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Biometrics-Based Mobile User Authentication for the Elderly: Accessibility, Performance, and Method Design

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ABSTRACT

Assistive technology is extremely important for maintaining and improving the elderly's quality of life. Biometrics-based mobile user authentication (MUA) methods have witnessed rapid development in recent years owing to their usability and security benefits. However, there is a lack of a comprehensive review of such methods for the elderly. The primary objective of this research is to analyze the literature on state-of-the-art biometrics-based MUA methods via the lens of elderly users' accessibility needs. In addition, conducting an MUA user study with elderly participants faces significant challenges, and it remains unclear how the performance of the elderly compares with non-elderly users in biometrics-based MUA. To this end, this research summarizes method design principles for user studies involving elderly participants and reveals the performance of elderly users relative to non-elderly users in biometrics-based MUA. The article also identifies open research issues and provides suggestions for the design of effective and accessible biometrics-based MUA methods for the elderly.

1. Introduction

With the ubiquity and pervasiveness of mobile devices (e.g., smartphones), users increasingly store personal and even sensitive or classified information on their mobile devices (Gubernatorov et al., 2020). Accordingly, ensuring the security of mobile devices is extremely critical for safeguarding mobile users from security threats against the confidentiality, integrity, and privacy of their data (Kunda & Chishimba, 2021). Mobile user authentication (MUA) is an essential mechanism that incorporates one or more authentication methods to ensure secure access to a mobile device (Zhou et al., 2016). While traditional MUA methods (e.g., passwords and PINs) remain popular (Wang et al., 2019), biometrics-based MUA is gaining momentum in both research and practice (e.g., Corsetti et al., 2019; Iqbal et al., 2020; Sun et al., 2020). Thus, we focus on biometrics-based MUA methods in this study.

Aging is commonly referred to as the chronological age of 65 years old or older (Orimo et al., 2006). The Department of Economic and Social Affairs of the United Nations (World Population Prospects—United Nations, 2019) estimated that there were 728 million aging population worldwide in July 2020, and that number was projected to reach 1.5 billion by 2050, accounting for 10% of the overall population. Due to the improved socio-economic conditions, people tend to live longer than ever before (Huh & Seo, 2015). The rapid adoption of mobile handheld devices helps improve the quality of life of the elderly. Today, the elderlies are digitally penetrated due to their needs of staying in contact with their family and friends and keeping connected to the society and healthcare systems (Klimova & Marešová, 2016). Statistics show that smartphone adoption rate among the elderly is 30% among those 65–74 years old, 20% among those 75–84 years old, and 7% among those aged 85 and older (Petrovčič et al., 2018). According to the four-level pyramid of the elderly users' use of mobile devices (Nimrod, 2016), media players (e.g., music, radio, podcasts), internet-based functions (e.g., emails, web browsing, and downloads), basic functions (e.g., SMS and camera), and voice calls are often used by elderly users, which likely involve personal and sensitive information. Therefore, how to better support the elderly population in MUA to protect their personal information has become a critical issue.

Owing to the advancement of MUA technology, biometrics-based MUA is gradually replacing traditional MUA for the elderly (Ahmed et al., 2017). The biometrics-based MUA can be classified into two main categories: physiological and behavioral biometrics (Zhou et al., 2016). The features of the former category are mainly drawn from a human body part, while the latter are invariant features extracted from human behaviors. For example, fingerprint recognition (e.g., Blanco-Gonzalo et al., 2015; Iqbal et al., 2020; Zheng et al., 2020) and face recognition (e.g., Corsetti et al., 2019; Shien & Singh, 2017; Wu & Wang, 2019) are the most widely adopted physiological-based MUA methods, and keystroke- and touch gestures-based MUA are the two major types of behavioral-based MUA methods (Wang et al., 2020). In

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comparison to traditional MUA methods, biometrics-based methods offer several unique characteristics (Teh et al., 2016): (1) distinctiveness—precisely transforming a user's biometric patterns into multi-dimensional features, which are difficult to replicate; (2) enhanced security—augmenting MUA with an additional biometrics-based safeguarding layer; (3) continuity—constantly and implicitly monitoring a mobile user's interactions with a mobile device; (4) revocability—easy to replace original/old MUA template; and (5) autonomy—no intervention required from a mobile user. For example, fingerprint verification enables elderly customers to make an in-store payment at the point of purchase (Iqbal et al., 2020). Similarly, gait recognition takes advantage of the distinctiveness, enhanced security, continuity, and transparency of the gait-based MUA of elderly users (Sun et al., 2020). These advantageous characteristics of biometrics-based MUA enable us to address various accessibility needs of elderly users.

There has been a growing interest in biometrics-based MUA. Wang et al. (2020) provided a taxonomy of knowledge-, biometrics-, and ownership-based MUA methods by comparing the usability and security of different categories of existing MUA methods; Stylios et al. (2021) offered an update on behavioral biometrics, particularly focusing on machine learning performance; and Liu et al. (2022) provided an architecture of a biometrics-based MUA method. However, none of the above studies has focused on the biometrics-based MUA methods designed for the elderly.

Among the few literature surveys that focused on biometrics-based MUA for the elderly, Lanitis (2010) investigated how the aging-related variations in biometric templates would affect the performance of biometric modalities, including the recognition of face, iris, fingerprint, hand geometry, palmprint, voice, and body movement; Scheidat et al. (2011) conducted a review of studies that examined aging effects on authentication performance in the context of face, fingerprint, and iris recognition; and Solé-Casals et al. (2015) provided a preliminary review of biometrics-based MUA research using traits like handwriting, speech, and gait for monitoring the health status of the elderly. However, those studies are limited and differ from this study in several aspects. First, it remains unclear what are the accessibility needs of elderly users with respect to MUA, and how the existing biometrics-based MUA meet such needs. Second, previous survey studies related to elderly users were published in 2015 or earlier, which do not reflect the state-of-the-art biometrics-based MUA methods. Third, the evaluation of MUA methods with elderly users also faces unique methodological challenges, such as the difficulty in recruiting participants, which is overlooked by previous surveys. Fourth, despite a preliminary understanding of the effect of aging on biometrics (e.g., Lanitis, 2010; Scheidat et al., 2011), there is a lack of review of studies comparing the performances of biometrics-based MUA between the elderly and non-elderly users, which limits our understanding of the unique requirements of the elderly for biometrics-based MUA.

To address the above-mentioned research gaps, this research conducts a comprehensive review of the state-of-the-art biometrics-based MUA methods for the elderly and aims to answer the following research questions:

1. What are the accessibility needs of elderly users for MUA?
2. What are the state-of-the-art biometrics-based MUA methods for elderly users? How do they address the elderly users' accessibility needs?
3. What are the methodological design guidelines for biometrics-based MUA studies with elderly participants?
4. How does the performance of biometrics-based MUA of elderly users compare with non-elderly users?

This literature survey study makes 4-fold contributions to the MUA research. First, this study investigates several important aspects of the state-of-the-art biometrics-based MUA design via the lens of accessibility needs of elderly users. Second, this study provides guidelines for the method designs for user studies on biometrics-based MUA that involve elderly participants. Third, this study reveals a performance gap in biometrics-based MUA between the elderly and non-elderly users. Fourth, this study identifies several critical yet understudied issues with existing biometrics-based MUA and suggests future research opportunities in this area.

The mobile technology design for the elderly requires an interactive process and active learning (Iancu & Iancu, 2020). An effective design procedure includes problem identification, information gathering, building a solution, prototyping, and evaluating prototypes (Watzman, 2002). Accordingly, we organize this article based on the main stages of a technology design process. Section 2 illustrates the methodology we used for the literature search and review. Section 3 (problem identification and information gathering) discusses the accessibility needs of the elderly and related mobile technology artifacts identified from the literature. Section 4 (solutions and/or prototypes, and method evaluation—biometrics-based MUA performance) categorizes and synthesizes biometrics-based MUA methods that help address the accessibility needs of elderly users and input features for MUA model development, as well as the performance comparison between elderly and non-elderly participants. Section 5 (method evaluation—methodology design and measurements) summarizes the design of evaluation methods for evaluating MUA methods. Finally, we discuss open research issues and future research directions in Section 6 and conclude the article with Section 7.

2. Literature search method

Our literature search and article selection proceeded in three major stages, including literature search, eligibility screening, and relevance identification, as shown in Figure 1.

The literature search took place in September 2021 using digital libraries, such as ACM, IEEE, PubMed, Google Scholar, Science Direct, and ResearchGate. Our literature search primarily focused on two topics: (1) accessibility needs

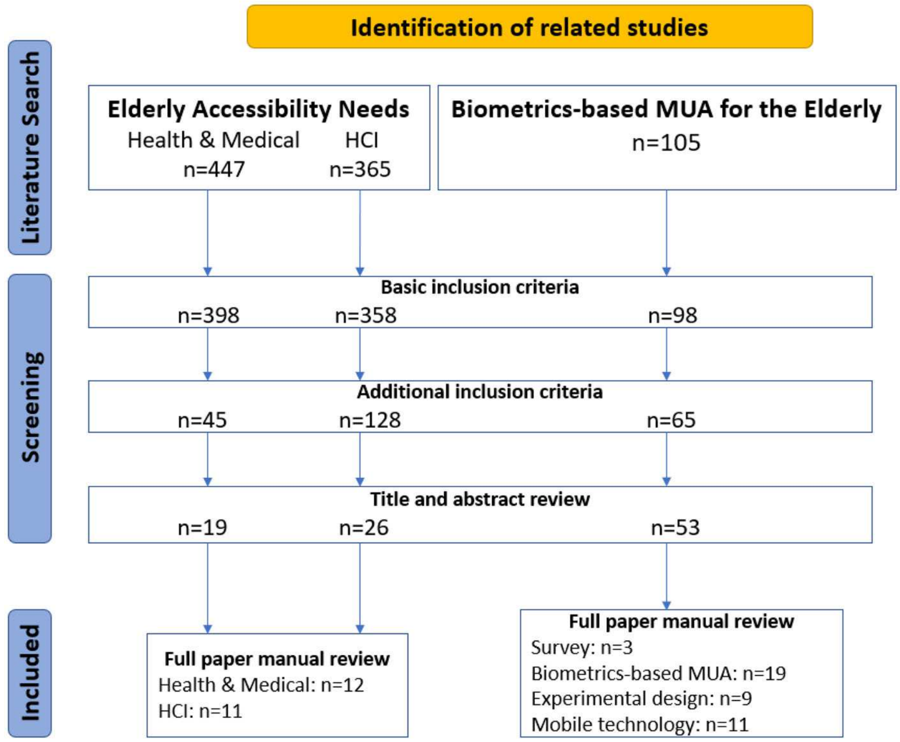

Figure 1. Literature search and selection process.

