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PAPER

User Age Group Recognition on Smartphones and Tablets Using Gesture Swiping Features

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ABSTRACT

Swiping is a common touchscreen interaction method. This study investigated the possibility of recognizing user-age groups automatically from swiping behaviors to support the progression of self-adaptive interfaces and authentication. The dataset was collected from 42 participants of younger adults (20–39 years) and older adults (60+ years). Four directions were performed by each participant (down, up, left, and right) on either a smartphone or mini-tablet, leading to over 2600 trials. Six features were extracted from the data: force pressure (FP), movement time (MT), swipe count (Swipe No), average distance (Avg Distance), speed, and ratio of MT to FP (RMF). KNN and Euclidean distance (ED) algorithms were applied using three training ratios. Classification accuracy was higher on smartphones than mini-tablets. Notably, younger adults were classified with 100% accuracy on smartphones, while older adults reached 96% accuracy on mini-tablets. Across both devices, younger adults were classified with higher accuracy. MT, Avg Distance, and FP emerged as the most age-sensitive features, whereby MT was highly significant ($p < 0.001$). The findings indicate the feasibility of swiping gestures to be leveraged for age group classification, supporting the development of novel authentication strategies.

KEYWORDS

user age group classification, dynamic recognition, user authentication, swipe gestures, feature extraction, KNN, touchscreens, human-computer interaction

1 INTRODUCTION

Smartphone devices have featured as a major topic of research within the field of human computer interaction (HCI). It has been widely observed that smartphone devices can be challenging for elderly users, specifically those with motor impairments [1] [2].

The two main challenges emerging on a worldwide scale are: (a) populations are aging rapidly, (b) widespread usage of technology is increasing. The World Health Organization (WHO) expects that the proportion of the world population aged 60+ years is going to be increased from 12% to 22% in the years of 2015

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to 2050 [3]. Specifically, in the UK, approximately 25% of the population are 60+ years old and this is predicted to rise to 35% by the year of 2050 [4]. Meanwhile, the statistical department of the European Union suggests that people born in the 2010s are expected to reach a life expectancy exceeding 85 years [5]. Moreover, there has been a noticeable increase in the usage of computers, smartphones, and other forms of technology [6] [7]. Despite this increase, older users continue to demonstrate lower rates of smartphone usage compared with younger users [8] [23], largely due to physical, cognitive, and motor constraints, and difficulties adapting to rapidly evolving technologies [10].

Despite increasing motivation between users to be involved in the development of digital technologies, many of them continue to face considerable accessibility obstacles [7], which drives the rationale of the present research. One of the key factors in this inaccessibility is the standardized design of user interfaces, and touchscreen responses for all users, thereby not adequately accounting for individual variations in ability [11]. These limitations refer to a gap in existing touchscreen technology, since the setting of the interface configuration is frequently adopted as appropriate for all users. In an effort to enhance the usability, the present research explored the possibility of recognizing and classifying user age-groups from the analysis of swipe gestures on the devices of smartphones and mini-tablets, with the aim of improving usability for older users. The outcomes of the present research have the potential to inform novel adaptive systems that are capable of customizing interface configurations, which are appropriate for detected user age groups, such that the system can turn into a particular setting that will serve the users based on their ability and needs. Through the detection of swiping patterns, this approach can support interfaces that adapt automatically without requiring users to manually change accessibility settings. This is particularly advantageous for users with less ability to customize settings manually, as well as for public devices that serve different users of different age demographics.

Both younger and older users participated in the present research, and the following features were extracted from the devices based on swipe gestures: force pressure (FP), movement time (MT), swipe count (Swipe No), average distance (Avg Distance), speed, and ratio of MT to FP (RMF). These particular features were selected based on previous findings from the literature indicating that they reflect age differences in device interaction [31], [32]. The Euclidean distance (ED) algorithm was used to calculate the distances between the coordinates (x, y) of finger movements on the touchscreen for training and testing exemplars, whilst a nearest neighbor (NN) method was used to determine the age group to which each swiping exemplar belonged to. Thus, the motivation of the present research is focused on improving adaptive interface design. By understanding age differences in swipe gestures, user interface content and setting can be dynamically customized to suit the abilities of the users detected.

The results indicated higher classification accuracy for smaller smartphones compared to mini-tablets. Particularly, when combined features were extracted, classification accuracy was 100% for younger adults using smaller smartphones, and 96% for older adults using mini-tablets. These results demonstrated the feasibility of classifying user age groups based on swiping gestures on touchscreen devices.

Although prior studies have investigated age classification on touchscreens [15], this has tended to focus on finger-based handwriting or complex gestures. Such studies involve more demanding finger patterns and place more cognitive burdens on participants accordingly, with only moderate accuracy levels being reported. In contrast, the four directional swipes we examined are simpler and consist with common everyday usage patterns, but have been under examined for user age recognition. We demonstrated classification accuracy exceeding handwriting-based classification previously reported for the same age ranges. Given the real-world relevance and applicability, our study presents a more practical and suited approach to dynamic recognition in adaptive interfaces.

As opposed to relying on traditional static methods, a more dynamic recognition method is required [14]. Behavioral traits are simpler and more cost-effective to obtain than biological markers due to the potential for implicit collection [13]. Modern smartphones typically use finger-based touchscreens as the principal input method [12]. Finger movements on the touchscreen consist of features that can be captured through the screen. As such, appropriate combinations of touchscreen-derived features can be used for the purpose of classification. The proposed feature extraction method has implications for enabling interfaces to adapt and tailor device settings to the individual abilities of users, particularly benefitting older users facing usability challenges. Although the current study is based on smartphone interfaces, the implications could extend to further user interfaces, such as shared touchscreen devices [15].

This paper explores the feasibility of using finger-based swiping gestures on smartphone touchscreens to dynamically classify users by age group. The aim of this study was to identify the most effective combination of features for user classification. The novel contributions of this work are summarized as follows:

1. extracting touch features (FP, MT, Swipe No, Avg Distance, Speed, and RMF) dynamically from vertical and horizontal swipe gestures covering 50 images per direction in a custom-developed Android application;
2. use of ED and a k-nearest neighbors (KNN) classifier on individual and combined touch features derived from smartphones; and
3. providing evidence supporting the classification of users by age group based on swipe gestures, alongside recommendations for the most effective individual and combined features for classification.

The present study builds upon existing work that uses swipe gestures, zoom, and drag-drop interactions to classify user demographics, and extends them by comparing classification accuracy on two screen sizes.

The remainder of this paper is organized into the following structure: Section 2 provides background information on the key features under investigation and outlines the classification system employed. Section 3 reviews related work, including studies utilizing gesture swiping on touchscreens. Section 4 presents the methodology, detailing the data collection processes and procedures. Section 5 presents the results of the study alongside a discussion in the context of the background work. Finally, Section 6 will summarize the main conclusions of the present research, as well as highlighting key contributions and proposing directions for future research.

2 BACKGROUND

Several experimental studies were conducted involving extensive datasets. However, processing such information manually can be effortful, time-consuming and limiting. Thus, a range of methodologies have been used, ranging from simple automation to sophisticated machine learning methods [16].

The classification method is a type of machine learning, whereby the model aims to predict a label for the input data. The classification process involves training the data and subsequently evaluating the model using a separate test dataset, prior to being deployed for performing predictions on novel datasets [17]. In the present study, the KNN classifier was utilized. As a result of its simplicity and interpretability, KNN is among the most frequently used algorithms for classification. It is the preferred algorithm in the present study due to the focus on feasibly classifying user age groups on the basis of fewer data points.

To classify a given test example, KNN calculates the distance between the test example and every example in the training dataset, subsequently using these distances to derive the final classification. Thus, KNN identifies the most similar examples by locating the nearest neighbor to the test within the training dataset [29]. The similarity is commonly measured using Euclidean distance (Equation 1).

$$d(p,q) = \sqrt{\sum_{i=1}^{n}(qi - pi)^2} \quad (1)$$

Equation 1: Where: p, q: are points in n-space. pi, qi: Euclidean vectors. n: n-space.

