Getting the Residents' Attention: The Perception of Warning Channels in Smart Home Warning Systems

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ABSTRACT

About half a billion households are expected to use smart home systems by 2025. Although many IoT sensors, such as smoke detectors or security cameras, are available and governmental crisis warning systems are in place, little is known about how to warn appropriately in smart home environments. We created a Raspberry Pi based prototype with a speaker, a display, and a connected smart light bulb. Together with a focus group, we developed a taxonomy for warning messages in smart home environments, dividing them into five classes with different stimuli. We evaluated the taxonomy using the Experience Sampling Method (ESM) in a field study at participants' (N = 13) homes testing 331 warnings. The results show that taxonomy-based warning stimuli are perceived to be appropriate and participants could imagine using such a warning system. We propose a deeper integration of warning capabilities into smart home environments to enhance the safety of citizens.

CCS CONCEPTS

• **Human-centered computing → Field studies**.

KEYWORDS

smart home warning system, public warning, crisis informatics, taxonomy, user perceptions

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1 INTRODUCTION

Smart home systems are becoming more and more popular, with an expected increase from 141 million households using them in 2017 to more than 478 million by 2025 [22]. At the heart of these systems lies the *voice user interface* (VUI) which interacts with users by processing voice commands. But touchscreens are also increasingly being used. The focus of current smart home research is on comfort and automation [24], as well as security and privacy [27]. With *machine learning* (ML) and *artificial intelligence* (AI), the input sensors' data could be interpreted better [23], strengthening the application of monitoring and warnings. With smart light bulbs and speakers spread across rooms, and actuators like automated shutters or locks integrated into smart homes, they could be used to warn inhabitants and instantly react to serious threats. By updating the software, the infrastructure of existing smart home systems could be leveraged by re-purposing existing actuators like light bulbs or voice assistants for these warning systems.

A wide range of threats could be detected in the smart home environment, such as fires, water leakages, intruders, or serious health situations of inhabitants. Because fire is still a serious threat, smoke detectors are widely used and in some countries even mandatory. Notably, fire detectors are gradually becoming smart. Apart from smoke-based detection [10, 49], current research focuses on temperature-based [32] and image-based fire detection [13]. A lot of these systems are based on ML techniques. Salhi et al. [32] for example applied ML and data mining methods to detect anomalies in the air to predict risky incidents. But not all situations that can be detected are time critical or pose a severe danger. Inhabitants also want to be warned if they forgot to lock the door, the humidity in the bathroom is too high, or too much energy is being consumed [33]. In addition to situations detected by the household system itself, data can also come from authorities warning about crises like earthquakes, flooding, or heavy weather situations which normally would be provided by cell broadcast, warning apps, radio, or social media [40]. But these could also serve as a source for smart home systems to then alert inhabitants.

In the following, we refer to such an *internet of things* (IoT) based system that gathers data from sensors and public data sources about dangers for property and inhabitants and warns them, as a *smart home warning system* (SHWS). SHWSs are not limited to the previously presented applications but refer to all types of smart home applications that aim to alert a user about a situation, regardless of the criticality, the design, or the domain of the grievance. Despite the differences of SHWSs, these systems have in common that they use different stimuli to get the user's attention in case of an alert. This differs from the interaction pattern normally used with VUIs in smart homes, where the user, not the system, starts the interaction [46].

The range of different warning channels extends from acoustic warnings, e.g. conventional loudspeakers, to warnings via Facebook messages [26]. A warning channel could be a display, lamp,

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or speaker, where the stimulus is the sensory signal like a blinking red light or an alarm sound. Acoustic warnings are the most common signals in recent studies, followed by warnings via email and *light-emitting diode*s (LEDs) [35]. While auditory and flashing visual stimuli are used to instantly raise the user's attention, silent notification on a user's smartphone may take some time to be noticed. The appropriate warning channel for each application must be selected conscientiously. Research shows that badly designed warnings that are imprecise and not addressed to recipients counteract the intended purpose of warning systems [20]. False alarms or frequent exposure lead to desensitization and habituation [19, 45]. Because warnings in smart home environments may indicate a serious threat to life and property and require an immediate reaction by the homeowner, ignoring warnings could have serious consequences.

This stresses the need for user studies to verify appropriate warning channels for different situations. As means of getting a person's attention, visual and auditory stimuli are well understood in the field of perceptual psychology [11] and human factors domains of automotive [37], aviation [7], or control centers [38]. But the application of warnings in private homes raises new research questions since devices, and the corresponding possible stimuli like smart light bulbs or speakers, are spread across several rooms. Therefore, there is a need to investigate users' perspective on how warnings in smart home environments should be designed to meet users' demands on successful SHWSs.

The goal of this paper is to elaborate the field of SHWSs for choosing appropriate warning channels which warn effectively while also being accepted by users in their homes and perceived as unobtrusive, disturbing everyday life only when necessary. In this paper, we therefore narrow down the term SHWSs, provide examples, and highlight the role of warning channel stimuli (Section 2). Based on related work, we used a focus group method with 4 young adults to find a taxonomy of different warning classes in SHWS with warning channel stimuli for each class (Section 3). Finally, we used a Raspberry Pi based prototype to conduct a field-study with university members at participants' homes to evaluate the taxonomy generally using the *experience sampling method* (ESM) [21] (Section 4). The key contribution of our work is the positive evaluation of the taxonomy of warnings in SHWS (Section 5), which can be used as a design base or for further research (Section 6).

2 RELATED WORK

Recently introduced systems that aim to warn households are known as *smart home monitoring systems* [48], *smart home alert systems* [18, 41] or *smart home warning system*s (SHWSs) [34]. "Monitoring" is a more technical term, which in our case does not fit our work, as the output modality of warnings is central. In contrast to "alert", "warning" includes critical situations but non-critical ones as well. Therefore, we use the latter term. SHWS include all systems in the smart home environment that scan the domestic environment for threats using sensors, process the data, and distribute alerts via actuators. This can encompass many different sensors, from motion sensors to air sensors.

In the following, we first describe related work mentioning obstacles and needs of users regarding SHWS followed by introducing how several different setups use input data to determine a harmful situation. At the end, we take care of the output modalities and present possible warning channels and stimuli in general within the smart home and why we think a flexible and simple taxonomy is needed to support users' with a range of warning scenarios.

Research shows that users have problems with the configuration of SHWS capabilities in a smart-home, even when there is a need to it. In a long-term study, Salovaara et al. show that while users of smart homes mentioned security and safety features like "hazard-prevention, warnings, and monitoring" as a use case, they did not or could not configure such a feature in their smart homes [33]. Brush et al. show, that users think they would have to face high costs or that easy to implement SHWS solutions do not exist [6]. They studied 14 households in 2011 and show that despite a strong desire to integrate alarm systems and warnings into smart homes, users had problems with finding technical solutions or avoided costs. One key reason why we consider our research important is that while it is possible to connect different safety and security related data sources as input, people and engineers need to know what to do with this data and more importantly not only interpret the data but how to present it with meaningful and convenient stimuli to warn people, which we will address in the paper.

