Let the Door Handle It: Exploring Biometric User Recognition Embedded in Doors

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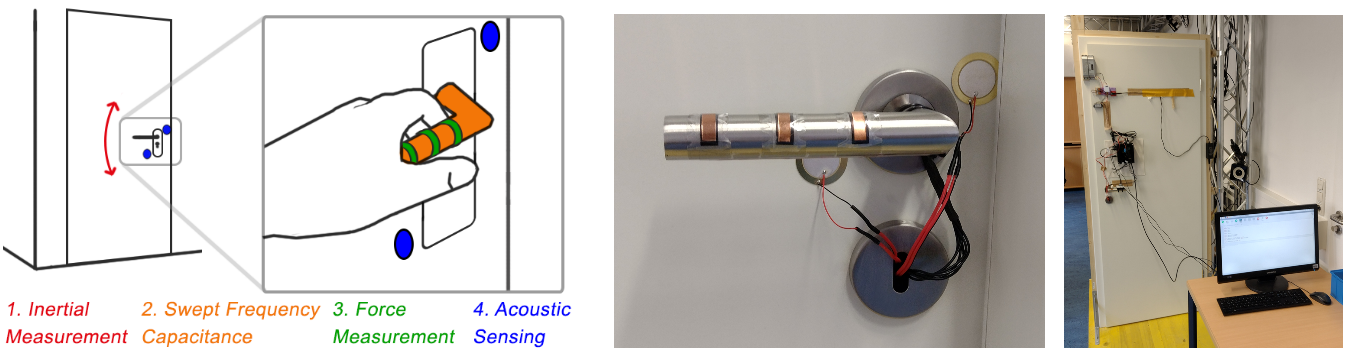

(a) Schematic overview of our setup **(b) Front view (handle and sensors)** **(c) Back view (electronics)**

Figure 1: We propose using behavioral patterns when opening a door for recognizing users. To capture such patterns, we measure inertia, capacitance, force, and acoustic resonance (a) when opening a door. The electronics are integrated into the handle (b) or hidden on the backside of the door (c).

Abstract

In this work, we explore the use of behavioral biometrics when opening doors to enable user recognition on demand. We propose a combination of inertial, capacitance, force, and acoustic sensors embedded in a door for capturing user interaction with the handle. This way, we collect data only when needed, i.e., when the handle is used to open the door. No additional device (e.g., a smartphone) or knowledge is required, enabling a seamless and unobtrusive identification experience for users. We use tangible interaction data captured from 20 participants in two sessions, at least 5 days apart, for building a random forest classifier and an LSTM neural network, and compare and discuss the impact of the sensors on their performance. We found that random forest yields the best accuracy, and performance is better within one session than between sessions. Within one session, a few interactions are sufficient for recognition.

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CCS Concepts

• **Computer systems organization → Embedded hardware**; • **Security and privacy → Biometrics**.

Keywords

behavioral biometrics, embedded sensing, user recognition on demand, tangible security

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1 Introduction

Doors naturally separate and define distinct physical spaces like rooms, offices, or shared facilities. As such, they present ideal transition points where environments can adapt to the preferences and needs of specific individuals. This includes the potential for personalization of settings like lighting or temperature control, adaptation of access privileges like smart home controls, or handover of digital context like logged-in accounts on different devices. However, these opportunities depend on the system's ability to recognize who is entering a space.

While cameras or continuous monitoring systems could offer such recognition, they raise substantial privacy concerns, as they require constant data collection and can incidentally pick up on (sensitive) data not necessary for user identification. In contrast, users interact with doors only when they intend to enter or switch to a different space, making them ideal for on-demand recognition. Therefore, leveraging the door handle as a recognition interface allows for minimal and situational data capture, aligning well with privacy-by-design principles.

In this paper, we focus on door-opening *behavior* to facilitate this recognition, as it is unobtrusive, naturally integrated into everyday interaction, and only captured when users physically interact with the door. This makes it well-suited for recognizing individuals without requiring explicit additional actions or external tokens. While prior work has demonstrated the feasibility of using such behavioral patterns for user authentication (e.g., [18, 19, 29, 64]), most studies have prioritized maximizing recognition performance and relied on data from a single session. As a result, little is known about the stability and robustness of these interaction patterns over time or under varying conditions. In this paper, we close this gap and focus on a more fundamental understanding of what factors influence the performance of such a system and how robust it is against changes over time and in usage behavior.

To this end, we collected tangible interaction data from 20 participants over two sessions. To enable easy replication, we use simple, commercially available electronic components for our study prototype. We use the collected data to compare the *performance of multiple sensors*, to capture different aspects of the interaction (see Figure 1), and to understand the *persistence of door-opening behavior.* Furthermore, we explore the *impact of using only parts of the interaction or a few samples (i.e., measured data points) for training* recognition models and the *robustness of our approach to changing the hand* used to open the door.

Contribution Statement. The contribution of this work is twofold: we contribute 1) an easy-to-replicate hardware setup to capture humans' natural tangible interactions with a door handle and 2) a comparative analysis of the factors impacting recognition performance based on the door-opening behavior of 20 participants.

2 Background and Related Work

Our work is based on related literature on behavioral biometrics in the context of doors.

2.1 User Recognition in Indoor Environments

Researchers have explored a range of user recognition methods for smart indoor environments. Proposed methods include recognizing the presence of users' devices and biometric systems.

2.1.1 Device-Based Recognition. Both research prototypes and commercial products frequently detect the presence of personal devices for user recognition. They make use of Radio-Frequency ID (RFID) [2, 11, 51], Bluetooth [5, 39] or WiFi [14, 60, 61] to detect nearby smartphones [5, 61], smart cards [51], or wearable devices.

