Indoor Photovoltaic Interactive Surfaces for Sustainable Smart Home Control: Gesture Design using Guessability and Production Methods

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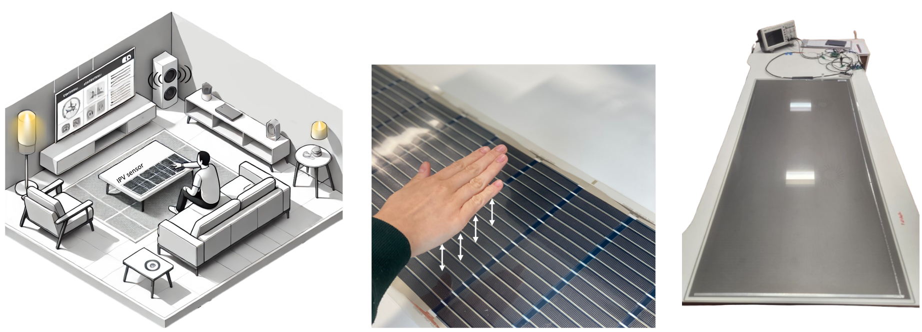

(a) (b) (c)

Fig. 1. (a) A user controls a smart home device (i.e., selects and turns on lights) by moving his or her hands above the coffee table, which incorporates an Indoor Photovoltaic (IPV) sensor to recognize appropriate user-defined registration and control gestures. (b) A user performs a gesture with the hand movement casting a shadow on the IPV sensor, which generates a gesture signal. (c) A semi-transparent IPV tabletop as shown in (a).

Indoor photovoltaic materials are novel low-cost light sensors that can be flexible, decorative, self-powered, and battery-free, and can be embedded in various surfaces throughout the home. They offer a unique opportunity for contextual control of multiple different devices in a smart home using guessable and favorite gestures. Currently available gesture vocabularies are survey-based and sensor-agnostic, but still require experimental validation. Therefore, we present experimentally generated and validated original gesture vocabularies using two user elicitation methods, the *guessability* and *production* methods, for such sensors. The capabilities of the sensor was used to prime participants for design thinking to *multi-control* smart home devices. We provide guidelines for designing gesture vocabularies using the two elicitation methods and report on their similarities and differences. The methodological findings and experimentally validated gesture sets would inform HCI

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ACM 2573-0142/2025/12-ARTISS003
https://doi.org/10.1145/3773060

researchers in the design of user-elicited interactions for such versatile light or electromagnetic field sensors and similar gesture-driven applications.

CCS Concepts: • **Human-centered computing** → **User studies**; **User centered design**; **Gestural input**.

Additional Key Words and Phrases: Indoor Photovoltaic Materials; User-defined Hand Gestures; Elicitation Study; Gesture Guessability; Gesture Production; Interactive Surface; Smart Home Control

ACM Reference Format:
Nora Abdullah Almania, Sarah Yousef Alhouli, and Deepak Ranjan Sahoo. 2025. Indoor Photovoltaic Interactive Surfaces for Sustainable Smart Home Control: Gesture Design using Guessability and Production Methods. *Proc. ACM Hum.-Comput. Interact.* 9, 8, Article ISS003 (December 2025), 23 pages. https://doi.org/10.1145/3773060

1 Introduction

Smart home devices such as televisions, speakers, lights, air conditioning/heating, ovens, security cameras, etc. can be conveniently controlled through their dedicated smartphone applications or voice assistants. However, such interaction methods may become increasingly cumbersome [103] or less preferred due to security and privacy concerns [28] when controlling multiple different types of devices shared by multiple different types of users. Expert users may often prefer to use smartphone applications, while others may be more satisfied with traditional methods such as dedicated remote controls or traditional physical controls on the device control panel. Gestural interfaces for controlling smart home devices are gaining popularity due to their convenience and accessibility. Gesture control is seen as an innovative and futuristic way to interact with smart home devices. A gestural interface that can be conveniently placed or embedded on surfaces around the home to control multiple different types of smart devices could be highly desirable. Imagine people in the home being able to select and control the cooker, oven, the lights, etc., smart devices by moving or hovering their hand over the kitchen countertop or the coffee table with gestures without wearing a control device [45].

There are many sensors that enable hand gesture interaction, such as an ordinary camera [34], an infrared camera [39], a time-of-flight camera [100], an acoustic system [66], an ultrasonic Doppler sensor [70] and a lidar [45], etc. These sensors are relatively expensive and cannot be embedded or installed on many surfaces in a house. Recently developed Indoor Photovoltaic (IPV) materials are inexpensive [48] and have been used for indoor light energy harvesting and to power many other sensors to create self-powered [18] and battery-free [67] 'internet of things' sensors for smart homes. The IPV materials can be flexible [69] and decorative [7, 80], and can be placed or embedded on many surfaces in a home. They may be used as large area light sensors for hand gesture recognition [4, 75], and users may prefer to use them for smart home control [3, 55]. To this end, we have explored the contextual control of multiple smart home devices by multiple users using such an embeddable IPV tabletop sensor and a gesture vocabulary, i.e., by performing a unique 'registration' gesture to select a device and then performing distinct 'control' gestures to operate the device.

The design of gesture vocabularies has been a focus of HCI research to make interaction more intuitive and user-friendly [93]. Gesture vocabularies have been designed using expert-led, user-led or computationally based methods [102]. User-led gesture design could help to achieve 'preferred' gesture vocabularies that are more learnable, memorable and discoverable by target users than expert-led designs [27, 59, 60, 72, 99, 102]. The *guessability* method [98] has been widely used to generate user-defined gesture vocabularies in a wide variety of devices, applications, environments and usage contexts [19, 52, 56, 87, 88]. It recommends first presenting the 'effect' of a gesture (or a 'referent'), and then asking users to perform its 'cause' (or a gesture) in order to collect user-defined gesture suggestions. This method is often used to create a gesture vocabulary targeted at interacting with or controlling a specific device [37]. To control multiple devices from a single IPV interactive surface as a multi-controller, a more universal gesture is required for which we present a more generalized guessability method [20, 27, 90, 91].