Just as the term SHWS is not limited to specific IoT devices, there are a variety of possible setups regarding sensors and actuators. Before mentioning output channels, we show examples of local input sources and public warning messages as they determine the general scope of warning capabilities. Although most smart home systems already include relevant sensors for SHWS, people often do not initially think about this capability and mention other purposes [29]. Our work considers both internal and external data sources, such as govermental warnings, to present suitable warning stimuli. SHWSs interpret data collected from the surrounding environment via sensors to trigger alarms via actuators. Recently introduced implementations of SHWSs are often domain specific. They focus on intrusion detection, fire detection, gas detection, or health issues of elder inhabitants. Sarhan et al. analyzed differences in the architecture of recently published SHWSs [35] and showed that most of the systems connect the sensors via wires to a central hub. But wireless sensors are emerging that transmit data wirelessly using *ZigBee*, *Wifi* or *Bluetooth* [42]. Compared to other approaches which are often domain-specific (e.g. only focus on fire detection) we consider a more holistic view on SHWSs. Our taxonomy considers all kind of events independent from specific domains. Using cameras in the field of smart homes is often associated with emerging security and privacy issues [28]. Tan et al. show that users of cameras in smart homes mention the general purpose of security and safety, although they often have different underlying motivations like monitoring pets, feeling safe regarding intruders, spying on neighbors, or interacting with visitors [12]. They do not mention the possibility of detecting fires or other hazards, while it is technically possible. For example, Bhoi et al. introduced a system that combines temperature sensors, carbon dioxide sensors, and carbon monoxide sensors to classify conditions as "fire", "no fire", or "may be fire" [4]. In case of a detected fire, a message is sent to a mobile number. Salhi et al. combine a fire detection system and a gas leakage system by applying a ML approach that detects abnormal air state patterns and triggers a warning [32]. The approach introduced by Alqourabah et al. also aims at early detection of fire with heat, smoke, and flame detectors [1]. When a fire is detected, the system not only triggers an alert, but also automatically informs emergency services using a *Global System for Mobile Communications* (GSM) modem and activates an automatic water sprinkling system to directly tackle the threat. Our taxonomy can integrate harm of a possible fire whether it is detected by the system itself or from other data sources.

Furthermore, a SHWS is not limited to processing data originating from the immediate home environment. Some threats, for example, flooding, extreme weather, or major fires, originate outside the home. Warnings for these events are distributed using public warning channels, for example broadcasting stations or mobile warning apps [16]. However, relatively few people still use warning apps in many countries in Europe [14, 16]. We think it is a major chance for public warnings to be integrated in SHWS to reach as many people as possible. Using a SHWS to warn within the apartment thus immensely expands the possibilities of public warnings by establishing immediate awareness, especially for people that do not use mobile devices in general or are not using them at that moment. Many crises directly relate to the user's home, like earthquakes, hurricanes, bomb disposals, wildfires, flooding, or heavy rainfalls. In these cases, actions related to the homes need to be taken, such as packing for an evacuation, installing barriers, or seeking shelter in the basement. For users it is not important whether a warning is sourced internally or externally, but they need to know if there is a danger , and how to be prepared [15].

Besides differences in the way that SHWSs sense and process data, there are also differences in how warnings are distributed in case of an anomaly. Designing alerts to immediately get users' attention in critical situations, while being less invasive in non time critical situations is a challenge. When using stimuli to indicate a warning or danger, it is crucial to avoid both habituation and gradual neglect of signals, as well as the overlooking of important warnings concerning acute threats. In our work, we mitigate this by developing a taxonomy for warning stimuli depending on the characteristics of a warning. Sarhan et al. showed that the most popular warning channel for distributing a warning in recent work is an acoustic warning, followed by optical warnings [35]. Since it is crucial to select the correct sound to avoid annoyance [5], the most intense alarm sound is not always the best choice. Regarding optical warnings (using LEDs), the color, as well as the choice to use a flashing light instead of a static one, are important design decisions. Furthermore, SHWS have the possibility to use all smart light bulbs of a household as an output device. Including the capabilities of smart light bulbs in our taxonomy is rational and closes this gap. But to understand a warning, additional information than a warning level via audio or visual stimuli is needed. While Esau et al. show that displays are not easily integrated in Intelligent Personal Assistants (IPAs) can lead to confusion with a VUI [8], we think optical warnings channels of a SHWS can also include a display to show text or camera footage. Research shows that when presenting text based warnings, habituation and appropriateness can be a problem, where slight variations can mitigate the effect [3, 45]. To warn house owners that are currently not at home, smartphone notifications are used. While the systems have been positively evaluated regarding their sensing and false alarm rates, user evaluations of the perception of the warnings are so far lacking. Therefore, we aim to elaborate a guideline for choosing the correct warning channels for SHWSs that is based on the needs and expectations of the users.

To summarize, there are a variety of different designs of SHWSs and a high degree of freedom regarding the sensors and warning channels used. What the systems have in common at the core is the existence of an input component (sensors or regional warnings), a processing unit to detect anomalies, and an output component that consists of different actuators that distribute a warning to the household or to fight the hazard. For the scope of this paper and in comparison to other work, we consider a SHWS as a centralized system in a smart home environment that combines warnings from several domains in the domestic field as well as regional warnings. Together with participants in a focus group interview workshop, we characterized warnings of such a system on a general level to have a guidance on how to design such a system and use output modalities that are domain independent. As a result, we found key properties of warning events and a taxonomy of warning stimuli which we evaluate in a user study with the ESM. It allows for short and immediate feedback from participants to single events at the place where they happen using the advantage of touchscreens [43].

3 TAXONOMY FOR SMART HOME WARNING SYSTEMS

To classify warnings and find suitable warning channel stimuli for SHWSs, we decided to develop a taxonomy. First, we analyzed the properties of warnings and then proposed a taxonomy of warnings in SHWSs. To integrate users' point of view into the design process of the taxonomy, we conducted a focus group discussion with a free brainstorming about the taxonomy, but also based on a first design step of our prototype. This discussion helped to better understand users' expectations towards a SHWS and choose suitable warning channel stimuli for the taxonomy. After establishing the taxonomy, we conducted a field study at participants' homes with a Raspberry Pi based prototype with taxonomy based vs. non-taxonomy based stimuli using ESM.

3.1 Key properties of Warnings

We analyzed several systems that have recently been introduced for commercial or scientific purposes regarding used warning channels and warning capabilities [1, 2, 4, 17, 25, 26, 30, 32, 33, 35].

The basic goal of a SHWS is the same for all systems regardless of the domain. A SHWS should warn a user in case of an anomaly in the smart home environment. Depending on the used sensors, a system is only able to detect a limited number of anomalies. A SHWS that has a temperature sensor connected to the system will not be able to warn in case of upcoming severe weather while on the other hand, a system that uses weather information as an input will not trigger a warning in case of a fire.

Despite their differences in architecture, domain, and design, we identified the following two key properties that allow us to classify warnings within a SHWS: (1) *Potential Impact of the Event* (i), (2) *Time Criticality of Reaction* (t). We will use these properties later to classify events for our taxonomy.