In this paper, machine learning classifiers predict user age based on the following features collected from a smartphone application as illustrated in Figure 1, [11], [25], [22]:

- Force Pressure (FP): This metric represents the average force applied to the touchscreen surface during each trial, measured at each coordinate [i.e., (x, y)] on the screen. Pressure values were obtained from the device operating system at each point across the swipe trajectory and then averaged across the gesture. These are reported as units provided by the operating system, as such comparable within but not across devices. It is exerted at each point (i.e., (x, y) coordinate on the screen) on the trajectory when performing gestures in each direction. $\text{FP} = \left(\sum_{i=1}^{n} fpi\right)\Big/n$. Where n is the number of exerted values for each trial of each participant.
- Movement Time (MT). MT measures the time elapsed between the initial finger-down position and the point of reaching the target when gesture swiping. MT was measured in milliseconds (ms) and computed as MT = $t_{start} - t_{end}$ where t_{start} and t_{end} represents the time at the start and end of the swipe gesture, respectively.
- Average Distance (Avg Distance): For each of five trials per participant, the ED is computed from the initial coordinates when the user's finger first touches the screen (x, y) to the final coordiantes when the user reaches the target (x, y). Avg Distance was reported in pixels. This was calculated as the mean ED covered during a swipe as formula. $\text{Avg Distance} = \left(\sum_{k=1}^{5} d(p,q)\right)\Big/5$. Where $d(p, q)$ is the results of Euclidean distance for each trials divided by the five trials of each participant.
- Swipe Count (Swipe No): This feature denotes the total number of swipes performed to reach the target in each trial, represented as a count.
- Speed: It is used to assess the efficiency of swiping, which is calculated by dividing Avg Distance by MT. Speed was expressed in pixels per millisecond (pixels/ms). Speed = Avg Distance/MT.
- Ratio of MT to FP (RMF): It is the ratio between movement time (MT) to finger pressure (fp), indicating the smoothness of gesture swiping on smartphone devices. A higher ratio indicates a smoother gesture. RMF computed as RMF = MT/FP. A unitless ratio indicating smoothness.

These six features (FP, MT, Swipe No, Avg Distance, Speed, and RMF) were selected because they can be extracted directly from standard touch event records. This is dissimilar to other commonly used features such as acceleration or trajectory curvature, which require additional sensors or trajectory reconstruction. Previous works also indicated consistent age-related differences in the selected features [31], [32], making them appropriate for classification in this research.

To clarify this rationale, Table 1 summarises the distinctions between the selected features in our study and common alternatives that we have omitted.

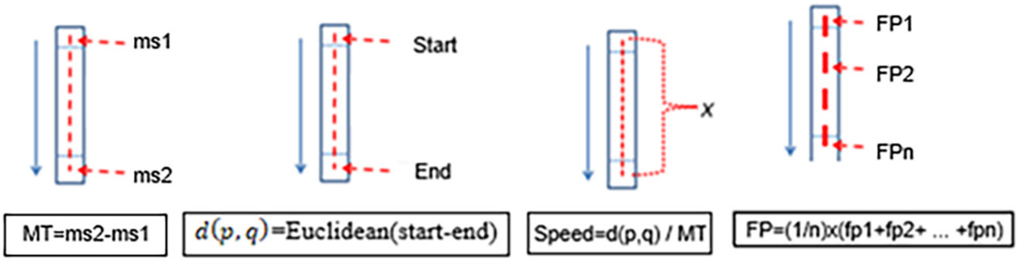

Fig. 1. How the metrics are calculated

Table 1. Rationale for included and omitted features

Feature	Included or Omitted	Rationale
MT	Included	Age-sensitivity well-established; no additional sensors required.
FP	Included	Directly available from touch events; captures motor control differences.
Avg Distance	Included	Reflects swipe amplitude and efficiency; requires only positional start and end points.
Swipe No	Included	Indicates control and accuracy; simple to extract.
Speed and RMF	Included	Provides motor efficiency and smoothness information.
Acceleration/jerk	Omitted	Brevity of gesture paths offers less robust estimation; requires high frequency sampling.
Curvature/trajectory	Omitted	Requires continual trajectory reconstruction.
Pressure variability	Omitted	Often increased noise level on devices; pressure sensors can be overly variable.
Angular velocity/ orientation drift	Omitted	More suitable for handwriting; offers limited value for directional swipes.

The above comparisons reflect the practicality of the selected methods alongside advantages such as age sensitivity and interpretability, making them appropriate for our gesture-based age classification study.

3 RELATED WORK

The research conducted on user age group classifications using swiping gesture interactions is a growing field. The distinctive characteristics of touch gestures are used to infer age-related behavioral tendencies in touchscreen interactions. Key metrics used in this process include: gesture accuracy, speed, movement time, and force pressure exerted during touchscreen interaction [23]. However, a number of previous studies have mainly focused on different shapes of gestures such as complex gestures or handwriting, whereas everyday interactions such as directional swipe gestures remain underexplored despite their widespread prevalence in the smartphone use. For example, the study in [21] examined age-group detection based on touch input, using data collected from 89 users aged between 3–6 years and 30 years. They used a support vector machine (SVM) classifier, and the users repeated the task 50 times with performance measured using the average correct classification rate. Meanwhile, studies such as [25], [26] have investigated different gestures like zooming, drag-and-drop, and complex interaction patterns. In contrast, the present study focuses on swipe gestures in four different directions. We focused specifically on these simple, frequently used directional swipes, and compared classification across devices of different sizes of screens, namely a smartphone and mini-tablet screen. These factors together present a novel approach to investigating the classification of user age groups.

Previous research has illustrated the efficacy of features collected form gestures in conjunction with nearest neighbour (NN) classifier, resulting in promising results in differentiating between age groups based on touch interactions [23]. However, it focused on handwritten features rather than directional swipe gestures. While the present research differentiates itself by analysing four standardized swipe directions. This distinction is important because swipe gestures are fundamental to most smartphone interactions and therefore represent a practical basis for real time age recognition.

A previous study investigated the age group classification of children through time series analysis of the ChildCIdb dataset [19]. Their dataset was collected from children from colouring a tree using a tablet and a stylus. From these interactions, 25-time series were extracted that captured the following features: spatial, pressure, and kinematic. They used several time series selection methods to identify the most discriminative features for age groups. Classification models using dynamic time warping (DTW) barycenter averaging and hidden markov models yielded 85% accuracy. Such classification accuracy outperformed prior methodologies and maintained robustness in exceedingly challenging classification scenarios. Combining the 25-time series stylus inputs with other ChildCIdb tasks or sensor data may enhance robustness, but it would not reflect the intuitive performance of users, particularly when the goal is to adapt the interfaces of public shared devices based on individual ability.

Another investigation aimed to differentiate between children and older users based on touchscreen interaction patterns [21]. This research used two sets of features: one based on the sigma-lognormal theory of rapid motor movements, and another reflecting universal characteristics of touchscreen interaction. An active detection framework facilitated the continuous monitoring of user interactions, whilst the extracted features were classified using SVMs into age groups. Using feature fusion from both smartphones and tablets led to classification accuracies exceeding 96%. Moreover, the system could reliably recognise a child using only four gestures, thereby highlighting the discriminative power of the neuro-motor-inspired features.

Another investigation was conducted to research the gesture-based user authentication by integrating dynamic security questions with finger pattern recognition via inertial measurement units [20]. The security questions were generated dynamically based on smartphone usage, while the finger movement patterns were captured using four different inertial sensors: accelerometer, gyroscope, gravity sensor, and magnetometer. The combination of behavioral responses and finger movement patterns allowed for reliable user authentication. The dataset was collected from 24 users, comprising an equal proportion of device owners and potential adversaries. The findings showed high recognition accuracy, whereas usage-based questions related to calls, SMS, and app activity achieved rates exceeding the accuracy of 90%. Using inertial measurement units enhanced classification accuracy from 76% to 90.99% when compared to prior research, and further enhanced the true positive from 79% to 99% compared to prior benchmarks.

