessed October 16, 2018].

[10] CNN. Cops use murdered woman’s Fitbit to charge her husband, 2018. https://edition.cnn.com/2017/04/25/us/fitbit-womans-death-investigation-trnd/index.html [Online; accessed December 18, 2018].

[11] Big Brother Awards DE. Consumer protection: Amazon Alexa, 2018. https://bigbrotherawards.de/kategorie/verbraucherschutz [Online; accessed November 7, 2018].

[12] Colin Dwyer. Arkansas prosecutors drop murder case that hinged on evidence from Amazon Echo, 2018. https://www.npr.org/sections/thetwo-way/2017/11/29/567305812/arkansas-prosecutors-drop-murder-case-that-hinged-on-evidence-from-amazon-echo [Online; accessed November 30, 2018].

[13] Kiran K. Edara. Key word determinations from voice data, August 2014.

[14] The Guardian. Amazon’s Alexa recorded private conversation and sent it to random contact, 2018. https://www.theguardian.com/technology/2018/may/24/amazon-alexa-recorded-conversation [Online; accessed December 3, 2018].

[15] Allen P. Haughay. User profiling for voice input processing, August 2018.

[16] Huafeng Jin and Shuo Wang. Voice-based determination of physical and emotional characteristics of users, October 2018.

[17] Bret Kinsella. Apple HomePod has a privacy flaw that no one is talking about, 2018. https://voicebot.ai/2018/02/11/apple-homepod-privacy-flaw-no-one-talking/ [Online; accessed December 12, 2018].

[18] Bret Kinsella. U.S. smart speaker users rise to 57 million, 2018. https://voicebot.ai/2018/10/30/u-s-smart-speaker-users-rise-to-57-million/ [Online; accessed December 13, 2018].

[19] Deepak Kumar, Riccardo Paccagnella, Paul Murley, Eric Hennenfent, Joshua Mason, Adam Bates, and Michael Bailey. Skill squatting attacks on Amazon Alexa. In 27th USENIX Security Symposium (USENIX Security 18), pages 33–47, 2018.

[20] Issie Lapowsky. How Russian Facebook ads divided and targeted US voters before the 2016 election, 2018. https://www.wired.com/story/russian-facebook-ads-targeted-us-voters-before-2016-election/ [Online; accessed November 23, 2018].

[21] Josephine Lau, Benjamin Zimmerman, and Florian Schaub. Alexa, are you listening?: Privacy perceptions, concerns and privacy-seeking behaviors with smart speakers. Proceedings of the ACM on Human-Computer Interaction, 2(CSCW):102, 2018.

[22] Nest. Transparency report: Requests for user information, 2018. https://nest.com/legal/transparency-report/ [Online; accessed December 19, 2018].
[23] NPR and Edison Research. The smart audio report, spring 2018, 2018. https://www.nationalpublicmedia.com/wp-content/uploads/2018/07/Smart-Audio-Report-from-NPR-and-Edison-Research-Spring-2018_Downloadable-PDF.pdf [Online; accessed November 15, 2018].

[24] Amazon Customer Service. Alexa and Alexa device FAQs, 2018. https://www.amazon.com/gp/help/customer/display.html?nodeId=201602230 [Online; accessed November 9, 2018].

[25] Jun Tang, Aleksandra Korolova, Xiaolong Bai, Xueqiang Wang, and Xiaofeng Wang. Privacy loss in Apple’s implementation of differential privacy on macOS 10.12. arXiv preprint arXiv:1709.02753, 2017.

[26] Willie Walker, Paul Lamere, Philip Kwok, Bhiksha Raj, Rita Singh, Evandro Gouvea, Peter Wolf, and Joe Woelfel. Sphinx-4: A flexible open source framework for speech recognition. Technical report, 2004.

[27] Zack Whittaker. Amazon turns over record amount of customer data to US law enforcement, 2018. https://www.zdnet.com/article/amazon-turns-over-record-amount-of-customer-data-to-us-law-enforcement/ [Online; accessed December 9, 2018].

[28] Zack Whittaker. Amazon won’t say if it hands your Echo data to the government, 2018. https://www.zdnet.com/article/amazon-the-least-transparent-tech-company/ [Online; accessed January 3, 2019].

[29] Zack Whittaker. Judge orders Amazon to turn over Echo recordings in double murder case, 2018. https://techcrunch.com/2018/11/14/amazon-echo-recordings-judge-murder-case/ [Online; accessed December 1, 2018].

[30] W. Xiong, L. Wu, Fil Alleva, Jasha Droppo, Xuedong Huang, and Andreas Stolcke. The Microsoft 2017 conversational speech recognition system. CoRR, abs/1708.06073, 2017.

[31] Nan Zhang, Xianghang Mi, Xuan Feng, XiaoFeng Wang, Yuan Tian, and Feng Qian. Understanding and mitigating the security risks of voice-controlled third-party skills on Amazon Alexa and Google Home. arXiv preprint arXiv :1805.01525, 2018.