(1) An event that is detected by a warning system has a *potential impact*, either on other systems in the smart home network or a

physical impact on the house or its inhabitants. Since the range of potential events is wide in the domestic field, the impact of the events also varies widely. Some events may have no impact at all, for example, a robot vacuum cleaner that stops working due to a failure does not have any severe consequences. If the sprinkler system in the garden fails, the damage caused will be limited to some plants that may suffer water shortage. On the other hand, an excessive carbon monoxide saturation in the air threatens the health of inhabitants and therefore its impact can be considered serious.

(2) The reason why a warning is triggered by a SHWS is the need of a reaction of a person that may prevent a problem from causing damage. The *time criticality* of a person's reaction to a warning differs. For some events, a reaction might not even be required. A low water level of a rain barrel, for example, will be fixed when it rains without any intervention needed. Other events may require a human reaction to overcome a failure, but they can be considered non time critical because the consequences of not fixing the problem are low. An example of this is the event of a malfunctioning robotic vacuum cleaner or low heating supplies. It is unlikely that the problem will be solved without human intervention, but it is also not time critical since no other systems are affected or any damage is caused. In extreme cases, such as an event where a fire alarm goes off, an immediate response is necessary to prevent harm to life and property.

Having these key properties and an idea of SHWS, we conducted a focus group with the results to further carry out how warnings in SHWSs should be presented.

3.2 Focus Group

Szopinski et al. suggest conducting a focus group discussion with potential users in order to evaluate a taxonomy as their framework based on a meta analysis on taxonomy development [39]. We followed this recommendation and set up a one-time discussion with four participants. All participants (aged 22 to 24, 2 female, 2 male, 0 diverse) were students from the local university. They were granted participation hours for attending the 90 minutes workshop. We welcomed the participants and asked them to fill out a questionnaire in order to evaluate their previous experiences regarding smart home systems, SHWS and their affinity for technology using the *affinity for technology interaction* (ATI) scale [9]. One participant actively used a smart home system while the others did not and the ATI scale was balanced with a minimal tendency towards affinity (Mdn = 3.5). This is important because we want to avoid having only very experienced or only novice users in our focus group. After finishing the welcome session, the focus group did exercises consisting of four phases:

(1) **Events and use cases:** First, we asked the participants to write down potential use cases for a SHWSs and discuss the ideas. As an outcome, we noticed that they not only considered critical events, as for example a fire or an intruder, but also less critical events, for example hardware or software failures of the SHWS itself. Overall, the participants came up with 14 diverse use cases for a SHWS, which we summarized to malfunctioning kitchen devices, power outages, medical situations, fire, terrorism and theft protection.

(2) **Dimensions of SHWSs**: Secondly, in a card sorting task, participants grouped the events (Figure 1). In addition, a caption was determined for each group. We chose this task in order to identify dimensions of SHWSs that allow building classes for the taxonomy. The participants came up with several ideas, for example considering the degree of cross-linking of the systems as a relevant factor or splitting the use cases into public and private events. After a discussion, they agreed to group the use cases with respect to the urgency of the required reactions. This confirmed our decision to include the *time criticality of a reaction* (t) as a key dimension for our taxonomy.

(3) **Warning channel stimuli**: In the next step, we introduced a prototype of a SHWS to the participants (which we describe later in section 4.1) in order to guarantee a common understanding of what a SHWS is and how such a system could work. Participants were asked to think about and write down potential warning channel stimuli that could be added to a SHWS to ensure that a system warns in time. The participants came up with more warning channels than we had selected for our prototype. They, for example, suggested using a vibrating mat or a smartwatch to warn at night. The participants also stressed the need for selecting different levels of acoustic and optical warnings depending on the criticality of the event.

(4) **Bringing everything together**: The focus group sorted the cards again and assigned the determined warning channels to the use cases, which helped us to finalize the taxonomy.

As a result of the focus group, the use cases mentioned were considered in the characteristics of the taxonomy regarding *Potential Impact of the Event* (i) and *Time Criticality of a Reaction* (t) as key properties of warnings which we also extended by a third category *Safety Failure of the System* (f):

(3) Some SHWSs are designed to warn of a danger that may cause serious damage to the whole property. In such an event, the SHWS itself is also threatened. A soon-to-occur power outage, for example, has the potential to disable the SHWS if there are no resilience precautions, such as an alternative power source like batteries. Systems that are threatened by the event itself should warn before going down.

With the extended three key properties, we used the proposed warning channels of the focus group for the events to finalize our taxonomy.

3.3 Taxonomy of Warnings in Smart Home Warning Systems

By conducting the focus group discussion, we were able to express ranges for the key properties of warnings (Table 1) and integrate valuable feedback for our final taxonomy version (Table 2). We learned that from the users' point of view not only critical events are in the scope of a SHWS. These general properties allow to calculate the criticality of all kinds of warnings and selecting the right class in our taxonomy, when impact, time criticality and effect on the system are known.

After all three key properties of warnings have been identified for an event, the overall criticality score (W_c) of a warning is determined

(a) "Very urgent" and bottom "Not very urgent" with the following order (top to bottom): (1st row) terrorist attack, civilian protection, burglary protection, theft protection, criminal acts, fire in civil service; (2nd row) nearby church burns; (3rd row) power outage, health monitoring; (4th row) Cyber attack, increased body temperature, fridge malfunction; (5th row): increased power consumption, oven needs cleaning.

(b) "High degree of networking" and bottom "Low degree of networking" with the following order (top to bottom): (1st row) civilian protection, fire in civil service, terrorist attack, nearby church burns; (2nd row) Burglary protection, power outage, theft protection, cyber attack; (3rd row) criminal acts, increased power consumption; (4th row) increased body temperature, oven needs cleaning, fridge malfunction, health monitoring.

(c) "Very urgent" and bottom "Not very urgent" with the following order (top to bottom): (1st cluster) siren, shutdown devices, SMS; (2nd cluster) wifi, warning sound, vibration, light; (3rd cluster) smartwatch, Bluetooth.

Figure 1: In the focus group, participants discussed potential events for a warning, features and warning channels of a smart home warning system and used a card sorting method to find connections.

by adding the individual values, as in equation 1.

$$W_c = i + t + f \tag{1}$$

With this equation, we decided against adding factors to each property to have a simple to understand model which considers the safety of life more than the continued operation of the system. Because a high W_c scoring always includes immediate reactions of inhabitants, e.g. to leave the house in case of a fire, we think that the remaining functionality of the system is not as important.