A number of previous studies have been focusing on the touchscreen interactions of older users. Such studies investigated tasks like drag, rotate, and zoom using multi-touch gestures on mini-tablet interfaces [25] [26]. Results showed the need for user interface adaptations, including larger touch targets/icons, spacing between interface components, and simplified layouts of interface [27]. Most of the previous studies including: [8], [18], [27], [28] recommended conducting research studies that enable technology to support older users' abilities and needs. This recommendation is considered as one of the key motivations for the present experimental research. Recent investigations into mobile phone usability among elder users found a preference for features such as non-fading screens, separate keypads for text and numbers, and multilingual support [28]. They recommended reducing cognitive demands through intuitive design and limiting functionalities such as cameras, which may not be essential for this demographic. Further work has compared performance across device screen sizes [23], and offered guidelines for improving and developing usability for older users, such as increasing the spacing between contents of interactive elements [9].

Various studies have investigated the effects of interface metaphors on the navigational performance of older users [18]. Their results illustrated that the metaphors could support mental model development, and this benefit was contingent upon higher perceptual speed between users. They designed tasks to be performed based on the complexity, content similarity, and prior technology experience, which were found to significantly influence navigation performance. These provide insights to the researchers and developers in determining the applicability of interface metaphors for older users.

Finally, research investigating the handwriting on touchscreens has yielded significant results regarding the classification of user age groups. For example, a study in [23] investigated the use of dynamic handwriting features for identifying the user age group. The research investigated finger-based handwriting of ten different English words on smartphones and mini-tablets. The process involved in the experiment included data acquisition, feature extraction, and classification, with experiments conducted using varying training set sizes for different scenarios (100%, 50%, and 1%). In this case, the percent figure (%) refers to the proportion of total data used across the dataset when training with all users, half of users, or a single user, respectively. The results showed higher classification accuracy on smaller smartphones compared to mini-tablets, with overall accuracies reaching to 82% and 77%, respectively. These findings further support for the feasibility of user age group classification using gestures on touchscreen devices [15].

In summary, the related work overall demonstrates the possibility of gesture-based user classification, but has not yet addressed standardised directional swiping as a basis for age recognition, whilst comparing performance across different screen sizes. The present study addresses this gap by demonstrating how directional interaction features can be used to support automatic age-appropriate adaptive interfaces.

4 THE STUDY METHODOLOGY

4.1 Data collection devices

Two touchscreen devices were employed for the collection of data. The first device was a Samsung Galaxy Ace S5830 (112.4 × 59.9 × 11.5 mm, 3.5-inch screen), representing a smaller screen size, and the second was a Samsung Galaxy Tab 2 (193.7 × 122.4 × 10.5 mm, 7-inch screen), representing a mini-tablet sized screen.

4.2 Participants

A total of 42 individuals participated, comprising 16 older adults aged 60 and above (M = 65 years) and 24 younger adults aged 20–39 (M = 26 years). The following are examples of previous studies that used small sample sizes ([37] [38] [39] [40]) respectively.

Of these participants, 22 completed the trials on the smaller smartphone, while 20 were assigned the mini-tablet device for the task completion. All participants in the experiments had experience of using touchscreens, and they were university students, university staff members, or residents of the local community. The average experience for calling and texting on touchscreen devices was 1.13 years for the younger adults and 0.96 years for the older adults. In this context, experience refers to the timeframe participants reported regularly using a mobile phone to place voice calls and send text-based messages (e.g. SMS or instant messaging). This measure reflects general familiarity with basic touchscreen interaction rather than proficiency with advanced smartphone applications.

4.3 Gesture swiping procedure

Each participant was seated at a table containing either the smartphone or mini-tablet device fixed flat on the surface and oriented landscape at a distance of 10–15 cm from the nearside edge of the table, similarly to prior experimental processes in [30]. Each participant used their dominant hand to perform the swiping. This procedure was used to avoid any confounding movement that would occur if the users held the device in hand. For example, finger pressure measurements could be impacted due to downward pressure applied during swiping gestures on the screen and upward pressure from holding the device in the other hand. The standardized screen positioning allowed consistent interaction conditions across participants that helped to prevent potential movement of the device from interfering with the touchscreen interactions.

An android based application was developed to collect the swipe gesture data from participants. In the experiment, four directions of swiping were applied: down swipe, up swipe, left swipe, and right swipe. A total of 50 images were allocated to each direction of swiping, labelled from 1 to 50 (see Figure 2). Each participant was asked to intuitively perform four swipes per image in the four directions. The developed application traced the user finger movements on the screen surface to record all finger movements, from the initial first touch on an image through to the final contact with the touchscreen.

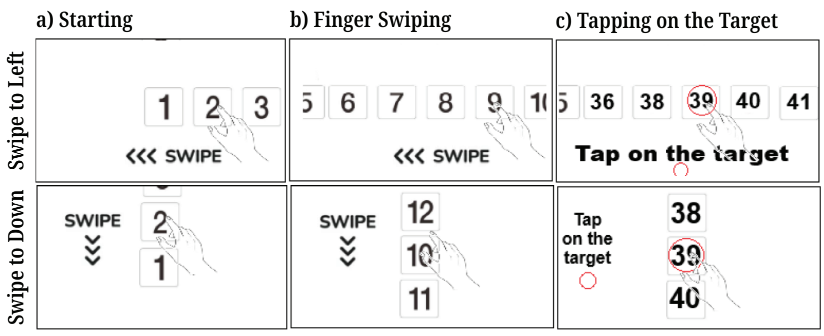

Fig. 2. Illustration of the swipe gesture interaction sequence on the touchscreen

Notes: The figure shows (a) the initial touch at the starting point, (b) examples of the directional swipe motions performed, and (c) the user tapping on the target to complete the gesture.

In each trial, participants were given a target number. Each participant was asked to swipe numbered images and tap the target number. Once the participant tapped the target number, it moved to the center of the screen, which indicated the end of the gesture swiping task for that target number. The participants were asked to tap the target as quickly as possible. The numbers were selected randomly. Furthermore, the targets were varied to avoid any influence of familiarity on performance. In total, each participant contributed four trials comprising 200 swipe gestures, providing a consistent dataset across users and devices.

4.4 Age classification processes

Figure 3 illustrates the following steps that were considered to classify participants into age groups:

Step 1: Data Acquisition. Two cohorts were employed for swipe gesture data collection, specifically younger and older users. The Android application traced the finger movements on the touchscreen of each participant to compile the data.

Step 2: Feature Extraction. The six features were extracted based on finger movement on the touchscreen: FP, MT, Swipe No, Avg Distance, Speed, and RMF.

Step 3: Classification. The classification process consists of three subdivided segments:

Step 3.1: Training. One trial of four swipes across all four directions was conducted for each user. Combining the six features (FP, MT, Avg Distance, Swipe No, Speed, and RMF) yielded 20 data values. Subsequently, the mean value for each feature across the four directions was computed, and separated into two exemplars to represent younger and older adults in the training matrix D (4 × 2). Algorithm 1 shows how the training dataset and the testing dataset were extracted for one age group on one device for only one metric by using the first sample of each swipe gesture performed by each participant from that age-group. The classification accuracy was for an individual metrics as well as combinations of them.

Step 3.2: Testing. The remaining three trials of swipes per user were included in the testing matrix M (4 × Z), where Z = 3 * (number of users).

Step 3.3: Classification. The classifier KNN algorithm was used to classify each user to one of the exemplars (i.e., younger, older users) based on ED between the training features matrix D (4 × 2) and testing features matrix M (4 × Z).