of elderly users for MUA, and (2) biometrics-based MUA methods in support of elderly users. The search queries of the first topic consisted of a combination of variant expressions of the elderly, such as "aged," "old," "elderly," "senior," and "gray," and variants of "accessibility needs," such as "disease," "frailty," and "vulnerability" in the domains of healthcare, medical, and human–computer interaction (HCI). We used this set of search query combinations for the first topic is because those vulnerable conditions of the elderly can directly reflect the situational/accessibility needs of the elderly in MUA; The search queries for the second topic consisted of a combination of variants of the three groups of terms, including biometrics, such as "biometric," "physiological," and "behavioral," MUA, such as "mobile user authentication" and "user authentication," and the elderly variants as shown above.

The eligibility screening included reviewing the titles and abstracts of the retrieved candidate articles and applying the following basic inclusion criteria: (1) participants aged 65 years or older; (2) peer-reviewed articles; and (3) articles written in English only. Moreover, we applied additional inclusion criteria to reflect the most recent research focuses. Given the increasing research on the accessibility needs of elderly people in healthcare and medical domains, we anchored on the highly cited articles (i.e., >500 citations) published in between 2011–2021. In addition, the identification of the accessibility needs of elderly users in HCI was focused on the most recent five years (2017–2021). Similarly, the state-of-the-art biometrics-based MUA methods were limited to those studies published in between 2011–2021 and involved empirical evaluations with elderly participants. Furthermore, we used a snowball sampling approach to identify additional articles from a list of the references cited by the selected articles and manually reviewed the titles and abstracts of the screened articles. Last but not least, we performed a full article review to identify the relevance of the selected article to our research objectives.

Among the 812 articles in relation to the vulnerabilities of elderly people, we selected 23 articles for inclusion in this review, including 12 articles in healthcare and medical domains and 11 articles in HCI. Among the 105 retrieved articles in MUA, we identified 3 literature survey articles on biometrics-based MUA for elderly users, 19 articles on individual biometrics-based MUA for elderly users, 9 articles on the experimental design with elderly participants, and 11 articles on mobile technology design for elderly users.

3. Accessibility needs of the elderly and mobile interaction design

Research on biometrics-based MUA emphasizes usability and accessibility while enhancing the security of mobile devices (Zhou et al., 2016). Based on the context of this research, we focus on analyzing the accessibility needs of elderly people, which in turn drive the design of related technological solutions.

Aging causes the decline of body functions, loss of independence, and accumulation of chronic diseases (Clegg et al., 2013). An earlier survey (Crews et al., 2017) reported that about 77% of people older than 65 years would suffer from various types of chronic diseases, including mobility decrease, visual discomfort, cognitive decline, and hearing loss. These issues can influence an elderly's daily routine. From an HCI point of view, elderly people are considered less knowledgeable, with fewer operational skills (e.g., scrolling, clicking), and with less experience with operating systems and software on mobile devices than younger users (Damant & Knapp, 2015). They are also perceived as being hesitant to use technology and assistance-dependent (Iancu & Iancu, 2020). HCI researchers have developed accessible methods ranging from evaluation method designs (e.g., Allah et al., 2021; González-Bañales & Ortíz, 2017) and interface designs (e.g., Iancu & Iancu, 2020; Sakdulyatham et al., 2017; Villegas et al., 2019) to intelligent system development (e.g., Hong et al., 2017; Meurer et al., 2018). Based on the focal accessibility needs examined in previous studies, we therefore categorize the accessibility needs of the elderly into four types, including vision, hearing, mobility, and cognition (see Table 1).

Technology not only creates opportunities for social connectivity for the elderly to meet their informational, emotional, and communicative needs but also has the potential to improve their physical and mental well-being. Thus, how to enable technologies to meet the elderly's special needs becomes critical. For each of the accessibility needs, we extracted the related interaction design artifacts and concrete design recommendations from the related literature (see Table 2). For instance, the design artifacts that have been used to address the elderly's vision decline include using a larger font size and icon, enlarging space between texts, and increasing adjustable contrast between text and the background. Mobility decrease of the elderly people can be assisted with the design of interface elements, such as simple and static menus to support navigation, simplified operations (e.g., minimizing the number of clicks/gestures), and material design (e.g., using light and not slippery materials). It is worth noting that the same design artifacts and recommendations can serve different accessibility needs, which have implications for the design of biometrics-based MUA.

4. Biometrics-based MUA for the elderly

This section introduces how biometrics-based MUA offers explicit assistance to elderly users to address four types of accessibility needs (i.e., vision, hearing, mobility, and cognition). We also discuss the strengths and weaknesses of each MUA method. Furthermore, we categorize a variety of biometrics-based MUA features and compare the differences in biometrics-based MUA performances between elderly and non-elderly users.

4.1. A schema of biometrics-based MUA for the elderly

The uniqueness and richness of human beings' biometric data produce numerous vital signs and hidden behavioral patterns. To demonstrate the capabilities of existing MUA methods that address the accessibility needs of elderly users, we cross-tabulate the biometrics-based MUA methods with the accessibility concerns of elderly users identified in the previous section in Table 3.

Physiological-based biometrics tend to be secure and difficult to be stolen and forged but raise privacy concerns. Particularly, fingerprint recognition (e.g., Blanco-Gonzalo et al., 2015; Iqbal et al., 2020; Zheng et al., 2020) and face recognition (e.g., Corsetti et al., 2019; Shien & Singh, 2017; Wu & Wang, 2019) are the most prevalent physiological-based biometrics in use and have proven to be the most easy-to-use methods. Both are free of hearing and cognition requirements. Although fingerprint-based MUA also supports the elderly with vision impairments, it faces usability [e.g., those elderly users who have dry skin and skin tears (White-Chu & Reddy, 2011)] and security challenges [i.e., bypassed by using fingerprint residue or a gummy fingerprint (Matsumoto et al., 2002)]. Face recognition-based MUA also has its own vulnerabilities, such as presentation attacks [e.g., photo, video, and 3D mask attacks (Mohammadi et al., 2018)] and sensitivity to the background lighting (Wang et al., 2018). Additionally, the facial expressions of the elderly are limited (Corsetti et al., 2019).

As a natural communication technology, voice recognition (e.g., Shuwandy et al., 2020; Wulf et al., 2014) has the potential to address all the accessibility needs of elderly users except for those with voice loss. Nor does it work for elderly users who suffer from hearing impairments and are

Table 1. Focal accessibility needs of elderly users in HCI studies.

Context	Accessibility focuses
Evaluated the usability of the customized user interfaces of the LINE application with different combinations of fonts, colors, and brightness with elderly users (Sakdulyatham et al., 2017)	Vision
Introduced a qualitative analysis technique to explore various perspectives on how elderly users say, do, see, hear, feel, and think during mobile interactions (González-Bañales & Ortíz, 2017)	Oral, vision, hearing, mobility, and cognition
Used a UTAUT2 acceptance model to investigate the acceptance of health-related information and communication technology among elderly people (Vassli & Farshchian, 2018)	Mobility, and cognition
Proposed a novel visual aids system to assist hearing-impaired elderly users in making a cell (Hong et al., 2017)	Hearing
Reviewed elderly's physical activities via exergames (Kappen et al., 2019)	Mobility
Investigated the effect of information and communication technology on the elderly's mobility via way-finding practices (Meurer et al., 2018)	Mobility
Proposed an interface to provide accessible interactions to elderly users, using an imaging system to identify hand position over a tabletop by locating the projected images and menu selections (Villegas et al., 2019)	Vision, hearing, mobility, and cognition
Assessed cognitive functionality of elderly users in a voice-based dialogue system (Kobayashi et al., 2019)	Cognition
Proposed a new approach for measuring the visual complexity of elderly users during web browsing (Sadeghi et al., 2020)	Vision
Reviewed the most important design principles and device features of mobile technology for elderly users (Iancu & Iancu, 2020)	Vision, hearing, mobility, and cognition
Explored the perspective of the elderly users and their interactions with search engines via an empathy map-based instrument (Allah et al., 2021)	Mobility and cognition

Table 2. Mobile technology design for the elderly.