For each of the three dimensions, a value of the key properties (Table 1) must be determined. The highest score possible within our taxonomy for a warning is $W_c = 9$, the lowest $W_c = 0$, and the higher the score, the more critical the warning is. Depending on the criticality, the requirements for the warning channel stimuli of a system change. A warning with a high criticality score must be able to attract the attention of inhabitants immediately to alert harm. On the other hand, a warning with a low criticality score should not use alerts that are too invasive to cause inhabitants to become indifferent to the alerts. For this reason, we defined five different groups for our taxonomy, where each group covers a specific range of the criticality score and comes with recommendations on which warning channels to use (Table 2). Multiple warnings can therefore not only have the same criticality score, but they can also have a similar score resulting in the same class with same stimuli. This is because we think it is important to consider the whole range of warning events, but not have too many different stimuli combinations to have a simple, meaningful taxonomy that helps people to quickly recognize the situation and react.

As a result of the focus group workshop, we have thought about in more detail which gradations of the warning channels make sense. Although our focus group mentioned a vibrating mat or smart watch as an output channel for nighttime situations, we decided against this in our taxonomy because it cannot be easily integrated into a standard smart home setup with speaker and lamp, requiring separate devices. In addition our study aims to daytime situations in first place. Consequently we use acoustic (permanent vs. short), optical warnings (color and static vs. blinking), and smartphone notification (SMS) as stimuli for our field study.

4 FIELD-STUDY

Due to the nature of smart home technologies like SHWS, evaluation often takes place in the users' environment. While gathering relevant behavioral and perceptual data, special attention is paid to choosing a study design that minimizes confounding factors, creates a realistic environment and does not interfere with everyday life. By letting participants use the prototype at home for several days, the ESM allows many short feedback loops that take less than

Table 1: Key properties of events to determine the criticality of a warning.

Potential Impact of the Event (i)	
0	No damage is caused at all
1	Minor damage may be caused but is limited to a single system or small areas
2	Minor damage may be caused affecting multiple systems or a large area
3	Significant damage to the whole property may be caused
4	Significant damage that threatens the physical integrity of the inhabitants may be caused
Time Criticality of Reaction (t)	
0	No reaction is required (System is able to restore / solve the problem)
1	No time critical reaction is required and the situation will not deteriorate for a certain time
2	No time critical reaction is required, but the situation will deteriorate without intervention
3	Time critical reaction is required to prevent the deterioration of the situation
4	Immediate reaction is required to prevent the deterioration of the system
Safety Failure of the System (f)	
0	Event does not affect the warning system
1	Event may cause the warning system to fail

a minute, which is practical when having many events to rate per participant [43]. To ease the situation, it is a good idea to use a smartphone or touchscreen to gather feedback instantly [44].

4.1 Prototype

To conduct the field study for evaluating the taxonomy, we developed three identical prototypes of a SHWS consisting of a box-shaped hub (22 x 10 x 14 cm) and a smart lamp (Figure 2). It is based on our initial version used in the focus group (Section 3.2), but finally configured on the results of the focus group taxonomy e.g. by choosing the visual stimuli colors. The Raspberry Pi 4 based prototype with a Python script serves as a centralized hub of a smart home system running warning messages from a *JavaScript Object Notation* (JSON) file, simulating all sensor systems connected to the smart home. It converts the warnings into alerts perceptible to humans controlling RGB smart light bulbs, a speaker, and sending / receiving *Short Message Service* (SMS) as smartphone notifications (Figure 4 , appendix). A 5-inch touch display with a resolution of 800 x 480 pixels is integrated into the case of sturdy cardboard. The touchscreen serves as a display for presenting warning messages as well as as an input device for generating participant feedback after each alarm. In addition to the hub, we used a standard light stand and a smart ZigBee-based E27 light bulb wirelessly connected to the ZigBee dongle of the hub. The components list and source code of the prototype can be found in our public repository[1].

[1]https://github.com/LOEWE-emergenCITY/SmartHomeWarningTaxonomy

Figure 2: Prototype in study condition showing an alarm on the touchscreen in addition to different visual (white, blue, red light flashing or static) and auditory (siren sound or beeping) stimuli as well as possible smartphone notifications (not shown in this image). The prototype and the light bulb are connected via Zigbee protocol.

4.2 Ethical Concerns

As warning messages can reactivate traumas or frighten people, we requested an institutional review board (IRB) approval for our study, which was granted. In addition, we implemented several precautions to avoid a harmful experience for participants which included a briefing, debriefing, and supplementary information sheets for household members. To ensure participants could follow their normal life and would not disturb other household members when leaving the home, they were able to pause the study on the touchscreen of the prototype. Even when forgotten, roommates could stop alarms with a special button. In addition, participants could withdraw from the study at any time.

4.3 Participants

We recruited N = 15 participants (6 female, 9 male, 0 diverse, aged M = 23.27, SD = 3.33) from our local university. The participants were granted 7 study participant hours for attending. Among all participants, 14 were undergrad and 1 graduate students. 1 lived alone in an apartment with multiple rooms, 3 in a one-room apartment or dorm, and 11 in a shared apartment. All were asked to use the prototype on three consecutive days during which they were mainly at home, which was possible because we conducted the study in the semester break. Participants with visual or hearing limitations, prior traumatic experiences related to warnings or catastrophes, or with household members under 18 years of age were excluded from the study.

4.4 Design

We decided for a *within-subject design*, in which participants used the prototype in their homes for three days. They sometimes received taxonomy based warnings (in which the warning properties

Table 2: Taxonomy with classes based on the criticality score of a warning and specific warning channel stimuli.

Class	W_c	Properties	Warning Channel
1	0-1	- Not time critical - Event has almost no consequences - Information rather than a warning	- Light (white)
2	2-3	- Not time critical - Ignoring the event will have minor consequences only	- Blinking light (white)
3	4	- Reaction required but not time critical - Ignoring the event for a longer time may lead to serious consequences	- Blinking light (red) - Smartphone notification
4	5-6	- Time critical reaction required to prevent damage or deterioration - Event may have serious consequences	- Blinking light (red) - Smartphone notification - Sound
5	7-9	- Immediate reaction required - Impact of the event causes serious damage and may be life threatening	- Blinking light (red) - Smartphone notification - Alarm sound

matched the stimuli), at other times non-taxonomy generated stimuli (in which the stimuli were matched to the warning at random). This represents the independent variable. We considered this approach rather than using an existing system as a baseline because no single system we analyzed covered the bandwidth of local warnings or integrated regional warnings. Furthermore, these systems did not integrate all modalities, such as smart lightbulbs, into a home environment. All participants experienced the same 30 stimuli (15 taxonomy-based and non-taxonomy-based each) but in a random order to avoid sequence effects (Table 3). Even though our taxonomy can be applied to all kinds of warnings, we chose 15 events for the study which represent local and regional warnings, consider different input modalities, represent most of the use cases the focus group mentioned, and cover the range of the taxonomy with different W_c scores. If the focus group mentioned events which were too close to each other and were only considered once, these were merged or omitted. For the control group with non-taxonomy generated stimuli, we balanced the deviation with random stimuli by either presenting a stimuli representing a higher or lower criticality score W_c or by shifting the stimuli to a different coding using a blue light. The exact calculation of each warning used can be found in the appendix.