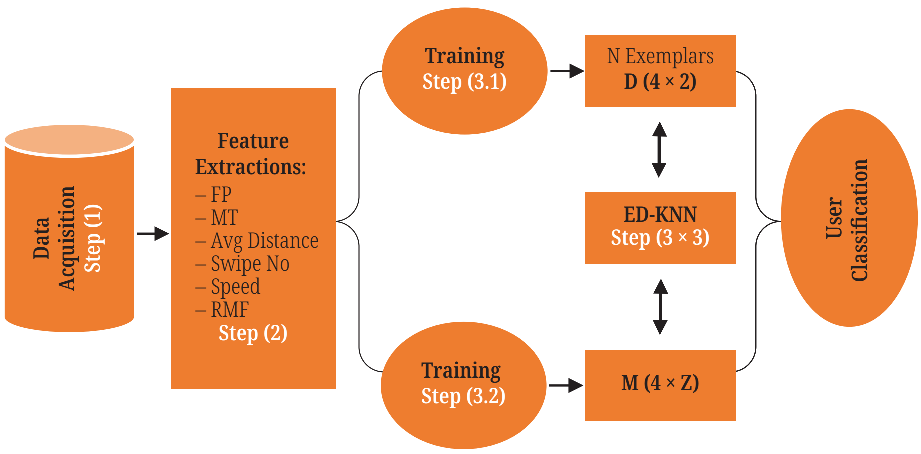

Fig. 3. Overview of the user age group classification process consisting of three main stages: (1) data acquisition of swipe gestures collected from younger and older users, (2) feature extraction of six swipe-based metrics, and (3) KNN-based classification using Euclidean distance to assign users to younger or older age groups

Algorithm 1: Swipe Gesture Feature Vector Construction and Classification

Input:
Device sizes ={D1, D2}.
User groups Groups={g1, g2}; Users belonging to each group Users(g);
Gesture shapes Gestures={S1,S2,S3,S4}; Trials T1…T5 ;
Metrics ={M1…M8};
Output:
Classification accuracy for individual and combined metric feature vectors.
Begin

1. Initialize an empty training set.
2. For each device size d in *DeviceSizes*: [from 1 to 2]
3. For each group g in *Groups*: [from 1 to 2]
4. Initialize an empty feature vector FVg.
5. Let N be the number of users in group g.
6. For each user u in *Users(g)*: s=0
7. For each gesture shape s in *Gestures*: [from 1 to 4]: r=0
8. For each Trial T in gesture shapes: [from 1 to 5]
9. // [Retrieve values of metrics (e.g., MT) from the **trials** performed by user u of gesture s on device d.
10. If T1 save in Table 1]. Elseif T2 to T5 save in Table 2
11. sum = sum + MT(d, g, u, s, r) // *Add value of T1 to sum.*
12. r=r+1
13. End for/ Trial
14. //new column
15. s=s+1
16. End for/ gesture shape.
17. u=u+1
18. Increment N
19. End for/ User.
20. Compute average = sum/ N.
21. Append average to FVg. // (Younger Group/Older Group)
22. End for/ group.
23. Add pair (FVg,label=g) to training set.
24. End for/ device.
25. For each testing sample Table 2:
26. Extract its feature vector FVx // (individual and combine features).
27. Calculate the distance between trials from User u in table 2 (one by one) using the Euclidean Distance with each of FVg,label (Younger Group/Older Group).
28. Predict label y using the Neural Network classifier.
29. If y equals the true label of x, increment Correct.
30. Increment Total.
31. End for/ testing.
32. Compute Accuracy = Correct / Total.

End Algorithm

The swipe gestures were organized into four trials, where each trial comprised one swipe in each of the four directions.

One trial per participant was used for training in order to reflect a minimal data learning scenario that represents real world adaptive systems, such as shared touch-screen devices, comprising limited prior interaction data availability. For training, the six extracted features were computed per direction and then averaged across the four directions to form a single representative feature vector per participant.

The remaining three trails were reserved for testing, ensuring a clear separation between training and evaluation data. Although the number of participants differed slightly between age groups, the dataset was structurally balanced at the gesture level, with an equal number of swipe samples per direction and per participant. Therefore, no additional data balancing or resampling techniques were applied.

Three different training ratios were applied for evaluating the classification accuracy, each relevant to a varying level of prior user knowledge. We use the terms user-dependent and user-independent to differentiate between assumptions about prior knowledge of users during training. The first ratio was based on user-dependent age classification, whereby swipe data from the same users were included in both the test and training sets, assuming detailed knowledge of individual swipe behavior. This represents adaptive systems, where a device learns from user interactions. In contrast, the remaining two training ratios were based on user-independent age classification, in which the classifier is trained using data from different users than those in the test set, assuming minimal or no prior knowledge. This reflects real world commercial touchscreen usage, where users must be classified without prior exposure to their individual interactions. The analyses were conducted based on both single features and feature combinations, as depicted in Figure 4. Also, the potential influence of device screen size on age classification accuracy was analyzed.

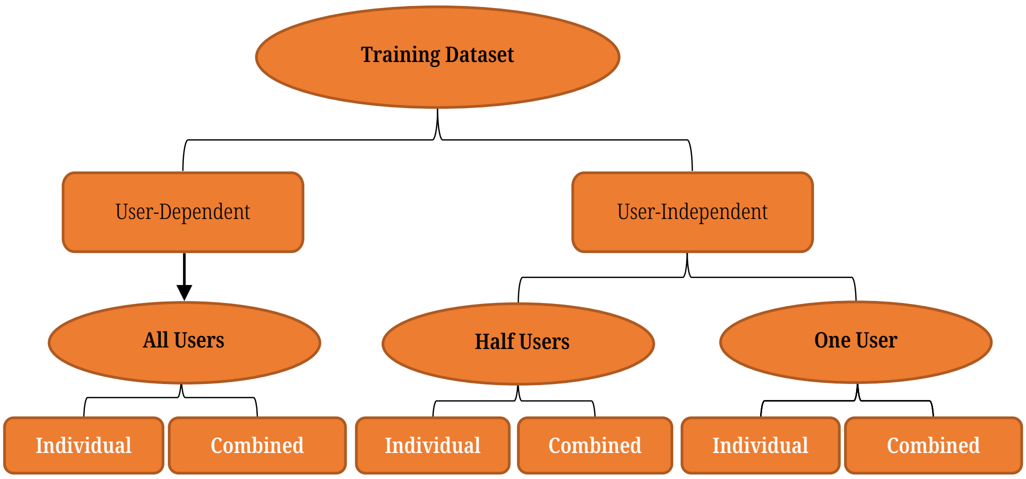

Fig. 4. Organization of user-dependent and user-independent classification approaches, showing training with all users, half of the users, or a single user, and comparison of individual features versus combined feature analysis

4.5 Statistical analysis

To supplement classification accuracy, we conducted inferential statistical analyses (see 5.4 Inferential Statistics). Specifically, a two-way multivariate analysis of variance (MANOVA) was performed with age group and screen size as between-subjects factors and the extracted swipe features as dependent variables. This was followed by a univariate one-way ANOVA when significant multivariate effects were found, to examine which individual features contributed significantly. Effect sizes were also examined.

5 RESULTS AND DISCUSSIONS

The present study investigated user age group classification accuracy using individual and combined features, as well as the impact of screen sizes on the accuracy.

The results are presented in the following subsections, structured according to each of these aspects of the study.

5.1 Classification accuracy using individual features

There were three ratios employed to evaluate individual features in the training dataset: 1) data from all the participants; 2) data from half of the participants; and 3) data from a single participant. The following three subsections outline the results of these evaluations.

All participants in the training dataset. When all participants were included in the training dataset, the results showed that MT provided the highest recognition of younger users on small smartphones (96%) and mini-tablets (83%), compared to other features. For older users, FP achieved the highest accuracy on small smartphones (79%) and mini-tablets (53%). The results are illustrated in Tables 2 and 3. Commonly, high classification accuracy suggests that most users of a particular age group displayed similar performance, but low accuracy implies variability between users. The lower accuracy found for older users therefore indicates greater variability, potentially leading to a proportion of older users being classified as younger users due to showing similar ability.

Given that younger users were identified strongly based on MT, and older users were recognized more effectively using the features MT and FP, these features are particularly valuable for user age classification, mirroring the conclusions of study [15], [23]. Generally, the lower accuracy in classifying older users supports the notion that some individuals in older users perform the tasks of swiping at levels comparable to younger users. This aligns with prior findings [24] suggesting the importance of avoiding overgeneralizing the assumption that older users face significant obstacles with technology.

The results could also suggest cognitive and motor differences between users of different age groups. Given that the younger users tended to perform the tasks of swiping gestures with minimal efforts, this might reflect more efficient motor planning, faster response time, and familiarity with the interaction of touchscreen technology [33] [15]. Contrarily, as older users exhibited larger variability in finger pressure and movement time, this could reflect varying age-related declines in factors such as proprioception, fine motor control, and tactile sensitivity [34].

