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Adversary Models for Mobile Device Authentication

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Mobile device authentication has been a highly active research topic for over 10 years, with a vast range of methods proposed and analyzed. In related areas, such as secure channel protocols, remote authentication, or desktop user authentication, strong, systematic, and increasingly formal threat models have been established and are used to qualitatively compare different methods. However, the analysis of mobile device authentication is often based on weak adversary models, suggesting overly optimistic results on their respective security. In this article, we introduce a new classification of adversaries to better analyze and compare mobile device authentication methods. We apply this classification to a systematic literature survey. The survey shows that security is still an afterthought and that most proposed protocols lack a comprehensive security analysis. The proposed classification of adversaries provides a strong and practical adversary model that offers a comparable and transparent classification of security properties in mobile device authentication.

CCS Concepts: • Security and privacy → Mobile platform security; Trust frameworks; Authentication;

Additional Key Words and Phrases: Mobile device authentication, adversary model, survey

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1 INTRODUCTION
Mobile devices carry an increasing variety of personal data. For instance, recent proposals to include electronic identities into smartphones to replace classical photo identification such as driver’s licenses or passports [124] as well as applications and sensors to more accurately capture the wearer’s health status [119], audible interaction,¹,²,³ and even emotional state [110, 168] highlight the breath of sensitive data.

¹https://www.apple.com/ios/siri/.
²https://developer.amazon.com/alexa.
³https://assistant.google.com/.

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Mobile devices are therefore becoming a critical component in terms of security and privacy not only in the digital domain but also for interactions in the physical world, with users unlocking their smartphones for short (10–250 s) interactions about 50 times per day on average [80, 121].

In this article, we address user-to-device (U2D) authentication, i.e., users authenticating themselves before being able to use certain functionality of a device [211, 267], as well as two other forms of authentication, device-to-device (D2D) [50, 94, 183], and device-to-user (D2U) [89, 181]. For an excellent discussion and history of adversary models also in other domains, please refer to Reference [78].

U2D authentication can be performed by one or a combination of four factors\(^4\) [84, 175]:

1. something a user knows (passwords, PIN codes, graphical patterns, etc.)
2. something a user possesses (hardware tokens, keys, etc.)
3. something a user is (static biometric, e.g., fingerprint, face, iris, hand geometry, vein patterns)
4. something a user does (dynamic biometric, e.g., gait, handwriting, speech)

Many authentication methods have been proposed for mobile devices, however, a canonical U2D authentication did not yet converge. Instead, approaches have their respective advantages and disadvantages [66, 120]. Second factor authentication with something a user possesses often demands D2D authentication through wireless communication. Secure D2D authentication is thus a condition to using wireless devices as hardware token for U2D authentication. In this article, we do the following:

- Survey security analyses in the state of the art and derive their assumptions (which are often not explicitly stated) about attackers of such authentication methods. These so-called adversary models are a sub-set of threat models commonly applied to cryptographic protocols.
- Show that existing security evaluations of these methods often lack, with many proposals using an insufficient number of volunteers or missing independent analysis by others.
- Propose a qualitative classification of adversaries to mobile device authentication that enables a more systematic adversary modeling, and use this scheme in our review.

We design our classification scheme by studying the requirements for useful adversary models at a meta level, with the aim of applying specific instances of these model classes to individual authentication methods. Our intention is for this scheme to be used for future research, giving authentication methods a concrete security level to aim for and to test against. Finally, this article is also a call for action to improve the state of the art in security testing of mobile device authentication.

2 AUTHENTICATION ON MOBILE DEVICES

General threats for user authentication, which include brute-force, password guessing, installing malware, and hardware-level exploits to bypass authentication, typically also apply to mobile devices. Mobile device security, however, is inferior to security on desktop computers [51, 214]. In mobile device scenarios, additional security threats exist [23] because of usability issues or limitations due to smaller size (e.g., watches), and in some cases even due to computational and storage capabilities, for instance, on implanted, medical or wearable devices (e.g., pacemakers, earables, hearing aids) [35, 125, 220].

2.1 Adversary Models for User Authentication

In a recent meta survey by Ferrag et al. [12], impactful surveys on mobile device authentication are analysed [7, 82, 105, 116, 147, 159, 188, 211, 214, 252, 267]. In total, these articles describe 26

\(^4\) For D2D and D2U authentication, various factors and physical channels have been proposed, but no systematic classification has so far been accepted as common knowledge.
attacks, 5 threat models, and 4 authentication categories. By complementing this work on attacks and countermeasures, we target adversary models.

To describe the security properties of a particular protocol, formal models are employed in the literature. The most famous of these adversary models for communication channels is the Dolev–Yao model. It assumes that communication partners trust their encrypted messages to an adversary for delivery [79]. The adversary may use any information obtained from previous messages in attempts to decrypt the information and is, in particular, not constrained by other assumptions. The Dolev–Yao model is indistinguishable under chosen plaintext attacks, respectively chosen ciphertext attacks (IND-CPA/IND-CCA) for formal cryptographic protocol verification [24].

The existence of such accepted standards is crucial for the field, since it (1) helps to build trust in security mechanisms, (2) generates a common ground on which approaches are comparable, and (3) creates incentives to build stronger security schemes. It is also a necessary requirement for (4) the generation of business models grounded on secure technology.

In mobile device authentication, however, the literature has yet to converge on a common adversary model. While the Dolev–Yao model has been applied also for mobile device authentication [247, 275], this approach has shortcomings as it does not reflect the specific nature of mobile device authentication. For instance, authentication on mobile devices is performed in public spaces, potentially under video surveillance. Furthermore, the user interface is limited, and thus prevents some strong authentication mechanisms.

The landscape of mobile device authentication methods is fragmented and methods are hardly comparable to each other. This creates uncertainty on the security properties and on the appropriateness of any mobile device authentication method. Challenges to selecting appropriate security margins and cryptographic parameters are that (1) real-world applications require different security levels [153] and that (2) the resources (e.g., attention, constrained or absent interfaces) in mobile settings place limitations on the authentication method [44]. Adversaries differ, for instance, in their capability (ability, training, knowledge), e.g., typical user, developers, or manufacturers, and in the effort (storage, computational, monetary) they invest, e.g., individuals, organizations, or nation states.

Table 1 summarizes recently proposed security models sorted by their year of publication. In particular, the discussion on the best suited modality to condition and build the threat model on, has not yet converged. For instance, Ong et al. and Boyd et al. define security levels based on key size, block size, and type of data [38, 207], while Hager et al. and Burmester et al. consider performance, energy and resource consumption to be most relevant [44, 113]. This relates to Damgard et al. who analyse the tradeoff between complexity and security [58]. Likewise, also Ng et al. and Paise et al. see computational complexity as the relevant measure to distinguish adversarial classes [202, 209]. Instead, Sun et al. suggest the quality of protection to measure the level of security [259], while Ksiezopolski et al. distinguish between types of applications to define the adversary model [153]. An adversary model for mobile settings that is based on a Dolev and Yao–type adversary model has been proposed in Reference [76]. A different approach is taken by Ahmed et al. [4], who identify a least-strong attacker by iteratively testing against decreasing security strength.

A number of further adversary models have been proposed for specialized cases within the larger frame of mobile device settings. Specifically, this regards the adversary model by Gligor, which is specifically targeted toward mobile ad hoc networks [106] as well as a collection of adversary models toward forensic investigations on mobile phones, which were proposed by Azfar et al. [18] and Do et al. [77]. Notably, Do et al. defined their adversary via her goals, assumptions and limitations. This framework was later applied by them also to an app-based adversary model, where the classes were slightly modified to replace limitations with capabilities [78].

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5Other types of formal definitions for authentication can be found, for instance, in static analysis or type theory [1, 34].
Table 1. Previously Proposed Adversary Models

| Paper | Brief summary of the proposed contribution | Year |
|-------|--------------------------------------------|------|
| Ong et al. [207] | Security levels based on key size, block size, and type of data | 2003 |
| Hager [113] | Security levels conditioned on performance, energy and resource consumption | 2004 |
| Ksiezopolski et al. [153] | Different applications require different security levels | 2007 |
| Gligor [106] | Adversary model specifically focused on mobile ad hoc networks | 2007 |
| Sun et al. [259] | Evaluation model based on quality of protection | 2008 |
| Damgård et al. [58] | Tradeoff between complexity and security in symmetric cryptography | 2008 |
| Ng et al. and Paise et al. [202, 209] | Security model with adversarial classes based on computational complexity | 2008 |
| Burmester et al. [44] | Mobile device security suffers from limited resources | 2009 |
| Ahmed et al. [4] | Model conditioned on iterative testing of security strength | 2011 |
| Boyd et al. [38] | Defines security levels conditioned on key size, block size and type of data | 2013 |
| Do et al. [77] | For forensic investigation, using adversary goals, assumptions and limitations | 2015 |
| Song et al. [251] | Metric to measure the strength of pattern lock systems | 2015 |
| Do et al. [76] | Dolev and Yao type of adversary model for mobile covert data exfiltration | 2015 |
| Azfar et al. [18] | Adapt an adversary model for forensic investigations on mobile phones | 2016 |
| Miettinen et al. [191] | Security levels conditioned on the entropy of the context source | 2018 |
| Do et al. [78] | Adversary classified by assumptions, goals and capabilities | 2019 |
| Ferrag et al. [84] | Survey on threat models for mobile devices | 2020 |
| Hosseinzadeh et al. [126] | Adversary model for RFID: grounded on Gong-Needham-Yahalom logic | 2020 |

Specifically, for pattern lock systems on smartphones, Song et al. conditioned their model on characteristics of the pattern-lock design [251], while Hosseinzadeh et al. focus on strictly resource limited RFID devices and base their scheme on Gong-Needham-Yahalom logic [126]. In particular, similar to Reference [4], their model also includes attackers of various strength [202, 209].