The one-to-one cause-and-effect approach may not be the most effective way to create such a versatile gesture set that is also users' favorite. In this respect, the *production* method allows users to suggest multiple gestures for each referent and to nominate their favorite gesture [58]. Gesture elicitation studies in the literature have not examined the guessability and production methods together. There is a lack of direct comparisons of the similarities and differences in their outcomes and guidelines. The two methods aim to create gestures with two different core characteristics: guessable versus favorite. Therefore, we pose the following research questions: (RQ1) How do the guessable and favorite combinations of gestures and referents found using the two methods compare?, and (RQ2) How do users' levels of agreement differ for the matching combinations of gestures and referents found using the two methods? In the production method, participants are primed using various techniques that lead to more creative and reflective gesture suggestions and reduce legacy bias – the tendency for participants to suggest gestures influenced by previous technological interactions [16, 25, 35, 42, 51, 53, 54, 57, 58, 63]. Popular priming techniques are the use of prerecorded videos or the Wizard of Oz technique to present the referents or effects [1, 57]. It is not clear what priming techniques could be used with new sensor technologies and new form factors [58]. We therefore propose a priming technique that asks participants to create different shapes of signals by playing with arbitrary hand movements to explore the capabilities of the sensor. However, a traditional lab-based elicitation study with a typically smaller number of participants is not recommended for validating a priming technique (with a priming and a no-priming control group), as it may not produce statistically significant results [1, 35]. Therefore, we pose the following research questions: (RQ3) To what extent is the legacy bias effect reduced in the production method compared to the guessability method?, and (RQ4) What design guidelines can be derived through a direct comparison of the two methods? We explore these research questions while designing a gestural interface using the IPV sensor.

In this paper, we investigate the use of an IPV sensor as a multi-controller for user-agnostic smart home control via contactless hovering surface interaction. Taking a holistic approach, we design user-elicited gesture vocabularies by applying the *guessability* (one gesture suggestion for one effect) and *production* (many gesture suggestions for one effect) methods described by Wobbrock et al. [98] and Morris et al. [58], and experimentally validate their usability. We contribute the following:

(1) user elicited and experimentally validated agreed, popular, and primitive dynamic hand gestures for hovering surface interaction in the smart homes context,
(2) a comparison of guessability and production methods for creating dynamic hand gestures,
(3) guidelines for designing new dynamic hand gestures using the gesture vocabulary.

2 Related Work

2.1 Indoor Photovoltaic Gesture Sensing Technologies

Recently, Indoor Photovoltaic (IPV) technologies have been demonstrated as systems using the light energy harvesting principle, which has been applied to various applications, leading to future sustainability [24]. Photovoltaic (PV) cells utilize the PV effect to convert natural sunlight and artificial indoor light into electricity [49]. PV cells have been used in many HCI applications. For example, ultra-thin PV cells have been used in a flexible, wearable wristband designed for electromyography (EMG) gesture sensing for healthcare applications [40]. Similarly, XSolar is a (PV) solar cell-based gesture sensing system that also uses a self-powered wearable device to detect hand gestures. Their system uses a cross-model framework that captures hand gestures through the light variations that generate PV current variations [101]. An ultra-low power smart camera was used to sense hand gestures, which is powered by PV cells harvesting ambient light [5]. SolarSense is another self-powered gesture recognition system that uses solar cells to detect gestures. These cells demonstrate the versatility of using the PV technology for power generation and gesture sensing, providing a sustainable approach to HCI [47]. Recent studies have emphasized the use of IPV cells for the purpose of decorative interactive surfaces such as PV-Tiles and PV-Pix [55, 71]. Previous related work has shown how self-powered technologies have been used in various devices, making these PV materials more popular for gesture sensing. However, there is no prior research that has explored large area IPV sensors as indoor interactive surfaces or to control multiple different devices such as in a smart home. There is no prior research to create hovering or dynamic gesture vocabularies suitable for IPV-type electromagnetic field sensors.

2.2 On Gesture Elicitation Methods

Elicitation methods are a popular user-centered or participatory design approach [9, 11, 17, 31, 38, 41, 44], allowing participants to shape their technological futures [89] and designers and developers to gather requirements to build a user-derived interface [30] or to draw on the "wisdom of the crowd" for interaction or gesture design [102]. Williams and Ortega [97] have provided a comprehensive, concise guide to the methodological foundations of gesture elicitation methods by highlighting a framework for designing and analyzing gesture-focused elicitation studies. Nielsen et al. [64] have presented the basic principles of gesture elicitation through participatory design, such as finding the functions (or effects, referents, outputs), collecting gestures from users, extracting gesture vocabularies, and testing for guessability, memory, and stress. Wobbrock et al. [98] then proposed to maximize the guessability of a referent by collecting gestures (one gesture per referent) from participants and presented an 'agreement' formula to evaluate and analyze the guessability elicitation data [83]. Wobbrock et al. [99] thus formalized the guessability method by generating user-defined multi-touch gestures for tabletop interaction. They used recorded animation and speech in the experiment, restricted users to suggesting one gesture per referent, did not allow users to see all referents before starting, and did not allow users to change their suggestion by going back, in order to maximize guessability. This approach is widely used as the standard method for gesture elicitation for interactive surfaces such as touchscreen [77], public display [72], on-body [19] and in interactive spaces [10, 56] and devices such as mobile phones [104].

Morris et al. [58] suggested a different approach – conducted the elicitation study in a group (partners), introduced the referents at the beginning of the study, allowed participants to suggest more than one gestures (production) and asked participants to think and imagine the capability of the gesture sensor (priming). The priming technique also varies in the related work. For example, participants were primed by showing them gestures outside computing scenarios (e.g., by sports referees) [58]. Hoff et al. [35] used covert kinaesthetic priming and made participants to do some physical activities. Also, Chan et al. [16] showed various tap and swipe etc. gestures for priming, and the gesture vocabulary consisted of similar tap and swipe etc. gestures. Moreover, Williams et al. [94] have utilized the elicitation production method to explore its impacts on the legacy bias. The authors found that legacy bias was reduced within the production technique by moving beyond their initial and familiar proposal as participants proposed more than one gesture for each referent, causing later proposals to be less biased. Recently, Danielescu and Piorkowski [25] reported that 34% of participants' preferred gestures occurred after the first three gestures and that limiting production may prevent participants from finding their preferred gestures, as they investigated unlimited production techniques within their elicitation study. Priming and production have helped to reduce legacy gestures, but often marginally and not statistically significantly [35], even negatively affecting the agreement rates [16] and reducing the consensus on preferred proposals [94]. The existing literature has used elicitation techniques to compare different scenarios, for example, elicitation on different types of surfaces that take into account the properties and texture of the surface (i.e., rigid and soft) [15] or moderated and unmoderated elicitation methods that consider the researchers' supervision on the study [14]. However, the two elicitation methods *guessability* and *production* have not been investigated together in the literature.

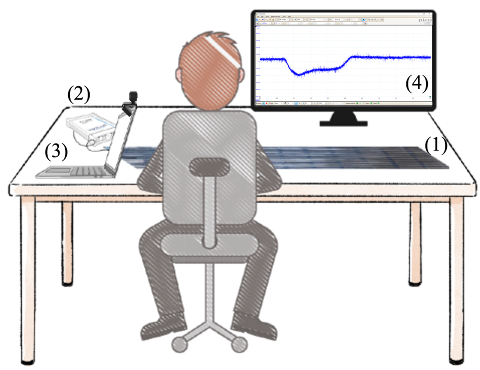


Fig. 2. Experimental setup: (1) A flexible IPV light sensor, (2) an oscilloscope, (3) a laptop with a USB camera placed on top to record the session, (4) a PC monitor to view the gesture signal.

