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(**Research Article**)

Human Performance in Identifying Medical Masked Face

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Abstract: Humans who spend most of their time looking at faces throughout their lives can be quite successful in facial recognition. When faces are partially covered by medical masks, glasses and accessories, this identification success may decrease. The purpose of this study is to determine how successfully people who witnessed the events can identify faces that are mostly covered by medical masks in the event that a crime is committed. The study referred to 195 participants and used 40 facial images (20 masked, 20 unmasked). The obtained data was statistically analyzed using SPSS 20.0, including frequency analysis, regression analysis, and ANOVA. While there was no substantial difference in identification performance across sexes, age had an impact on identification. However, participants identified medical masked faces more accurately than unmasked ones.

(**Araştırma Makalesi**)

Medikal Maskeli Yüz Tanımlamada İnsan Performansı

Anahtar Kelimeler:
Yüz Tanımlama,
Kimliklendirme,
Maskeli Yüz,
Maskesiz Yüz

Özet: İnsanlar, yaşamları boyunca zamanlarının çoğunu yüzlere bakarak geçirirler; dolayısıyla yüz tanımada oldukça başarılı olabilmektedirler. Yüzler medikal maske, gözlük ve aksesuarlarla kısmen kapandığında, bu tanımlama başarısı düşebilmektedir. Bu çalışmanın amacı, adli olaylara tanık olan kişilerin, bir suç işlenmesi durumunda medikal maskeyle kapatılan yüzleri ne kadar başarılı bir şekilde tanımlayabildiklerini belirlemektir. Çalışmada 195 katılımcıya yer verilmiş ve tanımlamaları için 40 yüz görüntüsü kullanılmıştır (20 maskeli, 20 maskesiz). Elde edilen verilerin istatistiksel analizi SPSS 20.0 aracılığıyla frekans analizi, regresyon analizi ve ANOVA ile test edildi. Cinsiyetler arasında tanımlama performansında önemli bir fark olmasa da yaşın tanımlama üzerinde etkisi olmuştur. Ancak katılımcılar, medikal maskeli yüzleri maskesiz yüzlerden daha doğru bir şekilde tanımlamışlardır.

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1. INTRODUCTION

The fact that people all over the world went out to public places wearing various types of medical masks as a precaution during the pandemic period, and that this situation continues in certain places (such as hospitals, schools, and pharmacies), even though it is not mandatory, has added a new dimension to the issue of facial recognition.

As medical masks became a must over the world during the pandemic, it was discovered that the ability to recognize masked faces was sufficient [1]. Wearing face masks in public places causes major obstacles for facial recognition [2], emotion recognition [3], and face matching [4].

During the pandemic, the use of medical masks was used as a tool to hide the identity of people involved in crime. In addition to the medical mask, wearing accessories like glasses makes identification more difficult. The purpose of this study is to measure how successfully the person(s) who witnessed the event can identify faces that are mostly covered by medical masks in case a crime is committed.
Throughout life, humans spend most of their time looking at faces. As a result, the assumption that a naturally developed expertise in noticing and recognizing various types of faces has a great intuitive appeal [5].

Security cameras are widely used in public places in case of a crime. Images from security cameras serve as evidence in determining the identification of the perpetrator or victim [6]. Face recognition is a very difficult task in situations where there is a need to distinguish between similar images of people with different identities, as well as generalization between different images of the same person. Although people think that they are very successful at recognizing faces, some studies show that people's facial recognition abilities are superior to identifying familiar faces than unfamiliar faces [5, 7].

Eyewitness identification of faces is predictably inaccurate [8, 9, 6]. However, many countries rely significantly on eyewitness testimony [10]. Image identification is a typical method, although the individual performing the check is rarely familiar with the person being identified. According to studies, most people struggle to match unknown faces [11, 12, 6].

Additionally, adding glasses/sunglasses to an image changes the person in the image, resulting in decreased face matching ability [13, 14]. Most people think they are good at recognizing faces, and this idea is widely used in the literature. But it is only an accurate characterization of recognizing familiar faces. Identifying unfamiliar faces can be surprisingly error-prone. Neglecting the important feature of image variability leads to some misleading conclusions [7].