Finally, in recent years, context-based device pairing schemes have been proposed that rely on shared access to common contextual stimuli for device-to-device authentication. For this setting, Miettinen et al. [191] have proposed an adversary model that is conditioned on the entropy of the context source.

A survey on threat models for mobile devices has also been presented by Ferrag et al. [84]. In summary, although recent publications on device authentication bring forward a discussion on potential security threats or attacker studies [47, 136, 151], a single universally accepted model is lacking.

Due to the diversity of mobile devices and applications, a single common adversary model might not be feasible. To be useful in general practical application, a meta model, exploiting a set of models that account for different usability requirements is needed to qualitatively assess the security level. Therefore, in Section 4 we introduce a classification scheme for adversary models to support such qualitative comparison.

### 2.2 Limitations of Traditional Authentication Schemes

Electronic devices are traditionally protected via alphanumerical passwords or PIN codes [99]. Due to restrictions in the user interfaces of mobile devices, passwords generate a tradeoff between usability and security. A frequently employed alternative for authentication are graphical patterns. However, such patterns are vulnerable to shoulder surfing or smudge attacks [15, 28]. In shoulder surfing, the adversary either directly or through video [300] observes the authentication sequence and reproduces it. In smudge attacks, the adversary visualizes smears on the touch interface left behind as a consequence of user authentication. The frequent changing of authentication challenges to counter these attacks again compromises usability [73].
Fig. 1. Visualisation of generic attack vectors in biometric systems (based on Reference [219]). The right side depicts the components of a bU2D authentication system and their interplay while on the left side, various attack vectors on the respective components are exemplified.

Alternatively, biometrics, recognising individuals from behavior and biological characteristics, gained attention for authentication. This is attributed to biometric sensors included in smartphones, such as fingerprint [139] (pore and ridge structure [256]), voice [48] (mel frequency cepstral coding, today deep neural networks [144]), gait (heel-strike ratio [237] or cycle matching [200]), face (features learned in deep neural networks [134]), keystroke dynamics (key-press latencies [195]), or iris [290] (image intensity maps from Hough-transformed Daugman rubber sheet models [281]).

Since biometrics inherit noise, fuzzy pairing is used to account for dissimilarities in the key sequences [140]. Sequences are mapped onto the key-space of an error correcting code (for instance, BCH or Reed Salomon codes), where \( t \) bits can be corrected. This process also boosts the success probability of an adversary. Assuming \( |c| \) bit long sequences of which \( t \) bits are corrected to result in \(|c| - t\) bit long keys, the success probability of a single randomly drawn sequence is then only

\[
\sum_{i=0}^{t} \binom{|c|}{i} / 2^{|c|} = \sum_{i=0}^{t} \frac{|c|!}{(|c|-i)! \cdot i!}.
\]  

However, biometrics cannot be kept secret and they cannot be revoked [85, 235, 236]. Consequently, they cannot withstand strong attackers under the assumption of targeted spoofing.

Figure 1 shows attack vectors for biometric systems [219]: (1) biometric spoofing [158, 193, 200, 244, 254, 298], (2) replay attacks [112, 230, 268], tampering with (3) feature extraction [167], (4) biometric feature representation, (5) stored templates [102, 255], (6) modifying template data [112, 230], (7) corrupting the matcher, and (8) overriding the final decision. Suggested countermeasures include liveliness detection, supervised enrollment, and securing all stored biometric data [255].

2.3 Adversary Models for Device-to-device Authentication

Device-to-device authentication is used to pair devices under mutual trust. The information relevant for the pairing can be present at the devices, provided by human interaction, or acquired from the device’s software or hardware sensors. Also, for D2D authentication, capabilities and effort of the adversary are of key relevance for adversary models.

Figure 2 summarizes attack vectors for D2D authentication. In particular, devices acquire data (stored, human interaction, or sensed), quantize it to bit strings after pre-processing, apply error
correction, and agree on a key. Attack vectors are (1) sensors (forcing the device owner to behave in certain ways), (2) bypassing acquisition through replay, and (3) biased feature processing. Some protocols employ communication before the actual key agreement [109, 237, 298] that might (4) potentially leak information; after error correction, which might be (5) corrupted, the key agreement is executed between both devices, thus enabling potential (6) Man-in-the-Middle (MitM) (also referred to as Person-in-the-Middle or on-path attacks), (7) exploitation of weak or false assumption-based key agreement, as well as (8) impersonation attacks.

To prevent exhausting the key space, adversaries should be forced into a one-shot model [280]. For instance, **Password Authenticated Key Exchange (PAKE)**, implemented, e.g., by Bluetooth 4.2 **Secure Simple Pairing (SSP)**, IPSec, and ZRTP [143, 262, 303], ensures that the chances of a successful attack depend solely on interactions in the protocol and not on offline computing power [183, 233]. They thus provide sufficient security margin even with short keys $K$. Most PAKEs allow for multiple parallel protocol runs [280] and threat models that allow implicit error correction choose a relatively high $K = 24$ to still have a negligible attacker success probability even if only 16 out of 24 bits are compared correctly [81]. Similar margins have been chosen in Bluetooth for PIN comparison with $K = 20$ and ZRTP for word comparison with $K = 20$. Modern PAKEs also provide resilience to dictionary, replay, unknown key-share, and Denning-Sacco attacks [274], as well as toward mutual authentication, key control, known-key security, and forward secrecy.

Implicit pairing derives secure secrets from similar patterns, e.g., acceleration [90, 109, 118, 185, 253], audio [238], magnetometer [138], or RF features [179], from devices co-present in the same context.

### 2.4 Device-to-user Authentication

An adversary able to deceive a user into wrongly trusting the identity of a (malicious) device, can harvest user credentials (biometric or knowledge-based) on a subsequent attempt to log in to the device. Device-to-user authentication attempts to address this issue by establishing a means of authenticating the device to the user. One approach is to visually reveal secret information to establish trust, e.g., by displaying variations of secret images to assure authenticity [225, 226].
such systems are prone to shoulder surfing. Device-to-User authentication is intended to be used frequently and must therefore mitigate usability drawbacks. Although mutual authentication is well established in D2D authentication (e.g., IPsec [60]), it is rarely used for authentication involving humans. A reason for this is that device-to-user authentication is bandwidth limited due to the limited attention span and cognitive resources for the recognition of patterns by the user [181]. Initial approaches with vibration patterns have been analyzed [89] but seem impractical.

3 ATTACKS AND MODALITIES

For all authentication settings (U2D, D2D, D2U) we distinguish various attack types. An authentication system shall at least prevent accidental login from non-authorized users: evaluation against blind guesses (knowledge-based authentication) or samples (biometric) [64, 83, 96, 108].

Any targeted attack will be more powerful [240], for instance, biometric spoofing to exploit weaknesses of specific biometric modalities [21, 276], such as using a picture of a target person in an attempt to spoof face recognition.

An informed adversary may also attempt to attack the software implementation [217], or to exploit security breaches in the operating system to leak confidential information about the authentication challenge [164], for instance, obtaining extraordinary privileges to install a keylogger.

In some cases, historical or other publicly available data can be used to elevate chances of a successful attack. For instance, Reference [20] exploits population statistics to launch an attack on a handwriting biometrics system, while Reference [239] leverages a typing-database to attack keystroke authentication.

Adversaries can also steal authentication samples to, e.g., replay them [217], to train adversaries to forge patterns [200, 268], or to distort the victim’s template and expose it to further attacks [288].

The victim sometimes enables attacks through careless actions that lower the effective security (disabling authentication [96], inadvertently providing access to credentials [19]). Mobile systems can counter this by, e.g., careful choice of images [11] or geometric transformations [234].

Another threat is automated attacks against mobile authentication by robotic systems [240].

Finally, side channels are a common threat to mobile systems, such as smudge [15] and shoulder surfing attacks [95, 115]. Others are the use of on-device accelerometers to recover a PIN [16] or inferring credentials from channel state information (CSI)9 [165]. Countermeasures include input methods that integrate haptic and audio feedback [28], or applying geometric image transformation [234]. Another countermeasure is to lower the number of authentication challenges presented by introducing a limited access safe-mode to access non-critical functions without authentication, while falling back to authentication for other functions [45].