3 User Elicitation of Gestures

Experimental setup: The experimental setup shown in Fig. 2 was used in both guessability and production gesture elicitation studies. The IPV sensor is a 110 cm long and 28 cm wide unfurled sheet (infinityPV). The IPV sensor generates gesture signals from the subtle variations in light intensity across its surface from the distinct shadow patterns and temporal signature of each gesture, which modulates the current and voltage output of the sensor. The detection signal is a one-dimensional time series data collected from the two electrodes, i.e., the positive and negative terminals. We recorded the signal using a digital oscilloscope (PicoScope 5442D) and displayed it on a PC monitor to allow participants to visualize and verify that the gesture signals were perceptible. A laptop with a USB camera was used to record the session, e.g., the hand gesture video and the think-aloud audio. The IPV sensor is particularly suited for *dynamic hovering* (non-contact) gestures which are more comfortable to perform than similar contact gestures. For example, swiping or moving a hand from left to right would be similar contact/non-contact gestures, but the hovering action is more comfortable. We asked the participants to explore such gestures in the elicitation studies.

Participants: We conducted both guessability and production studies with different groups of participants. We recruited 20 non-experts (10 female and 10 male; aged 26−35 years, *mean* = 28.4, *std.* = 6.2) and 25 new non-experts (15 female and 10 male; aged 26−35 years, *mean* = 29.4, *std.* = 4.6) for the guessability and production studies, respectively, from the university campus through an open call for participation via physical and digital advertisements. We chose this sample size because it is the most popular option in the literature [88]. None of the participants had previously used IPV sensors or had experience with gesture elicitation studies. In both studies, only two participants were left-handed, and rest were right-handed. The studies were designed to last for approximately one hour. The experiment was approved by our university's the independent ethics committee.

Informed consent was obtained from the participants after an initial briefing at the start of the session.

Guessability study: The guessability study was designed using common smart home devices (15) and their commands (18) that we found in the literature [6, 12, 14, 22, 29, 33, 36, 37, 44, 50, 76, 91]. This resulted in 78 referents (see Fig. 3 and Fig. 4) with 15 device registration commands and 63 device control commands. Participants were given the 78 referents in the text format [95] in random order on a sheet of paper. The referents were randomized uniformly across the 20 participants to minimize bias [94]. Participants were instructed to design unique device registration gestures that could be used to independently select a particular smart home device regardless of context at any point in the interaction, and distinct control gestures in the context of the device to control it. They were also asked to look at the PC monitor for a noticeable change in the signal while suggesting the gestures, without worrying about the uniqueness and distinctiveness of the waveform. In the end, we obtained $20 \times 78 = 1560$ gestures from the guessability study.

Production study: The production study was conducted after the guessability study with new participants. In order to limit the study to one hour, it was designed after considering the 15 smart home devices from the guessability study and the literature [91, 92] that could possibly allow capturing all or more of the gestures found in the guessability study. We selected the 3 smart home devices TV, lights, and audio/video players with speakers (AP.VP.S) and 22 referents, all of which were control commands. We did not choose registration commands because of time constraints and also because the production method allows participants to suggest an unlimited number of gestures, which would lead to low agreement rates with different icons and symbols suggested for device registration, as found in the guessability study. Before starting the gesture design session, we conducted a short *priming* session, in which we asked the participants to playfully create innovative shapes of waveforms with arbitrary midair hand gestures. We suggested, they start with simple, natural and intuitive gestures and observe the IPV signal shown on the PC monitor and then try to create newer waveforms. The real-time signal visualization not only demonstrated the capabilities of the sensor to the participants but also provided real-time feedback to think creatively. Participants were then given the 22 referents in the text format [95] in random order on a sheet of paper. The referents were randomized uniformly across the 25 participants to minimize bias [94]. Participants were asked to look at the PC monitor for a noticeable change in the signal while suggesting the unlimited number of gestures for each referent, but also to try to create unique and distinct waveforms in the IPV signal for subsequent gesture suggestions for each referent. In the end, we obtained 1055 gestures from the production study.

4 Results

4.1 Gesture Vocabulary

After labeling the 1560 and 1055 gesture proposals from the guessability and production methods, we used the binning procedure in [105] to combine the similar gestures into equivalence groups. For the equivalence criteria, we considered left or right hand use, flat or angled hand pose, palm direction, hand position, and area covered, etc. as equivalent. The binning analysis resulted in 147 and 144 *distinct* gesture proposals for the guessability and production methods, respectively. We conducted two different agreement analyses for the two studies, and propose and compare three vocabulary gesture sets – (1) the “Agreed” gestures for control and registration commands (see Figs. 4 and 5), which are based on the agreement rate of each referent, (2) the “Popular” gestures (Fig. 6(a)), which are control gestures frequently suggested by the participants, and finally (3) the “Primitive” gestures (Fig. 6(b)), which are the basic components of the agreed and popular registration and control gestures.

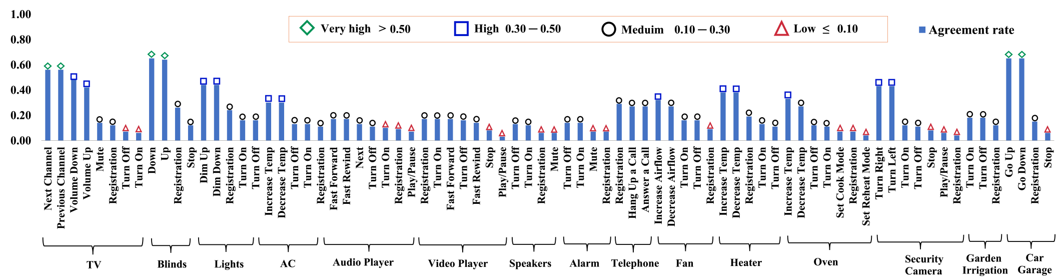


Fig. 3. The agreement rate (sorted from highest to lowest values) for each referent for each device from the guessability study is shown. Markers of different colors and shapes indicate very high (green diamonds), high (blue squares), medium (black circles), or low (red triangles) level of agreement.

Guessability study analysis: We followed the agreement analysis method in [82, 99] and AGATe toolkit to calculate the Agreement Rate (AR) for the 78 referents in the guessability study, and show them in Fig. 3. The level of agreement is indicated as low (AR≤0.1), medium (0.1<AR≤0.3), high (0.3≤0.5) and very high (AR>0.5), according to [82] (see Fig. 3). In the guessability study, out of 78 referents, 6 (8%), 12 (15%), 41 (53%), and 19 (24%) referents have very high, high, medium, and low agreement, respectively, which means that consensus was reached for 18 (23%) out of the 78 referents in the guessability study. The level of agreement did not seem to depend on the number of referents per device (see TV vs. Audio Player, and Blinds vs. Garden Irrigation).