2.1.2 Physiology-Based Biometrics. In recent years, biometric features have gained traction for user recognition across various contexts due to their usability advantages (i.e., they cannot be forgotten or lost) [43]. Prior work has explored physiological biometrics such as fingerprints [4, 10, 48, 56], iris [42], ear shape [49], face recognition [3, 38, 58, 63], as well as anatomy [35] and impedance [53] at doors for physical access control or personalization in smart indoor environments. These *physiology-based biometrics* typically require an *explicit* action (e.g., scanning a fingerprint), which adds user effort and may cause annoyance. In contrast, *behavioral biometrics* identify users based on unique behavioral patterns and can *implicitly* recognize legitimate users with minimal effort.

2.1.3 Behavioral Biometrics. Behavioral biometrics have been investigated for a large range of features like keystrokes [6, 34, 68], touch [1, 21], mouse [23, 50], gait [40, 41, 70] or eye-movement patterns [28, 57, 69]. Researchers have also suggested embedding behavioral biometrics into physical context since they offer the unique advantage of enabling a non-disruptive integration into users' existing routines [13, 14, 18, 20, 22, 25–27, 37, 47, 61, 64, 64, 70].

2.2 Measuring User Behavior Indoors

Implicit user identification based on behavior is especially promising, as it requires neither explicit interaction nor specific devices, enabling truly effortless authentication. Accordingly, related work has proposed various methods to unobtrusively measure users' behavior in indoor environments – particularly by tracking movement patterns or interactions with specific objects.

2.2.1 User's Movement Patterns. User movement in sensor-equipped environments can be leveraged for identification. For example, the FreeSense system analyzes how human movement affects WiFi signal patterns to distinguish between individuals in a home setting [66]. Orr et al. [46] developed a smart floor that uses footstep force profiles to identify people as they walk through a space.

Krašovec et al. [32] measured behavior during everyday tasks at a desktop PC, including mouse and keyboard usage, system resource activity, and in-room movement. Similarly, Krawiecka et al.'s [33] BeeHIVE system uses existing sensors in everyday devices (e.g., printers, coffee machines) to identify users without requiring hardware modifications.

2.2.2 Behavioral Biometrics in Door Contexts. Building on prior work [15, 16, 18, 19], we focus on door interactions for user identification, as doors mark key transition points in physical contexts. They often separate public, shared, and private areas, or distinct indoor environments with specific functions. These spaces typically contain smart or computational devices tailored to their context, which may benefit from recognizing who is entering – for personalization, tracking, security, or access control. Moreover, users' interactions with doors have been shown to be particularly well suited for identification purposes [20].

Researchers have measured users' behavior while interacting with doors for recognition purposes using different prototypes that also frequently measured physiological traits of the user unobtrusively. While some integrated sensors in the door frame to measure height profiles and movement patterns while walking through a door [24–27], others additionally situated sensors on the floor to collect data on the users' weight [7], gait [70] or induced vibrations [13]. Compared to the previously presented approaches, we propose using the primary user interaction when opening the door for data

Table 1: Comparison of related works implementing behavior-based user recognition at doors. Factors that are compared in the respective analysis are marked with (*). Inertial measurements such as acceleration, velocity, or orientation measures are summarized as "Motion" features. Capacitive and pressure sensors (this includes acoustic sensing) are labeled as "Touch". The "Mode" column describes if the systems were evaluated for recognition (1:n) or verification (1:1). Papers that did not disclose or restrict which hands participants used to interact with the door contain "either" in the "Hands" column.

Authors	Systemname	Features	Hands	N	Sessions	Mode
Futami et al. [15]	-	Motion	either	4	1	1:n
Garcia et al. [16]	-	Motion	dominant	20	1	1:n
Gupta et al. [18]	*SmartHandle*	Motion	either	11	1	1:n
Gupta et al. [19]	*Step&Turn*	Motion, Footsteps*	right	40	1	1:1
Han et al. [20]	*SenseTribute*	Motion	either	5*	1	1:n
Ishida et al. [22]	-	Motion, Touch	either	7; 8	1; one week	1:n
Klieme et al. [29]	*recorDOOR*	Motion, Touch, Video, Ultrasonic	both*	8	1	1:n
Klieme et al. [30]	*DoorCollect*	Motion, Touch	either	4	-	-
Konishi et al. [31]	-	Touch	left	25	1	1:n & 1:1
Piltaver et al. [47]	-	Motion	either	12	1	1:n
Tietz et al. [59]	-	Touch*	either	25	1	1:n
Vegas et al. [62]	-	Motion	either	47	1	1:n
Wu et al. [64]	*MoMatch*	Motion	either	27	1	1:n

collection, rather than the person stepping through the door frame. This way, we only collect user data if necessary for the recognition process, making our system more privacy-preserving by design.

2.3 Identification Through Interactions With Objects

2.3.1 On-Demand Tangible User Recognition. Prior work suggests augmenting everyday objects with sensing capabilities to assess usage patterns for authentication [9, 15, 18, 20, 65].

For example, sensor-enhanced wristbands or smartwatches can authenticate users when they touch or move specific objects [36, 64, 67]. The sequence of tangible interactions with multiple objects – measured via capacitive touch sensors – can serve as a hybrid (explicit and implicit) authentication mechanism that is perceived as both usable and secure [9]. Other approaches attach inertial sensors to movable household items (e.g., cabinet doors, drawers, remote controls) and successfully use unique movement patterns for identification [20, 64].