4 CLASSIFYING ADVERSARY MODELS IN MOBILE DEVICE AUTHENTICATION

Our classification of adversary models in mobile device authentication is related to the ISO/IEC 62443 security levels that have been specified in ISA99 [131]10:

SL0 “No special requirement or protection required”

SL1 “Protection against unintentional or accidental misuse”

---

9Changes in electromagnetic signals at a radio receiver caused by movement of a user or object reflecting the signals are visible in the CSI.

10Only a summary document of this standard is available online at the time of this writing, in the form of public slides by Pierre Cobes; Available online at http://isa99.isa.org/Public/Meetings/Committee/201205-Gaithersburg/ISA-99-Security_Levels_Proposal.pdf. In this article, we use the slightly more detailed wording from https://en.wikipedia.org/wiki/IEC_62443.
We formally classify adversaries in mobile device authentication along the dimensions “capabilities” and “effort” (cf. Figure 3).

In particular, capabilities in terms of sophistication of specific attacks on mobile device authentication defines an upper bound on the capability of an adversary and which information and secrets she has access to. This is roughly comparable to the definition of oracles in cryptographic protocol verification.

The effort in terms of time, computation, (volatile or non-volatile) memory, and other resources is the upper bound on the amount of energy an adversary is prepared or capable to spend. This limits the number of trials to attack an authentication method (e.g., the number of guesses in a brute-force attack).

Note that effort and capabilities define qualitative (ordinal) aspects in mobile device authentication that are not absolute but vary in their severity with the context in which mobile device authentication is performed. Classifying attacks along these dimensions allows systematic comparison of authentication methods with respect to adversary models. Capabilities and effort are the essential characteristics for adversary classification, which are found prominently in many adversary models in the literature, such as References [25, 78, 208]. They also relate loosely to the terms “skills” and “resources” from the IEC 62443 standard. These two categories are essential and sufficient to describe an adversary model in mobile device authentication. Separating those two dimensions indeed supports a formal classification of adversary models. Practical experience shows an increasing number of attacks with low sophistication (capabilities), but high computational resources (effort), such as cloud-support or networks of compromised machines. A preliminary version of our distinction between adversary classes has appeared in Reference [200].

Using the attack modeling abstractions of “collusion” and “oracles” that is also used to argue on the security of cryptographic protocols, we can compare these two categories to the security levels defined in IEC 62443:

| Capabilities | Resources (time, computation, memory, etc.) available to an average individual (dependent on culture, country, time, etc.). | Resources available to an organization (capture-the-flag teams, organized crime, multinational companies, etc.). | Resources available to a nation state (assumed to be able to compel organizations or individuals to assist). |
|--------------|---------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------|
| **C1**       | Capabilities attributed to an average user (benign user of the system, with no additional knowledge).                           |                                                                                                 |                                                                                                |
| **C2**       | Capabilities of a developer (knowledge about internal structure: no privileged access or possession of cryptographic keys (Kerckhoff’s principle)). |                                                                                                 |                                                                                                |
| **C3**       | Capabilities of manufacturer, owner, operator (in-depth knowledge; access to cryptographic keys, instructions, or hardware ports (insider [182])). |                                                                                                 |                                                                                                |

Fig. 3. Adversaries differ with respect to their capabilities and the effort they are prepared to invest.

SL2 “Protection against intentional misuse by simple means with few resources, general skills and low motivation”

SL3 “Protection against intentional misuse by sophisticated means with moderate resources, (IACS-specific) knowledge and moderate motivation”

SL4 “Protection against intentional misuse using sophisticated means with extensive resources, (IACS-specific) knowledge and high motivation”

11Within the scope of this article, we do not distinguish between an original manufacturer of a system, the current owner, and a technical operator, but assume the superset of all their capabilities. In terms of cryptographic protocol analysis, this class is most similar to a collusion between all parties besides the actual target system of an attack.

12We explicitly do not distinguish between original developers and outsiders, as the internal structure can typically be reversed engineered.
Fig. 4. Summary of adversary classes; The table may be used during the classification and to help for easy identification of adversary classes. Some combinations of capability and effort leave freedom to the practitioner with respect to the choice of the most appropriate class and should be decided based on the severity of the attack.

- \( \leq C_1 \) (no oracle access) \( \Rightarrow \leq SL_2 \) (“general skills”)
- \( \leq C_2 \) (access to an oracle with source code and all other implementation details, but not to private keys of devices protected with the relevant authentication method) \( \Rightarrow \leq SL_3 \) (“specific knowledge”)
- \( \leq C_3 \) (access to an oracle with all long-term keys (explicitly including private keys of individual devices), just not the session keys of past authentication interactions) \( \Rightarrow \leq SL_4 \) (“sophisticated means and specific knowledge”)
- \( \leq E_1 \) (a single adversary, no collusion with other parties allowed) \( \Rightarrow \leq SL_2 \) (“few resources”)
- \( \leq E_2 \) (a group of colluding adversaries, e.g., multiple angles to observe an authentication event at the same time or multiple tokens correlated for learning something about the internal state) \( \Rightarrow \leq SL_3 \) (“moderate resources”)
- \( \leq E_3 \) (a collusion of all parties besides the actual, legitimate user) \( \Rightarrow \leq SL_4 \) (“extensive resources”)

These are upper bounds for security levels that can be reached under the assumption of the respective capability and effort classes. Our scheme assumes that all authentication methods can be broken by an adversary with sufficient capabilities and effort. However, the required level of capability and effort to do so differs between authentication methods. We define four classes of adversaries to provide an ordinal scale to compare the security efforts different authentication methods have been tested against (cf. Figure 4).

In particular, we distinguish between zero effort, minimal effort, advanced effort, and guaranteed success attack cases. As can be seen from the figure, in mobile device authentication, the distinction between these attack classes inherits a limited degree of fuzzyness, which stems from the context in which the attack is performed. The same attacker with identical effort and capabilities may conduct attacks of different severity, depending on the context in which the authentication method is situated. For instance, contexts that demand a higher mental load (e.g., due to distraction; higher loudness; impaired vision (e.g., water, smoke, light)) or higher degree of exposedness to public may render attacks of adversaries with same resources and capabilities more significant. Since the context space is infinite, including context means to abandon generality. Therefore, our model tolerates limited degree of fuzzyness in the definition of the attack type.

4.1 Zero Effort Attacks

It is common procedure to measure false-positive and false-negative rates for biometric authentication, and this is also adopted to evaluate authentication schemes such as graphical
passwords [8, 223, 263]. Most quantitative evaluations use subjects with ground truth and compute the confusion matrix of authentication attempts against stored templates. Common measures such as accuracy, precision, recall, true-/false-positive/negative rates, or F-measure are all based on this same principle [31, 42]. We refer to this as a zero effort attack, because no malicious adversary other than benign subjects exists (adversaries with basic capabilities (C1), and small effort (E1)). Zero effort attacks represent the risk of random success and include naïve (non-targeted) brute force attacks. Examples are honest-but-curious office colleagues, or a stranger who chances upon a misplaced device.

In terms of IEC 62443, zero effort attacks can happen in both SL0 and SL1 (random or unintentional misclassification).

4.2 Minimal Effort Attacks
A minimal effort attack is targeted, for instance, mimicking gait, but not with particular sophistication. The adversary has no specific system knowledge (C1), but moderate effort (E1–E2). Minimal-effort adversaries have the explicit intention of attacking an authentication method and a specific target. Many published approaches used minimal effort attacks in their analysis, typically with students or colleagues from the same research group, with low effort and low to average sophistication.

Minimal effort attacks are possible up to SL2 with a growing spectrum of computational resources available to otherwise unskilled attackers.

4.3 Advanced Effort Attacks
Advanced effort attacks show higher sophistication (C1 and C2), such as, e.g., professional actors trained in imitating body motions, and significant effort (E1–E3), loosely mapping to SL3. We explicitly exclude the combination of (insider) advanced developer-level sophistication with nation-state effort (E3, C2), which would map to SL4. However, it does not seem helpful for evaluating mobile device authentication methods.

4.4 Guaranteed Success Attacks
A guaranteed success attack succeeds in breaking the security of an authentication method. It allows for any system to describe which capabilities or effort are required for a successful attack. Authors of device authentication methods are advised to include this adversary class to define the minimum adversary expected to break the system. An adversary in this class may possess all capability (C2–C3) and effort (E1–E3). Note that low-effort guaranteed success attacks are possible, for instance through access to cryptographic credentials (E1, C3).

Our notion of guaranteed success does not have a correspondence in IEC 62443 security levels; it is one area where we argue that existing standards are lacking in explicitly defining which adversary assumptions are outside the scope of security designs.