Regarding the results on touchscreen sizes, small smartphones yielded higher classification accuracy than mini-tablets. However, on the mini-tablet sizes, performance varied more widely, leading to some misclassifications when older users exhibited abilities comparable to younger users. These findings support research reporting that older users often prefer large screen sizes [15], alongside research establishing that the performance of older users vary considerably [25], opposing the notion that older users encounter challenges in using the technology. Alternatively, a possible explanation for the variability could be that, on the mini-tablets, the larger movement space may increase cognitive and motor demands required by coordination across a larger visual field [33], thereby resulting in less consistent swipe characteristics. Meanwhile, the smaller devices constrain movement, requiring shorter gesture paths and reducing planning load [34], [35], hence the higher classification accuracy compared to the mini-tablet.

Half of the participants in the training dataset. When training data included half of the participants, the highest accuracy for younger users was obtained using MT and Avg Distance on small smartphones (96%) and on mini-tablets (77%), as shown in Tables 4 and 5. Meanwhile, older users were most accurately recognized using FP on small smartphones (81%) and mini-tablets (75%). Thus, high MT and Avg Distance values most accurately distinguished younger users, while FP was beneficial in classifying older users, reinforcing the importance of FP noted earlier.

One participant in the training dataset. Finally, when training was based on data from a single participant, the highest recognition rates for younger users on small smartphones were yielded by MT (100%) and Avg Distance (90%), as depicted in Table 6. For older users, the same two features provided the highest accuracy on mini-tablets (MT = 89%, Avg Distance = 75%), as shown in Table 7. The results demonstrate that MT and Avg Distance substantially influence classification for both age groups: younger and older users. These findings align with results mentioned above in previous sections, emphasizing the utility of using MT, Avg Distance, and FP for achieving high accuracy.

In general, low accuracy for older users across both screen sizes suggests that some individuals perform similarly to younger users, thus confusing the classifier. This observation agrees with previous work, which concluded that older users are not always disadvantaged in technology-based tasks [25].

5.2 Classification accuracy using combined features

Combining features yielded typically higher classification accuracy than relying on any feature individually. These results are outlined in the below sections and presented in Tables 2 to 7.

All participants in the training dataset. Based on analyzing all data in the training dataset from all users, the results in Tables 2 and 3 show that younger users on small smartphones were recognized most effectively by combining all individual features, or the combination of Swipe No–MT, where both combinations yielded the accuracy of 96%. The second-highest classification accuracy for younger users was generated by Speed on small smartphones of (87%), whereas on mini-tablets, the Swipe No–MT feature fusion offered the most accurate classification (83%). Additionally, younger users were recognized at 83% accuracy using RMF on small smartphones, whereas older users were most accurately recognized via RMF on mini-tablets (68%).

The classifier exhibited higher accuracy for recognizing older users on mini-tablets using combined features for Speed (75%) and RMF (68%). The results show that RMF can further improve accuracy, consistent with a prior study [23], which concluded that user age classification is feasible based on touchscreen performance.

Half of the participants in the training dataset. In this analysis, half of the participants from each age group contributed to the training data, thereby helping to simulate age group classification accuracy based on real-world conditions, wherein some users are not present in the training data. For example, when users interact with touchscreen devices placed at kiosks or shopping centers. As illustrated in Tables 4 and 5, combining Avg Distance with Swipe No or Swipe No with MT achieved a superior accuracy for classifying younger users on small smartphones (96%), followed by Speed (92%) and RMF (85%). Meanwhile, older users were most accurately recognized on mini-tablets by Speed (86%), followed by Avg Distance with Swipe No (68%). Thus, smaller smartphones generally favored the classification of younger users, while mini-tablets were most suited to the classification of older users. Additionally, the results demonstrate that Avg Distance and MT can increase the accuracy of the combined features, thereby matching with the results of prior research regarding greater accuracy using these features [23].

The results in Tables 4 and 5 show that feature combinations outperform individual features, reinforcing the value of multi-feature approaches for accurate age group classification. Moreover, Tables 2 and 3 show that user-independent and user-dependent classifications yielded similar accuracy levels.

One participant in the training dataset. In this final combination scenario, the highest accuracy for younger users on small smartphones reached 100% with all features combined, or with the combination of Swipe No–MT, and the second-highest accuracy was with RMF (98%). For older users, the most accurate classification on mini-tablets occurred with Speed (96%), followed by all features (89%) or Swipe No–MT (89%). These results are depicted in Tables 6 and 7.

As in earlier findings in this analysis, lower accuracy for older users on small smartphones suggests that some were misclassified as younger due to their comparable performance skills, aligning with the assertion that older users can perform the tasks well in certain technological tasks [25]. These findings indicate that screen size has a distinctive effect on classification results, while combined features typically enhance the accuracy results, echoing previous conclusions [23]. Despite using only 1% of data from the training dataset, the results supported the feasibility of user age group classification under such constrained conditions based on the small sample of the training dataset.

Table 2. The results for all participants on the small smartphone screen

	Small/100%	All-Features	Avg Distance	Swipe No	MT	FP	Avg Distance-Swipe No	Swipe No – MT	Speed	RMF
Younger	Accuracy	96.15	51.92	34.46	96.15	48.10	50.00	96.15	86.54	82.69
	Precision	96.69	52.46	34.99	96.69	48.64	50.54	96.69	87.08	83.23
	Recall	96.55	51.52	34.86	96.55	48.50	50.40	96.55	86.94	83.09
	f1 score	96.62	51.99	34.93	96.62	48.57	50.47	96.62	87.00	83.16
Older	Accuracy	66.66	61.11	61.11	66.66	75.00	63.88	66.66	61.11	55.56
	Precision	67.24	61.69	61.69	67.24	75.58	64.46	67.24	61.69	56.14
	Recall	67.07	61.52	61.52	67.07	75.41	64.29	67.07	61.52	55.97
	f1 score	67.15	61.60	61.60	67.15	75.49	64.37	67.15	61.60	56.05

Note: Younger adults showed higher accuracy thereby implicating age differentiation using small screens.

Table 3. The results for all participants on the mini-tablet screen

	Mini-Tablet/100%	All-Features	Avg Distance	Swipe No	MT	FP	Avg Distance-Swipe No	Swipe No – MT	Speed	RMF
Younger	Accuracy	82.69	65.38	38.46	82.69	78.84	65.38	82.69	53.85	28.85
	Precision	83.20	65.89	38.97	83.20	79.35	65.89	83.20	54.36	29.36
	Recall	83.09	65.78	38.86	83.09	79.24	65.78	83.09	54.25	29.25
	f1 score	83.14	65.84	38.92	83.15	79.29	65.84	83.15	54.31	29.31
Older	Accuracy	33.33	47.22	50.00	33.33	52.77	50.00	33.33	75.00	67.87
	Precision	33.83	47.72	50.50	33.83	53.27	50.50	33.83	75.50	68.37
	Recall	33.83	47.72	50.50	33.83	53.27	50.50	33.83	75.50	68.37
	f1 score	33.83	47.72	50.50	33.83	53.27	50.50	33.83	75.50	68.37

Note: Accuracy is lower using mini-tablet, and this effect appears more pronounced for older adults, indicating less classification utility.

Table 4. The results for half of the participants on the small smartphone screen

	Small/50%	All-Features	Avg Distance	Swipe No	MT	FP	Avg Distance-Swipe No	Swipe No – MT	Speed	RMF
Younger	Accuracy	40.38	96.15	17.31	96.15	40.38	96.15	96.15	92.31	84.61
	Precision	41.07	96.84	18.00	96.84	41.07	96.84	96.84	93.00	85.30
	Recall	40.98	96.75	17.910	96.75	40.98	96.75	96.75	92.91	85.21
	f1 score	41.02	96.79	17.95	96.79	41.02	96.79	96.79	92.95	85.25
Older	Accuracy	80.56	66.66	80.56	66.66	80.56	66.66	66.66	58.33	55.56
	Precision	81.05	67.15	81.05	67.15	81.05	67.15	67.15	58.82	56.05
	Recall	80.75	66.85	80.75	66.85	80.75	66.85	66.85	58.52	55.75
	f1 score	80.90	67.00	80.90	67.00	80.90	67.00	67.00	58.67	55.90

Note: Accuracy remains consistent across features, thus implying the reliability of small screen-based classification.