Closely related to this paper, related work has focused on using only users' tangible interaction with the door by measuring the movement of a door (handle) [15, 18, 47, 64], users' motion [16] or the touch itself [22, 31, 59].

2.3.2 Tangible Behavior-Based User Recognition at Doors. Table 1 provides an overview of approaches that use tangible door interactions to recognize users based on their behavior.

We observe that most related work leverages the motion of the door (handle) as the main feature for recognition. These systems rely on inertial measurements (i.e., angular velocity, acceleration, and magnetic field) collected from lever-style door handles [15, 16, 18, 19, 29, 30, 62] or from the door itself [20, 22, 47, 62] to recognize users. These approaches achieved classification accuracies of >= 90% with 12–47 participants [16, 47, 62]. Some also integrated additional sensors beyond motion data [19, 22, 29, 30].

Only Tietz et al. [59] and Konishi et al. [31] relied solely on touch features (i.e., without motion sensing), yet still achieved comparable accuracies of 88% and 93%, respectively.

Moreover, most related work focused on recognition scenarios (1:n) [1]. To the best of our knowledge, none of the related work conducted a second session to increase the ecological validity of their results. Ishida et al. [22] conducted a more longitudinal study, which captured tangible interaction data with a fridge door during one week, and Konishi et al. [31] mentioned having conducted 5 sessions, but they were performed with pauses of only 1 minute. In contrast to our work, neither of these works analyzed recognition performance within and between days.

3 Research Approach

With our paper, we follow related work and investigate user recognition (1:n) in multi-user scenarios based on unique behavioral patterns while interacting with a door. To achieve this, we see the greatest potential in approaches that integrate sensing in the door (handle) [15, 18, 52, 53]. This is motivated by the following advantages of such a system:

- they identify users *without requiring additional tokens or knowledge* [64]
- they *leverage users natural tangible interaction* with the door for data collection [64]
- they are *privacy-preserving*, as they *only collect data when it is necessary without incidentally picking up data non-essential for recognition* (as opposed to, for example, a camera)

Figure 2 provides an overview of our research approach. We extend related work by gaining more fundamental insights into factors that influence the performance of these behavioral biometric systems that only collect data on demand. Hence, we shift the focus from achieving a high recognition score to making comparisons between different implementations and tangible interaction variants. In particular, we analyze (a) the *performance of multiple sensors*, (b) the *persistence of door-opening behavior*, (c) the impact of using *only parts of the interaction for training* recognition models, and (d) the robustness of our approach *if different hands are used* for opening.

[1] Verification (1:1) confirms a claimed identity by comparing input to a specific stored pattern — this is how most authentication works. Recognition (1:N) (or classification) identifies someone by comparing input against multiple stored patterns to find a match [54]

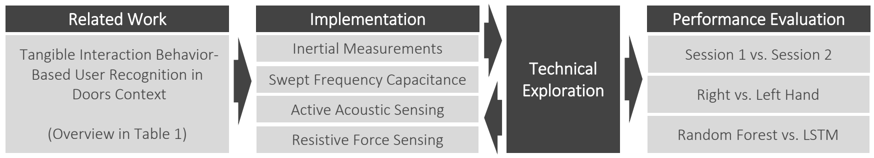

Figure 2: Building on related work, we implemented a prototype to measure user interaction with a lever-style door handle. It integrates multiple sensing technologies, including an inertial measurement unit, swept-frequency capacitive sensing, active acoustic sensing, and resistive force sensing. After refining the prototype through technical exploration, we used it in a user study with 20 participants to examine (a) sensor performance, (b) persistence of door-opening behavior, (c) the effect of using partial interactions for training, and (d) robustness when different hands are used.

To this end, we implemented an easily replicable prototype using commercially available electronic components (cf. Section 4)[2]. Inspired by related work, we measured users' touch, the applied force, and the movement of the door handle (see Table 1). Thus, we extend promising previous approaches that measure inertia [15, 18] and also collect touch features [22, 30]. Opening a door usually involves touching the handle, pushing it down, swinging the door, and releasing the handle. To make sure we can collect data during all these phases of interaction, we first performed a technical exploration using an initial version of our prototype (cf. Section 5) [8]. Based on the resulting insights, we improved our prototype and informed our final study design.Next, we used the improved prototype to collect tangible interaction data from 20 participants over two sessions (cf. Section 6), as usually done to evaluate the user identification performance of novel approaches [16, 20, 62, 65]. We extend previous work by introducing a second session of data collection to investigate the robustness of user recognition over time.

With our work, we contribute to a deeper understanding of the underlying interaction factors contributing to performance and robustness over time and across different usage scenarios (cf. Sections 7 and 8).

4 Implementation

In this work, we instrument a door to measure user behavior when opening it. We propose capturing a combination of inertia, capacitance, force, and acoustic resonance. Force measurement was not part of the initial setup used for our technical exploration (see Section 5) but was added based on its results. However, for the sake of consistency and clarity, we collect the implementation of all components in our final setup (see Figure 1) in this section. We list the different sensing technologies and provide the rationale for including them in our system. We focused on technologies that can be used to unobtrusively enhance already existing doors.

4.1 Sensor Selection

To capture all parts of user interaction with door handles (gripping, pushing down, swinging open, and releasing), we aimed at unobtrusively sensing the (a) users' touch, (b) the applied force, and (c) the movement of the door and the handle. Building upon the related works presented in Section 2.3.2, we chose sensors that allowed us to achieve this goal.