5 LITERATURE SURVEY: ADVERSARY MODELS FOR MOBILE AUTHENTICATION
We discuss proposals for mobile authentication and adversary models used, and group the literature according to the adversary class utilized to allow a domain-specific discussion of adversary models. A summary of the publications covered is given in Tables 6 to 9. We recommend to use the survey as a reference and refer the informed reader to the overview in Figure 5 to quickly navigate to the section of her interest. In addition, attack schemes are collected in Tables 2, 3, and 4.
5.1 Biometric User-to-device Authentication (bU2D)

A large body of work has exploited biometric stimuli for mobile authentication [189]. Measures cover, for instance, spoken audio, keystroke dynamics, face biometrics, gaze, application usage, iris, gait, or fingerprints [132].

Most work in this domain show the general feasibility of a working principle (E1, C1; zero effort), by using a small number of subjects distinguished by the modality, but no threat model, attack scenario, or analysis of password space. Table 2 summarizes attacks on biometric authentication.

5.1.1 Speech and Audio. A number of zero effort attacks has been considered for biometric systems based on speech and audio. For instance, in speakersense [173], during a voice phone call a person is identified. The system was tested with 17 subjects, achieving over 95% of accuracy.

However, an adversary actively trying to break the system has not been considered (E1, C1; zero effort). For instance, already a minimal effort attack using voice impersonation (replay) might trick the system [48]. A protection against such attack is proposed by exploring the magnetic field emitted from loudspeakers to distinguish between playback and live voice. Note that, an informed advanced adversary, not using magnetics based loudspeakers with access to respective resources (advanced microphones) could easily circumvent this protection.

Another example for a system tested only with respect to minimal effort attacks is Reference [302]. The authors utilize the audio system of the phone as a doppler radar to obtain further evidence on speaker identity. The authors launched mimicry attacks (adversary with access to video recording and practice) but did not consider advanced (e.g., developer) sophistication.

An example of a comprehensive security discussion in this domain is the usable two-factor authentication based on proximity measured from ambient sound is Reference [142]. Starting from false acceptance and false rejection rates (zero effort), advanced effort attacks are considered (similar environment, same media) and the analysis further distinguishes remote from co-located attacks, which then includes definite success attacks (E3, C3; guaranteed success).

5.1.2 Keystroke and Touch Dynamics. Keystroke and touch dynamics, specifically the usage patterns of keyboard or a touch screen interaction inherits features of a biometric and has thus been considered for means of bU2D authentication. An overview on the use of keystroke-dynamics for mobile devices is provided in Reference [267]. A number of studies consider zero effort attacks only, such as Reference [52], to authenticate phone users via keystroke analysis of their PIN input [52]. Authors report equal error rates (E1, C1; zero effort) but ignore active adversaries with access to advanced resources, such as key-press latencies that can be spoofed with a generative keystroke dynamics model [195] via trained replay attacks [217] or utilizing audio [268] or video [300].
Table 2. Attacks on Mobile Biometric Authentication Systems

| Paper                          | Modality | Attack scheme                      | Year |
|-------------------------------|----------|------------------------------------|------|
| Gafurov [103]                 | Gait     | Impersonation                      | 2006 |
| Stang [254]                   | Gait     | Continuous visual feedback impostors| 2007 |
| Gafurov [102]                 | Gait     | Spoof/各种各样攻击                 | 2007 |
| Ruiz et al. [230]             | Iris     | Fake images                        | 2008 |
| Derawi et al. [72]            | Gait     | Active impostor                    | 2010 |
| Mjaland et al. [193]          | Gait     | Active long-term trained impostors  | 2010 |
| Rahman et al. [217]           | Keystrokes| Snoop-forgereplay attack            | 2013 |
| Tey et al. [268]              | Keystrokes| Imitation through Mimesis technique | 2013 |
| Karapanos et al. [142]        | Audio    | Advanced co-located attackers      | 2015 |
| Kumar et al. [158]            | Gait     | Treadmill attack                   | 2015 |
| Liu et al. [170]              | Keystrokes| Snooping Keystrokes with mm-Audio   | 2015 |
| Monaco et al. [195]           | Keystrokes| Spoof keypress latencies           | 2015 |
| Gupta et al. [112]            | Iris     | Attacks: Masquerade, Replay, Database| 2016 |
| Xu et al. [298]               | Gait     | Passive/active impostor (imitation), MitM| 2016 |
| Zhant et al. [302]            | Speech   | Mimicry                            | 2017 |
| Abdelrahman et al. [2]        | Keystrokes| Thermal attacks on mobile user authentication | 2017 |
| Muaz et al. [200]             | Gait     | Active impostor (imitation)        | 2017 |
| Trippel et al. [161]          | Gait     | Poisoning acoustic injection attack | 2017 |
| Khan et al. [146]             | Keystroke| Real-time mimicry attack guidance system | 2018 |
| Tolosana et al. [273]         | Signature| Analysis of different spoofing (presentation) attacks | 2019 |
| Marcel et al. [176]           | Biometrics| Handbook of biometric anti-spoofing | 2019 |
| Vyas et al. [285]             | bio-sensors| Attack types on body area networks using bio sensors | 2020 |
| Tiefenau et al. [270]         | Biometrics| Attacks bypassing authentication on mobile devices | 2020 |
| Neal et al. [201]             | Behaviour| Spoofing (presentation) attacks on various biometrics | 2020 |
| Jia et al. [135]              | Face     | Evaluation of 30 face spoofing attacks | 2020 |
| Hagedestl et al. [114]        | Eye      | Attacks on Classifiers for Eye-based User Modelling | 2020 |

Examples for studies considering minimal effort adversaries targeting specific subjects are References [33, 129] or Reference [64] to authenticate from dynamics of using pattern-unlock (E1, C1; minimal effort). However, all these approaches omit investigation on protocol weaknesses or potential bias in the keystroke dynamics patterns due to statistical distributions over a larger set of users [239].

5.1.3 Face. Face features may be used for authentication and are adapted also in commercial hardware\textsuperscript{13} [74, 231]. An example for a zero effort study is Reference [149] who test their approach using face, teeth (stereo cameras), and voice on a database with 50 subjects to report EER, FAR, and FRR (E1, C1; zero effort), but ignoring targeted attacks using advanced resources such as replay or database attacks.

Examples for minimal effort studies are References [57, 74, 88], who consider to break face-based continuous authentication of 24 subjects by an impostor with no specific system insight (E1, C1; minimal effort). These studies were not tested against advanced attacks, such as impersonation or dodging via image manipulation [244] or using images from online social networks [167].

5.1.4 Iris. Features from the iris are considered as one of the strongest biometrics, and are, consequently, also employed in bU2D authentication. Iris recognition on mobile phones has, at that time, been constrained by the limited resources of the phone and have been respected in the zero effort study in Reference [148]. Without an adversary study, only successful instrumentation has been verified (E1, C1; zero effort). A number of advanced effort attacks against iris verification

\textsuperscript{13} e.g., Apple FaceID: https://support.apple.com/en-us/HT208108 (an exact adversary model is not publicly documented).
comprise fake images [230], masquerading (dilation and contact lenses), database and template hacking attacks [112].

5.1.5 Application Usage Patterns. Application usage patterns constitute another biometric for mobile device authentication. This has been tested, for instance, in a zero effort study in Reference [284] with 50 subjects. However, an attack study is missing (E1, C1, zero effort), as well as monitoring application usage via other apps on the phone [249].

5.1.6 Gait. Gait characterizes the way a person is walking and is believed to be difficult to mimic by adversaries. Despite studies suggesting gait as biometric feature [71, 100, 132, 228], investigations on security features and entropy of gait are lacking, for instance, with respect to impact of natural gait changes over time by clothing, footwear, walking surface, walking speed and emotion [36, 205, 250].

Early studies on gait-based mobile authentication (shoe-mounted [22, 127, 196]; waist-mounted [5, 46, 72, 122, 123, 197, 227]; hand, breast pocket, hip pocket [282]) used zero effort adversaries, mainly investigating feasibility (E1, C1; zero effort) and did not consider attacks.

Examples for minimal effort studies on gait-authentication are References [101, 103], which consider from pairs of 22 subjects the robustness of gait-authentication against impersonation attacks (E1, C1; minimal effort). In an advanced effort study in Reference [200], professional actors were instead employed to mimic the gait of 15 subjects with close physical properties (E2, C2; advanced effort). Other advanced effort study comprise control of the speed, step-length, thigh lift, hip movement and width of steps [158] (E2, C2; advanced effort), intensively training individuals over multiple days [193] (E2, C2; advanced effort) or exploiting a 100+ subject database of gait sequences [101, 102] (E1, C2; advanced effort). In addition, the high accuracy of video-based gait recognition systems also empowers an adversary to generate a database of gait information on multiple subjects unnoticed [236].