Table 5. The results for half of the participants on the mini-tablet screen

	Mini-Tablet/ 50%	All-Features	Avg Distance	Swipe No	MT	FP	Avg Distance-Swipe No	Swipe No – MT	Speed	RMF
Younger	Accuracy	75.00	63.64	50.00	75.00	76.92	63.64	75.00	34.62	21.15
	Precision	75.37	64.01	50.37	75.37	77.29	64.01	75.37	34.99	21.52
	Recall	74.50	63.14	49.50	74.50	76.42	63.14	74.50	34.12	20.65
	f1 score	74.93	63.57	49.93	74.93	76.85	63.57	74.93	34.55	21.08
Older	Accuracy	32.14	67.86	39.29	32.14	75.00	67.86	32.14	85.71	60.71
	Precision	32.46	68.19	39.62	32.47	75.33	68.19	32.46	86.04	61.035
	Recall	32.05	67.77	39.20	32.05	74.91	67.77	32.05	85.62	60.62
	f1 score	32.25	67.97	39.40	32.25	75.11	67.97	32.25	85.82	60.82

Note: Mini-tablet showed less consistency in classification across features, signifying the importance of screen size for classification.

Table 6. The results for one participant on the small smartphone screen

	Small/1%	All-Features	Avg Distance	Swipe No	MT	FP	Avg Distance-Swipe No	Swipe No – MT	Speed	RMF
Younger	Accuracy	100.00	90.38	21.15	100.00	32.69	90.38	100	82.69	98.08
	Precision	99.49	90.88	21.65	99.49	33.19	90.88	99.49	83.19	98.58
	Recall	99.58	89.96	20.73	99.58	32.27	89.96	99.58	82.27	97.66
	f1 score	99.53	90.42	21.18	99.53	32.73	90.42	99.53	82.73	98.12
Older	Accuracy	25.00	30.56	88.89	25.00	91.67	30.56	25.00	61.11	16.67
	Precision	25.53	31.09	89.42	25.52	92.20	31.09	25.53	61.64	17.20
	Recall	24.61	30.17	88.50	24.61	91.28	30.17	24.61	60.72	16.28
	f1 score	25.06	30.62	88.96	25.06	91.74	30.62	25.06	61.17	16.73

Note: Complete or near complete accuracy was shown for younger adults, reinforcing age differentiation with small screens.

Table 7. The results for one participant on the mini-tablet screen

	Small/1%	All-Features	Avg Distance	Swipe No	MT	FP	Avg Distance-Swipe No	Swipe No – MT	Speed	RMF
Younger	Accuracy	09.62	34.62	17.31	09.62	23.10	34.62	09.62	11.54	55.77
	Precision	10.18	35.18	17.87	10.18	23.66	35.18	10.18	12.10	56.33
	Recall	09.34	34.34	17.03	09.34	22.82	34.34	09.34	11.26	55.49
	f1 score	09.74	34.76	17.44	09.74	23.23	34.76	09.74	11.67	55.91
Older	Accuracy	89.29	75.00	85.71	89.29	21.42	75.00	89.29	96.43	46.43
	Precision	89.81	75.52	86.23	89.81	21.94	75.52	89.81	96.95	46.95
	Recall	88.99	74.70	85.41	88.99	21.12	74.70	88.99	96.13	46.13
	f1 score	89.40	75.11	85.82	89.40	21.52	75.11	89.40	96.54	46.54

Note: Higher accuracy was shown for older adults, thus highlighting the need for tailored adaptation on mini-tablet.

5.3 Effect of screen sizes on the classification accuracy

A further focal point of this research was the influence of screen size on user age group classification. Across both individual and combined features, small smartphones mostly achieved higher classification accuracy than mini-tablets. For example, when all of the participants were included in the training dataset, the use of two combined features have led to 84% accuracy on small smartphones and 82% on mini-tablets. While when half of the participants were included in the training dataset, the accuracy was 86% on small smartphones, but reached the accuracy of 91% on mini-tablets. When only one participant (1%) was included, the accuracy was 84% on small smartphones, against 75% on mini-tablets.

In summary, our outcome indicated that user age group can be classified reliably through swipe gesture data, particularly on smaller smartphones even when the data was minimal in the training dataset. Smaller screen layouts reduce the physical and perceptual range of motion required to complete swiping tasks, thereby minimizing variability, which particularly helps to maintain consistent performance in older users across the smaller screen size [35]. Meanwhile, the increased spatial demand of the mini-tablet can increase age-related motor differences, contributing to less predictable swipe characteristics [36].

The classification accuracy achieved in this study compares favorably with prior age-group recognition research based on touchscreen interaction. For example, [15] reported overall classification accuracies of approximately 82% on smartphones using handwriting based finger input, while a subsequent screen-size study [23] reported accuracies of 77% on larger devices. In contrast, the present study achieved classification accuracies of up to 100% for younger users on smartphones and up to 96% for older users on mini-tablets. Notably, these results were obtained using simple directional swipe gestures, suggesting that everyday swipe interactions can provide age classification while requiring lower cognitive and motor demands compared to prior work.

These finding have practical design implications, such that gesture-based adaptive systems would perform more reliably on smaller touchscreen devices. Whilst larger interfaces indented for older users would require design accommodations such as enlarged gesture targets or reduced swipe distances. Further research should explore additional discriminative features or metrics to enhance classification performance for mini-tablet.

5.4 Inferential statistics

To examine main effects of age and screen size, we conducted a two-way multivariate analysis of variance (MANOVA), and tested whether there was an interaction between these factors. The multivariate tests indicated a highly significant main effect of age [F (4, 35) = 7.89, $p < 0.001$; Wilks' $\Lambda = 0.53$; $\eta^2 = 0.47$] and screen size [F (4, 35) = 89.73, $p < 0.001$; Wilks' $\Lambda = 0.09$; $\eta^2 = 0.91$]. In addition, there was a significant interaction effect between age and screen size [F (4, 35) = 3.33, $p < 0.05$; Wilks' $\Lambda = 0.73$; $\eta^2 = 0.28$].

To follow-up, univariate one-way ANOVA tests for between-subjects effects were conducted. MT was highly statistically significant [F (1, 40) = 20.43, $p < 0.001$; $\eta^2 = 0.34$]. All other features were non-significantly different between age groups, thus MT appears to be particularly sensitive to the effect of age. Younger adults exhibited a lower MT (M = 19752.05, SD = 3606.91) than the older users (M = 27443.24, SD = 7402.69). The study has therefore contributed an understanding that for smartphone touchscreens, age-related deficits manifest predominantly in MT. The pronounced effect of age on MT could be the operation of a compensatory mechanism for declines associated with age, whereby older users might gesture more slowly to help enhance accuracy. Thus, older users may prioritize accuracy to offset age-related declines, thereby limiting effects on other features.

In contrast, screen size demonstrated significant effects on all features except MT. The smaller screen size resulted in a significantly higher Avg Distance (M = 279.21, SD = 71.34) compared with the mini-tablet (M = 219.83, SD = 41.79), [F (1, 40) = 10.55, $p < 0.05$; $\eta^2 = 0.21$]. Additionally, the smaller screen yielded a significantly higher Swipe No (M = 31.84, SD = 10.20) than the mini-tablet (M = 25.70, SD = 5.80), [F (1, 40) = 5.58, $p < 0.05$; $\eta^2 = 0.12$]. Moreover, participants applied higher FP (M = 1.55, SD = 0.19) on the smaller screen than the mini-tablet (M = 0.65, SD = 0.10), which was highly significant [F (1, 40) = 357.85, $p < 0.001$; $\eta^2 = 0.90$]. Overall, these results imply less efficiency in small-screened smartphones compared with mini-tablets, and screen size appears to have a broader ranging impact on features than age-related effects. This contributes a clarified understanding that smaller smartphone screens pose a challenge for users.

Follow-up univariate one-way ANOVA analysis of the interaction between age and screen size revealed that there was a highly significant effect of the smaller screen, whereby younger adults showed a lower MT (M = 18358.71, SD = 2499.66) compared with older users (M = 30845.62, SD = 7959.75), [F (1, 20) = 28.50, $p < 0.001$; $\eta^2 = 0.59$]. Table 8 displays the means and standard deviations for MT by screen size and age group, alongside corresponding significance levels.