4.1.1 Touch. Self-capacitive touch sensing only requires one electrode [17], which is repeatedly charged and discharged for sensing touches. This technology can therefore use the conductive door handle itself as this electrode, making it ideal for our specific use case. Sato et al. [52] enhanced self-capacitive touch sensing by looping through different charging cycle frequencies (aka. frequency sweeps), instead of using a fixed one. This allowed them to recognize different touch gestures instead of just measuring the presence of a touch. One of their application examples was a rotary door knob, which leave us optimistic that the additional features can be useful for user recognition in our context, too.

4.1.2 Force. A well-researched approach to retrofitting touch force and posture sensing capabilities to existing objects is acoustic sensing [44, 45]. This technology is based on the resonant properties each object has, which are influenced by different touch and grasp gestures, as well as force. This technology is also easily reproducible, since commercial audio interfaces can generate the required sinusoidal frequencies and also read the sensor output through a normal audio input interface. Moreover, related work has shown that this sensing technology can serve to identify users in door contexts [31]. However, after conducting pilot tests with the initial version of our prototype, we realized that active acoustic sensing did not perform as desired, so we added force-sensitive resistor strips as suggested by Tietz et al. [59].

4.1.3 Movement. As highlighted in Section 2.3.2, most related works measured the movement of a door handle in 3D-space, its angular velocity, and acceleration by fixing an inertial measurement unit to it. For example, Gupta et al. [18] achieved promising user recognition results using inertial measurements (TAR of 87.27%; FAR of 1.39%; 11 participants). Hence, we build upon their approach.

4.2 Inertial Measurement

We use a 9 degrees of freedom inertial measurement unit (IMU)[3] to measure angular velocity, acceleration, and magnetic field in 3 axes. Replicating Gupta et al. [18]'s work, we attach the IMU to the handle to capture door and handle motion.

4.3 Swept Frequency Capacitance Measurement

We leverage Sato et al. [52]'s swept frequency self-capacitive sensing technique for our work to capture rich touch features. We

[2]Please find all resources necessary to replicate our prototype and our behavior dataset here: http://doi.org/10.17605/OSF.IO/UV2YZ.

[3]https://learn.adafruit.com/nxp-precision-9dof-breakout, last accessed in July 2024

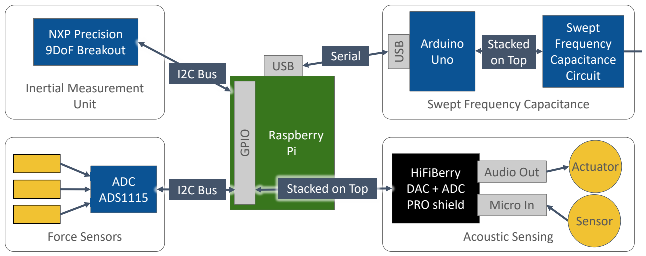

Figure 3: Our setup consists of an Arduino Uno, a circuit for swept frequency capacitive sensing, a Raspberry Pi 4, a HiFiBerry DAC+ ADC pro shield, an ADS1115 ADC, three self-built force sensors, and an Adafruit precision NXP 9-DoF breakout board.

generate square waves with an Arduino Uno[4] and approximate sinusoidal waves using an LC circuit. We use the frequencies (0.6 kHz to 4 MHz in 189 irregular steps over 130 ms with at least 1.5 kHz between frequencies) to approximate the parameters used by [52].

4.4 Active Acoustic Measurement

When generating and measuring an acoustic signal on an object, the resonant response changes according to whether and how it is touched [44, 45]. We use this approach to approximate the properties of the hand and the force used to grip the handle. We use a Raspberry Pi with a HiFiBerry DAC + ADC pro shield[5] at a sampling rate of 192 kHz. As actuator and sensor, we use two unimorph piezoelectric elements (200 Ohm, 4.4 kHz, 27 mm diameter). We use sweeps from 100 Hz to 5 kHz (in 91 uniform steps) in 310 ms, as our tests showed the strongest effects in this range.

4.5 Resistive Force Measurement

To measure the force the handle is gripped with, we built pressure-sensitive strips measuring the change in resistance between two copper layers separated by Velostat[6] and protected the outside with non-conductive foil. We use three such pressure-sensitive strips with a width of 5 mm (bent around the handle) evenly distributed across the surface as a compromise between the resolution of force measurements and leaving enough of the handle exposed for capacitance measurements (see Figure 1b). We measure the resistance with a voltage divider connected to an ADS1115[7] module (ADC with 16-bit resolution). This module is connected to the Raspberry Pi via I2C. We opted for this DIY approach rather than using commercial planar pressure sensors like [22] because our door handle is cylindrical.

4.6 Hardware Composition

All electronics (see Figure 3) were attached to a free-standing door in our lab (see Figure 1c). Where possible, we hid the electronics on the back side of the door to present a clean look to the participants (see Figure 1b). We used a lever-style door with a conductive metal handle so we could measure capacitance without further modification. For non-conductive handles, a solution like copper foil would be needed. A future iteration of our system could attempt to embed the electronics completely in the door and thus make the system invisible.

[4]https://www.instructables.com/Touche-for-Arduino-Advanced-touch-sensing/, last accessed in July 2024
[5]https://www.hifiberry.com/shop/boards/hifiberry-dac-adc-pro/, last accessed in July 2024
[6]Electrically conductive material composed of a polymer and carbon [12].
[7]https://www.ti.com/product/ADS1115, last accessed in July 2024

Table 2: Mean recognition accuracy of the sensing technologies for opening/closing the door.

	technology	unique samples overall	for testing	accuracy mean	std
opening	IMU	6938	1780	**90.00%**	2.24%
	capacitance	2460	630	77.75%	2.08%
	acoustic	1075	277	55.50%	2.70%
	all sensors	7248	1862	84.25%	3.17%
closing	IMU	9918	2625	**94.75%**	0.75%
	capacitance	3433	908	78.75%	3.40%
	acoustic	1471	387	76.00%	1.66%
	all sensors	10356	2746	83.50%	2.29%

5 Technical Exploration

To gain an initial impression of user recognition feasibility with our prototype, we recorded the full door handle interaction cycle – i.e., opening and closing the door. We asked 4 subjects from our personal environment to open the door, enter the room, return, and close it again. Each participant repeated this procedure 40 times.