Production study analysis: The agreement equation and analysis used in the guessability method are not suitable for the production method due to the unlimited number of gesture proposals for each referent [2]. Therefore, we followed the agreement analysis procedure in [57] and calculated for each referent the max-consensus (i.e., the percentage of participants suggesting the most popular gesture for the referent) and consensus-distinct ratio (i.e., the percentage of the distinct gestures proposed for the referent by at least two participants) metrics [25]. Nine out of 22 (41%) of gesture-referent combinations had a max-consensus greater than 0.3, meaning a high consensus, compared to 23% high consensus reached in the guessability study.

1) Agreed gesture set: We then obtained the agreed 'control' gestures with the associated control referents for the guessability study following the procedure in [82, 99], and show them in Fig. 4. We found 11 agreed gestures for the 78 referents to control the 15 smart home devices. All of them were also the most frequently proposed gestures (popular) for the referents. The G1:'Move down' and G2:'Move up' were the most frequently proposed gestures, followed by G3:'Move right' and G4:'Move left'.

The agreed 'registration' gesture set for registering the 15 smart home devices for the guessability study is shown in Fig. 5. The agreed gestures used letters to represent the devices and were different from the gestures used to control the respective devices. The number of participants out of the 20 who proposed them and the level of agreement are (RG1) "T" (11; 0.29) for telephone; (RG2) "B" (10; 0.26) for blinds; (RG3) "L" (10; 0.24) for lights; (RG4) "H" (9; 0.19) for heater; (RG5) "V" (8; 0.17) for video player; (RG6) "C" (8; 0.15) for car garage; (RG7) "TV" (7; 0.13) for television; (RG8) "G" (7; 0.12) for garden irrigation; (RG9) "AC" (6; 0.11) for air conditioner; (RG10) "F" (5; 0.09) for fan; (RG11) "A" (6; 0.09) for audio player; (RG12) "M" (3; 0.07) for alarm; (RG13) "E" (2; 0.07) for oven; (RG14) "S" (5; 0.06) for speakers; and (RG15) "SC" (4; 0.04) for security camera. The agreed registration gesture set had no consensus gesture because they had medium to low agreement levels, i.e., there are no registration gestures that received high or very high agreement rates.

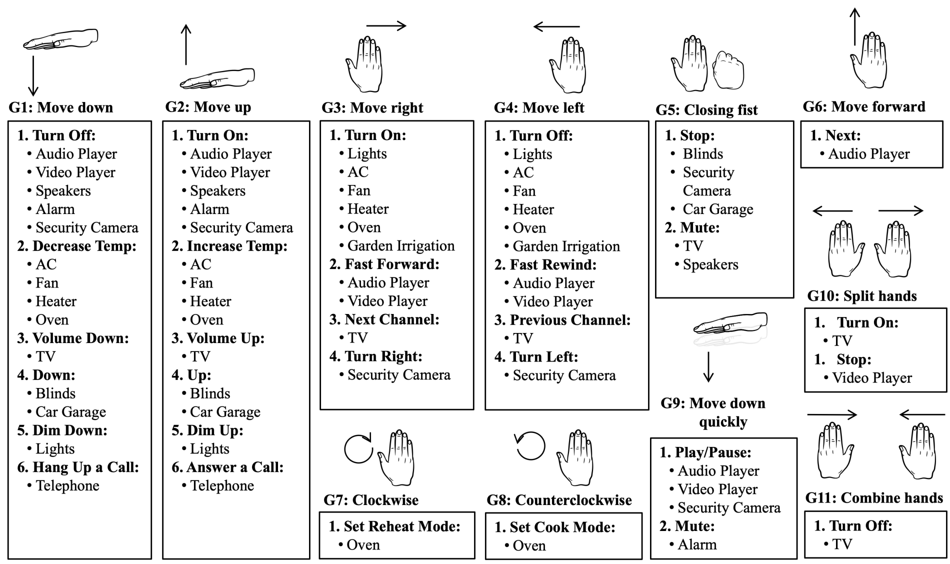


Fig. 4. The agreed gesture set to control 15 smart home devices is shown.

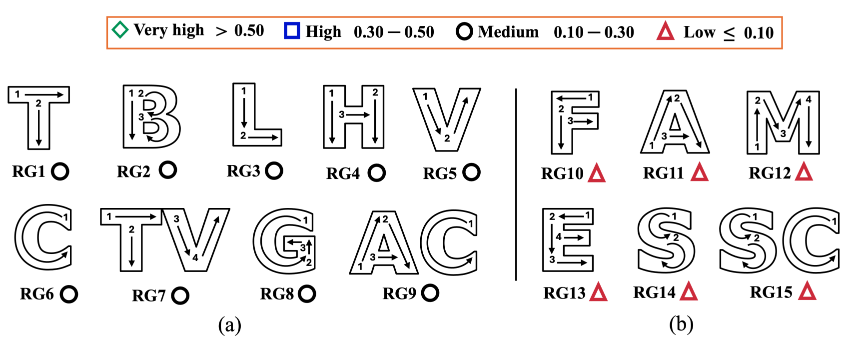


Fig. 5. The agreed gesture set for registering 15 smart home devices is shown with their level of agreement. (a) Registration gestures that received medium agreement: RG1 (T, Telephone); RG2 (B, Blinds); RG3 (L, Lights); RG4 (H, Heater); RG5 (V, Video Player); RG6 (C, Car Garage); RG7 (TV, Television); RG8 (G, Garden Irrigation); RG9 (AC, Air Conditioner); and (b) registration gestures that received low agreement; RG10 (F, Fan); RG11 (A, Audio Player); RG12 (M, Alarm); RG13 (E, Oven); RG14 (S, Speakers); and RG15 (SC, Security Camera). There are no registration gestures that received high or very high agreement rates.

The agreed 'control' gestures for the 22 control referents of the three smart home devices (TV, lights, and AP.VP.S) used in the production study are shown in Table 1. Interestingly, the agreed gesture sets from the guessability and production studies were identical. G1:'Move down' and G2:'Move up' (3×) were the most frequently proposed gestures, followed by G3:'Move right' and G4:'Move left' (2×), as in the guessability study. Interestingly, G5:'Closing fist' and G10:'Split hands' were also the most frequently proposed(3×), followed by G11:'Combine hands'. All but 7 (68.2%) of the gesture-referent combinations in the production study are the same as in the guessability study. The agreed combinations are the same for TV. Interestingly, the gestures agreed upon in the production study seem to be more preferable, for example, 'Clockwise' and 'Counterclockwise' rather than ‘Move right’ and ‘Move left’ for ‘Fast forward’ and ‘Fast rewind’, even though they have medium level scores in both studies. Another example could be, ‘Split hands’ and ‘Closing fist’ for ‘Lights on/off’ in the production study versus ‘Move right’ and ‘Move left’ in the guessability study, where they have medium level of agreement or max-consensus scores.