A field study was preferred over a lab study because of the long evaluation time (three days) and realistic conditions. Besides demographic variables, we asked for the location where the prototype was installed, as well as general feedback regarding the warning modalities (audio, visual, and text-based) and a *system usability scale* (SUS) scoring:

Independent variables: Warning Messages (Taxonomy vs. Non-Taxonomy).
Dependent variables (ESM after each warning): Reaction time, warning distraction, warning modalities, warning intensity, appropriateness of visual, auditory, and mobile warning.
Demographic variables: Age, Sex, Degree, household type.
Control variables: Smart Home experience, usage of warning apps.
Ethical and study monitoring (daily): Disturbance of roommates, working prototype, stress perception, the imagination of real crisis situation.
Prototype feedback: Location of prototype, general suitability of warning channels, SUS, likelihood to activate warning messages in a smart home.

Table 3: Used warnings (15 taxonomy based, 15 non-taxonomy generated) presented to participants in a randomized order with criticality score W_c, used stimuli. Detailed warning message text and calculation of W_c can be seen in the appendix (Table 5).

		Taxonomy				Non-Taxonomy			
#	W_c	A	C	F	M	A	C	F	M
1	2		W	$\cdots$		$\sim$	R	$\cdots$	
2	2		W	$\cdots$		$\sim$	R	$\cdots$	✓
3	1		W	$\cdot$		$\sim$	B	$\cdots$	✓
4	1		W	$\cdot$		$\cdot$	B	$\cdots$	
5	2		W	$\cdots$		$\sim$	R	$\cdots$	✓
6	4		R	$\cdots$	✓		W	$\cdots$	
7	6	$\cdot$	R	$\cdots$	✓		W	$\cdot$	
8	6	$\cdot$	R	$\cdots$	✓		B	$\cdots$	✓
9	5	$\cdot$	R	$\cdots$	✓		B	$\cdot$	
10	5	$\cdot$	R	$\cdots$	✓	$\cdot$			
11	7	$\sim$	R	$\cdots$	✓	$\cdot$			
12	8	$\sim$	R	$\cdots$	✓		B	$\cdots$	
13	9	$\sim$	R	$\cdots$	✓		W	$\cdot$	
14	9	$\sim$	R	$\cdots$	✓	$\cdot$	R	$\cdot$	
15	7	$\sim$	R	$\cdots$	✓		W	$\cdots$	✓

A = Auditory stimulus ($\cdot$ beep, $\sim$ alarm siren)
C = Color of light (W = white, B = blue, R = red)
F = Flashing of light ($\cdot$ static, $\cdots$ flashing)
M = SMS (✓ SMS sent).

4.5 Procedure

We scheduled an appointment with each participant at our office to collect the prototype. Prior to the appointment, a student assistant configured the prototype with the participant's mobile number we asked them for upon registration. After reading the information sheet about the study, participants signed the consent form and were then instructed on how to use the prototype. We demonstrated how to set up the prototype and run a test alert to familiarize the participants with the different warning channels and the touchscreen-based ESM questions. They also received a manual with instructions, an information sheet for roommates, and a daily questionnaire. When at home, participants were free to find a suitable place for the prototype and the lamp (living room or other space where they spent a lot of time). They should power the device on an agreed time frame. After the prototype was plugged in, it started to present the scheduled warning messages. The warning messages were randomly assigned to time slots between 8 AM and 10 PM, with 10 warnings per day. All participants were shown the same 15 taxonomy-based warnings, as well as the same 15 assorted pre-generated non-taxonomy-based warnings in the three consecutive days (Table 3). Each event consisted of a short description of the event displayed on the touch display of the prototype (Table 5 in the appendix) and a combination of different warning channel stimuli (Figure 2). Even when the device is unplugged or the power circuit is interrupted it remains to the initially started schedule after being powered again from where it left off. For situations not being at home like shopping for groceries, or before going to sleep, participants could pause the study to avoid alarms. Previously scheduled alarms were re-scheduled and presented when checked in again if possible.

The task of the participants was to react to the alarms by acknowledging the perception of an alarm. This could be done by either pressing a button on the touch display of the prototype or by sending an SMS to the prototype after being alerted via SMS. The time needed to acknowledge the perception was measured for each alarm. A time limit of 5 minutes for each alarm was set, otherwise, the alarm was registered as missed. After each alarm, participants had to answer our ESM questionnaire on the touchscreen by giving feedback on a 5-point Likert scale each (Figure 4):

(1) Did you feel disturbed by the warning? [1 Didn't disturb me at all - 5 Disturbed me a lot]
(2) Would you like to have more warning channels for the same event in the future (e.g. additionally via SMS or alarm sound) [1 Much less - 5 Much more]?
(3) Would you like to see a more intense warning (e.g. additional channel, louder/brighter) for the same event in the future [1 Much less intense - 5 Much more intense]?
(4) Was the presentation of the visual warning (color, flashing vs. not flashing) appropriate? [1 Not at all appropriate - 5 Very appropriate]
(5) Was the presentation of sound/no sound appropriate? [1 Not at all appropriate - 5 Very appropriate]
(6) Was the presentation of the mobile warning/no mobile warning appropriate? [1 Not at all appropriate - 5 Very appropriate]

While the first three questions focus on the alert in general, the last three questions aim at receiving feedback about each warning channel individually. The participants were asked the questions in the same order as presented in the above listing. There was no time limit for answering the questions and while the participants answered the questions, the execution of further alarms was blocked. After each day, participants filled out a daily paper-based questionnaire providing feedback on the general functionality of the prototype, perceived stress, and disturbing situations in the household due to the study. Following the three days, participants brought back the prototype and filled out a final paper-based questionnaire with demographics, prior experience with smart home systems, the chosen location of the prototype and type of household, and the general eligibility of the warning messages stimuli (Speaker, Light Bulb and notification), the willingness to activate such a function in a smart home system if available and the SUS for the interaction with the prototype.

5 RESULTS

All statistical calculations are based on alpha = 0.05. Out of 15 participants, 2 had to drop out due to technical problems with the prototype, which we could not immediately fix due to the study situation at the participants' homes, resulting in N = 13 data sets. Feedback was requested after each alarm was acknowledged. In the total experimental time of 39 days, 390 warnings were scheduled, from which 331 were presented, while 59 were not shown due to participants pausing the study. Of the 331 warnings, 275 were acknowledged within 5 minutes, while 56 were missed by not acknowledging them within these 5 minutes (Table 4). The prototype logged the reaction time for alarms acknowledged by the touch screen or by a text message, the latter was used by 5 participants for a total of 11 alarms in reaction to an SMS warning.

Table 4: Number of alarms in the field study where participants tested our prototype for three consecutive days each.

Alarms	Taxonomy	Non-Taxonomy	Total
Scheduled	195	195	390
Not presented (Paused)	25	34	59
Presented	170	161	331
Missed (>5 min)	26	30	56
Acknowledged (<5 min)	144	131	275

Regarding the reaction time and ESM feedback, we calculated the mean across the 15 warnings per group (Taxonomy / Non-Taxonomy) per participant (Figure 3). We compared differences using Wilcoxon's signed rank test [47] and report the median for each group and provide the effect size. There was no significant difference in reaction time between taxonomy based alarms (Mdn = 31.16) and non-taxonomy based alarms (Mdn = 23.25), p = .455, r = -.207. Among the events missed, the median W_c score (from 0 to 9) was Mdn = 2 (Class 2 in our taxonomy) in the taxonomy-based group and in Mdn = 5 in the non-taxonomy group. The reaction over all events was 35 seconds on average.