5.1 Performance Analysis

We split each repetition into opening and closing phases, using a specific capacitive touch feature (320 kHz) to determine interaction duration and timestamps, as it proved stable for touch detection. To account for differing sampling rates (e.g., acoustic: 3.2 Hz vs IMU: 25.9 Hz), values were backward filled (i.e., repeated) until a new value was measured.

Our final dataset consists of 18,600 samples from 320 interactions (80 per participant) and includes 288 features: 9 IMU features (angular velocity, acceleration, and magnetic field along all three spatial axes), 189 swept-frequency capacitance features, and 90 acoustic sensing features. The capacitance and acoustic features comprise measurements across all applied frequencies.

To determine the overall prediction for each captured interaction in the testing subset, we predicted a label for each sample and assigned the final label based on the prevailing class (*winner-takes-it-all*). For example, if most predictions for an interaction pointed to participant 5, the entire interaction was classified as participant 5 and then compared to the true label to assess prediction accuracy (i.e., was it actually participant 5?). To account for the effect of randomness on the accuracy, we report the mean accuracy over 10 executions. Overall, we found a mean recognition accuracy for the combination of all three sensing technologies of 84.25% (opening the door) and 83.5% (closing, see Table 2).

5.2 Implications for User Study

Acoustic sensing consistently performed worst (55.50% and 76.0%) in our initial test. *We, thus, decided to add additional pressure-sensitive strips to capture force directly* (see Section 4.5) and understand if force is a weak predictor in general or if the performance was caused by our specific approach (acoustic sensing).

We observed comparable performance between opening and closing the door. Yet, we see more practical relevance in using the opening motion as personalization inside the smart environment would be triggered when entering a space. *Hence, we focus on opening doors in our user study.*

6 User Study

With our user study, we explored whether our embedded user recognition approach is suitable for real-life applications. To this end, we recruited 20 participants and conducted two study sessions to compare both intra- and inter-session performance. Correspondingly, our dependent variable was user identification accuracy.

Participants visited the lab for two *sessions* at least five days apart. In each session, they opened the door with both *hands* successively. Hence, we used a within-subjects design with two independent variables: *session* and *hand*, each with two levels (session: 1, 2; hand: left, right). During data analysis, we added a third independent variable – the *machine learning model* (random forest, LSTM).

6.1 Procedure

Participants were briefed about their task and the aim of the study. We informed them that their behavior while opening the door was recorded to distinguish them by their individual behavior.

Participants' main task was to open the door (and walk through it) 11[8] times with their right hand, then 11 times with their left. Afterward, they completed a questionnaire about their experience and impressions of the interaction with the door, as well as demographic data. The procedure was repeated for the second session.

6.2 Ethical Considerations

Based on institutional and local regulations, low-risk user studies – like ours – do not require approval by an IRB board. However, we referred to guidelines on ethical best practices when designing the study. Hence, before consenting to participate in the study, participants were provided with detailed information on which data would be collected, the purpose of the data collection, how it would be stored, and that participation was voluntary and could be aborted at any time. We did not collect any audio or video recordings and used random identifiers to anonymize the collected data. Participants received a compensation of 10 euros.

6.3 Participants

We recruited 20 participants with an average age of 25.75 years (std = 6.26, range 19-49) from our local university and personal environment. Most of them (13) were students. Ten participants identified as male, nine as female, and one as diverse. All but two participants indicated being right-handed.

[8]We used the first repetition for participants to get used to the setting and removed it for the analysis, yielding 10 repetitions.

6.4 Data Collection

During our study, we collected readings from all four of our sensors. Those were further processed as described in the next section. In addition, participants filled out a short questionnaire with Likert items to describe their interaction with the system and reported on demographics. Finally, we captured the hand that users preferred for opening the door. From our observation, this varies for different doors. Hence, we captured the preference for our specific setup instead of a general preference. All but one participant indicated they would use their left hand to open the door in our setup.

6.5 Preprocessing

We removed data from the first repetition of all conditions as well as any identifying information about the participants. Results from acoustic sensing were Fourier transformed and smoothed by applying a Savitzky-Golay filter. Similar to the technical exploration, we repeated values of acoustic sensing and swept frequency capacitance until new readings were available to account for different sampling rates between the sensors. To detect the bounds of interactions (i.e., distinguish interactions from idle time), we used the gyroscope measurement on the z-axis. We changed this step compared to the technical exploration, as the capacitive reading we had used was not reliable for a larger population. We determined a baseline (background signal without interaction) as the mode of all readings and determined the start of the interaction when it was crossed by a fixed threshold of 0.05. To account for potential readings in other sensors that could have occurred earlier, we added 0.5 seconds to both the start and end of the interaction.

This resulted in ten repetitions for 20 participants for each hand and two sessions with 288 features each: 9 IMU features, 189 features for swept frequency capacitance, 90 features for acoustic sensing, and 3 force measurements. Interactions with the door handle took between 1.78 and 4.53 seconds ($mean = 2.49, std = 0.33$)[2].