Table 1. The max-consensus (sorted from the highest to the lowest values) for each referent for each device and consensus-distinct ratio (using a consensus threshold of 2) for the production study are shown for each referent. The highest scoring referent(s) for each metric are indicated with green shading, and the lowest scoring are indicated with gray shading.

Devices	Referents	Gestures with Highest Consensus	Max Consensus	Consensus-Distinct Ratio
TV	Previous Channel	G4: Move left	40%	44%
	Next Channel	G3: Move right	39%	41%
	Volume Down	G1: Move down	31%	69%
	Volume Up	G2: Move up	29%	36%
	Mute	G5: Closing fist	26%	44%
	Turn On	G10: Split hands	23%	64%
	Turn Off	G11: Combine hands	15%	52%
Lights	Dim Up	G2: Move up	29%	53%
	Turn Off	G5: Closing fist	28%	63%
	Turn On	G10: Split hands	25%	42%
	Dim Down	G1: Move down	21%	47%
AP.VP.S	Previous	G4: Move left	40%	35%
	Next	G3: Move right	36%	33%
	Play/Pause	G9: Move down quickly	36%	28%
	Stop	G6: Move forward	34%	47%
	Volume Up	G2: Move up	33%	42%
	Volume Down	G1: Move down	32%	50%
	Mute	G5: Closing fist	29%	50%
	Turn On	G10: Split hands	24%	37%
	Turn Off	G11: Combine hands	24%	39%
	Fast Forward	G7: Clockwise	22%	20%
	Fast Rewind	G8: Counterclockwise	22%	21%
Mean			29%	44%
SD			7%	13%

2) Popular gestures: The agreed gesture set did not include many gestures that were frequently proposed by different participants. Therefore, we present an additional set of popular gestures, shown in Fig. 6(a) (G12 – G15) with a threshold of 10 (i.e., proposed at least by 10 times). All agreed gestures were proposed more often than these popular gestures and are also considered as popular gestures as well. The gestures G12:‘Move backward’ and G13:‘Opening fist’ came second in the agreement analysis and were not included in the agreed gesture set, but are included in the popular gesture set. They are the inverse gestures of G6:‘Move forward’ and G5:‘Closing fist’. The popular gestures account for a total of 81.7% of the proposed 20×63 control gestures. Many popular control gestures were also proposed as registration gestures by some participants (e.g., G7:‘Clockwise’ as ‘O’ for oven), but were not included in this calculation. We did not find any other popular registration gestures. Participants mainly proposed icons and letters as registration gestures.

The additional set of popular gestures from the *production* study were also obtained with a threshold of 10. We found two new popular control gestures in the production method, (G16) ‘Move down diagonally to the left’ (10, 0.9%) and (G17) ‘Move up diagonally to the right’ (10, 0.9%) along the vertical direction (see Fig. 6(a)). They were mainly proposed for ‘Volume Down/Up’ referents. The agreed and popular gestures represented 72.3% of all the proposed gestures in the production study. This is less than the guessability method (81.7%), possibly due to the higher number of unusual gesture proposals. The number and percentage of popularity of the gestures decreased in the production method, as they were more distributed than in the guessability study.

3) Primitive gestures: We analyzed the distinct gestures from the guessability and production studies for distinct simpler gestures that repeated or combined to create the more complex gestures, and to obtain a primitive gesture set. For both guessability and production studies, it turned out that the set of primitive 'control' gestures for controlling the devices was the same as the respective set of popular gestures shown in Fig. 6(a). G16 and G17 are the additional gestures found in the production study. We then analyzed the 147 distinct gestures from the guessability study to create a set of primitive 'registration' gestures for registering smart home devices. These primitive gestures for registering smart home devices are shown in Fig. 6(b). Interestingly, the gestures did not include two cardinal directions, south-west ('move backward to the left') and north-west ('move forward to the left'). This may be due to more right-handed participants and how the English alphabets are written. We did not explore registration referents in the production study.

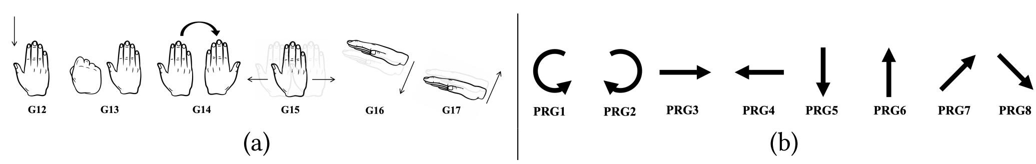


Fig. 6. (a) The set of additional popular control gestures is shown that were proposed more than 10 times. G12 to G15 are from the guessability study and G16 and G17 are from the production study. (b) The set of primitive gestures for registering smart home devices is shown. These gestures are performed with a horizontal hand hovering over an interactive tabletop surface.

4.2 Experimental Validation of Gesture Vocabulary

We experimentally validated the registration, agreed, popular and primitive gesture sets by conducting two preliminary experiments and collecting the data from a single user using two different types of IPV sensors (see Fig. 1 (b) and (c)). The primary objective of these experiments was to verify the ability of the IPV sensors to detect the gestures via machine learning (ML) classification. These experiments were conducted after the guessability and production studies because repeated measurements were needed to train the ML models. In the first experiment, we used the more portable IPV tape sensor shown in Fig. 1(b) to classify the agreed control (G1 − G11), registration (RG1 − RG15), and primitive gestures (PRG1 − PRG8) shown in Figs. 3, 4, and 5 (b). For this, we collected 32 samples as time series data for one user at 3 kHz and 5 seconds length. In the second experiment, we used the IPV tabletop sensor shown in Fig. 1(c) to classify the all popular control gestures from both studies (G1 − G17). For this, we collected 10 samples as time series data for one user at 333.3 Hz and 3 seconds length.

We applied data preprocessing techniques such as augmentation (e.g., noise injection, time shifting, and scaling) [46] to increase the diversity of the datasets and improve the robustness and performance of the machine learning model. This helped us to mitigate the risk of overfitting. We then used different supervised machine learning classifiers to train 70% of our data and test the predicted accuracy with 30% of the remaining data. The Random Forest classifier [13] achieved the highest accuracy for all the gesture vocabulary sets, ranging from 99% (agreed registration and popular sets) to 100% (agreed control and primitive sets). The confusion matrices of the datasets are shown in Fig. 7 and Fig. 8. For the agreed registration gesture set, the confusion was between RG12: Draw 'M' and RG1: Draw 'T', while for the popular gesture set, the confusion was between G5: 'Closing fist' and G14: 'Flip hand'. These results demonstrate that an IPV sensor can recognize

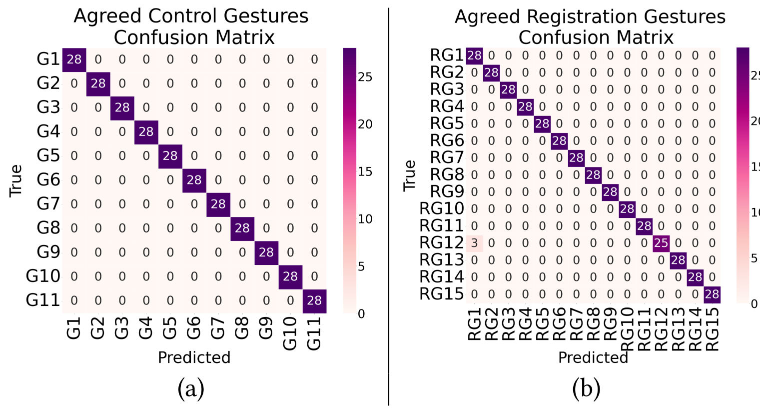


Fig. 7. The Random Forest confusion matrices of the (a) 11 agreed control gestures and (b) 15 agreed registration gestures.