5.1.7 Fingerprint. Biometric authentication using fingerprints is frequently installed in mobile systems [276]. Typical attack vectors are (1) and (2) in Figure 4, since fingerprint impressions are easily left on surfaces touched [235]. Attacks on fingerprint-based systems are discussed in Reference [139]. An advanced effort study providing countermeasures against such attacks presents a system combining biometrics, possession, and continuity features for progressive authentication (switching between different security levels conditioned on the confidence in the authentication) [224]. The study comprises 26 attack attempts using 3 attack scenarios in which the attacker had system knowledge and tried to avoid detection via video and audio sensors (E1, C2; advanced effort).

5.1.8 Body Impedance. Rasmussen et al. propose a pulse-based biometric for two-factor or continuous authentication. In their approach, a metal keyboard sends small electric current through the user’s body of which the frequency response is used for authentication [178]. The study investigates usability and discusses the theoretical password space (E1, C1; minimal effort). However, it lacks a targeted attack study and an investigation on the uniqueness of body impedance in a larger population.

5.2 Usably Secure User-to-Device Authentication

Similarly to biometrics, usably secure user-to-device authentication (uU2D) schemes are conditioned on specific patterns have been presented for authentication. Attacks on these authentication schemes, as summarized in Table 3, are either related to traditional attacks on authentication systems or tailored to the respective modality, such as shoulder-surfing or imitation attacks.
Table 3. Attacks and Security Analysis of User-to-Device Authentication Systems

| Paper                      | Modality | Attack scheme                                                                 | Year |
|----------------------------|----------|-------------------------------------------------------------------------------|------|
| Dhamila et al. [73]        | Image    | Brute force, observer, intersection attacks                                  | 2000 |
| Thorpe et al. [269]        | Image    | Dictionary attack                                                            | 2004 |
| Davis et al. [61]          | Image    | Password distribution                                                        | 2004 |
| Ku et al. [155]            | Image    | Dictionary, replay, compromise password file, DoS, predictable n, insider     | 2005 |
| Dirik et al. [75]          | Image    | Dictionary attack                                                            | 2007 |
| Hayashi et al. [117]       | Image    | Brute force, educated guess, observer, intersection                           | 2008 |
| Brostoff et al. [39]       | Image    | Human bias in password choice                                                | 2010 |
| Sun et al. [258]           | Multi-touch | Shoulder-surfing (video observation and disclosure of exact password)     | 2014 |
| Yue et al. [300]           | Touch    | Technical challenges of blind recognition of touched keys from video         | 2014 |
| Huhta et al. [128]         | Acceleration | Attack on the ZEBRA system [177], discuss improvements              | 2015 |
| Li et al. [166]            | Acceleration | Imitation of head movement                                                   | 2016 |
| Nguyen et al. [203]        | Image recall | Shoulder surfing                                              | 2016 |
| Cha et al. [47]            | Pattern  | Optimal conditions for smudge attacks, protection, mitigation strategies    | 2017 |
| Zhang et al. [301]         | Voice    | Dolphin attack: inaudible voice commands                                    | 2017 |
| Kraus et al. [151]         | Emoji recall | Shoulder surfing                        | 2017 |
| Chen et al. [48]           | Audio/Magnetom. | Machine-based voice impersonation                        | 2017 |
| Miettinen et al. [191]     | Audio    | Impersonation, Man-in-the-Middle                                             | 2018 |
| Prange et al. [216]        | various  | Threats and design flaws of smart home environments                         | 2019 |
| Prange et al. [215]        | various  | Model of security incidents with personal items in public; survey and stories | 2019 |
| Shin et al. [245]          | pattern  | Attacks on Android pattern lock systems                                     | 2020 |
| Alqahtani et al. [9]       | image    | Attacks on machine learning for image-based captcha                         | 2020 |
| Bhana et al. [27]          | Various  | Usability and security comparison of authentication schemes                  | 2020 |
| Vyas et al. [285]          | Various  | Attack prevention schemes for body area networks                             | 2020 |

5.2.1 Image. In image-based uU2D authentication, the user is presented one or more challenges based on images, such as image content or sorting of images. Image-based authentication has an advantage [261, 292] over password or PIN-based authentication due to improved usability [293], and since it is easier to recognize or recall an image than a text [62, 73]. However, memorability and security strength of image-based recognition in comparison to PIN and password based solutions when multiple (10–20) of such passwords need to be remembered, has not been considered in the literature. Davis et al. [61] further found that (1) user password selection is biased by race and gender [39], thus lowering password entropy, (2) the need for several rounds to provide a reasonably large password space impairs usability, and (3) recognition-based systems are vulnerable to replay attacks [15, 266]. It is a research challenge to exploit memorability to improve freshness of authentication challenges [203].

Recognition-based. Recognition-based systems condition authentication on the selection of a specific image or groups of images in a particular order. A commercial example is Passfaces,14 which uses images of faces for authentication. Zero-effort studies proposing implementations of this approach with no security investigation, are, for instance, References [6, 62, 263] (E1, C1; zero effort).

A minimal effort study was presented in Reference [73], in which the authors show that failed logins raised to 30–35% for PIN and password based authentication, while it dropped only to 10% and 5% for artwork and photo images. Several attacks are discussed (brute-force, observer, intersection), while other attacks, e.g., on the image database or on the system are disregarded (E1, C1; minimal effort). Another example for a minimal effort study is Reference [151] (replace numerical PIN-pads with emojis), which studied memorability and robustness against shoulder surfing (E1, C1; minimal effort) but did not consider any strong adversaries.

Recall-based. These graphical password schemes require that a pattern is recalled, e.g., drawing a shape [133]. Since the precision required to establish a sufficiently large password space is high,

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Cued recall schemes provide cues that help to achieve sufficient precision [30, 32], such as images to guide the input or distorted and blurred images [117]. Example zero effort studies are Reference [69] (pure recall) or References [8, 213] (cued recall), which focus on usability and the risk of observation attacks (E1, C1; zero effort), but lack an attack study or security analysis.

A minimal effort study is Reference [150], which calculates the size of the password space and remarks that chosen passwords are clustered [150] (only $10^{-8}$ of the space is used 25% of the time) (E1, C2; minimal effort). Other attack vectors, such as shoulder surfing or smudge attacks are not exploited.

In their advanced effort study, Ku et al. [155] study a variation of this scheme for its repara- bility [130], resistance against dictionary attacks, replay attacks, compromising the password file, denial-of-service, predictable $n$ attack and the insider attack [26, 154, 192, 269] (E2, C2; advanced effort). Another example is Reference [75], who analyze the PassPoints scheme (regions in an image constitute an authentication challenge), originally presented in a zero effort study in Reference [293]. The authors present an evaluation approach for graphical password schemes, in which a password consists of a sequence of click points in an image. For the attack study, the probability of click points was considered as well as attention-related saliency features (luminosity contrast, color contrast, foreground) in a study with more than 100 subjects. For the images used, the observed entropy was derived from the observed FoA map (clicking probability to every grid square) (E2, C2; advanced effort). Definite success cases and nation state adversaries with strong capabilities are not considered.

5.2.2 Multi-touch. The concept of multi-touch has been proposed to increase the password space, to reduce time to input a password and to address security risks through shoulder-surfing and smudge attacks.

In References [206, 223], usability issues are in the focus of their discussion while security threats appear as after-thoughts (E1, C1; zero effort). For instance, References [17, 264, 265] propose finger-tapping for multi-touch pin authentication and investigate only usability in their 30-user case study (E1, C1; zero effort).

In an advanced effort study on multi-touch input in Reference [258], the authors recruited 30 volunteers to test rotation-invariant multi-touch free-form passwords. Ten adversaries with access to video recorded password inputs and exact password shapes attacked the system (E2, C1; advanced effort).

5.2.3 Gaze-based. Eye-gaze may be tracked and thus may serve as an input modality for uU2D authentication. Gaze-based password entry exploits the movement of the eye for password input [68].

In zero-effort usability studies in References [68, 157, 291], the subjects had to focus on some location on the screen or perform eye gestures (E1, C1; zero effort), without any attacker consideration. A similar approach was investigated in a minimal effort study in Reference [95], where a subject stares for a certain period (the dwell time) at an area on the display to perform an action [289]. The authors evaluated their approach in a study with 18 subjects and achieved an error rate for the password input of 96% (E1, C1; minimal effort). However, an attack study was not conducted.

An advanced effort study has been presented in Reference [41] and authors investigated the security of gaze-based graphical passwords using saliency masks by theoretical estimation of password space and discussion of threat models (E2, C2; advanced effort).

An example of a medium effort and capability guaranteed success study is Reference [63]. Password input by 24 subjects was video-recorded so that attackers could break the system in a single
try in 96% of the cases while the method was robust against simple shoulder surfing (E2, C2; guaranteed success).

5.2.4 Audio based. It is possible to use auditory stimuli for uU2D authentication. A targeted but unsophisticated attack study (advanced effort) over audio-based PIN input has been presented in Reference [28]. Subjects have been instructed and conducted targeted attacks after observing the login process of the target. However, attackers were artificially limited in their access to the recorded material (e.g., no audio, reduced quality) and time (E2, C2; advanced effort). In particular, it was derived in Reference [191] that time is critical in impersonation and Man-in-the-Middle attacks and that otherwise the secure establishing of a shared secret is possible.