Accessibility needs	Design artifacts	Design recommendations
Vision	Font size (Iancu & Iancu, 2020)	Bigger than 16 pixels, a height of characters of ∼4.2 mm, and the minimum font should be 12–14 points with Times New Roman/Arial/Helvetica.
	Space (Interaction Design Foundation, 2016)	0.2 cm in a sequence manner and 1 cm apart between unrelated items.
	Icons (Iancu & Iancu, 2020)	9.6 millimeters diagonally.
	Illumination (Nedopil et al., 2013)	Dim light, adjustable light, and increased and adjustable contrast between the background and the text while avoiding background images.
Hearing	Background noise (Nedopil et al., 2013)	Eliminating noise.
	Sound volume and sensorial warnings (Fisk et al., 2020)	Providing tactile and/or audible feedback, augmenting warning signals using a supplementary sensory channel, and alarming for a longer duration.
	Compatibility (Fisk et al., 2020)	Speech recognition, voice-command, and voice-response technology.
	Rhythm (Nedopil et al., 2013)	Computer-generated voices should be avoided and a natural speech intonation should be used.
	Voice characteristics (Fisk et al., 2020)	Female voice is preferred.
	Speech rate (Fisk et al., 2020; Nedopil et al., 2013)	140 words per minute and high frequencies sound below 4000 Hz.
Mobility	Interface elements (Fisk et al., 2020; Interaction Design Foundation, 2016; Nedopil et al., 2013)	Large screen, large fonts, big buttons, and adequate space between buttons to prevent pressing two buttons at the same time.
	Interaction (Iancu & Iancu, 2020)	Grouped in sequence-of-use.
	Navigation support (Lewis & Neider, 2017; Nedopil et al., 2013)	A simple and static menu is preferred.
	Operations (Lewis & Neider, 2017; Nedopil et al., 2013)	Simple and with a low workload (e.g., double click, scrolling, and multiple gestures should be minimized).
	Material design (Andronico et al., 2014; Kim et al., 2007)	Light and not slippery materials.
Cognition	Operations (Campbell, 2015)	Longtime interval in actions is critical and shunning multitasking or splitting a task into different parts, and feedback and reminders are required if a heavy task is indeed.
	Navigation assistance (Fisk et al., 2020; Lewis & Neider, 2017; Nedopil et al., 2013)	Simplification of the process (e.g., least pages, steps, and options needed), task-oriented (i.e., clearly indicate the steps and status of a task, text and number key rather than icon (e.g., using a short phrase for explanation), and easy access (e.g., offering a few memorable shortcuts for direct access).

Table 3. Biometrics-based MUA.

Types of biometrics	Methods	Vision	Hearing	Mobility	Cognition
Physiological	Fingerprint (Blanco-Gonzalo et al., 2015; Iqbal et al., 2020; Zheng et al., 2020)			✓	
	Face (Corsetti et al., 2019; Shien & Singh, 2017; Wu & Wang, 2019)	✓		✓	
	Voice (Shuwandy et al., 2020; Wulf et al., 2014)		✓		
	Iris (Azimi et al., 2019b; Gorodnichy & Chumakov, 2019; Kowtko, 2014)	✓			
Behavioral	Keystroke (Dandachi et al., 2013)	✓		✓	✓
	Thumbstroke (Zhou et al., 2016)			✓	✓
	Handwriting (Al-Showarah, 2019; Blanco-Gonzalo et al., 2015)			✓	✓
	3D Pattern Lock (Shuwandy et al., 2020)	✓		✓	✓
	Gait (Sun et al., 2020)			✓	
	Gaze (Klaib et al., 2019; Kocejko & Wtorek, 2012)	✓			✓

vulnerable to audio disturbance and recording attacks. Similarly, iris recognition (e.g., Azimi et al., 2019b; Gorodnichy & Chumakov, 2019; Kowtko, 2014) holds great promise for addressing all the accessibility needs of elderly users except for those with vision impairment. Despite that iris recognition uses independent textures and achieves great performance in terms of accuracy (Huang et al., 2002), this method is less effective with the elderly who have cataracts and diabetes (Azimi et al., 2019a) and is vulnerable to security attacks (e.g., using a high-quality image of an iris).

Human behaviors are rich, engendering a variety of patterns (Sundararajan & Woodard, 2019). The invariant characteristics of human patterns can be derived from a host of user inputs, which to some extent help mitigate the elderly's efforts in MUA. Behavioral biometrics are generally immune from a user's hearing loss. Among them, keystrokes and touch gestures are two types of user behavior commonly used for MUA on touch-screen mobile devices (Wang et al., 2020). Keystroke-based MUA is based on an individual's typing behaviors (e.g., key-press, and the time of key holding and releasing), which has been widely studied (e.g., Dandachi et al., 2013; Giot et al., 2015) given the pervasive use of the conventional Qwerty keyboard. This method is easy to learn; however, it requires a significant amount of effort from a user (e.g., remembering and entering a password via a soft keyboard on the touch screen of a mobile device), increasing the cognitive load of elderly users. In addition, keystroke behaviors are not resistant to security attacks (e.g., shoulder-surfing and brute-force attacks).

Touch gesture-based MUA distinguishes users based on the movements of fingers on the touchscreen of a mobile device (Vuletic et al., 2019), such as thumb strokes (Zhou et al., 2016), and handwriting behaviors (Al-Showarah, 2019; Blanco-Gonzalo et al., 2015). Compared with keystroke-based MUA, touch gesture-based MUA can also meet the accessibility needs of elderly users with vision impairments. For instance, Thumbstroke (Zhou et al., 2016) supports sight-free password entries (i.e., interacting with a mobile device without looking at the screen) with a keypress-free design that allows one or two consecutive thumb strokes for entering a character. Given the nature of its design, the thumbstroke-based MUA takes a relatively longer time for password entries than that of direct typing (e.g., entering a password on a QWERTY keyboard), which can serve as an effective mechanism for elderly users who enter passwords in low-motion (Zhou et al., 2016). Depending on the complexity of touch gesture design, however, touch gesture-based MUA may require a steep learning curve. Handwriting behavior (Al-Showarah, 2019) can take place at any location on a touchscreen and can be performed naturally. However, due to the handwriting instability of some elderly users (e.g., those who suffer from the rhythmic tremor of Parkinson's disease), wide adoption of handwriting-based MUA is impractical. 3D Pattern Lock (Shuwandy et al., 2020) is an enhanced MUA method of the traditional pattern lock on Android devices, which adds additional layers of the safeguarding mechanism to its system. The number of additional layers can be determined based on the user's preference, and the method embeds a transition process that allows a user to perform a sequence of pattern locks using the same touch screen of a mobile device. Yet, the increased workload (i.e., completing pattern lock multiple times on a touch screen) is contradictory to the recommendation of alleviating the cognitive needs and actions of elderly users (Fisk et al., 2020; Lewis & Neider, 2017; Nedopil et al., 2013).

Leveraging body movements for authentication and monitoring of elderly people is not new, especially in the domain of healthcare (Sun et al., 2020). Gait is one of the ramifications of body movements (Sun et al., 2020). It addresses the intra-subject gait fluctuation in the mobility of elderly people and improves authentication of an elderly based on his/her unique body movements (e.g., sitting and walking) with low computational overhead (Chakraborty et al., 2019). Thus, gait-based biometrics can assist the elderly with visual and cognitive impairments. However, such methods become ineffective when significant behavior changes occur (e.g., muscle atrophy may impact movement rhythm and speed). The recent development of gait recognition sheds a light on continuous authentication and tracking of the elderly's daily actions (Sun et al., 2020). Nevertheless, its practical application is highly restricted due to high computational overhead. Furthermore, gaze movement (Klaib et al., 2019; Kocejko & Wtorek, 2012) is difficult to forge and has little requirement for user mobility, yet it may cause fatigue of the eyes (e.g., following a specific pattern to complete authentication) and does not support those users with visual impairments.

4.2. Categorization of input features of MUA models

Measuring and capturing static and dynamic behavior patterns of a human is a vital step in MUA. Depending on the nature of user-device interactions from which human behavioral patterns are extracted, those behaviors can be captured using either built-in sensors of a mobile device or external hardware. Given that modern mobile devices are equipped with sophisticated sensors (Majumder & Deen, 2019), such as gyroscopes and accelerometers, it becomes convenient and cost-effective to leverage the state-of-the-art sensing technology to collect valuable data from user interactions actively with the touch screen of a mobile device. For instance, Wang et al. (2020) and Zhou et al. (2016) extract the dynamic trajectory of thumb strokes using accelerometers and proximity sensors that come with a mobile device. Sometimes external hardware is required to support data collection. For instance, capturing gaze movement requires an external eye-tracking device (Klaib et al., 2019; Kocejko & Wtorek, 2012), and recognizing gaits can rely on acceleration sensor nodes (Sun et al., 2020).

Extracting feature(s) from user inputs or data is another critical step toward building an MUA model (Al-Showarah, 2019; Wang et al., 2020). Based on the nature of the extracted features, we classify them into six major categories, as described below.

- *Physiological* features refer to the singular points and local components of a human body that remain immutable, such as ridges and bifurcations in a finger, and eyes and nose on a face.
- *Orientational* features indicate the directivity of a pattern on a touchscreen. For example, swiping from the bottom of a device screen to the top right creates a right-deviated trajectory on the screen.
- *Spatial* features pertain to geometric locations and coordinates of different physiological parts of a human body or behavior patterns, such as the length of a trajectory of a thumb stroke or a swipe.
- *Temporal* features reflect the duration, acceleration, and time deviation of human behaviors, such as the duration of speaking out a sentence for voice recognition.
- *Rhythmic* features refer to a regular succession of behavior in terms of frequency and tempo, such as walking speed and the degree of foot lifting.
- *Intonational* features are discriminative phonation and utterance with voice, ranging from soprano to alto and from tenor to bass.

The percentage distribution of the categories of input features used in existing biometrics-based MUA methods is plotted in Figure 2. Among the different feature categories, physiological features are used consistently across all the methods due to their invariant characteristics. The orientational and spatial features have been frequently used by behavioral- and physiological-based MUA methods. For example, touch gestures can infer both the directivity of the coordinates of finger movements on a touch screen, and a user's hand shape can also be used for authentication via multi-dimensional geometry. Despite the differences between temporal and rhythmic features, they collectively reflect the temporal dynamics and tempo of human behaviors (e.g., shorter duration implies higher frequency). Both types of features have been widely used by both behavioral- and psychological-based MUA methods utilizing the vital signs of users for MUA. The intonational features are comparatively unique and available only in the voice-based MUA methods (e.g., Shuwandy et al., 2020; Wulf et al., 2014), but they can supplement other types of MUA methods.