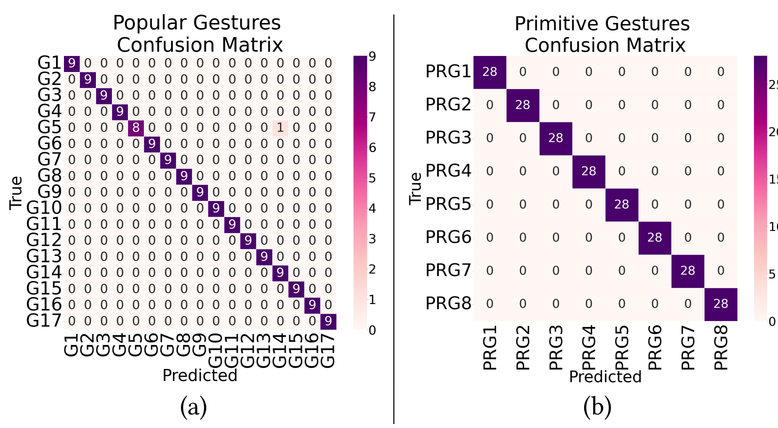


Fig. 8. The Random Forest confusion matrices of the (a) 17 popular gestures and (b) 8 primitive gestures.

various hovering registration and control hand gestures performed by one user, enabling them to interact with multiple smart home devices. Further research is needed to demonstrate the IPV sensor's ability to recognize registration and control gestures from multiple users.

4.3 Data Saturation

We calculated the cumulative number of unique gestures [25] across participants for the guessability and production studies on the 15 popular gestures (see Fig. 4 and Fig. 6(a)), and show a comparison between the two in Table 2. We found that with 2 participants, 87% and 80% of the total popular gestures were proposed in the guessability and production studies respectively. With 5 and 4 participants respectively, the cumulative number of popular gestures increased to 100% in the guessability and production studies respectively, where the data saturation occurred. For both studies, we performed subsample permutations with n ≥ 2, which showed that 3 participants were sufficient to capture the most common gestures across the participants [79].

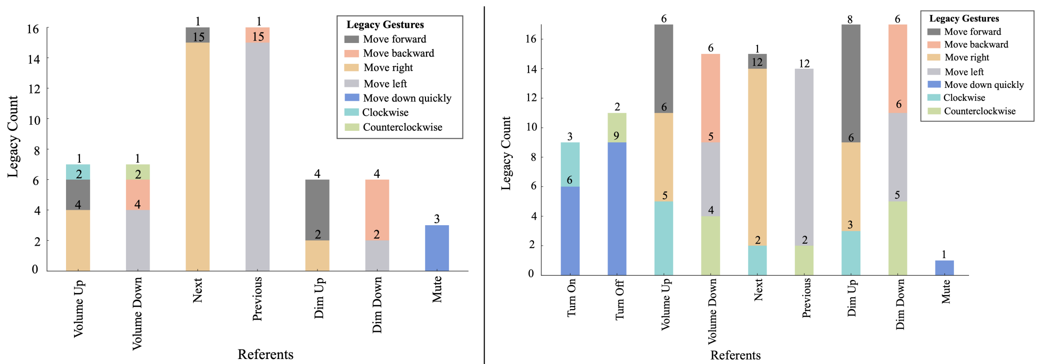
Table 2. Summary on comparison of data saturation of both studies guessability and production on 15 popular gestures.

Parameters	**Guessability Elicitation**	**Production Elicitation**
Number of Devices	15 smart home devices	3 smart home devices
Number of Referents	78 referents	22 referents
Number of Participants	20 participants	25 participants
Initial Saturation Point	After 2 participants (87%)	After 2 participants (80%)
Time	Time took a little longer to reach the data saturation with 100%	Data saturation reached quicker with 100% due to unlimited production technique
Long-Tail gestures (100% Saturation Point)	Final Long-Tail gestures reached after 5 participants	Final Long-Tail gestures reached after 4 participants

4.4 Effect of Legacy Bias

The production method was later proposed to reduce the legacy bias in the guessability method. However, a direct comparison between the two methods considering the legacy bias has not been reported in the literature. We compare the effect of legacy bias on the two different elicitation methods *guessability* and *production*, considering the first 20 participants due to data saturation, along with two smart home devices, TV and Lights, common to both studies. The prevalence of legacy bias in gesture elicitation studies highlights the role of prior interaction experience with established technologies in influencing participants' proposals. We classified gestures that are known in the common usage of a certain device as legacy gestures [94, 96] by categorizing them from the 39 and 66 unique gestures of the guessability and production studies, respectively. The list of gestures we considered as legacy gestures are (G3) moving the hand to the right on the X-axis, (G4) moving the hand to the left on the X-axis, (G6) moving the hand forward on the Y-axis, (G12) moving the hand backwards on the Y-axis, and (G9) moving the hand down quickly like tapping, as well as (G7) clockwise and (G8) counterclockwise, like rotating a knob in stereo for "Volume Up/Down". These gestures could be found in common interactions on devices such as smartphones, tablets, and stereos. For example, participants suggested moving their hands to the right and left to navigate to the "Next/Previous" TV channel, which is a common interaction technique used on a tablet for flipping pages.

The legacy gesture counts for different referents are shown in Figure 9. In the guessability data, we had less number of referents (7 out of 9) that were affected by the legacy gestures, as we did not observe any legacy in the "Turn On/Off" referents that existed in production. The total frequency count in production was much greater with freq. = 116 than in guessability with freq. = 61; this is due to the higher number of gesture productivity. Additionally, we noticed an increment in the legacy gestures for certain referents in production. For example, we observed two extra gestures (G7) 'Clockwise' and (G8) 'Counterclockwise' in "Next/Previous" and "Dim Up/Down" referents. The "Mute" referent for both studies had the least count of legacy gestures with freq. = 1 to 3.



(a) Guessability (b) Production

Fig. 9. Legacy gesture count of referents in a) guessability and b) production elicitation studies.