6.6 Models

For our analysis, we employ two models. We chose a random forest classifier as an established (e.g. [47, 59]) and interpretable model that requires minimal preprocessing and is robust to outliers [55]. In addition, we trained an LSTM model for its ability to capture the temporal patterns and sequential dependencies in our collected behavioral data.The models were implemented using Python with sci-kit learn and Keras. We outline detailed configurations below.

6.6.1 Random Forest (RF). For our random forest model, we used the default parameters as in the initial technical exploration. We trained the model on 75% of the data, or on one full session when comparing across days. As mentioned in Section 5.1, we applied a winner-takes-it-all approach to determine the predicted label for each full interaction, since each interaction in our dataset consisted of multiple samples. Hence, the model first predicted a class label for each individual sample, and the most frequently predicted class was then assigned as the final label for the entire interaction. We then compared this predicted label to the ground truth to evaluate classification accuracy. To obtain a more robust estimate of model performance, we repeated the training and testing process 10 times.

6.6.2 *Long Short-term Memory Network (LSTM).*

We implemented a sequential model using Keras that combines dense and LSTM layers to account for the temporal structure in the data (see Appendix B for the full code). The model was trained using categorical cross-entropy as the loss function, which is commonly used for multi-class classification tasks to measure how well the predicted class probabilities match the true labels. To ensure consistency across sequences, we set the input window size to match the shortest recorded interaction. Unless stated otherwise, we split the data into 60% training, 20% testing, and 20% validation[9], and report performance on the test set. When comparing sessions, we used 60% of the first session for training, 40% for testing, and evaluated generalization performance on the entire second session.

6.7 Limitations

Our work focuses on gaining insights into the effect of different implementation variants and interaction factors rather than fine-tuning our models for competitive recognition accuracies. We also used a freestanding door situated in our lab for our setup to ensure a controlled study environment. This may impact the ecological validity of our results, and results may vary for different doors.

Moreover, we implement our prototype using low-cost commercial electronics to support replicability. This resulted in a rather large prototype, which was not integrated into the door (handle) itself. While we were able to avoid the resulting impact on user behavior in our lab study by placing the prototype on the other side of the door, it could certainly disturb natural behavior in real-world settings. The current implementation also emits a sweeping sound due to the acoustic sensing, which could have influenced participants. For future studies, we would, thus, avoid using acoustic sensing, as it also achieved the lowest recognition accuracy.

To investigate if the performance of behavioral biometric systems for door contexts is impacted by changes in behavior over time, we conducted two sessions with 5 or more days in between. However, to not burden our participants too much with traveling to our lab, we did not collect data on all days in between or during a longer period of time. We plan to conduct such a study in the future by recruiting locally situated employees.

7 Results

Here we report on the performance (baseline accuracy is 5%[10]) of the different sensors, recognition rates within and between sessions, the effect of using less training data, and the feedback participants had for our system.

7.1 Sensor Comparison

In the first step, we compare classification performance between sensors. We trained a classifier on both sessions and both hands for each of the sensors separately, as well as for the combination of all sensors. Results are shown in Table 3. The Random Forest classifier performed best for the combination of all sensors (acc=86.41%). Inertial measurement was the best-performing single sensor (acc=68.38%). The force sensor performed worst (acc=31.16%), but did contribute to performance (compared to not using it, as in our technical exploration (acc=82.12%)).

The LSTM model performed weaker but showed similar patterns. Results were similar between using all sensors (acc=41%), only the IMU (acc=43%), or only capacitance (acc=41%). Force again reached the lowest accuracy at 17%.

[9]We made this change compared to the random forest model to account for the introduction of a validation set which was necessary due to iterative testing to find a suitable model configuration.

[10]This is the chance for correctly guessing one out of 20 participants.

Table 3: Prediction accuracy of our random forest (RF) and neural network approach (LSTM) trained on different configurations of sensors as well as training and test data.

	Trained on		Tested on		RF		LSTM
sensor	*session*	*hand*	*session*	*hand*	acc	std	acc
IMU	both	both	both	both	**68.38%**	2.25%	**43%**
Force	both	both	both	both	**31.16%**	1.33%	**17%**
Capacitance	both	both	both	both	**54.04%**	2.22%	**40%**
Acoustic	both	both	both	both	**51.36%**	1.92%	**31%**
All Sensors	both	both	both	both	**86.41%**	1.34%	**41%**
No Force*	both	both	both	both	**82.12%**	0.87%	**34%**
All Sensors	1	both	2	both	**8.16%**	0.21%	**11%**
All Sensors	both	left	both	right	**68.73%**	0.99%	**31%**
IMU	1	left	2	left	**13.78%**	0.64%	**22%**
Force	1	left	2	left	**12.09%**	1.02%	**11%**
Capacitance	1	left	2	left	**5.26%**	0.25%	**8%**
Acoustic	1	left	2	left	**5.05%**	0.95%	**8%**
All Sensors	1	left	2	left	**7.81%**	0.42%	**11%**

**Configuration used in the Technical Exploration*

Table 4: Results from training a random forest with either only a few samples or only including samples from the press down or release of the door handle using the first session and the left hand.

	Samples		Accuracy	
condition	training	test	mean	std
train with 1 interaction per participant	411	3705	58.94%	1.75%
train with 2 interactions per participant	831	3285	69.18%	1.54%
train with 3 interactions per participant	1242	2874	81.01%	1.60%
train with 4 interactions per participant	1657	2459	80.00%	2.37%
train with 5 interactions per participant	2065	2051	**96.26%**	1.17%
press down handle	406	105	60.00%	2.49%
release handle	638	150	**61.00%**	2.54%

7.2 Transferability Between Hands and Days

In a second step, we investigated whether a model trained on one day or one hand would perform well when presented with the respective other one. When training a random forest classifier on both days but using only one hand and predicting on the other, we achieved an accuracy of 68.73% (LSTM acc=31%). When training the classifier on all data from the first session, we achieved a prediction accuracy of only 8.16% (LSTM acc=11%) in the second session.