4.3. Mua performance with elderly users

To compare the performance of biometrics-based MUA between elderly and non-elderly users, we conducted another round of literature search using the MUA terms (i.e., fingerprint, face, iris, keystroke, handwriting, and gait) identified in the elderly-related literature review that distilled the empirical evidence with respect to MUA performance of elderly users. In addition, the inclusion criteria are similar to those used for identifying elderly-related biometrics-based MUA methods, except for the participant's age (i.e., below 65 years old). We manually review the retrieved articles and extracted the best performance for each biometrics-based MUA method, resulting in 6 articles for the biometrics-based MUA methods related to non-elderly users.

Several biometrics-based MUA methods (e.g., Bazrafkan & Corcoran, 2018; Yin et al., 2019; Zou et al., 2020) have achieved superior performance in authentication with non-elderly users. Nevertheless, the performance of MUA with elderly users has been overlooked by previous studies. Among the empirical studies we surveyed, only two studies compared the MUA performance between the elderly and non-elderly users. For instance, Al-Showarah (2019) investigated the performance of handwriting-based MUA by varying the features (e.g., force pressure, duration of writing a word, and word similarity) and the sizes of the training data. They found that younger users achieved better performance than elderly users across most of the conditions. Wu & Wang (2019) investigated the effects of age and gender on face recognition. The study found that the recognition accuracy of the female group was slowly increasing with age (i.e., young = 71%; middle-aged = 73%; and elderly = 77%) and that the recognition accuracy of the male youth (84%) and the old age groups (83%) were better than that of the middle-aged group (71%). One possible explanation for the finding is that the appearance changes of females are more frequent than those of males, and young men and elderly men pay more attention to their appearance than middle-aged men (Wu & Wang, 2019).

Given the limited studies on direct comparisons between the non-elderly and elderly users, we compared the performance of the same type of biometrics-based MUA methods across different studies focused on each of the user populations separately. For instance, a fingerprint-based MUA achieved an equal error rate ranging from 30.4 to 35.8% for elderly users (Blanco-Gonzalo et al., 2015), compared to 95.7% in accuracy for non-elderly users (Minaee et al., 2019). Despite that the performances of a few biometrics-based MUA methods [e.g., iris scan (Azimi et al., 2019b) and gait recognition (Sun et al., 2020)] for elderly users are comparable to those of the non-elderly users, the overall performance of biometrics-based MUA is generally worse for elderly users than that for non-elderly users, as shown in Table 4.

5. Method design of MUA studies with elderly participants

This section discusses the method design for empirical studies on MUA with elderly participants from three perspectives: participant recruitment, research method, and

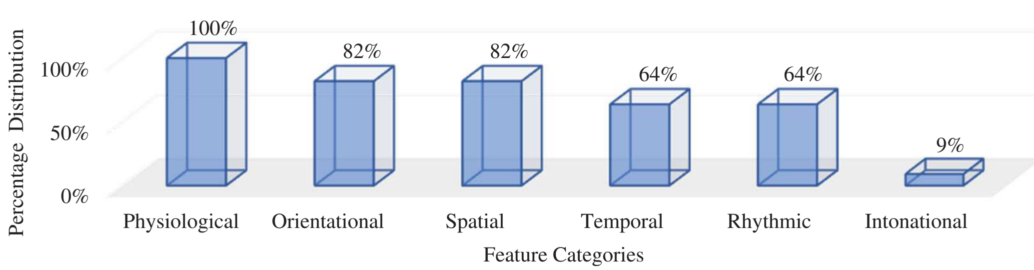

Figure 2. Percentage distribution of feature categories in biometrics-based MUA methods.

Table 4. Side-by-side comparison of the MUA performance for elderly *vs.* non-elderly users.

Biometrics used for MUA	Elderly	Non-elderly
Fingerprint	EER 30.4–35.8% (Blanco-Gonzalo et al., 2015)	Accuracy 95.7% (Minaee et al., 2019)
Face	ROC 77.0–83.0% (Wu & Wang, 2019)	Accuracy 99.2–99.6% (Yin et al., 2019)
Iris	AUC 78.0–96.0% (Azimi et al., 2019b)	Accuracy 97.1–99.3% (Bazrafkan & Corcoran, 2018)
Keystroke	Error rate 13.5–17.4% (Dandachi et al., 2013)	Accuracy 97% (Krishnamoorthy et al., 2018)
Handwriting	Accuracy 82.5% (Al-Showarah, 2019)	Accuracy 98.0% (Fang et al., 2020)
Gait	Accuracy 92.0% (Sun et al., 2020)	Accuracy 99.8%(Zou et al., 2020)

EER: equal error rate; ROC: receiver operating characteristic curve; AUC: the area under the curve performance measures. Table 5 provides a summary of the selected empirical studies of MUA conducted with elderly participants.

5.1. Participant recruitment

Given the tendency of social exclusion and decreased mobility of the elderly (Bong et al., 2018), it is extremely challenging to recruit them as research participants, especially for controlled lab experiments. In the previous studies (e.g., Andronico et al., 2014; Iqbal et al., 2020; Kim et al., 2007), the average sample size of the elderly participants was 21, which is relatively small. Common methods for recruiting elderly participants include recruitment through senior centers (Kononova et al., 2019), surveys (Iqbal et al., 2020; Kim et al., 2007), or personal networks (Kononova et al., 2019; Wulf et al., 2014). Depending on elderly individuals' personal health conditions, reasonable accommodations may deem necessary. For example, recruiting physically impaired elderly participants may require visiting special organizations, such as elderly universities (Andronico et al., 2014) and healthcare providers (e.g., clinics). Other alternative methods for recruiting elderly participants include school recruitment pools, local churches, Facebook groups, and local newspapers (Kononova et al., 2019).

5.2. Research methods

Longitudinal controlled lab experiments (e.g., Andronico et al., 2014; Iqbal et al., 2020; Kim et al., 2007; Kononova et al., 2019; Shuwandy et al., 2020) have been widely used in existing MUA studies with the elderly users, which help avoid confounding factors that may potentially influence research outcomes. In addition, it is also common for researchers to use site visiting [i.e., contextual research (Kim et al., 2007)], diary-taking at home (Andronico et al., 2014), or walking outside with speech interaction (Wulf et al., 2014) with elderly participants. For instance, writing an article-based diary is convenient for keeping track of an elderly person's daily progress in a longitudinal study (Andronico et al., 2014).

The majority of the prior studies used qualitative research methods by nature, including direct (Iqbal et al., 2020) or indirect observations [i.e., video recordings (Kim et al.,

Table 5. Method design of biometrics-based MUA studies with elderly participants.

Studies	Participant recruitment	Sample size	Experiment location	Research methods	Performance measurements
Universal Design on Mobile Phone (Kim et al., 2007)	Survey	11	Site visits	Interview observation system logs	Contextual and interaction experience (open-ended) and error situations
Digitally Extended Environment (Andronico et al., 2014)	Elderly university	–	Home	Diary	–
Activity Tracker (Kononova et al., 2019)	Senior Center, university listservs, school online recruitment system, local churches, Facebook groups, personal network, local newspaper	48	Lab and home (a subgroup of participants wore a tracker for a period of time)	Interview survey	Open-ended questions on the reasons to start using the technology and motivations for continued activity tracker use; benefits and barriers of activity tracker use and its influence on users' lives; reasons for abandoning the technology
Fingerprint for Points of Sale (Iqbal et al., 2020)	Survey	40	Lab	Observation survey	SUS (Brooke, 1996) and SUMI (Kirakowski & Corbett, 1993)
Fingerprint and Signature for Points of Sale (Blanco-Gonzalo et al., 2015)	–	–	Lab	System logs	EER and unsuccessful rate
Speech Interaction (Wulf et al., 2014)	Personal network	10	Field (walking outdoor)	Interview	SASSI questionnaire (Hone & Graham, 2000)
Pattern Lock and Voice Recognition (Shuwandy et al., 2020)	–	10	Lab	System logs	FAR, FRR, SR, and LD
Keystroke and Touch Gesture (Dandachi et al., 2013)	–	3	Lab	System logs	FAR and FRR
Handwriting (Al-Showarah, 2019)	–	16	Lab	System logs	FP, efficiency(duration of writing a word), and SR

2007)] and contextual interviews (Kim et al., 2007; Kononova et al., 2019; Wulf et al., 2014) with open-ended questions. Depending on the specific task assignments and workload for participants, the duration of existing user studies on MUA involving elderly participants ranged from 2 hours (Kononova et al., 2019) to 1.5 months (Shuwandy et al., 2020).

5.3. Performance measures

Previous studies primarily derived performance measures of MUA from the system logs of elderly participants' behaviors (e.g., Al-Showarah, 2019; Dandachi et al., 2013; Shuwandy et al., 2020) or from the survey responses that were based on the elderly participants' perceptions (e.g., Iqbal et al., 2020; Wulf et al., 2014). These measures can be referred to as *user performance* and *user perception* aspects.

User performance is focused on the effectiveness of MUA in user-device interaction, which can be further grouped into usability and security categories. Efficiency is the key measurement in usability testing, which refers to the time elapsed for the entire or a part of MUA [e.g., the time spent in writing a word (Al-Showarah, 2019), the time for typing a sequence of characters (Dandachi et al., 2013), and the time of a password entry using thumb strokes (Zhou et al., 2016)]. Among different security measurements, we summarize the commonly used security measurements as follows: *Accuracy* is defined as the percentage of authentication decisions that correctly accept or deny user access; *False Acceptance Rate (FAR)* is the percentage of authentication decisions that deny an authentic user; *False Rejection Rate (FRR)* is the percentage of authentication decisions that grant access to an imposter user; *Equal Error Rate (EER)* is the rate at which false acceptance rate and false rejection rate are equal; *Levenshtein Distance (LD)* is a string metric to measure the minimum number of single-character edits required to replace one word with another; *Similarity Rate (SR)* refers to the number of correctly entered/remembered characters, patterns, or even strings of a password; and *Force Pressure (FP)* refers to a finger pressure forced on a certain area of the touch screen of a mobile device.