According to studies, recognizing familiar faces is mostly dependent on internal facial features (eyes, nose, and mouth), but matching unknown faces is primarily based on exterior facial features (hair, facial features) [15, 16].
Matching a facial image to a face is required not only in situations such as passport control, but also in more common settings, such as verifying the age of a young individual looking to purchase alcohol [17]. According to research, people struggle to make comparisons between a person standing in front of them and an image [18, 19, 10]. Therefore, understanding the types of images displayed and the factors affecting the accuracy of face matching is very important both practically and theoretically [20].
Human facial recognition abilities are often considered a useful benchmark for biometric technology that algorithms should aim for [21]. Automatic facial recognition algorithms have advanced in recent years, and this progress can be seen in studies comparing the performance of facial recognition algorithms with humans [22].

People may be unable to recognize familiar faces, particularly if they have never seen them wearing medical masks before. On the other hand, wearing these medical masks compulsorily can also cause a security vulnerability. Most of the time, only the eyes and ears of a person involved in a crime in a public place are suitable for identification due to the mask (unless they use glasses etc.).

However, this skill may not be sufficiently convincing. Given this finding, it is expected that recognizing a person whose face is mostly hidden by a medical mask will give an even lower result than weak facial recognition of a person exposed to practically the entire face image.

As the Covid-19 pandemic spreads rapidly, certain precautions have been taken around the world. Medical masks have emerged as a vital protective measure during the pandemic [23, 24, 25]. Face recognition is currently the most accurate and contactless means of identification [23, 26, 27]. Face detection has a wide range of applications, from facial identification to capturing facial motions [24]. This technique works on non-occluded major facial features such as the eyes, nose, and mouth [28]. However, with the enforced usage of medical masks, the performance, reliability, and functionality of facial recognition systems have been called into question [26].

Scarves, face masks, glasses, hats, and other accessories can cause facial occlusion. Facial occlusion (partial covering of the face) is regarded as one of the most unsolvable difficulties since there is no prior knowledge of an occlusion area, which can be located anywhere in the facial image and of any size or shape [29]. The computer vision research community has focused on occluded face identification. Medical masked face recognition is a type of occluded face recognition that requires prior knowledge of the obscured portion of the target face [30]. The systems produced to solve the problems in this area include two different tasks: face mask recognition and masked face recognition. The first task checks whether the person is wearing a mask, while the other task focuses on recognizing a masked face based on the eyes and forehead area [31].

The purpose of this study is to determine how successfully witnesses to a criminal events can identify faces hidden in medical masks while a crime occurs.

2. MATERIALS AND METHODS

In the study, frontal images of 40 people, 20 female and 20 male, with and without medical masks, whose informed consent was obtained, were recorded. There are 3 steps in the online survey created to identify masked and unmasked face images:

- Step 1: The page where the study is introduced and demographic information is included
- Step 2: The learning page with medical masked face images of 10 people, followed by the test page with unmasked images of 15 people, 5 of which were among the 10 previously shown.
- Step 3: The learning page with unmasked facial images of 10 people, followed by the test page with medical masked images of a total of 15 people, 5 of which were among the 10 previously shown.

A total of 195 people, 142 female and 53 male, aged between 18 and 75, participated in the study. The majority of participants (63.6%) are between the ages of 18-29.

2.1. Technology

This application has been built on Oracle **APEX** (Oracle APEX 22.2.1). It's developed on **Oracle Cloud** Infrastructure so participants can access this application online and launch it within their internet browsers. Wizards look-a-like page design gives users a page flow experience. Each page has its own purpose. Some are for introduction and some other for collect the user responses. Non interactive page components, such as instructions, consent forms and other text-based contents are written in **HTML/CSS**. For input Forms, submit processes, page validations and in-page crosschecks **PL/SQL** used. Database is **Oracle 19c Enterprise Edition.**

2.2. Using the application

The first step of the study includes questions about demographic and descriptive information of the participants, such as age, sex, education information, whether they live in a big city or not.

The purpose of this application is to create a survey where users can participate anonymously. Hence no login required. First page welcomes the participant by showing a brief introduction and an approval request. Once **“Kabul Ediyorum”** (I accept) radio button selected and **“Gonder”** (send) button clicked, page gets submitted and next page renders to show consent form. User must click “Calismaya katilmayi kabul ediyorsaniz kutucugu isaretleyiniz ve devam ediniz” (If you agree to participate in this study, tick the box and continue) **Checkbox** to start survey. Survey consists of **radio** buttons, **dropdown** menus, **number** fields and **text** fields.