A guaranteed success study is presented in Reference [142], who propose to use similarity in ambient audio as a second factor to authentication. Weak and strong adversaries are considered up to guaranteed success attacks where the adversary is physically located in the same audio context (E3, C3; guaranteed success).

5.2.5 Acceleration-based. Acceleration sensors are nowadays integrated in a multitude of devices. Consequently, the stimuli that can be utilized for acceleration-based authentication are available across a broad range of devices. An example for a zero effort attack is Reference [171], in which gesture-based authentication from acceleration sequences was investigated for its usability with five subjects (E1, C1; zero effort). An attack study has not been conducted though.

A targeted but unsophisticated attack study (minimal effort) is, for instance, Reference [166] (authentication utilising head-movement patterns while listening to an audio pattern). The authors provided videos of successful authentication attempts to the non-trained amateur attackers to imitate the authentication movements (E2, C1; advanced effort).

An example of an attack study also covering guaranteed success is Reference [14]. An in-air hand gesture authentication system was evaluated through experiments including video-based attacks and allowing to watch the video multiple times, rewind, or to play in slow motion (E2, C2).

5.3 Device-to-device Authentication

Device-to-device authentication, or simply pairing, typically exploits similarity in context or proximity to achieve seamless authentication [180]. Alternatively, device-to-device authentication can also be realized following the principles of zero-interaction authentication [55], in which proximity is exploited to verify identity without explicit input, but relying on contextual cues derived from sensor measurements. In Reference [275], security properties of these schemes is evaluated with respect to different sensor modalities and with respect to a Dolev–Yao adversary. Table 4 depicts several attacks on device-to-device authentication.
5.3.1 Acceleration-based. For D2D authentication with acceleration, simultaneous movement during physical co-presence are exploited. Examples for zero effort studies exploiting vibration are References [162, 186, 187]. They exploit shared vibration sequences between physically connected smartphones or physical tapping of devices onto each other. The prototypes have been validated for their basic functionality but no attack or user study has been conducted (E1, C1; zero effort).

For this kind of key distribution that utilizes vibration as an out-of-band channel, Anand et al. [13] attack vibration-based pairing schemes by overhearing the audio signature of the vibration pattern (E2, C1; minimal effort).

In an advanced effort study, Reference [277] authenticate mobile devices toward a remote server, where the challenges are given by the duration of vibration and responses. A number of security issues is discussed, followed by a publicly available taxonomy and entropy analysis (E1, C2; advanced effort).

Alternatively, gait acceleration has been exploited for authentication between devices that are carried by the same (walking) subject. Instantaneous and characteristic variations in the acceleration and gait sequences, that can be extracted at different body positions constitute the features to a pairing key [54, 163]. This problem has been considered in the zero effort studies [198, 199, 260], which discuss general feasibility, usability such as averse affects for orientation differences as well as cross pocket gait-based authentication (left-to-right) but no adversary study (E1, C1; zero effort).

Advanced effort studies on gait-based D2D authentication are, for instance, References [221, 297, 298], who consider impersonation and man-in-the-middle attacks, passive eavesdropping, impersonation, entropy, randomness, key distribution analysis from a study conducted with 14 subjects analyze the randomness of the resulting key (E1, C2; advanced effort). Examples for guaranteed success studies on gait-based D2D authentication are References [40, 236], which concisely compare and evaluate several gait-based D2D authentication protocols, and consider brute-force attacks, gait mimicry, informed attackers that exploit protocol weaknesses, as well as powerful adversaries with access to video or possibility to attach malicious devices unnoticed on the persons body (E3, C2; guaranteed success).

A further attack on acceleration-based D2D authentication is to actively emit modulated acoustic interference at the resonant frequency of materials in MEMS sensors to control or modify measured acceleration, and thus inject changes to acceleration sequences [161].

Finally, minimal effort studies have been conducted on shaking-based acceleration-pairing [109, 172, 184, 185], where attacker–victim pairs have been built with the purpose of demonstrating the
Table 6. Summary Classification of Adversary Models—Zero Effort

| Modality       | Refer. | Performance                              | #   | Type | Remark                                                                 |
|----------------|--------|------------------------------------------|-----|------|------------------------------------------------------------------------|
| Gait           | [141]  | —                                        | E1  | C1  | 44/25/71 B2UD                                                          | 2003 |
| Iris           | [148]  | Detection rate: 99.4%                    | E1  | C1  | 100 B2UD                                                               | 2016 |
| Speech         | [222]  | Rejection rate: <94.1%                   | E1  | C1  | 16+44 B2UD                                                             | 2019 |
| Gait           | [123]  | Accuracy: 94.8%                          | E1  | C1  | 38 B2UD                                                                | 2013 |
| Gait           | [122]  | FAR: 0%, FRR: 16.18%                     | E1  | C1  | 38 B2UD                                                                | 2015 |
| Gait           | [5]    | EER-FAR: 6.4%, FRR: 5.4%                | E1  | C1  | 36 B2UD                                                                | 2005 |
| Gait           | [228]  | EER: 6.7%                                | E1  | C1  | 35 B2UD                                                                | 2007 |
| Gait           | [282]  | EER: 17.2/14/14.8%                      | E1  | C1  | 31 B2UD                                                                | 2006 |
| Gait           | [227]  | EER: 5.6%/21.1%                         | E1  | C1  | 21 B2UD                                                                | 2007 |
| Audio [173]    | Accuracy: >80%                          | E1  | C1  | 15+17 B2UD                                                             | 2011 |
| Gait           | [22, 196] | Accuracy: <95%        | E1  | C1  | 15 B2UD                                                                | 2008 |
| Gait           | [46]   | Accuracy: <98%                           | E1  | C1  | 10 B2UD                                                                | 2012 |
| Iris           | [174]  | FAR/FRR: <6%/18%                         | E1  | C1  | 10 ul2D                                                                | 2017 |
| Gait           | [127]  | Accuracy: 96.133%                        | E1  | C1  | 9 B2UD                                                                | 2017 |
| Touch          | [100]  | accuracy: 100%                           | E1  | C1  | — B2UD                                                                | 2019 |
| Gait           | [52]   | Success rate: 12.8%                      | E1  | C1  | 32 B2UD                                                                | 2007 |
| Touch          | [204]  | Accuracy: 12%                            | E1  | C1  | 12 ul2D                                                                | 2019 |
| M.touch        | [222]  | Accuracy: 90.35%                         | E1  | C1  | 30 ul2D                                                                | 2013 |
| Image          | [15]   | Accuracy: 97%                            | E1  | C1  | 53 ul2D                                                                | 2017 |
| Image          | [293]  | —                                        | E1  | C1  | 20 ul2D                                                                | 2005 |
| QR             | [59]   | Accuracy: 88%                            | E1  | C1  | 20 ul2D                                                                | 2019 |
| Gaze           | [157]  | Error rate: 4%                           | E1  | C1  | 18 ul2D                                                                | 2007 |
| Icons          | [294]  | Accuracy: 90.35%                         | E1  | C1  | 15 ul2D                                                                | 2006 |
| M.touch        | [17]   | Entropy: 15.6bits                        | E1  | C1  | 13 ul2D                                                                | 2012 |
| M.touch        | [269]  | —                                        | E1  | C1  | 10 ul2D                                                                | 2012 |
| Shaking        | [172]  | —                                        | E1  | C1  | 8 ul2D                                                                | 2014 |
| M.touch        | [264, 265] | —                                    | E1  | C1  | 6 ul2D                                                                | 2013 |
| Radio          | [53]   | TP/FN/PN: <95%/6%/51                     | E1  | C1  | 3 ul2D                                                                | 2017 |
| Image          | [263]  | —                                        | E1  | C1  | — ul2D                                                                | 2003 |
| Image          | [8]    | —                                        | E1  | C1  | — ul2D                                                                | 2013 |
| Image          | [6]    | —                                        | E1  | C1  | — ul2D                                                                | 2013 |
| Image          | [213]  | —                                        | E1  | C1  | — ul2D                                                                | 2013 |
| Image          | [292]  | Accuracy: >90%                           | E1  | C1  | — ul2D                                                                | 2004 |
| Image          | [30]   | —                                        | E1  | C1  | — ul2D                                                                | 2013 |
| Gesture        | [111]  | —                                        | E1  | C1  | — ul2D                                                                | 2006 |
| Gaze           | [294]  | Success rate: 83%                        | E1  | C1  | — ul2D                                                                | 2011 |
| Acceler.       | [90]   | TPR/TNR: 79%/86%                         | E1  | C1  | 29 D2D                                                                | 2014 |
| Gait           | [237]  | —                                        | E1  | C1  | 15 D2D                                                                | 2017 |
| Gesture        | [171]  | Accuracy: 98.6%                         | E1  | C1  | 5+5 D2D                                                                | 2009 |
| Acceler.       | [54]   | Accuracy: 85%                            | E1  | C1  | 7 D2D                                                                 | 2011 |
| Gait           | [260]  | Agreement rate: <89%                     | E1  | C1  | 5 D2D                                                                 | 2017 |
| Vibration      | [162]  | Success rate: <60%                       | E1  | C1  | — D2D                                                                 | 2018 |
| Vibration      | [89]   | Success rate: 97.5%                      | E1  | C1  | 12 D2U                                                                | 2015 |
| Image/text     | [225, 226] | —                                | E1  | C1  | — D2U                                                                | 2010 |

robustness against active attacks (E1, C2; zero to minimal effort). Attacks on shaking-based pairing protocols are, for instance, investigated in Reference [91] (observatory, cooperative, handshaking).