To sense a user's perception with respect to a specific MUA method, the survey instrument is a traditional yet convincing evaluation method. For example, the elderly participants' perceptions of fingerprint MUA can be evaluated via the System Usability Scale (SUS) (Brooke, 1996) and Software Usability Measurement Inventory (SUMI) (Kirakowski & Corbett, 1993). Those surveys cover different aspects of user perception of MUA, including efficiency, satisfaction, memorability, learnability, attractiveness, error tolerance, and security. In addition, the Subjective Assessment of Speech System Interfaces (SASSI) questionnaire has been used to assess the quality of speech recognition systems (Hone & Graham, 2000). Furthermore, additional performance measurements can be derived based on the content analysis results of qualitative data (e.g., Kim et al., 2007; Kononova et al., 2019).

6. Open issues and future research

Based on the characteristics of elderly users and the current state of biometrics-based MUA studies, we highlight several research issues that remain understudied and suggest future research directions for biometrics-based MUA research for the elderly.

6.1. Insufficient understanding of elderly users' needs

The majority of studies of elderly users in biometrics-based MUA focus on the development of accessibility solutions [e.g., gait-based behavioral biometrics (Sun et al., 2020) and voice-based methods (Shuwandy et al., 2020; Wulf et al., 2014)]. However, empirical investigations of actual accessibility needs or preferences of elderly users in MUA remain largely lacking. This practice is inconsistent with the human-centered authentication guidelines [e.g., inclusiveness, low cognitive load, and risk awareness (Still et al., 2017)], which may not be effective for this cohort.

To this end, surveys and contextual interviews could be effective methods for deepening the understanding of the accessibility needs of elderly users for MUA. Moreover, future studies should not only understand elderly users' perceptions of the usability and security of existing MUA methods but also focus on the elderly users' expectations of MUA designs that can better fit their accessibility needs in interacting with mobile devices.

6.2. Limited method generalizability

The generalizability of a biometrics-based MUA method can be understood by testing the method with diversified participants and performing direct comparisons between different user populations. In the context of this research, direct comparison refers to the comparison of the same MUA method between elderly and non-elderly users. Among the articles we reviewed, only two studies [i.e., handwriting recognition (Al-Showarah, 2019) and face recognition (Wu & Wang, 2019)] conducted direct comparisons. Nevertheless, other methods, such as keystroke-, fingerprint-, and voice-based MUA, remain overlooked. As a result, we have to perform indirect comparisons by drawing on the empirical results from two or more separate studies on the same type of biometrics-based MUA methods with different user populations (see Section 4.3). Our results (see Table 4) show that the empirical evaluation of biometrics-based MUA methods with elderly users is far underexplored compared with other user populations. Furthermore, the sample size of the user studies with elderly users is relatively small [e.g., 10 for voice recognition (Wulf et al., 2014), 16 for handwriting recognition (Al-Showarah, 2019), 17 for gait recognition (Sun et al., 2020), and 20 for fingerprint recognition (Iqbal et al., 2020)], compared with studies conducted with non-elderly users [e.g., 118 for gait recognition (Zou et al., 2020) and 500 for handwriting-based recognition (Fang et al., 2020)]. Without a reasonable size of elderly participants to support either direct or indirect comparison, it is extremely difficult to draw a conclusion on the generalizability of a proposed MUA method with elderly users.

The limited generalizability of biometrics-based MUA methods can be attributed to the challenges of recruiting elderly participants (Nedopil et al., 2013), among others. To overcome this issue, future research should consider recruiting elderly participants from the locations that attract abundant elderly's foot traffic, such as senior centers, clinics, and elderly universities, which is practically feasible (Andronico et al., 2014; Kononova et al., 2019). From a method design respective, hosting a series of information or education sessions with elderly people to increase their awareness of mobile security and to understand the value and importance of MUA are different ways of attracting elderly participants. Because not all elderly participants are appropriate for evaluating a biometrics-based MUA method, researchers should focus on the modification of the recruitment inclusion criteria with respect to the level of vision, hearing, mobility, and/or cognition abilities, which can be completed using widely adopted scales [e.g., color vision screening (Coren & Hakstian, 1988) and subjective cognitive load rating (Schmeck et al., 2015)]. Also, the experimental tasks should be tailored to the elderly participants, by having a short experiment duration and relatively light cognitive and mobile activities that likely do not go beyond the regular activities of elderly participants.

6.3. Inferior MUA performance for the elderly

Drawing on the direct and indirect comparison results, the performance of biometrics-based MUA is significantly lower for elderly users than non-elderly counterparts across all the methods, despite that iris- and gait-recognition achieve relatively satisfactory MUA performance for the elderly. We identify three main causes of the worse performance of MUA for the elderly. First, the elderly's adoption of MUA is low. For example, elderly people are used to signing documents but not interacting with a touch screen for finger scanning or handwriting (Blanco-Gonzalo et al., 2015). Additionally, the elderlies find it difficult to explicitly enter passwords on a mobile device (Dandachi et al., 2013). Second, physiological erosion can cause decreased mobility and dexterity for the elderlies, and it is even more challenging for those who have dry skin and skin tears (White-Chu & Reddy, 2011), limited facial expressions (Corsetti et al., 2019), or visual impairments (Azimi et al., 2019a). Third, the physiological instability of elderly people may directly cause erroneous judgment of MUA methods, which typically arises when a slight change occurs in an elderly user's biometrics input.

Improving the MUA performance with elderly users may be approached from both model-building and analytical aspects. A potential direction from the model-building perspective is to distill the most important biometrics-based MUA features from multi-dimensional features collected by the embedded sensors in mobile devices. In particular, the distilled biometrics-based MUA metrics should be leaning more toward subject-sensible and-accessible features (e.g., low-motion MUA behaviors) than those conventional features used in biometrics-based MUA with non-elderly users. From an analytical perspective, deep-learning is a dominant trend for building biometrics-based MUA models and has a great potential to improve MUA performance because of its robustness in extracting representative features from the elderly's overall biometric patterns or vital signs, even when part of features are missing or interrupted. Given that the performance of deep-learning techniques heavily relies on a large data set, we build a collection of publicly available datasets (see Table 6; details are available in Appendix Table A1) to facilitate MUA model training and improvement for elderly users.

6.4. The usability and security tradeoff

The tradeoff between the usability and security of MUA methods has been well recognized yet remains rarely

Table 6. Publicly available MUA datasets involving the elderly subjects.

Biometrics-based MUA Methods		Resources
Physiological	Fingerprint	FVC (*Second International Fingerprint Verification Competition*, 2002) BiosecurID (Fierrez et al., 2010)
	Face	Cas-peal face (Wu & Wang, 2019) Frontal faces (Wasnik et al., 2018) BiosecurID (Fierrez et al., 2010)
	Voice	Home automation speech (English) (Selva, 2015) Elderly Emotional Speech (Chinese) (Wang et al., 2016) BiosecurID (Fierrez et al., 2010)
	Iris	Iris with diabetes (Azimi et al., 2019b) NEXUS scores dataset (Gorodnichy & Chumakov, 2019) BiosecurID (Fierrez et al., 2010)
	Hand geometry	BiosecurID (Fierrez et al., 2010)
Behavioral	Keystroke	BiosecurID (Fierrez et al., 2010) DSL2009 (Giot et al., 2015)
	Touch gesture	Motor dysfunction (Klein et al., 2017) Corpus of Social Touch (CoST, 2016)
	Pattern lock	–
	Handwriting	BiosecurID (Fierrez et al., 2010) NewHandPD (Pereira et al., 2016)
	Gait	OU_ISIR (*OU-ISIR Biometric Database*, n.d.) Smart-Insole (Chatzaki et al., 2021)
	Gaze	ElderReact (Ma et al., 2019) Natural Viewing Behavior (Açık et al., 2010)

addressed for elderly users. Compared with security, the usability of biometrics-based MUA methods (e.g., efficiency, error resistance, and ease-of-use) is equally, if not even more, important for elderly users. In view that elderly people are considered less knowledgeable and less experienced with operating systems and software on mobile devices than younger users (Damant & Knapp, 2015), ease of use is particularly important for MUA for the elderly, but it opens a door to a variety of security attacks [e.g., shoulder-surfing attack, brute force attack, poisoning attack (Wang et al., 2021)]. Hence, tailoring biometrics-based MUA solutions to the needs of elderly users is deemed critical.

The recent developments in MUA go beyond passwords, such as behavioral-based, implicit, and/or continuous authentication can potentially address usability and security concerns (Alt & Schneegass, 2022). However, those MUA methods have rarely deployed for users. We envision that future research should focus on the integration of behavioral-based biometrics and graphic passwords that exhibit higher usability because some qualities of images are easily memorable (e.g., the presence of people and places) (Bainbridge, 2019). Moreover, future studies can use the match between the elderly's accessibility concerns and biometrics-based methods (see Table 3) as a guideline for developing useful yet secure MUA solutions.

6.5. Low-acceptance

The elderly's hesitancy with adopting biometrics-based MUA methods is attributable to several issues as discussed above. The low acceptance of MUA in turn may be attributed to other factors, such as the elderly's limited technical knowledge and familiarity with traditional MUA methods (e.g., Qwerty- or PIN-based MUA methods).

To increase the adoption rate of a new biometrics-based MUA method with elderly users, future studies can leverage the Senior Technology Acceptance Model (STAM) (Yu-Huei et al., 2019) as a starting point. The model consists of three dimensions: objectification (the phase in which the user forms an intention to use a device based on his/her social context and perceived usefulness), incorporation (the experimentation and exploration phase that helps with validating the ease of use and usefulness), and adoption *per se*. In addition, researchers should look into other confounding factors that may potentially impact the acceptance/adoption of a new biometrics-based MUA by elderly users (e.g., be content with the status quo).