In addition, we analyzed the legacy effect by following Williams et al. [94] in calculating the percentage of legacy gestures from each referent and the referent's contribution to the total legacy across the TV and Lights devices (see Table 3). We found that the guessability study had a higher legacy effect with a mean of 43% compared to 37% in the production study, as shown in Table 3. This indicates that in the guessability study, participants usually guess a gesture based mainly on their intuition, relying heavily on their knowledge and previous experience with existing technologies. On the other hand, in the production study, users mainly suggest more than one gesture due to the unlimited number of proposals, which is more likely to produce creative and varied gestures without any constraints and may not rely on pre-existing interaction techniques, as suggested in the literature.

4.5 Design Guidelines

We propose the following guidelines for the design of hovering tabletop interaction using IPV sensors to control multiple devices in smart home contexts. Our findings from the guessability and production studies should be transferable to other similar electromagnetic principle based gesture sensors because they work on similar principles, i.e., measuring the position or movement of the hands.

1) Which elicitation study: A guessability study with about 10 or less participants may be enough to find all the popular gestures considering about 10 or more smart home devices. In our study, all popular gestures were found after the first 5 participants considering 15 smart home devices. Many gesture-referent mappings with medium to very high agreement levels (76% in our case) may be found with this approach. However, with the production method, all popular gestures may be found after about 5 participants (4 in our case) considering about 5 smart home devices. Interestingly, most gesture-referent mappings with medium to very high agreement levels (100% in our case) may be found with the production approach. The guessability method would be more efficient at finding popular gestures (81.7% of the proposed gestures were popular in our case), but it has an increased legacy bias. The production method reduces legacy bias but is less efficient at finding popular gestures (72.3% of the proposed gestures were popular in our case) due to the higher number of creative gesture proposals.

2) Use a sensor for elicitation: Design effective gesture interactions using guessability or production elicitation methods with a sensor-based setup. This results in discoverable and recognizable

Table 3. The percentages of the legacy gestures and referents' contribution to total legacy for each referent of a) guessability and b) production studies are shown. The highest scoring referent(s) for each metric are indicated with green shading, and the lowest scoring are indicated with gray shading

(a) Guessability

Devices	Referents	Legacy Gestures	Percentage	Referents' Contribution to Total Legacy	Percentage
TV	Turn On	7/20	35%	0/7	0%
	Volume Up	7/20	35%	7/7	100%
	Next Channel	16/20	80%	16/16	100%
	Volume Down	7/20	35%	7/7	100%
	Mute	3/20	15%	3/3	100%
	Turn Off	7/20	35%	0/7	0%
	Previous Channel	16/20	80%	16/16	100%
Lights	Dim Up	6/20	30%	6/6	100%
	Turn On	10/20	50%	0/10	0%
	Turn Off	10/20	50%	0/10	0%
	Dim Down	6/20	30%	6/6	100%
Mean			43%		64%
SD			21%		50%

(b) Production

Devices	Referents	Legacy Gestures	Percentage	Referents' Contribution to Total Legacy	Percentage
TV	Turn On	16/41	39%	5/16	31%
	Volume Up	17/39	44%	17/17	100%
	Next Channel	18/34	53%	15/18	83%
	Volume Down	15/36	42%	15/15	100%
	Mute	7/29	24%	1/7	14%
	Turn Off	12/40	30%	6/12	50%
	Previous Channel	17/32	53%	14/17	82%
Lights	Dim Up	17/41	41%	17/17	100%
	Turn On	7/39	18%	4/7	57%
	Turn Off	7/38	18%	4/7	57%
	Dim Down	17/42	40%	17/17	100%
Mean			37%		71%
SD			12%		30%

elicited gesture vocabulary sets aligned with real-time physical execution and sensor capabilities that have been experimentally validated to ensure robust system performance.

3) Use letters for device registration: In a multiple device environment, users may find that drawing the first letter of the name of the device is a good first guess to register the device to set the context (e.g. Fig. 5). The second best guess might be to draw the first two letters of the device name. Another guessable gesture could be drawing a unique shape representing the device.

4) Use a primitive gesture set: A primitive gesture set may be found for the agreed and popular registration and control gestures by decomposing them into smaller gestures (e.g. Fig. 6(b)) from the guessability or production study. The gesture recognition algorithm may detect them sequentially to detect the intended gesture.

5) Start with popular gestures: Popular gestures (see Figs 6(a)) can be used as a starting point, as they can save designers time by minimizing the need to filter through numerous gesture options, for example, by excluding the icons or letters for control commands because they were not popular with participants.

6) Use some popular gestures for no-context control: With registration gestures setting a context, and some devices having only a few commands, it may be possible to use spare popular gestures for non-contextual interaction. This can be particularly useful if a gesture and referent of one device are not confused with a referent of another device.

7) Use consistent gestures for similar commands across devices: It is possible that multiple devices will have similar commands. With the registration gesture setting the context, it is possible to use consistent gestures for similar commands across devices.

8) Use inverse gesture for inverse command: Many devices have commands that also have an inverse, such as 'on' and 'off'. Similarly, many popular gestures also have associated inverse gestures. As users also prefer inverse gestures for inverse commands this approach would be consistent across devices.

5 Discussion

Limitations: In our study, participants mostly agreed at medium to low levels to draw the first or first two letters of the device names as registration gestures (see Fig. 5). This is consistent with the literature highlighting the use of letters as preferred gestures due to their familiarity and simplicity [81, 84]. However, this approach has drawbacks because device names differ across languages and different character sets. Non-letter suggestions include unique shapes or actions to indicate the devices, which could be possible alternatives. However, the agreement levels were low, with only 1 or 2 participants out of 20 suggesting them. Interesting shape suggestions were drawing a rectangle (TV), a pentagon (car garage), two adjacent circles (video player), four adjacent circles (oven), a circle within a rectangle (security camera), a circle with a sine wave (air conditioner), a sine wave (fan), a flower (garden irrigation), and a music note icon (audio player). Interesting action suggestions were bringing both hands together and separating them as if opening curtains (blinds), opening and closing a fist with both hands as if depicting blinking lights (lights), opening and closing a hand as if talking (speaker), shaking a hand (alarm), closing a fist and moving the hand up as if picking up a telephone (telephone) and shaking both hands and moving them up to depict flames (heater). Future work could consider such cultural aspects of gesture design with participants from different language backgrounds.

We conducted our user studies in a controlled environment to eliminate external distractions. However, observing users in real-world contexts could expand our understanding of how their behavior changes in spaces where smart home interactions typically occur. For example, we could observe users interacting with a smart home in real time, such as sitting in a living room or cooking in a kitchen while controlling lights, speakers, the air conditioner, or the oven with hand gestures. The IPV sensors that we used are flexible and sustainable, and can be embedded in various surfaces throughout the home. However, they present some challenges, particularly regarding their reliance on ambient lighting conditions.