To understand this better, we trained separate classifiers for each sensor in the first session and evaluated them in the second session. Results can be seen in Table 3. None of the sensors performed well. The IMU and force sensors performed best at an accuracy of 13.78% and 12.09%, respectively. The LSTM results showed the same tendencies again, though the IMU performed meaningfully better at an accuracy of 22% while other results were comparable.

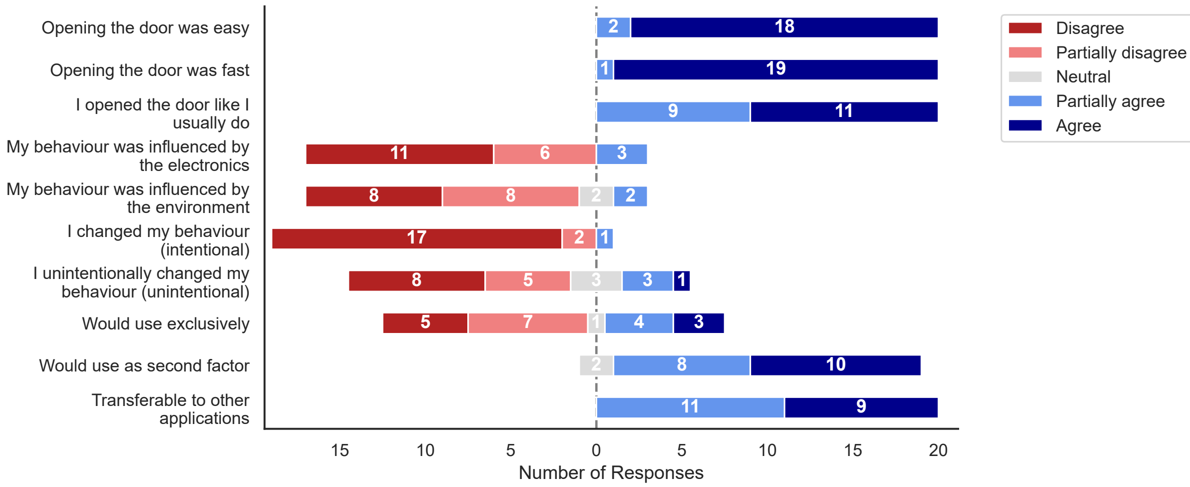

Figure 4: Results from the Likert Statements presented after the second session of our study.

7.3 Learning With Limited Samples

Finally, we noticed that our models seemed to perform well with few training samples. We explored this further in two directions: 1) To understand if scenarios with few or potentially only one training interaction would be possible, we trained models for different numbers of available interactions. 2) To understand if particular phases of the interaction would be sufficient, we trained models on only the data when the handle is pressed down and released again, respectively. As this is exploratory, we omitted to do this for all conditions and used RF in a single session scenario with the left hand (preferred by almost all users) only.

Results are shown in Table 4. Even with only one repetition (i.e., one door opening action), we get an accuracy of 58.94% that increases up to 96.26% when using five repetitions for training. For the phases of the interaction, we found comparable results for both pressing down and releasing the handle, with an accuracy of 60.0% and 61.0% respectively.

7.4 Likerts & Open Feedback

In order to assess possible confounding variables, we also asked our participants to complete a short questionnaire after the second session. Refer to Appendix A for an overview of the questionnaire items. In particular, participants rated various Likert statements on a 5-point scale ranging from disagree to agree (see Figure 4). Participants found it easy (*Mdn = 5*) and fast (*Mdn = 5*) to use the door and interacted as usual (*Mdn = 5*). They did not feel any influence of the electronics (*Mdn = 1*) or environment (*Mdn = 2*) nor did they actively change their behavior (*Mdn = 1*) or were aware afterward that they could have changed it unintentionally (*Mdn = 2*). When asked if they could imagine using our system, opinions were more undecided. Participants leaned towards not wanting to use our approach as a sole factor (*Mdn = 2*) but could imagine using it as a second factor (*Mdn = 4.5*). They also believed that behavior collected this way could be utilized for other applications (*Mdn = 4*). We also asked participants to list potential further applications. They mentioned the extension to handles of car doors or lockers, and safes. Further comments described where the system could be used: participants suggested offices, dormitories, laboratory areas, and residential homes as potential application areas.

In summary, we found no indication that participants felt influenced by the prototype or study setup. They described the interaction as easy and fast – consistent with typical door use. This suggests our data is ecologically valid despite being collected in a lab setting, though further studies are needed to confirm this. Moreover, participants appeared sufficiently convinced by the concept of identification via door-related behavior to consider using it for authentication and other use cases. We interpret this as motivation for further research, as it suggests potential for high user acceptance of such systems.

8 Discussion

In this paper, we extended setups from previous work with additional hardware, a second data collection session, and additional analysis. Here we discuss our insights and identify opportunities for further research.

8.1 Force Is Less Useful Than Inertia

Based on our technical exploration, we added three pressure-sensitive stripes to measure the force used to grip the door handle. Our results are inconclusive as to whether this was beneficial. For both the random forest classifier and the neural network, the force sensor achieved the lowest classification accuracy. It was consistently less reliable than the acoustic sensing that it was supposed to potentially replace. At the same time, we did observe that the combination of all sensors worked better than a setup without force sensors. This indicates that overall, they do seem to contribute to performance. We also believe that measuring force could become more important in usage scenarios where a decision should be made before the interaction is complete – i.e., from only touching the handle or from pressing it down while the door is still locked – force may become more relevant, as less movement data is available.