7. Conclusion

Mobile device adoption among elderlies has become an increasing trend. The chronic diseases and functional decline of the elderly create barriers to the effectiveness of biometrics-based MUA for the elderly. This study summarizes the four accessibility needs of elderly users in MUA and reviews the state-of-the-art biometrics-based MUA methods that potentially accommodate the elderly's needs. In addition, we synthesize the experiment design guidelines with the elderly via participant recruitment, research methods, and performance measures. Furthermore, we identify inferior performance of elderly users in biometrics-based MUA. Ultimately, we present open issues and future research directions that can facilitate further development in MUA research for elderly users.

This study has some limitations that could invite future research. The scope of this review is close-fitting to the MUA for elderly users. This study can be furthered by providing an in-depth comparison of the elderly in different age groups and with different levels of education and familiarity with mobile devices. Despite that this review covers various biometrics features that MUA methods extract from user data, it does not focus on the techniques for building MUA models for elderly users. An interesting future issue might be examining the technical methods supporting MUA for elderly users.

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References

Açık, A., Sarwary, A., Schultze-Kraft, R., Onat, S., & König, P. (2010). Developmental changes in natural viewing behavior: Bottom-up and top-down differences between children, young adults and older adults. *Frontiers in Psychology*, *1*, 207. https://doi.org/10.3389/fpsyg.2010.00207

Ahmed, E., DeLuca, B., Hirowski, E., Magee, C., Tang, I., & Coppola, J. F. (2017). Biometrics: Password replacement for elderly? In *2017 IEEE Long Island Systems, Applications and Technology Conference (LISAT)* (pp. 1–6). https://doi.org/10.1109/LISAT.2017.8001958

Allah, K. K., Ismail, N. A., & Elrobaa, H. (2021). Empathy map instrument for analyzing human–computer interaction in using web search UI by elderly users. In *2021 International Congress of Advanced Technology and Engineering (ICOTEN)* (pp. 1–5). https://doi.org/10.1109/ICOTEN52080.2021.9493548

Al-Showarah, S. A. (2019). Dynamic recognition for user age-group classification using hand-writing based finger on smartphones. In *2019 10th International Conference on Information and Communication Systems (ICICS)* (pp. 140–146). https://doi.org/10.1109/IACS.2019.8809083

Alt, F., & Schneegass, S. (2022). Beyond passwords—Challenges and opportunities of future authentication. *IEEE Security & Privacy*, *20*(1), 82–86. https://doi.org/10.1109/MSEC.2021.3127459

Andronico, P., Minutoli, S., & Kuruoglu, E. E. (2014). Understanding elderly needs for designing a digitally extended environment via tablets. In C. Stephanidis (Ed.), *HCI International 2014—Posters'*

Extended Abstracts (pp. 284–287). Springer International Publishing. https://doi.org/10.1007/978-3-319-07854-0_50

Azimi, M., Rasoulinejad, S. A., & Pacut, A. (2019a). The effects of gender factor and diabetes mellitus on the iris recognition system's accuracy and reliability. In *2019 Signal Processing: Algorithms, Architectures, Arrangements, and Applications (SPA)* (pp. 273–278). https://doi.org/10.23919/SPA.2019.8936757

Azimi, M., Rasoulinejad, S. A., & Pacut, A. (2019b). Iris recognition under the influence of diabetes. *Biomedizinische Technik. Biomedical Engineering*, *64*(6), 683–689. https://doi.org/10.1515/bmt-2018-0190

Bainbridge, W. A. (2019). Chapter one – Memorability: How what we see influences what we remember. In K. D. Federmeier & D. M. Beck (Eds.), *Psychology of learning and motivation* (Vol. 70, pp. 1–27). Academic Press. https://doi.org/10.1016/bs.plm.2019.02.001

Bazrafkan, S., & Corcoran, P. (2018). Enhancing iris authentication on handheld devices using deep learning derived segmentation techniques. In *2018 IEEE International Conference on Consumer Electronics (ICCE)* (pp. 1–2). https://doi.org/10.1109/ICCE.2018.8326219

Blanco-Gonzalo, R., Sanchez-Reillo, R., Martinez-Normand, L., Fernandez-Saavedra, B., & Liu-Jimenez, J. (2015). Accessible mobile biometrics for elderly. In *Proceedings of the 17th International ACM SIGACCESS Conference on Computers & Accessibility* (pp. 419–420). https://doi.org/10.1145/2700648.2811332

Bong, W. K., Chen, W., & Bergland, A. (2018). Tangible user interface for social interactions for the elderly: A review of literature. *Advances in Human–Computer Interaction*, *2018*(2018), 1–15. https://doi.org/10.1155/2018/7249378

Brooke, j. (1996). SUS: A "quick and dirty" usability scale. In *Usability evaluation in industry*. CRC Press.

Campbell, O. (2015). Designing for the elderly: Ways older people use digital technology differently. *Smashing Magazine*. https://www.smashingmagazine.com/2015/02/designing-digital-technology-for-the-elderly/

Chakraborty, B., Nakano, K., Tokoi, Y., & Hashimoto, T. (2019). An approach for designing low cost deep neural network based biometric authentication model for smartphone user. In *TENCON 2019 – 2019 IEEE Region 10 Conference (TENCON)* (pp. 772–777). https://doi.org/10.1109/TENCON.2019.8929241

Chatzaki, C., Skaramagkas, V., Tachos, N., Christodoulakis, G., Maniadi, E., Kefalopoulou, Z., Fotiadis, D. I., & Tsiknakis, M. (2021). The smart-insole dataset: Gait analysis using wearable sensors with a focus on elderly and Parkinson's patients. *Sensors*, *21*(8), 2821. https://doi.org/10.3390/s21082821

Clegg, A., Young, J., Iliffe, S., Rikkert, M. O., & Rockwood, K. (2013). Frailty in elderly people. *The Lancet*, *381*(9868), 752–762. https://doi.org/10.1016/S0140-6736(12)62167-9

Coren, S., & Hakstian, A. R. (1988). Color vision screening without the use of technical equipment: Scale development and cross-validation. *Perception & Psychophysics*, *43*(2), 115–120. https://doi.org/10.3758/BF03214188

Corpus of Social Touch (2016). [Data set]. 4TU.ResearchData. https://doi.org/10.4121/uuid:5ef62345-3b3e-479c-8e1d-c922748c9b29

Corsetti, B., Sanchez-Reillo, R., Guest, R. M., & Santopietro, M. (2019). Face image analysis in mobile biometric accessibility evaluations. In *2019 International Carnahan Conference on Security Technology (ICCST)* (pp. 1–5). https://doi.org/10.1109/CCST.2019.8888437

Crews, J. E., Chou, C.-F., Sekar, S., & Saaddine, J. B. (2017). The prevalence of chronic conditions and poor health among people with and without vision impairment, aged ≥65 years, 2010–2014. *American Journal of Ophthalmology*, *182*, 18–30. https://doi.org/10.1016/j.ajo.2017.06.038

Damant, J., & Knapp, M. (2015, May). *What are the likely changes in society and technology which will impact upon the ability of older adults to maintain social (extra-familial) networks of support now, in 2025 and in 2040?* [Monograph]. Government Office for Science. https://www.gov.uk/government/organisations/government-office-for-science

Dandachi, G., El Hassan, B., & El Husseini, A. (2013). A novel identification/verification model using smartphone's sensors and user behavior. In *2013 2nd International Conference on Advances in Biomedical Engineering* (pp. 235–238). https://doi.org/10.1109/ICABME.2013.6648891

Fang, L., Zhu, H., Lv, B., Liu, Z., Meng, W., Yu, Y., Ji, S., & Cao, Z. (2020). HandiText: Handwriting recognition based on dynamic characteristics with incremental LSTM. *ACM/IMS Transactions on Data Science*, *1*(4), 25:1–25:18. https://doi.org/10.1145/3385189

Fierrez, J., Galbally, J., Ortega-Garcia, J., Freire, M. R., Alonso-Fernandez, F., Ramos, D., Toledano, D. T., Gonzalez-Rodriguez, J., Siguenza, J. A., Garrido-Salas, J., Anguiano, E., Gonzalez-de-Rivera, G., Ribalda, R., Faundez-Zanuy, M., Ortega, J. A., Cardeñoso-Payo, V., Viloria, A., Vivaracho, C. E., Moro, Q. I., … Gracia-Roche, J. J. (2010). BiosecurID: A multimodal biometric database. *Pattern Analysis and Applications*, *13*(2), 235–246. https://doi.org/10.1007/s10044-009-0151-4

Fisk, A. D., Czaja, S. J., Rogers, W. A., Charness, N., & Sharit, J. (2020). *Designing for older adults: Principles and creative human factors approaches*. CRC Press.