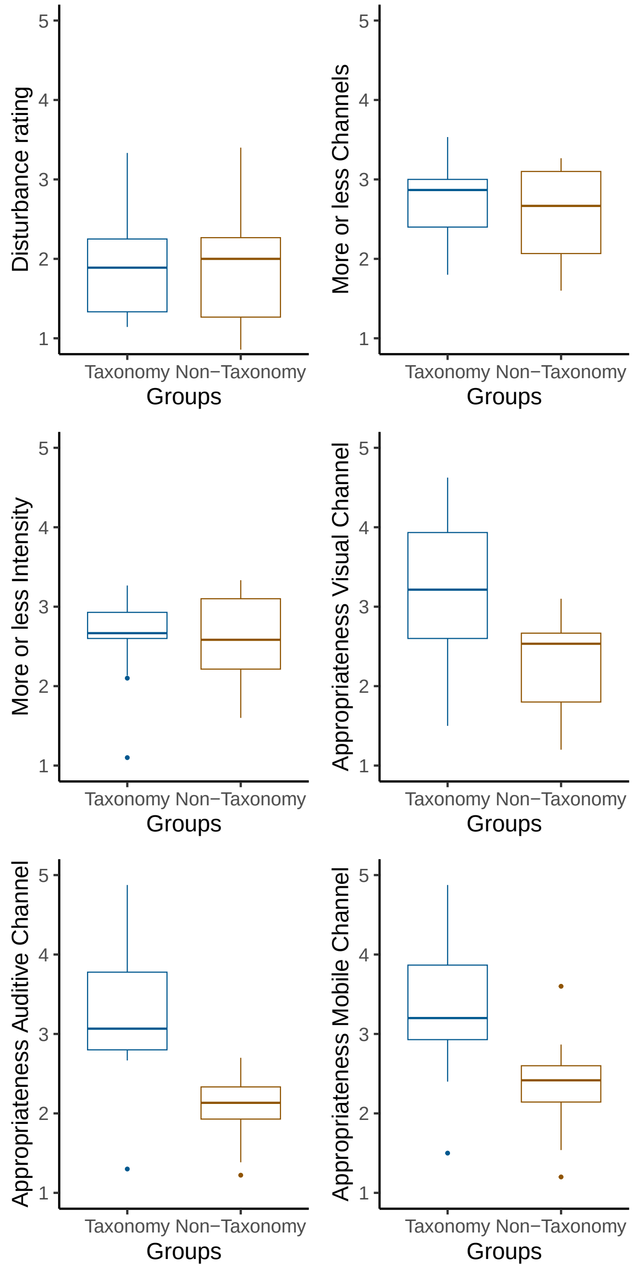

Figure 3: Feedback by participants regarding the ESM questions, which were answered after each alarm. Plot based on mean across the 15 warnings per group (Taxonomy / Non-Taxonomy) per participant.

Participants were asked whether they felt disturbed by each warning. The disturbance rating was close in both groups (Taxonomy: Mdn = 1.89, Non-Taxonomy: Mdn = 2). There was no significant difference concerning the distraction between taxonomy and non-taxonomy based alarms, p = .484, r = -.194. Asked whether they would have liked more warning channel stimuli for the same event, there was no significant difference in warning modalities between taxonomy-based alarms (Mdn = 2.87) and non-taxonomy-based alarms (Mdn = 2.67), p = .305, r = -0.284. Similarly, there was no significant difference in perceived warning intensity between taxonomy based alarms (Mdn = 2.67) and non-taxonomy based alarms (Mdn = 2.58), p = .946, r = -.018.

In contrast, significant differences were found regarding the appropriateness rating of the alarms between groups: The visual stimuli were rated significantly more appropriate when delivered in accordance with the taxonomy (Mdn = 3.21) rather than at random (Mdn = 2.53) p = .000488, r = -.967. The same is true for the auditory stimuli (Taxonomy: Mdn = 3.07, Non-Taxonomy: Mdn = 2.04), which were rated significantly better for the taxonomy based alarms than the non-taxonomy based ones, p = .002099, r = -.853. The smartphone notification stimuli via SMS or no SMS were also rated as more appropriate with taxonomy based warnings than with non-taxonomy based warnings (Taxonomy: Mdn = 3.2, Non-Taxonomy: Mdn = 2.42) with a significant difference, p = .00371, r = -0.805 (Figure 3).

To measure the burden and impairment of co-inhabitants for the study, we logged whether alarms were turned off by roommates and asked participants daily about their perceived stress, which would have allowed us to terminate the study in case of an ethical problem. Only one event was turned off by a roommate and it was also mentioned in the daily questionnaire of the affected study participant, but the study could be continued without problems, and no further events were stopped by roommates. The personally perceived stress level due to the experiment was rated low on a 5-point Likert scale rated in the daily questionnaire (M = 2.13, SD = 0.8). To check if the participants were biased towards or against smart home systems and what smart home technologies they used, we asked them in our final questionnaire: Our sample of 13 participants was balanced regarding prior and current smart home experiences where at least 8 do not use smart home devices: Asked if participants are familiar with the term "Smart home" on a 5-Point Likert scale, they indicated moderate familiarity (M = 3.46, SD = 0.78). Asking for prior experience with smart home technology, participants are in the middle (M = 2.92, SD = 1.19). Asking what type of smart home technologies, the 13 participants use (multiple answers allowed), 2 use it to connect and control devices, 3 use it to control lights, 2 use it for smart home appliances, 3 for entertainment, and 8 answered not using smart home technologies.

We then also asked participants where they had installed the prototype in their homes. They had been free to choose and allowed to find separate places for the prototype and the light bulb. Participants had mainly chosen the bedroom (6), desk (2), own room (1), hallway (1), and living room (3). Regarding the experience with governmental warning apps, 4 (17.30 %) use them on their smartphone, while 9 do not, which is close to the average of 21 % in 2019 [14]. With the final questionnaire, we asked participants for general feedback on the prototype. The SUS score for prototype usage was high (M = 88.46, SD = 7.81). Asked if they would activate such a feature in a smart home system, participants rated it as very likely (M = 4.08, SD = 0.95, a 5-point Likert scale). In the daily questionnaire, participants were similarly positive about the usefulness of the prototype (M = 4.23, SD = 0.71) on a 5-point Likert scale, when imagining that the warnings had been real. When asking for feedback about the warning channels in general, the speaker was rated as most suitable (M = 4.54, SD = 0.52), followed by the mobile SMS warning (M = 4.15, SD = 1.07), with some distance to the suitability of the lamp (M = 3.38, SD = 1.12).