8.2 Behavior Is Not Persistent Between Sessions

Most related works have evaluated their approaches in a single session with convincing performance (cf. Table 1). When using a single session, we saw similarly promising results. However, in our work, we added a second session to see if the behavior when opening doors is persistent and could be used across sessions. Our results do not support this assumption. However, we observed trends in the sensor performance that could serve as a starting point for further investigation: for both the random forest and the LSTM model, we saw better performance between sessions of the IMU and force sensors. Those sensors have a higher temporal resolution, whereas both acoustic- and captive sensing capture data over a time window of about 300 ms. Reducing the time those sensors need to collect data or including other sensors with higher temporal resolution may improve performance across sessions. Noticeably, this also underlines the importance of extending study setups after preliminary tests, as otherwise we would have missed those effects.

8.3 Behavior With One Hand May Transfer To The Other

In our study, we investigated whether behavior exhibited with one hand can be used to distinguish users when they use their other hand as well. To our surprise, results from both of our models show that this may be the case. Further research in this direction is needed, but such an effect would be an important step toward the real-world applicability of our system. In daily situations, it is not uncommon that one hand is not available (e.g., when carrying something), and users may prefer one or the other hand to open a door depending on the room layout. This suggests that a model trained on interactions with one door could potentially generalize to similar doors and still distinguish between users.

8.4 One Interaction May Be Enough

While our results do not indicate that behavior between sessions is persistent, we did find that training on a per-session basis is viable. Using as few as one interaction, we were able to achieve an accuracy of about 58%. Each additional interaction improved recognition substantially. Keep in mind that we did not optimize our models for performance, so further improvements to the model could enable scenarios like registering in the morning and using recognition throughout the day. However, it remains unclear how stable the behavior is over longer periods. Further analysis, for example, over the course of a day, would be needed to understand when retraining becomes necessary.

8.5 Doors Can Be Leveraged For More Than Access Control

Our results show that reliable user recognition before the door swings open or from the pressing motion alone is challenging. However, this does not rule out meaningful applications. Rather than serving as a primary access control mechanism, we see our approach better suited for on-demand recognition scenarios where real-time decisions or contextual adaptations can occur *after* the door interaction is underway. Recognized users could trigger personalized environmental settings (e.g., lighting or temperature), initiate seamless context handovers across devices, or enable access to certain features or information within a space. Additionally, user interaction patterns with door handles may offer implicit cues about their physiological or emotional state, such as stress levels, or serve as an explicit, tangible input method in smart environments. These directions point to a broader design space where behavioral recognition at doors can support ambient intelligence, situational awareness, and nuanced security responses like silent alarms for unauthorized entry. Overall, we see many opportunities to leverage our system both for security research and beyond.

8.6 Investigating User Perception

We explored the feasibility of tangible behavior-based identification in door contexts in a broader manner, by analyzing (a) the *performance of multiple sensors*, (b) the *persistence of door-opening behavior*, (c) the impact of using *only parts of the interaction for training* recognition models, and (d) the robustness of this method *if different hands are used*. The above sections described how our findings inform future implementations and research on the performance of this approach. However, user acceptance and perceptions of such systems remain largely unexplored, as related work has also provided few findings in this area. We therefore see strong potential for future studies specifically focused on these aspects.

9 Conclusion

In this paper, we explored user recognition during the door-opening process by combining four sensors embedded in a door handle. In a two-session study with 20 participants, we demonstrate that users can be recognized within a single session—even with only a few samples. While cross-session recognition remains challenging, our findings show promising results for transferring models between hands. With our work, we provide fundamental insights and inform directions for future research on enabling seamless behavioral biometrics at doors.

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A Questionnaire

- Opening the door was easy. [5-point Likert-Scale]
- Opening the door was quick. [5-point Likert-Scale]
- I opened the door like I usually do. [5-point Likert-Scale]
- My behavior was influenced by the electronics on the door (e.g., cables, noises). [5-point Likert-Scale]
- My behavior was influenced by the environment (e.g., lab, other participants). [5-point Likert-Scale]
- I intentionally changed my behavior during the study (e.g., grabbed the door handle harder). [5-point Likert-Scale]
- I think I unintentionally changed my behavior during the study (e.g, touched door handle in different places). [5-point Likert-Scale]
- I trust the technology and would feel comfortable using the prototype exclusively as a security and authentication factor. [5-point Likert-Scale]
- I trust the technology, but would feel more comfortable if the prototype were used as a second factor in an authentication system. [5-point Likert-Scale]
- I can imagine that the authentication of a person by the individual behavior of opening the door is also transferable to other applications. [5-point Likert-Scale]
- Can you think of any other fields the prototype could be applied to in order to improve security? [Free Text]

B LSTM network

We used the following code to generate the neural network used for our experiments:

```
model = Sequential()
model.add(Dense(32, kernel_regularizer=keras.
    regularizers.l2(1e-5) , input_shape=input,
    activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Dense(16, kernel_regularizer=keras.
    regularizers.l2(1e-5), activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Bidirectional(LSTM(16, return_sequences=
    True, activation='tanh')))
model.add(Bidirectional(LSTM(16, return_sequences=
    False, activation='tanh')))
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Dense(16, kernel_regularizer=keras.
    regularizers.l2(1e-5), activation='relu'))
model.add(Dense(output, activation='softmax'))
```