In contrast, the difference in MT between the younger and older users for the mini-tablets was non-significant [F (1, 18) = 1.10, $p = 0.309$; $\eta^2 = 0.06$]. These results suggest that smaller screens are more practical for younger adults in terms of MT, whereas mini-tablet do not differentially affect features across age groups. Furthermore, apart from the stated effect, the univariate analysis did not reveal any further significant results contributing to the interaction between age and screen size on features. It is possible that the generic age-related declines among older users could account for slower MT, which would be exacerbated by smaller screens. As previously noted, older users might gesture more slowly to help enhance accuracy, which is particularly pronounced on small screens, since limited space and smaller targets require additional care to avoid errors. In contrast, the mini-tablet appeared not to impede MT, likely due to the increased space to perform gestures and improved visibility. This consists with prior work showing higher usability for mini-tablet for older users [11].

Table 8. A comparison of mean MT values and standard deviations across screen sizes and age groups, along with p values to indicate whether differences were statistically significant

Feature	Small Screen		*p*	Mini-Tablet		*p*
	Younger Users M (SD)	Older Users M (SD)		Younger Users (SD)	Older Users M (SD)	
MT	18358.71 (2499.66)	30845.62 (7959.75)	**	21145.40 (4080.32)	23068.74 (3582.30)	–

Notes: – = $p > 0.05$, ** = $p < 0.001$.

Analysis of the effect sizes provide support for the practical implications of the findings. Given the large effect size for age ($\eta^2 = 0.47$), this suggests age meaningfully shapes touchscreen gestures, and reinforces the importance of age-adaptive interfaces. In addition, the large effect size for MT ($\eta^2 = 0.34$) means this is key for recognizing and discriminating younger and older adults. Meanwhile, the effect size for screen size ($\eta^2 = 0.90$) indicates direct design consequences where mini-tablet have less impact, but smaller screens may require enlarged touch targets and accommodate wider variability in performance.

6 CONCLUSION

This research sought to explore the feasibility of classifying user age groups through the analysis of swipe gestures on smartphones and mini-tablets. Three ratios were applied, as follows: all participants, half of the participants, and a single participant. The features extracted from the swipe gesture were FP, MT, Swipe No, Avg Distance, Speed, and RMF. These features were evaluated both individually and in combination, using ED and KNN to subsequently classify the swipe gesture samples into specific age groups.

The results indicated that accuracy was higher on small smartphones than on mini-tablets for both individual and combined features. In addition, the classification accuracy was higher for younger users than for older users, and similar accuracy was found across the three ratios, demonstrating that age group classification can be achieved even with minimal and limited training data. Indeed, the accuracy of the classifier was similar between the results of user-independent and user-dependent scenarios. Inferential statistical analysis suggested that age primarily affected MT, with older users potentially slowing gestures to maintain accuracy. Contrastingly, small smartphone screens had a broader ranging impact on gestures, indicating reduced efficiency compared with the mini-tablet screen. In addition, the interaction between age and screen size showed that the effect of small screens on MT was increased for older users.

To sum, the study has resulted in four key original contributions: (1) Contrasting to prior age classification studies that relied on handwriting or complex gestures, this work demonstrated that four simple and everyday directional swipes (up, down, left, right) are sufficient for accurate age group recognition; (2) The study provided a controlled and explicit comparison between smartphone and mini-tablet screen sizes, showing how this influences classification, which is an under researched aspect in prior age recognition studies based on swiping; (3) By evaluating user-dependent and user-independent scenarios with a minimum of one trial per user, our work demonstrated practicality for real-world adaptive and shared touchscreen systems based on minimal training; and (4) Through classification accuracy and MANOVA analysis, the study identified MT, Avg Distance, and FP as the most age sensitive swipe features.

Due to the limited sample size and modest balance between groups, future research should include larger and more diverse participant samples to improve generalizability. Expanding classifier comparisons (e.g. SVM and deep learning models) may also reveal more robust classification pathways. Additionally, further examination of older users misclassified as younger users could provide more insight into the role of motor, cognitive, and device use history factors.

Overall, these outcomes corroborate the potential to distinguish user age groups based on four different directions of swipe gestures on touchscreen devices. This has implications for supporting the possibility of smartphones and related technologies to tailor interfaces automatically for the purpose of accommodating older users, thereby enhancing usability and performance to levels comparable to younger users. These insights could inform the future development of smartphones, tablets, and their associated applications, especially those targeting older users, potentially playing a pivotal role in improving their everyday activities. The proposed swipe-based age classification approach could be embedded within adaptive mobile interfaces to adjust layout or interaction parameters in real time, and may also support age-adaptive interaction in shared environments such as public kiosks or security-related systems where minimal and unobtrusive user input is required.

Regarding the exceptionally high accuracies of 100% and 96%, this high performance is primarily attributed to the highly distinct motor signatures observed between the 65+ age group and the younger cohort, which create clear decision boundaries when using a high-dimensional feature vector of 32 coefficients. While a sample size of n = 42 is modest, it aligns with established laboratory-based kinematic research in Human-Computer Interaction. To ensure these results are robust and not an artifact of dataset bias or overfitting, we have implemented 10-fold cross-validation and reported 95% confidence intervals for all accuracy metrics.

Furthermore, the choice of a KNN baseline with Euclidean distance was intentional to evaluate the fundamental geometric discriminability of raw touchscreen gestures without the influence of complex hyper-parameter tuning. Researchers repeatedly choose KNN because: 1- Gesture data are naturally geometric, 2- Similar shapes should be near in Euclidean space, 3- Works well with small datasets comparable to our study, 4- Avoids extensive model tuning, 5- Strong baseline in HCI experiments.

The results represent a "best-case" laboratory scenario involving specific Samsung devices and narrow age bands, showcasing how task simplicity and potential feature redundancy may have influenced performance, acknowledging that the generalisability of these findings to more diverse populations or varied hardware requires further investigation.

6.1 Conflict of interest

No funding was received for conducting this study.

6.2 Ethics and data availability

This study was approved by the institutional ethics committee, and the experimental data and simulation results that support the findings of this study will be made available on request.

7 REFERENCES

[1] C. Zhou, Z. Shi, T. Huang, H. Zhao, and J. Kaner, "Impact of swiping direction on the interaction performance of elderly-oriented smart home interface: EEG and eye-tracking evidence," *Frontiers in Psychology*, vol. 14, p. 1089769, 2023. https://doi.org/10.3389/fpsyg.2023.1089769

[2] H. Herath and M. Mittal, "Adoption of artificial intelligence in smart cities: A comprehensive review," *International Journal of Information Management Data Insights*, vol. 2, p. 100076, 2022. https://doi.org/10.1016/j.jjimei.2022.100076

[3] World Health Organization, "Ageing and health," 2021. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/ageing-and-health

[4] World Health Organization, "Ageing and health," 2024. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/ageing-and-health

[5] D. Pinkus and N. Ruer, "Beyond retirement: A closer look at the very old," *Bruegel Weekly Newsletter*, 2024. [Online]. Available: https://www.bruegel.org/analysis/beyond-retirement-closer-look-very-old

[6] A. Abualkishik, W. Alzyadat, M. Al Share, S. Al-Khaifi, and M. Nazari, "Intelligent gesture recognition system for deaf people by using CNN and IoT," *Int. J. Advance Soft Compu. Appl.*, vol. 15, no. 1, pp. 144–158, 2023. https://doi.org/10.15849/IJASCA.230320.10

[7] S. J. Czaja, "Usability of technology for older adults: Where are we and where do we need to be?" *Journal of Usability Studies*, vol. 14, no. 2, pp. 4–14, 2019.