Giot, R., Dorizzi, B., & Rosenberger, C. (2015). A review on the public benchmark databases for static keystroke dynamics. *Computers & Security*, *55* (November), 46–61. https://doi.org/10.1016/j.cose.2015.06.008

González-Bañales, D. L., & Ortíz, L. E. S. (2017). Empathy map as a tool to analyze human–computer interaction in the elderly. In *Proceedings of the 8th Latin American Conference on Human–Computer Interaction* (pp. 1–3). https://doi.org/10.1145/3151470.3156642

Gorodnichy, D., & Chumakov, M. (2019). Analysis of the effect of ageing, age, and other factors on iris recognition performance using NEXUS scores dataset. *IET Biometrics*, *8*(1), 29–39. https://doi.org/10.1049/iet-bmt.2018.5105

Gubernatorov, A. M., Teslenko, I. B., Muravyova, N. V., Vinogradov, D. V., & Subbotina, N. O. (2020). Information security of mobile systems. In E. G. Popkova (Ed.), *Growth poles of the global economy: Emergence, changes and future perspectives* (pp. 677–686). Springer International Publishing. https://doi.org/10.1007/978-3-030-15160-7_68

Hone, K. S., & Graham, R. (2000). Towards a tool for the subjective assessment of speech system interfaces (SASSI). *Natural Language Engineering*, *6*(3&4), 287–303. https://doi.org/10.1017/S1351324900002497

Hong, H.-T., Su, T.-Y., Lee, P.-H., Hsieh, P.-C., & Chiu, M.-J. (2017). VisualLink: Strengthening the connection between hearing-impaired elderly and their family. In *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems* (pp. 67–73). https://doi.org/10.1145/3027063.3049269

Huang, Y.-P., Luo, S.-W., & Chen, E.-Y. (2002). An efficient iris recognition system. In *Proceedings. International Conference on Machine Learning and Cybernetics* (Vol. 1, pp. 450–454). https://doi.org/10.1109/ICMLC.2002.1176794

Huh, J.-H., & Seo, K. (2015). Design and implementation of the basic technology for solitary senior citizen's lonely death monitoring system using PLC. *Journal of Korea Multimedia Society*, *18*(6), 742–752. https://doi.org/10.9717/kmms.2015.18.6.742

Iancu, I., & Iancu, B. (2020). Designing mobile technology for elderly. A theoretical overview. *Technological Forecasting and Social Change*, *155* (June), 119977. https://doi.org/10.1016/j.techfore.2020.119977

Interaction Design Foundation (2016). *Improving the user experience for the elderly*. Interaction Design Foundation. https://www.interaction-design.org/literature/article/improving-the-user-experience-for-the-elderly

Iqbal, S., Irfan, M., Ahsan, K., Hussain, M. A., Awais, M., Shiraz, M., Hamdi, M., & Alghamdi, A. (2020). A novel mobile wallet model for elderly using fingerprint as authentication factor. *IEEE Access*. *8*, 177405–177423. https://doi.org/10.1109/ACCESS.2020.3025429

Kappen, D. L., Mirza-Babaei, P., & Nacke, L. E. (2019). Older adults' physical activity and exergames: A systematic review. *International Journal of Human–Computer Interaction*, *35*(2), 140–167. https://doi.org/10.1080/10447318.2018.1441253

Kim, H., Heo, J., Shim, J., Kim, M., Park, S., & Park, S. (2007). Contextual research on elderly users' needs for developing universal design mobile phone. In C. Stephanidis (Ed.), *Universal access in human computer interaction. Coping with diversity* (pp. 950–959). Springer. https://doi.org/10.1007/978-3-540-73279-2_106

Kirakowski, J., & Corbett, M. (1993). SUMI: The Software Usability Measurement Inventory. *British Journal of Educational Technology*, *24*(3), 210–212. https://doi.org/10.1111/j.1467-8535.1993.tb00076.x

Klaib, A. F., Alsrehin, N. O., Melhem, W. Y., & Bashtawi, H. O. (2019). IoT smart home using eye tracking and voice interfaces for elderly and special needs people. *Journal of Communications*, *14*(7), 614–621. https://doi.org/10.12720/jcm.14.7.614-621

Klein, Y., Djaldetti, R., Keller, Y., & Bachelet, I. (2017). Motor dysfunction and touch-slang in user interface data. *Scientific Reports*, *7*(1), 4702. https://doi.org/10.1038/s41598-017-04893-1

Klimova, B., & Marešová, P. (2016). *Elderly people and their attitude towards mobile phones and their applications—A review study*. https://doi.org/10.1007/978-981-10-1536-6_5

Kobayashi, M., Kosugi, A., Takagi, H., Nemoto, M., Nemoto, K., Arai, T., & Yamada, Y. (2019). Effects of age-related cognitive decline on elderly user interactions with voice-based dialogue systems. In D. Lamas, F. Loizides, L. Nacke, H. Petrie, M. Winckler, & P. Zaphiris (Eds.), *Human–computer interaction – INTERACT 2019* (pp. 53–74). Springer International Publishing. https://doi.org/10.1007/978-3-030-29390-1_4

Kocejko, T., & Wtorek, J. (2012). Gaze pattern lock for elders and disabled. In E. Piętka & J. Kawa (Eds.), *Information technologies in biomedicine* (pp. 589–602). Springer. https://doi.org/10.1007/978-3-642-31196-3_59

Kononova, A., Li, L., Kamp, K., Bowen, M., Rikard, R. V., Cotten, S., & Peng, W. (2019). The use of wearable activity trackers among older adults: Focus Group study of tracker perceptions, motivators, and barriers in the maintenance stage of behavior change. *JMIR mHealth and uHealth*, *7*(4), e9832. https://doi.org/10.2196/mhealth.9832

Kowtko, M. A. (2014). Biometric authentication for older adults. In *IEEE Long Island Systems, Applications and Technology (LISAT) Conference 2014* (pp. 1–6). https://doi.org/10.1109/LISAT.2014.6845213

Krishnamoorthy, S., Rueda, L., Saad, S., & Elmiligi, H. (2018). Identification of user behavioral biometrics for authentication using keystroke dynamics and machine learning. In *Proceedings of the 2018 2nd International Conference on Biometric Engineering and Applications* (pp. 50–57). https://doi.org/10.1145/3230820.3230829

Kunda, D., & Chishimba, M. (2021). A survey of android mobile phone authentication schemes. *Mobile Networks and Applications*, *26*, 2558–2566. https://doi.org/10.1007/s11036-018-1099-7

Lanitis, A. (2010). A survey of the effects of aging on biometric identity verification. *International Journal of Biometrics*, *2*(1), 34–52. https://doi.org/10.1504/IJBM.2010.030415

Lewis, J. E., & Neider, M. B. (2017). Designing wearable technology for an aging population. *Ergonomics in Design: The Quarterly of Human Factors Applications*, *25*(3), 4–10. https://doi.org/10.1177/1064804616645488

Liu, S., Shao, W., Li, T., Xu, W., & Song, L. (2022). Recent advances in biometrics-based user authentication for wearable devices: A contemporary survey. *Digital Signal Processing*, *125* (June), 103120. https://doi.org/10.1016/j.dsp.2021.103120

Ma, K., Wang, X., Yang, X., Zhang, M., Girard, J. M., & Morency, L.-P. (2019). ElderReact: A multimodal dataset for recognizing emotional response in aging adults. In *2019 International Conference on Multimodal Interaction* (pp. 349–357). https://doi.org/10.1145/3340555.3353747

Majumder, S., & Deen, M. J. (2019). Smartphone sensors for health monitoring and diagnosis. *Sensors*, *19*(9), 2164. https://doi.org/10.3390/s19092164

Matsumoto, T., Matsumoto, H., Yamada, K., & Hoshino, S. (2002). Impact of artificial "gummy" fingers on fingerprint systems. IS&T/SPIE Electronic Imaging. https://doi.org/10.1117/12.462719

Meurer, J., Stein, M., Randall, D., & Wulf, V. (2018). Designing for way-finding as practices – A study of elderly people's mobility. *International Journal of Human–Computer Studies*, *115* (July), 40–51. https://doi.org/10.1016/j.ijhcs.2018.01.008

Minaee, S., Azimi, E., & Abdolrashidi, A. (2019). FingerNet: Pushing the limits of fingerprint recognition using convolutional neural network. ArXiv:1907.12956 [Cs]. http://arxiv.org/abs/1907.12956

Mohammadi, A., Bhattacharjee, S., & Marcel, S. (2018). Deeply vulnerable: A study of the robustness of face recognition to presentation attacks. *IET Biometrics*, *7*(1), 15–26. https://doi.org/10.1049/iet-bmt.2017.0079

Nedopil, C., Schauber, C., & Glende, S. (2013). *Knowledge base: AAL stakeholders and their requirements*. Ambient Assisted Living Association; A collection of characteristics and requirements of primary, secondary, and tertiary users of AAL solutions, and a guideline for user-friendly AAL design.

Nimrod, G. (2016). The hierarchy of mobile phone incorporation among older users. *Mobile Media & Communication*, *4*(2), 149–168. https://doi.org/10.1177/2050157915617336

Orimo, H., Ito, H., Suzuki, T., Araki, A., Hosoi, T., & Sawabe, M. (2006). Reviewing the definition of "elderly. *Geriatrics and Gerontology International*, *6*(3), 149–158. https://doi.org/10.1111/j.1447-0594.2006.00341.x

OU-ISIR Biometric Database (n.d.). Retrieved April 8, 2022, from http://www.am.sanken.osaka-u.ac.jp/BiometricDB/InertialGait.html

Pereira, C. R., Weber, S. A. T., Hook, C., Rosa, G. H., Papa, J. P. (2016). Deep learning-aided Parkinson's disease diagnosis from handwritten dynamics. In *2016 29th SIBGRAPI Conference on Graphics, Patterns and Images (SIBGRAPI)* (pp. 340–346). https://doi.org/10.1109/SIBGRAPI.2016.054

Petrovčič, A., Slavec, A., & Dolničar, V. (2018). The ten shades of silver: Segmentation of older adults in the mobile phone market. *International Journal of Human–Computer Interaction*, *34*(9), 845–860. https://doi.org/10.1080/10447318.2017.1399328

Sadeghi, Z., Homayounvala, E., & Borhani, M. (2020). HCI for elderly, measuring visual complexity of webpages based on machine learning. In *2020 Digital Image Computing: Techniques and Applications (DICTA)* (pp. 1–6). https://doi.org/10.1109/DICTA51227.2020.9363381

Sakdulyatham, R., Preeyanont, S., Lipikorn, R., & Watakakosol, R. (2017). User interface on smartphone for elderly users. *International Journal of Automation and Smart Technology*, *7*(4), 147–155. https://doi.org/10.5875/ausmt.v7i4.1339

Scheidat, T., Heinze, J., Vielhauer, C., Dittmann, J., & Kraetzer, C. (2011). Comparative review of studies on aging effects in context of biometric authentication. In *Multimedia on Mobile Devices 2011; and Multimedia Content Access: Algorithms and Systems V* (Vol. 7881, pp. 788110–788316). https://doi.org/10.1117/12.872417