5.3.2 Audio. Correlation in audio-readings from co-located devices may also be utilized for D2D authentication. An advanced effort audio-based D2D authentication was proposed in
### Table 7. Summary Classification of Adversary Models—Minimal Effort

| Modality     | Refer. | Performance | #   | Type | Remark                                                      | Year  |
|--------------|--------|-------------|-----|------|-------------------------------------------------------------|-------|
| Behavior     | [145]  |             | 40-158 | C1   | Non-sophisticated attacks on multiple biometric systems      | 2014  |
| Keystroke    | [287]  | EER: 12%    | 104  | C1   | Exploit adversarial noise; Non-targeted attacks             | 2019  |
| Keystroke    | [10]   | EER: 9.9%   | 100  | C1   | Non-targeted comparison of collected keystroke entries      | 2019  |
| Voice        | [302]  | EER: 1%, Accuracy: 99% | 21  | C1   | Liveness detection system to protect against replay attacks. | 2017  |
| behavior     | [194]  |             | 20   | C1   | Interactive biometric authentication; non-targeted attack    | 2019  |
| Gait         | [254]  | EER: 26%    | 13   | C2   | Targeted attacks; video-recordings; physical characteristics | 2007  |
| Face         | [231]  | Accuracy: >0.72 | 152 | C2   | Feasibility; database of 152 images; No security analysis  | 2015  |
| Gait         | [72]   | EER: 20.1%  | 51   | C1   | Focus on success cases                                      | 2010  |
| Gait         | [197]  | EER: 22.49% | 51   | C1   | No attack cases considered                                  | 2013  |
| Face         | [149]  | Error rates: <0.9% | 50  | C2   | FAR & FRR; no dedicated security study                      | 2010  |
| Handwriting  | [271]  | Mean EER: 14% | 50  | C1   | Non-targeted attack from database of samples                | 2020  |
| Keystroke    | [64]   | Accuracy: <5% | 48  | C1   | Intensive but untargeted (non-sophisticated) attacks       | 2012  |
| Gait         | [123]  | Accuracy: 94.93% | 38  | C2   | No dedicated attack cases; FAR & FRR                        | 2013  |
| Gait/Face    | [198]  | EER: 18.965 | 35   | C1   | EER for orientation-independent gait authentication.        | 2014  |
| Gait/Face    | [87]   | EER: 11.4 & 5.4 | 35  | C1   | Non-targeted blind matching of patterns between              | 2018  |
| Gait         | [122]  | FAR: 0; FRR: 16.18% | 34  | C1   | No dedicated attack cases; FAR & FRR                       | 2015  |
| Face         | [74]   | TP: 0.9781; TN: 0.9998 | 30  | C1   | Focus on positive case                                     | 2013  |
| Keystroke    | [129]  | EER: 13%    | 25   | C2   | Limited capability attackers: Password provided; pattern    | 2009  |
| Face         | [37]   | TP: 65%; FP: 35% | 24   | C2   | Victims first interacted with device before handing to impostor | 2015  |
| Gait         | [103]  | EER: 16%    | 22   | C2   | Active impostor; no matching person height, no actors       | 2006  |
| PPG          | [243]  | acc: 96.31% | 12   | C1   | Limited capability adversary; brute-force, shoulder surfing | 2019  |
| Face         | [88]   | TP: 93.89%; TN: 99.95 | 9   | C1   | Positive cases                                              | 2013  |
| Accelerat.   | [177]  | Accuracy: 83% | 20   | C2   | Bracelet verify typing of legitimate user; weak attacks.    | 2014  |
| Environ.     | [248]  | FNR: <14.5% | 2    | C2   | Relay attacks; system knowledge assumed                      | 2018  |
| Audio        | [48]   | FAR/EER/FRR: 0/0/<41% | 2   | C2   | Magnetic field from loudspeakers; No tailored attacks.     | 2017  |
| Magnet.      | [137, 186] | Accuracy: 92% | 2   | C2   | Comparison: password space PIN-based login                  | 2016  |
| Image        | [133]  |             | 25   | C2   | 'Draw a Secret' scheme; theoretical password space;         | 1999  |
| Image        | [269]  |             | 99   | C1   | Usability; Brute force, educated guess, observer, intersection A. | 2008  |
| Image        | [73]   | Success rate: 90% | 15   | C1   | HMD auth.; limited capab. attacks, brute force, shoulder surfing | 2019  |
| Image        | [117]  |             | 199  | C1   | Dictionary attacks against graphical password schemes       | 2004  |
| Image        | [284]  |             | 50   | C2   | Study positive case with professionals                      | 2016  |
| Headmove     | [166]  | EER: <7%, FAR: <5% | 37  | C2   | Reduced capability video analysis (no audio)                | 2016  |
| object       | [98]   |             | 20   | C2   | Discuss possible attacks and countermeasures                | 2000  |
| Impedance    | [178]  | Accuracy: >87% | 10   | C2   | User study and theoretical consideration of the password space. | 2017  |
| Drawing      | [241]  |             | 6    | C2   | Threat model; no attacks; No Entropy; no statistical analysis | 2014  |
| Keystroke    | [33]   | Accuracy: 99% | 5    | C2   | Random correlation attacks; no sophisticated or active attacker | 2013  |
| Shaking      | [109]  | Success rate: <5% | 1    | C1   | Entropy & security analysis; no trained, informed adversary | 2012  |
| Shaking      | [29]   | Success rate: 80% | 1    | C1   | Entropy analysis of the generated keys                      | 2007  |
| Pattern      | [266]  |             | 20   | C2   | Shoulder-surfing robust; low capability, non-trained attack. | 2006  |
| Pin          | [229]  |             | 8    | C2   | Shoulder-surfing robust; complexity analysis; weak attack.  | 2004  |
| Audio        | [13]   |             | 2    | C1   | Vibration of devices in contact; extract key from vibration noise | 2016  |
| Shaking      | [184]  | FN: 10.24%; FP: 0 | 8/50 | C2   | Competition among limited capability attackers              | 2007  |
| Gait         | [199]  | FMR/TNMR: <0.09/0.47 | 25  | C1   | No attack cases; false non match rate / false match rate (FMR) | 2015  |
| Vibration    | [86, 187] | FN+FP=EER: 9.99% | 23  | C2   | Synchronized vibration through device-tapping. No attacks.  | 2014  |
| Context      | [191]  |             | 2    | C1   | Impersonation, MitM, no guaranteed success (same context)    | 2018  |

Reference [107] in which devices in proximity (round-trip audio signals) are automatically paired. Non-sophisticated replay and spoofing attacks were identified but no attack study conducted (E2, C2; advanced effort).

A guaranteed success study is Reference [238], in which authentication is conditioned on ambient audio. Statistical properties of the keys are discussed, as well as limitations of the approach and a number of cases in various environments with different noise conditions is considered, also covering definite success attack scenarios where the attacker establishes the same audio context.
Table 8. Summary Classification of Adversary Models – Advanced Effort