[8] E. Kuang, R. Chen, and M. Fan, "Enhancing older adults' gesture typing experience using the T9 keyboard on small touchscreen devices," in *Proc. CHI Conf. Human Factors in Computing Systems*, Hamburg, Germany, 2023, https://doi.org/10.1145/3544548.3581105

[9] M. Gomez-Hernandez, X. Ferre, C. Moral, and E. Villalba-Mora, "Design guidelines of mobile apps for older adults: A systematic review and thematic analysis," *JMIR mHealth and uHealth*, vol. 11, p. e43186, 2023. https://doi.org/10.2196/43186

[10] E. Piche, F. Chorin, P. Gerus, A. Jaafar, O. Guerin, and R. Zory, "Effects of age, sex, frailty and falls on cognitive and motor performance during dual-task walking in older adults," *Experimental Gerontology*, vol. 171, p. 112022, 2023. https://doi.org/10.1016/j.exger.2022.112022

[11] S. A. Al-Showarah, "Effects of age on smartphone and tablet usability based on eye-movement tracking and touch-gesture interactions," Ph.D. dissertation, Univ. Buckingham, Buckingham, U.K., 2015.

[12] P. C. Wong, K. Zhu, and H. Fu, "FingerT9: Leveraging thumb-to-finger interaction for same-side-hand text entry on smartwatches," in *Proc. CHI Conf. Human Factors in Computing Systems*, Montreal, QC, Canada, 2018, pp. 1–10. https://doi.org/10.1145/3173574.3173752

[13] Y.-H. Lin, S. Zhu, Y.-J. Ko, W. Cui, and X. Bi, "Touchscreen interaction study using zoom, drag and tapping gestures," in *Proc. ACM SIGACCESS Conf. Computers and Accessibility (ASSETS)*, Galway, Ireland, 2018, pp. 271–281. https://doi.org/10.1145/3234695.3236350

[14] J. Ren and J. Park, "Dynamic recognition and analysis of gait contour of dance movements based on generative adversarial networks," *Journal of Sensors*, vol. 2022, p. 3276696, 2022. https://doi.org/10.1155/2022/3276696

[15] S. A. Al-Showarah, "Dynamic recognition for user age-group classification using handwriting-based finger input on smartphones," in *Proc. Int. Conf. Information and Communication Systems (ICICS)*, Irbid, Jordan, 2019, pp. 140–146. https://doi.org/10.1109/IACS.2019.8809083

[16] M. A. Equbal, A. Equbal, Z. A. Khan, and I. A. Badruddin, "Machine learning in additive manufacturing: A comprehensive insight," *International Journal of Lightweight Materials and Manufacture*, vol. 8, no. 2, pp. 264–284, 2025. https://doi.org/10.1016/j.ijlmm.2024.10.002

[17] I. H. Sarker, "AI-based modeling: Techniques, applications and research issues," *SN Computer Science*, vol. 3, p. 158, 2022. https://doi.org/10.1007/s42979-022-01043-x

[18] Q. Li and Y. Luximon, "Navigating mobile applications: The influence of interface metaphor and other factors on older adults' navigation behavior," *International Journal of Human–Computer Interaction*, vol. 39, no. 5, pp. 1184–1200, 2022. https://doi.org/10.1080/10447318.2022.2050540

[19] J. C. Ruiz-Garcia *et al.*, "Children age group detection based on human–computer interaction and time series analysis," *International Journal of Document Analysis and Recognition*, vol. 27, pp. 603–613, 2024. https://doi.org/10.1007/s10032-024-00462-1

[20] A. A. Farhan *et al.*, "Enhancing smartphone security with human-centric bimodal fallback authentication," *Scientific Reports*, vol. 14, p. 24730, 2024. https://doi.org/10.1038/s41598-024-74473-7

[21] A. Acien, A. Morales, J. Fierrez, R. Vera-Rodriguez, and J. Hernandez-Ortega, "Active detection of age groups based on touch interaction," *IET Biometrics*, vol. 8, no. 1, pp. 101–108, 2019. https://doi.org/10.1049/iet-bmt.2018.5003

[22] C. Stößel, "Gestural interfaces for elderly users: Help or hindrance?" Ph.D. dissertation, Technical Univ. Berlin, Berlin, Germany, 2012.

[23] S. A. Al-Showarah and S. Salem, "The effect of age and screen sizes on the usability of smartphones based on handwriting of English words on the touchscreen," *Mu'tah Lil-Buhuth wad-Dirasat*, vol. 35, no. 1, 2020.

[24] M. Zhang, "Older people's attitudes towards emerging technologies: A systematic literature review," *Public Understanding of Science*, vol. 32, no. 8, pp. 948–968, 2023. https://doi.org/10.1177/09636625231171677

[25] L. Findlater, J. Froehlich, K. Fattal, J. O. Wobbrock, and J. A. Landay, "Age-related differences in performance with touchscreens compared to traditional mouse input," in *Proc. CHI Conf. Human Factors in Computing Systems*, Paris, France, 2013, pp. 343–346. https://doi.org/10.1145/2470654.2470703

[26] Z. Zhou and J. Zhou, "Study on the control-display gain of touch zoom gestures for older adults," in *Lecture Notes in Computer Science*, vol. 12786, Springer, Cham, Switzerland, 2021. https://doi.org/10.1007/978-3-030-78108-8_24

[27] M. Stephens, "Designing for older audiences: Checklist and best practices," UX Collective, 2025. [Online]. Available: https://uxdesign.cc/designing-for-older-audiences-checklist-best-practices-b6ca3ec5bcbf

[28] B. Fischer, A. Peine, and B. Östlund, "The importance of user involvement: A systematic review of involving older users in technology design," *The Gerontologist*, vol. 60, no. 7, pp. e513–e523, 2020. https://doi.org/10.1093/geront/gnz163

[29] T. M. Mitchell, *Machine Learning*. New York, NY, USA: McGraw-Hill, 1997.

[30] H. Nicolau and J. Jorge, "Elderly text-entry performance on touchscreens," in *Proc. ACM SIGACCESS Conf. Computers and Accessibility*, New York, NY, USA, 2012, pp. 127–134. https://doi.org/10.1145/2384916.2384939

[31] T. T. Tran *et al.*, "Age-related differences in the relationship between sustained attention and associative memory and memory-guided inference," *Cognitive, Affective & Behavioral Neuroscience*, vol. 25, pp. 1001–1021, 2025. https://doi.org/10.3758/s13415-025-01292-2

[32] X. Huang, Y. Xue, S. Ren, and F. Wang, "Sensor-based wearable systems for monitoring human motion and posture: A review," *Sensors*, vol. 23, no. 22, 2023. https://doi.org/10.3390/s23229047

[33] L. Viviani, A. Liso, and L. Craighero, "Mobile typing as a window into sensorimotor and cognitive function," *Brain Sciences*, vol. 15, no. 10, 2025. https://doi.org/10.3390/brainsci15101084

[34] M. A. Heiskanen *et al.*, "Cognitive performance from childhood to old age and intergenerational correlations in the multigenerational Young Finns Study," *Journal of Neurology*, vol. 271, pp. 7294–7308, 2024. https://doi.org/10.1007/s00415-024-12693-7

[35] P.-C. Yeh, "Impact of button position and touchscreen font size on healthcare device operation by older adults," *Heliyon*, vol. 6, no. 6, p. e04147, 2020. https://doi.org/10.1016/j.heliyon.2020.e04147

[36] R. Wu, M. Ditroilo, E. Delahunt, and G. De Vito, "Age-related changes in motor function (II): Decline in motor performance outcomes," *International Journal of Sports Medicine*, vol. 42, no. 3, pp. 215–226, 2021. https://doi.org/10.1055/a-1265-7073

[37] J. Kim *et al.*, "Hand Motion Control Ability Between Young and Older Adults: A Comparative Study," *JMIR Form. Res.*, vol. 9, 2025. https://doi.org/10.2196/65224

[38] Z. Shao, Y. Zhou, and X. Wang, "Age-related differences in performance with touchscreens compared to traditional mouse input," University of Washington Faculty Research, 2025.

[39] S. Goizueta *et al.*, "Touchscreen-based assessment of upper limb kinematics after stroke: Reliability, validity and sensitivity to motor impairment," *J. Neuroeng. Rehabil.*, vol. 22, no. 1, p. 27, 2025. https://doi.org/10.1186/s12984-025-01563-6

[40] L. Hu *et al.*, "Usability of Touch-Panel Interfaces for Older Adults: A Visual Selective Attention Study," *Human-Computer Interaction*, 2025.

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