Generalization to other contexts and sensors: The gestural findings from our studies may be applicable to other scenarios that use interactive control surfaces, such as dashboards in the automotive, aviation, medical, gaming, and alternate reality interfaces [21, 68, 87]. We explored the device registration approach to set the context of controlling individual devices. This approach could be used in a car, for example, to select the audio player by drawing an 'A' in front of the dashboard and then choosing the next track with the 'move forward' gesture. In fields such as medicine and aviation, where different instruments are used, different letters would be required to register them via hovering hand gestures. This approach can also be used to invoke (register) a menu by drawing a letter and use (control) the menu with appropriate gestures from the agreed set. The menu would be useful where an audio or video feedback is available, as it is in most modern applications, including those mentioned above. However, the IPV interface allows for eyes-free interaction which would be useful. The IPV sensor uses the area and separation of the hand from the sensor surface to detect hand movements. Other sensors, such as capacitive [65, 86], infrared proximity [8, 23, 78], LiDAR [45], Doppler radar [70] and radio frequency (RF) [66] sensors work on similar principles and could sense hovering hand gestures over a relatively large area, like the IPV sensor. We believe that the gesture-referent combinations are transferable to systems using these sensors. Other sensors, such as depth cameras (table or wall mounted) or a wrist-worn sensors (inertial or accelerometers) could also be used to detect the hovering hand gestures and register and control devices. Many of these sensors may be used on systems using non-flat interfaces or on-body [12, 43]. We believe that our findings will be usable in these scenarios as well.

Connections to gesture interaction literature: Gesture vocabularies can be developed using survey-based methods, i.e., questionnaires and interviews, in which participants suggest gestures they find intuitive for specific tasks [21, 87, 88]. While these methods provide meaningful insights into the design of end-user gesture vocabulary, they often provide only verbal descriptions for the gestures. Sensor-based gesture vocabularies are performed in relevant contexts, ensuring gestures are performed ergonomically [102]. This reflects the validation of direct physical execution in more practical and implementable gesture vocabularies rather than only relying on theoretical assumptions. Additionally, this method gives an empirical foundation for a gesture classification system through an experimental validation of gesture vocabularies.

Our work provides a starting point that can be iterated upon to develop an application-specific interface. Xia et al. [102] recently identified 13 factors critical to gesture vocabulary design and proposed an iterative user-centered and factor-centered approach to gesture design. Reflecting on their work, we have addressed many important factors to a variety of levels. The framing of the intelligent environment in the elicitation studies considered the situation factor. The participatory design captured the cognitive factors through discoverability, intuitiveness, learnability, and transferability of the user-elicited gestures. The use of an interactive tabletop and hovering interaction captured some of the physical factors. The use of embedded sensors, as we have used, and hovering interaction while sitting on a chair would effectively address the occlusion and ergonomic factors. Some of the system factors are addressed by generating noticeable signals and creating a primitive gesture vocabulary. The effectiveness of a gesture vocabulary sets recognition were validated through machine learning. Nevertheless, full development and evaluation with a working system that addresses all the factors will be necessary.

Implications: The integration of IPV gesture sensing with surfaces such as walls, windows, or tables presents a promising direction for the HCI and smart home communities, enabling sustainable interaction design. For the HCI community, such sensors imply new possibilities for redefining interaction models in situations where power availability or hardware constraints constrain traditional input modalities. On the other hand, IPV sensors in a smart home system could augment the control of multiple devices, making the interaction more embedded and less dependent on other control mechanisms like physical controllers, voice, or touch displays. Ethical and inclusivity considerations are crucial in integrating sensing technologies within homes [32]. IPV sensing preserves privacy more than camera-based systems. However, socio-technical considerations are another aspect that takes into account user acceptance and usability of such gesture systems [85]. Additionally, using IPV sensors with hover gestures could also assist people with disability or mobility impairments [26], by using comfortable and user-friendly contactless gestures, such as hovering a hand momentarily above photovoltaic materials to activate a device, enabling low-effort interactions that tolerate imprecise or weak motions [61, 62, 73, 74].

Future Work: In this paper, we proposed and utilized a sensor signal waveform-based creative task as a priming technique for the production method. In the future, this technique may be validated by conducting an end-user elicitation study with two priming groups, i.e., a non-priming group and a sensor-based priming group, and analyzing the priming effect on participants' gesture proposals, e.g., time taken to think of a gesture and the number of legacy bias gesture, between-subjects from the two groups. Hoff et al. suggested that a large-scale experiment, e.g., with 170 participants, would be required to expect to find statistically significant differences [35]. Ali et al. conducted a large-scale distributed end-user elicitation study over the internet to validate a priming effect [1, 35]. Our sensor-based priming technique requires an experimental setup to conduct the end-user gesture elicitation study. In the future, a web-based simulation system may be developed for a distributed end-user elicitation study to validate the technique with statistically significant outcomes. However, Hoff et al. investigated a covert kinaesthetic priming technique, so validation of the sensor-based priming technique could be attempted in a lab-based study.

In the future, the use of the IPV sensor for multimodal interaction may be explored. For example, a feedback mechanism embedded within the tabletop surface could offer seamless interaction by providing haptic or auditory responses that confirm users' gestures. Additionally, projected prompts on the tabletop interface could provide visual cues offering immediate instructions on how to perform specific gestures and serve as a guide for users.

6 Conclusion

In this paper, we explored the potential use of indoor photovoltaic sensors as gesture sensors for controlling smart home devices. We conducted two gesture elicitation studies using the guessability and production methods to design a more guessable and favorite universal vocabulary of dynamic hovering surface gestures and consequently present the agreed, popular, and primitive gesture sets for both registration and control commands. We found that more participants drew the first or first two letters of the devices to register them, but there was no consensus among them with medium to low agreement levels. The agreed set offers an adequate number of gestures (11) for controlling multiple smart home devices, with an additional (6) gestures in the popular set. Similar commands across the devices can be invoked with the same gestures, and opposite commands with opposite gestures. The IPV sensor offers gesture-referent combinations most (68.2%) of which could be both guessable and favorite, and can be found using either the guessability or production method. All control and registration gestures can be decomposed into simpler primitive gestures for sequential recognition to select and control multiple devices. We experimentally validated all gesture sets with a user and found that all gestures can be recognized with about 99% accuracy. Our comparison of the guessability and production methods revealed similarities in the agreed gesture sets, but some differences in the agreed gesture-referent assignments. The guessability method reached saturation faster, however, the production method reached full saturation with fewer participants. We provide a starting point with user-elicited gesture sets and guidelines to help HCI designers to further refine them through user testing, to create guessable and favorite surface gestural interaction for smart home control and beyond using many types of indoor photovoltaic materials as sensors.

Acknowledgments

This work was supported by the Engineering and Physical Sciences Research Council grant EP/W025396/1.

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Received 2025-03-14; accepted 2025-06-20