6 DISCUSSION

The results show that the taxonomy was rated significantly better regarding the appropriateness of all warning channels compared to the non-taxonomy-based alarms. This shows that the taxonomy worked in this setup. Together with the good SUS score and acceptance rate, the SHWS prototype indicates what suitable warning stimuli in smart households could look like. As a novelty, our taxonomy brings together local IoT-sensed warnings and regional warnings (e.g., from civil protection), mapping them all together into simple output modalities that can be easily used in an off-the-shelf smart home system. Compared to other approaches [35], we show that the differentiated use of multiple warning channels is feasible and makes sense. Often, these systems aim to warn of a potentially life-threatening events only, that requires an immediate response (class 5 of our taxonomy). However, these systems often have an acoustic warnings only [31], which can vary in intensity (horn and bell sound). As the results of our work show, however, an additional visual warning and an SMS-based warning would be useful from the user's point of view. We hope that the taxonomy can help future work to improve and evaluate the output channels of SHWSs. Having a two-step approach, first having a guided brainstorming with a focus group and then conducting the field study helped us to develop the Taxonomy where there had not been any prior work proposing a taxonomy in the field of SHWS. Our experiences from warnings in crisis research were only partially transferable because we knew a lot about crisis events, but not about the experience with IoT based output modalities. The focus group helped us to widen the lens but also come back to break it down to a very simple equation to conduct the field study. The field study itself helped to test our prototype in real environments conducting application-oriented research. We think that the results indicate that there is a lot of potential with public warning integrated SHWS as demonstrated with our prototype, and the taxonomy a valuable contribution to designers of domain specific SHWS, although further development needs to be done.

6.1 Missing Alarms and Ethics

There was no significant difference in disturbance rating and the rating of the number of warning channels and intensity between taxonomy-based alarms and non-taxonomy alarms. This shows that both conditions were comparably weighted and the warning channels fit. One might think that the non-taxonomy based warnings should be less or more intense than other warning channels, but that would have implications on non-taxonomy warnings, in general, to be too far away from a realistic setup, easily having a better rating for the taxonomy based alarms. That the alarms were not perceived as too disturbing is not only due to comfort reasons, but is also to be considered ethically that no harm should come from a SHWS. Because SHWSs touch upon the home as an intimate safe space for people, questions arise beyond the feeling of being disturbed by a non-critical warning. These questions ask for social and psychological answers on how constant signal cues affect us in our homes. However, these questions exceed the scope of this paper.

That alarms were noticed in a short reaction time with 35 seconds on average shows that the SHWS can warn for critical events within time. Nevertheless, 16.91 % (56) of the alarms overall and 15.29 % of the alarms based on the taxonomy were not acknowledged within 5 minutes. The median criticality score of the unconfirmed taxonomy-based alarms (N = 26) is 2, suggesting that mainly weaker alarms went unnoticed for 5 minutes. According to our taxonomy, these events are not classified as time-critical, indicating that missing these alarms would not result in harm.

6.2 Integration of Smart Home Warning Systems

The overall positive evaluation of the prototype indicated an interest in implementing a SHWS in households. With the result, that the majority would activate such a system in a smart home, interesting conclusions about the perception and needs of the users have been given. That is not only about the warnings itself, but also about the location of the system, where we have seen the different installation locations of participants, and the distribution of the warning channels in the apartment.

While some people might not prefer to install an alarm system in their home or their landlord might not allow to do so, many people already have the hardware installed, but the software and the application is missing. People who already have at least a smart speaker and smart light bulbs, could, without further investment, upgrade their homes to a warning system level that could save lives. Precisely because our prototype works with warning channels that can be found in nearly every smart home that contains smart lamps and a voice assistant, it would be easy to implement at least the output of regional warnings such as severe weather or terrorist attacks, even without local sensors available to detect danger. Many of these regional warnings are available via public API [16]. Text messages of our prototype can also be substituted with other push notifications using messenger apps [26]. In addition to issuing alarms, it is also conceivable that such a SHWS could react proactively by controlling locks, shutters or switching off household appliances. Since our study only used one lamp and one speaker and could thus only warn one location at a time, it would be exciting to investigate the potential of using several smart lamps and several smart speakers, as they are found in many households.

6.3 Taxonomy

Beside technical variations and different setups, the taxonomy we developed could be tested against mentioned setups, other user groups, more warning scenarios, and advanced regarding the calculation of the criticality score W_c. The field of public warnings and IoT based SHWS can both benefit from each other's experience and a clear guidance of output modalities for users' homes from HCI perspective. We think that it is important to consider warnings more holistically and not rule out regional warnings in the context of SHWS as they threaten inhabitants the same way local warnings do. While the taxonomy development is not finished by our work, it creates a domain independent common ground for all kind of works in the field of SHWS, such as usability patterns in interaction design. Regarding the equation of W_c, in line with the focus group, we did not implement weights for each factor, which can result in situations, where the criticality score W_c does not help alone. This particularly the case, because "Safety Failure of the System" (f) is dependent on the individual local setup, where we propose a weighting factor in the future. But as the warning is also provided with a text, the taxonomy based stimuli should lead to an initial reaction with a appropriate integration in everyday life, still allowing users to read the message to gather more details.

6.4 Different Needs and User Groups

One case we mentioned as a possible scenario is a medical problem (e.g. detected by a smartwatch or fall detection), where it would be interesting to see how an alert can be triggered for the rest of the co-inhabitants by having warning channels that do not worsen the panic level of a sick person but also relatives or housemates [36]. As it is crucial that a warning alerts everyone, SHWS should alert everyone and in the best case compensate disadvantages that smart phone based warnings or notifications have. Elderly people could be a first key group for future studies, to test if they need more configuration possibilities than just changing intensity (loudness, brightness) of the stimuli used in our study. But also unconventional warning channels which our focus group came up, e.g., vibrating mat for a bed could be evaluated, when evaluating the taxonomy at night or with users who are hearing or vision impaired.

6.5 Limitations and Outlook

Our auditory stimuli deliberately avoided the use of voice outputs. In the current paradigm of smart home systems, voice assistants are reactive rather than proactive, which is partly due to the problem of first determining whether a user is present. Another interesting aspect to explore would thus be whether sensory data could be used to send targeted alarms to the locations where inhabitants are currently located. Using VUIs as proactive devices [46], warnings could not only be vocalized, but also feedback or questions can be expressed which could be particularly interesting user groups who can more easily interact via voice. Although we tested warnings via smartphone notification, it is technically possible to warn people on the move with our prototype, however, we focused on warnings at home. We found that warnings sent to the smartphone were accepted and rated positively, even when being at home. The situation in the homes of participants among types and roommates had a variety and was also biased towards typical living situations of younger people. Studies with other living situations and how to present different warnings for different household members is an interesting research question to follow up. Finally, despite the goal of serving all citizens and accommodating all levels of prior experience, the taxonomy was evaluated with subjects who were students between 20 and 30 years old in the Global North, and who had both prior experience and no prior experience with smart homes.