| Modality | Refer. | Performance | # | Type | Remark | Year |
|----------|--------|-------------|---|------|--------|------|
| Gait     | [193]  | EER: 6.2%   | E2 | C2 30 | uUF2D  | 2007 |
| Gait     | [158]  | FAR: 70% (attack) | E2 | C2 18 | uUF2D  | 2015 |
| Behavior | [156]  | EER/FAR: <5.9%/3.3% | E2 | C1 30 | uUF2D  | 2019 |
| Face     | [135]  | Classification Error rate | E2 | C1 55/40 | uUF2D  | 2020 |
| Gait     | [102]  | EER: 13%    | E1 | C2 100 | uUF2D  | 2007 |
| Behavior | [45]   | TAR: 99.35% | E2 | C1 85+6 | uUF2D  | 2019 |
| Fingerprint | [295] | Acc/FAR/FRR: <99/2/3 | E2 | C1 90 | uUF2D  | 2020 |
| Biometric | [224] | Precision = Recall = 93% | E1 | C2 20 | uUF2D  | 2012 |
| Image    | [75]   | TPR: >0.79, TNR: >0.68 | E2 | C2 100 | uUF2D  | 2007 |
| Force    | [152]  | –           | E2 | C1 50+10 | uUF2D  | 2017 |
| Pattern  | [65]   | –           | E2 | C2 32 | uUF2D  | 2014 |
| Pattern  | [67]   | Accuracy: 44% | E2 | C2 24 | uUF2D  | 2013 |
| Gaze     | [97]   | TPR/FPR: 81%/12% | E2 | C1 29 | uUF2D  | 2019 |
| Gaze     | [49]   | Success rate: >83% | E2 | C2 24 | uUF2D  | 2007 |
| Pattern  | [47]   | Success: attacks: <25% | E2 | C2 4+12 | uUF2D  | 2012 |
| Pattern  | [28]   | FAR: 74%    | E2 | C2 12 | uUF2D  | 2017 |
| Audio    | [28]   | –           | E2 | C2 12 | uUF2D  | 2011 |
| Radio    | [179, 278] | FPR: <0.3 | – | – | uUF2D  | 2011 |
| Image    | [155]  | –           | E2 | C2 – | uUF2D  | 2005 |
| Accl.    | [277]  | TPR/FPR: 0.7444/0.0978% | E2 | C2 – | uUF2D  | 2016 |
| Gaze     | [92]   | –           | E2 | C1 15+25 | uUF2D  | 2019 |
| Pattern  | [234]  | success rate: >70% | E2 | C1 20 | uUF2D  | 2014 |
| Multi-touch | [258] | TPR: 97.5%, FPR: 2.3% | E2 | C1 30 | uUF2D  | 2014 |
| Image    | [203]  | –           | E1 | C1 10 | uUF2D  | 2016 |
| Environm. | [247] | FPR: 16.25%, FNR: 8.57% | E1 | C2 – | uUF2D  | 2014 |
| Multi-factor | [175] | –           | E1 | C2 – | uUF2D  | 2020 |
| Gait     | [200]  | –           | E2 | C2 35 | D2D  | 2017 |
| Acceler. | [246]  | Prec/recall: >0.94/0.97 | E2 | C2 20 | D2D  | 2016 |
| Audio    | [107]  | FRR: 1-12%, FAR: <0.8% | E2 | C2 – | D2D  | 2017 |
| Gait     | [298]  | Agreement rate: <73% | E1 | C1 20 | D2D  | 2016 |
| Gait     | [297]  | Agreement rate: <73% | E1 | C1 20 | D2D  | 2017 |
| Gait     | [221]  | –           | E1 | C1 14 | D2D  | 2017 |

Table 9. Summary Classification of Adversary Models – Guaranteed Success

| Modality | Refer. | Performance | # | Type | Remark | Year |
|----------|--------|-------------|---|------|--------|------|
| Audio    | [142]  | FAR+FRR<0.01 | E3 | C3 32 | uUF2D  | 2015 |
| Generic  | [296]  | –           | E3 | C3 – | uUF2D  | 1998 |
| Gaze     | [63]   | FAR: 42% (attack) | E2 | C2 24 | uUF2D  | 2009 |
| Pattern  | [160]  | –           | E2 | C1 24 | uUF2D  | 2014 |
| Magnet.  | [14]   | EER: 96.6%  | E2 | C2 10-15 | uUF2D  | 2014 |
| Pattern  | [15]   | –           | E2 | C1 – | uUF2D  | 2010 |
| Pattern  | [283]  | Error rate: 9.5% | E2 | C2 24 | uUF2D  | 2013 |
| Gait     | [40]   | –           | E3 | C3 15+482 | D2D  | 2019 |
| Vibration | [169] | Accu/FPR: >95%<3% | E3 | C3 15 | D2D  | 2017 |
| Audio, light | [248] | –           | E3 | C3 – | D2D  | 2018 |
| Gait     | [236]  | –           | E3 | C3 15+482 | D2D  | 2018 |
| EMG      | [299]  | Bit mismatch rate: <0.4 | E3 | C2 10 | D2D  | 2016 |
| Varsus   | [275]  | FRR: <27%   | E3 | C2 – | D2D  | 2014 |
| Audio, light | [190] | –           | E2 | C2 – | D2D  | 2014 |
| Shaking  | [180]  | –           | E2 | C2 – | D2D  | 2007 |
| Shaking  | [91]   | EER: 0.1293 | E1 | C2 29 | D2D  | 2017 |
| Audio    | [238]  | –           | E1 | C2 2 | D2D  | 2013 |
at two distinct places as well as silent cases that would cause the protocol to fail (E1, C2; guaranteed success). An entropy estimation or adversaries with advanced technical support such as directional antennas have been postponed to later work though.

5.3.3 **Token-based.** The authors in Reference [204] propose a token-based system to verify user authentication at the time of touch interaction with the capacitive screen of the mobile device. A zero effort usability study is conducted with 12 participants (E1, C1; zero effort). An example of a minimal effort study is References [137, 138] who exploiting magnetic interaction through a touch screen for token-based implicit two-factor authentication. Technical feasibility and theoretical security in comparison to PIN based login are discussed (E1, C2; minimal effort). An advanced and targeted attack study was omitted.

The advanced effort study [91] proposes token-based mobile-device unlocking over a pre-established secure channel through conjoint shaking. Protocol-specific attacks, assuming accelerated knowledge of the adversary were considered (E1, C2; advanced effort).

5.3.4 **Electromagnetic Signals (RF).** In recent years, the radio interface has been increasingly exploiting for sensing purposes. Consequently, the entropy of reciprocal characteristics of a wireless channel between two devices has been exploited to independently compute a key pair for D2D authentication. Exploiting similarity in physical radio channel characteristics, References [179, 278] consider advanced effort attacks using only few subjects. They consider strong adversaries that might control the radio channel and induce channel fluctuation to bias correlation for devices in proximity (E2, C2; advanced effort). The adversary has access to historical channel information. Other advanced attack types, such as beam-tracing simulations are disregarded.

5.4 **Device-to-user Authentication**

As described in Reference [181], an adversary might attempt to exploit that a device or app is mistaken by a user for another, trusted device or app. In this manner, credential information might be derived by the adversary. This is especially critical when some devices in the usage chain of a mobile service are not physically exposed to the user such as, for instance, pointed out for 5G small cell installations in Reference [279]. To protect against such cases, the author of References [225, 226] proposes for a user interface to present a known secret for authentication toward the user. This document merely sketches the idea. An attack study or even a theoretical analysis of the attack surfaces has not been conducted (E1, C1; zero effort).

A device-to-user authentication approach exploiting vibration patterns has been proposed in Reference [89]. The authors propose to define specific vibration patterns specifically for a device to allow device-to-user authentication. The usability has been tested in a study with 12 subjects that targeted on the acceptance of the system. Patterns have been recognized with 97% accuracy; however, an attack scenario or adversaries with access to the device or audio in proximity (to potentially reveal the pattern) have not been considered (C1, E1; zero effort).

5.5 **Discussion on Applied Adversary Classes**

The proposed classification of adversary classes has proven useful to distinguish between various approaches in the literature, as summarized in Tables 6 to 9. It is striking that more than half of the literature considered falls into low security classes (zero effort or minimal effort). One reason for this is that authors focus on the usability of their approach solely and disregard security. We suggest that this lax habit need to be broken, to develop better authentication approaches. An insecure authentication might be convenient to use, but its usability is low. Security is also an aspect of usability and must not be taken lightly. We should refrain from stressing mostly convenience of usable security approaches.
This picture calls for a need of re-thinking and strengthening attacker models in mobile authentication schemes, and for further research in this direction. Similarly, benchmark datasets are needed to comprehensively compare mobile authentication approaches [118]. In Table 5, we provide a selection of open datasets in mobile authentication.

6 CONCLUSIONS

Too many publications use weak adversary models, which is comparable to the early work on cryptography, notably symmetric ciphers. In cryptography, nowadays, new cipher proposals are only considered secure candidates after many other, typically more capable, cryptographers have tried to break it.

We recommend to adopt this attitude for research on authentication methods and, in particular, in the domain of mobile/ubiquitous/wearable/embedded devices. Studies often mix usability and security concerns, which is commendable, because security is an important aspect of usability. However, security is often considered as an after-thought and employing non-security experts as participants can only provide an estimate for false negatives, but have little validity for the false positives of an authentication system. To estimate these false positives, a class of significantly stronger attackers is required.

Authors should use realistic attacker models of adversaries who have a real motivation in breaking the system and who are potentially either more skilled than the average user of the system and/or willing to spend significantly more effort than a legitimate user (i.e., false matches are allowed much more effort than true matches). For a comprehensive discussion of a new model—and new authentication papers should go this far in their own evaluation—authors should use additional attacker models that will indeed break that authentication method.

The boundary of what security a system can achieve lies between advanced effort and guaranteed success categories, i.e., how far it is capable of providing protection against targeted attacks. Good authentication methods should define this security level as precisely as possible.

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