Schmeck, A., Opfermann, M., van Gog, T., Paas, F., & Leutner, D. (2015). Measuring cognitive load with subjective rating scales during problem solving: Differences between immediate and delayed ratings. *Instructional Science*, *43*(1), 93–114. https://doi.org/10.1007/s11251-014-9328-3

Second International Fingerprint Verification Competition (2002). http://bias.csr.unibo.it/fvc2002/databases.asp

Selva (2015). *GUI environmental sound recognition*. https://de.mathworks.com/matlabcentral/fileexchange/45054-gui-environmental-sound-recognition

Shien, L. K., & Singh, M. M. (2017). A secure mobile crowdsensing (MCS) location tracker for elderly in smart city. *AIP Conference Proceedings*, *1891*(1), 020085. https://doi.org/10.1063/1.5005418

Shuwandy, M. L., Zaidan, B. B., Zaidan, A. A., Albahri, A. S., Alamoodi, A. H., Albahri, O. S., & Alazab, M. (2020). mHealth authentication approach based 3D touchscreen and microphone sensors for real-time remote healthcare monitoring system: Comprehensive review, open issues and methodological aspects. *Computer Science Review*, *38* (November), 100300. https://doi.org/10.1016/j.cosrev.2020.100300

Solé-Casals, J., Vancea, M., & Miquel March, J. (2015). A preliminary review of behavioural biometrics for health monitoring in the elderly. In *Proceedings of the International Joint Conference on*

Biomedical Engineering Systems and Technologies (Vol. 4, pp. 365–371). https://doi.org/10.5220/0005321603650371
Still, J. D., Cain, A., & Schuster, D. (2017). Human-centered authentication guidelines. *Information & Computer Security*, *25*(4), 437–453. https://doi.org/10.1108/ICS-04-2016-0034
Stylios, I., Kokolakis, S., Thanou, O., & Chatzis, S. (2021). Behavioral biometrics & continuous user authentication on mobile devices: A survey. *Information Fusion*, *66* (February), 76–99. https://doi.org/10.1016/j.inffus.2020.08.021
Sun, F., Zang, W., Gravina, R., Fortino, G., & Li, Y. (2020). Gait-based identification for elderly users in wearable healthcare systems. *Information Fusion*, *53* (January), 134–144. https://doi.org/10.1016/j.inffus.2019.06.023
Sundararajan, K., & Woodard, D. L. (2019). Deep learning for biometrics. *ACM Computing Surveys*, *51*(3), 1–34. https://doi.org/10.1145/3190618
Teh, P. S., Zhang, N., Teoh, A. B. J., & Chen, K. (2016). A survey on touch dynamics authentication in mobile devices. *Computers & Security*, *59* (June), 210–235. https://doi.org/10.1016/j.cose.2016.03.003
Vassli, L. T., & Farshchian, B. A. (2018). Acceptance of health-related ICT among elderly people living in the community: A systematic review of qualitative evidence. *International Journal of Human–Computer Interaction*, *34*(2), 99–116. https://doi.org/10.1080/10447318.2017.1328024
Villegas, M. F., Torres Munoz, J. C., Alrashidi, A. M. R., & Dow, D. E. (2019). Tabletop human computer interface to assist elderly with tasks of daily living. In *2019 IEEE 10th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)* (pp. 596–599). https://doi.org/10.1109/UEMCON47517.2019.8992972
Vuletic, T., Duffy, A., Hay, L., McTeague, C., Campbell, G., & Grealy, M. (2019). Systematic literature review of hand gestures used in human computer interaction interfaces. *International Journal of Human–Computer Studies*, *129* (September), 74–94. https://doi.org/10.1016/j.ijhcs.2019.03.011
Wang, C., Wang, Y., Chen, Y., Liu, H., & Liu, J. (2020). User authentication on mobile devices: Approaches, threats and trends. *Computer Networks*, *170* (April), 107118. https://doi.org/10.1016/j.comnet.2020.107118
Wang, F., Chen, L., Li, C., Huang, S., Chen, Y., Qian, C., & Loy, C. C. (2018). *The Devil of Face Recognition is in the Noise* (pp. 765–780). https://openaccess.thecvf.com/content_ECCV_2018/html/Liren_Chen_The_Devil_of_ECCV_2018_paper.html
Wang, K., Zhou, L., & Zhang, D. (2019). User preferences and situational needs of mobile user authentication methods. In *2019 IEEE International Conference on Intelligence and Security Informatics (ISI)* (pp. 18–23). https://doi.org/10.1109/ISI.2019.8823274
Wang, K., Zhou, L., Zhang, D., Liu, Z., & Lim, J. (2020). What is more important for touch dynamics based mobile user authentication? In *PACIS 2020 Proceedings*. https://aisel.aisnet.org/pacis2020/174
Wang, K., Zhu, Z., Wang, S., Sun, X., & Li, L. (2016). A database for emotional interactions of the elderly. In *2016 IEEE/ACIS 15th International Conference on Computer and Information Science (ICIS)* (pp. 1–6). https://doi.org/10.1109/ICIS.2016.7550902
Wang, X., Yan, Z., Zhang, R., & Zhang, P. (2021). Attacks and defenses in user authentication systems: A survey. *Journal of Network and Computer Applications*, *188* (August), 103080. https://doi.org/10.1016/j.jnca.2021.103080
Wasnik, P., Ramachandra, R., Raja, K., Busch, C. (2018). An empirical evaluation of deep architectures on generalization of smartphone-based face image quality assessment. In *2018 IEEE 9th International Conference on Biometrics Theory, Applications and Systems (BTAS)* (pp. 1–7). https://doi.org/10.1109/BTAS.2018.8698593
Watzman, S. (2002). Visual design principles for usable interfaces. In *The human–computer interaction handbook: Fundamentals, evolving technologies and emerging applications* (pp. 263–285). L. Erlbaum Associates Inc.
White-Chu, E. F., & Reddy, M. (2011). Dry skin in the elderly: Complexities of a common problem. *Clinics in Dermatology*, *29*(1), 37–42. https://doi.org/10.1016/j.clindermatol.2010.07.005
World Population Prospects—United Nations (2019). https://population.un.org/wpp/Download/Standard/Population/
Wu, S., & Wang, D. (2019). Effect of subject's age and gender on face recognition results. *Journal of Visual Communication and Image Representation*, *60* (April), 116–122. https://doi.org/10.1016/j.jvcir.2019.01.013
Wulf, L., Garschall, M., Himmelsbach, J., & Tscheligi, M. (2014). Hands free-care free: Elderly people taking advantage of speech-only interaction. In *Proceedings of the 8th Nordic Conference on Human–Computer Interaction: Fun, Fast, Foundational* (pp. 203–206). https://doi.org/10.1145/2639189.2639251
Yin, X., Yu, X., Sohn, K., Liu, X., & Chandraker, M. (2019). Feature transfer learning for deep face recognition with under-represented data. ArXiv:1803.09014 [Cs]. http://arxiv.org/abs/1803.09014
Yu-Huei, C., Ja-Shen, C., & Ming-Chao, W. (2019). Why do older adults use wearable devices: A case study adopting the senior technology acceptance model (STAM). In *2019 Portland International Conference on Management of Engineering and Technology (PICMET)* (pp. 1–8). https://doi.org/10.23919/PICMET.2019.8893767
Zheng, G., Yang, W., Johnstone, M., Shankaran, R., & Valli, C. (2020). 3—Securing the elderly in cyberspace with fingerprints. In N. K. Suryadevara & S. C. Mukhopadhyay (Eds.), *Assistive technology for the elderly* (pp. 59–79). Academic Press. https://doi.org/10.1016/B978-0-12-818546-9.00003-8
Zhou, L., Kang, Y., Zhang, D., & Lai, J. (2016). Harmonized authentication based on ThumbStroke dynamics on touch screen mobile phones. *Decision Support Systems*, *92* (December), 14–24. https://doi.org/10.1016/j.dss.2016.09.007
Zou, Q., Wang, Y., Wang, Q., Zhao, Y., & Li, Q. (2020). Deep learning-based gait recognition using smartphones in the wild. *IEEE Transactions on Information Forensics and Security*, *15*, 3197–3212. https://doi.org/10.1109/TIFS.2020.2985628

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Appendix

Table A1. Metadata of publicly available MUA datasets.

Dataset name	Data type	URL
FVC	Image	http://bias.csr.unibo.it/fvc2002/databases.asp
BiosecurID	Image, audio, float	http://atvs.ii.uam.es/databases.js
Cas-peal face	Image	http://www.jdl.ac.cn/peal/index.html
CMU Multi-PIE face	Image	http://www.cs.cmu.edu/afs/cs/project/PIE/MultiPie/Multi-Pie/Home.html
Home automation speech (English)	Audio	https://de.mathworks.com/matlabcentral/fileexchange/45054-gui-environmental-sound-recognition
Elderly Emotional Speech (Chinese)	Text and audio	Reach out to the authors (Wang et al., 2016)
Iris with diabetes	Image	Reach out to the authors (Azimi et al., 2019b)
NEXUS scores dataset	Image	Reach out the authors (Gorodnichy & Chumakov, 2019)
DSL2009	Float	https://www.cs.cmu.edu/∼maxion/datasets.html
Motor dysfunction	Float	Reach out to the authors (Klein et al., 2017)
CoST	Float	https://data.4tu.nl/articles/dataset/Corpus_of_Social_Touch_CoST_/12696869/1
NewHandPD	Image	Reach out to the authors (Pereira et al., 2016)
OU_ISIR	Float	http://www.am.sanken.osaka-u.ac.jp/BiometricDB/InertialGait.html
Smart-Insole	Float	Reach out at email—bmi@hmu.gr
ElderReact	Float	https://github.com/Mayer123/ElderReact