Nevertheless, it would be exciting to see if SHWSs notice whether a person is not at home and switches warning channels to smartphone notifications combined with sensory data from the home by, e.g., providing a temperature value or camera image. A longer study period and the inclusion of all smart lamps in an apartment could also provide exciting insights into the effects of habituation and integration into everyday life. For these situations, future studies with an improved prototype would be useful. However, the technical effort required to equip an entire apartment is enormous. In general, a more detailed evaluation of the influence of SHWS on emotions, thoughts, reactions, and social structures in homes could help to better understand the quantitative findings.

7 CONCLUSION

The goal of this work was to elaborate guidelines for further research in the field of SHWSs regarding the choice of suitable warning channels. SHWSs receive and process sensory input from the home as well as external data, e.g., from governmental crisis warnings, triggering alarms using different actuators to warn inhabitants or adapt the house to the situation. As there are many examples of such systems, the output stimuli are often not evaluated or do not consider the possibilities of a smart home. We established a taxonomy of smart home warning systems based on three key properties of modern warning systems that were derived from literature research and a focus group workshop: *Impact of the Event* (i), *Time Criticality of Reaction* (t), and *Safety Failure of the System* (f). The taxonomy divides warnings into five classes based on a scoring of the key properties, suggests suitable warning stimuli and can be used for further research and implementations in the domain of SHWSs. To further evaluate the taxonomy, we developed a Raspberry-Pi based prototype of a SHWS that provides auditory, visual, and text-based warnings that participants used at home for three consecutive days. Participants evaluated in total 331 alarms using ESM. The analysis of the results shows that the alarms that use warning channels according to the taxonomy are rated significantly more appropriate than non-taxonomy-based stimuli. Future research needs to be done to further evaluate the taxonomy in more complex or long-term scenarios considering other user groups, more ubiquitous setups, or additional output modalities.

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Table 5: Used warning messages presented to participants with details about the data source (local or regional), the criticality score (W_c) calculation determined by the factors Potential Impact of the Event (i) + Time Criticality of Reaction (t) + Safety Failure of the System (f) and the resulted taxonomy class. All 15 warning messages were used with taxonomy based and non-taxonomy stimuli in the within-subject design.

#	Input	Class	i	+	t	+	f	=	W_c	Warning Message
1	local	2	1	+	1	+	0	=	2	The tulips in the garden urgently need water
2	local	2	0	+	2	+	0	=	2	Robotic vacuum cleaner is defective and can not continue to work
3	local	1	0	+	1	+	0	=	1	The sewage pipe is heavily calcified
4	local	1	0	+	1	+	0	=	1	Low level in the heating oil tank
5	local	2	0	+	2	+	0	=	2	Exterior lighting of the garden house is defective
6	local	3	2	+	2	+	0	=	4	Pressure in the water pipes in the house is extremely low
7	regional	4	3	+	3	+	0	=	6	A severe storm (heavy rain and thunderstorms) is expected in a few hours
8	local	4	3	+	3	+	0	=	6	Suspicious data traffic in the home network (potential cyber attack)
9	local	4	2	+	3	+	0	=	5	Water intrusion in the basement
10	local	4	2	+	3	+	0	=	5	Several roof tiles damaged
11	regional	5	4	+	3	+	0	=	7	Large fire in nearby church (heavy smoke)
12	local	5	4	+	4	+	0	=	8	Gas leaks in boiler room
13	regional	5	4	+	4	+	1	=	9	Earthquake (warning by early warning system)
14	regional	5	4	+	4	+	1	=	9	Danger of flooding in the next few hours (severe flooding)
15	local	5	3	+	4	+	0	=	7	Fire in the garage

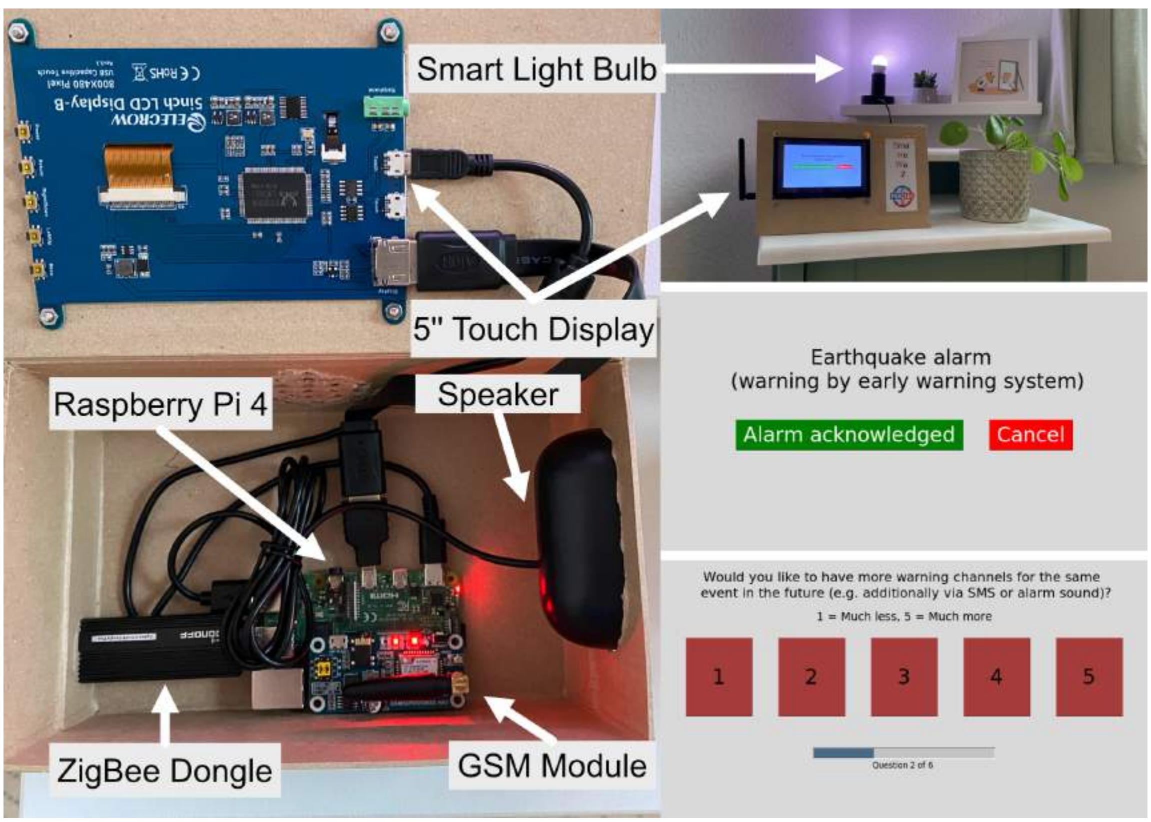

Figure 4: Left: Smart home warning system prototype based on a Raspberry Pi with a GSM module for sending and receiving SMS, a Zigbee dongle to control a smart light bulb, an integrated speaker, and a 5-inch touch screen. Right-Top: Prototype in the study situation showing an alarm. Right-middle: Display while showing an alarm. Right-bottom: Evaluation screen after acknowledging an alarm.