2.2.1. Test phase

Medical masked images, un-masked questions: On this stage, participants see a set of human faces, mouth area covered by regular medical masks, in a slideshow fashion. Each image is shown for a limited (parametrically set, i.e., 10 seconds per image) time. As soon as the slideshow is over, a button, named **Sonraki (next)** appears. Clicking this button will take participant to the questioning section: Now randomly selected images are shown, un-masked this time.

Each photo has the same **question**:

- Bu yuzu gormemistim (I haven’t seen this face)
- Bu yuzu tanidim (I remember this face)

And participant must give a response to each question. There are only several matching images, so **Bu yuzu tanidim** response cannot exceed a certain number. This information can be used for data analysis for eliminating false positives.

Un-masked images, medical masked questions: Once previous stage is completed, user gets to see another **Sonraki (next)** button. Clicking it takes participants to next chapter. This chapter technically has same rules and conditions. The only difference here is that participants are shown un-masked human faces, then asked to match with medical masked face images.

5 of the 10 face images on the learning page are on the test page, which includes 15 face images, and the remaining 10 contain images of faces that the participants have not seen before. An example was shared with the participants before the test page appeared on the screen. Clothing, accessories, hair, etc. were not taken into account when taking facial images of medical masked and unmasked people. For example, a person who appears on the screen with a red blouse in her medical masked image may also appear on the screen with the same blouse in her unmasked image. Here, it is not focused on whether clothing affects memory, but only the effect of the medical mask.

2.3. Database development and statistical analysis

This application relies on 4 main table:

- mos.sual_iller : look-up table
- mos.sual_photo : blob image contents
- mos.sual_demografik : look-up table
- mos.sual_cevap: master table, survey responses recorded into here.

The survey link was shared online via social media and email with individuals over the age of 18. The survey remained open in the system for an average of 3 months, and was removed from sharing at the end of this period. During this period, a total of 395 people participated in the survey. Some of these participations include people with no information (possible page loading error), and some of them include people with only one step of the test (possible closing the page thinking they have reached the end of the test). Participants for whom all or part of the information was not entered were eliminated, and the information of the remaining 195 people was recorded.

The demographic information of the participants and the statistical analysis of their answers in the survey were tested with SPSS 20.0 (20.0 SPSS, Chicago, IL, USA). The obtained data were tested with frequency analysis, regression analysis and ANOVA.

3. RESULTS

Participants were tested with 15 medical masked and 15 unmasked face images. The distribution of true and false answers given to a total of 30 images by sex is shown in Table 1. The **test images (TI) 8** was identified correctly at the highest rate in both sexes (female 93%; male 96.2%). While the lowest rate of correct identification in female (36.6%) was made for the **TI 17**, in male this occurred in the **TI 21** (32.1%).

Table 1. True and false distribution of the answers given by the participants according to sex

Test images	Female (N=142)		Male (N=53)	
	True (%)	False (%)	True (%)	False (%)
1	55,6	44,4	41,5	58,5
2	71,1	28,9	62,3	37,7
3	78,2	21,8	77,4	22,6
4	48,6	51,4	52,8	47,2
5	78,9	21,1	81,1	18,9
6	82,4	17,6	83,0	17,0
7	57,0	43,0	43,4	56,6
8	93,0	7,0	96,2	3,8
9	78,9	21,1	69,8	30,2
10	81,7	18,3	81,1	18,9
11	83,1	16,9	88,7	11,3
12	75,4	24,6	73,6	26,4
13	80,3	19,7	84,9	15,1
14	82,4	17,6	73,6	26,4
15	78,9	21,1	64,2	35,8
16	82,4	17,6	73,6	26,4
17	36,6	63,4	47,2	52,8
18	80,3	19,7	75,5	24,5
19	50,7	49,3	54,7	45,3
20	76,8	23,2	73,6	26,4
21	38,7	61,3	32,1	67,9
22	68,3	31,7	50,9	49,1
23	50,7	49,3	43,4	56,6
24	70,4	29,6	79,2	20,8
25	46,5	53,5	54,7	45,3
26	85,2	14,8	71,7	28,3
27	69,0	31,0	66,0	34,0
28	76,8	23,2	81,1	18,9
29	50,0	50,0	45,3	54,7
30	69,0	31,0	88,7	11,3

Picture 1. TI 17 (not included in the test images) with the lowest rate of correct identification in female [Published with permission of the participant]

The TI 17 which participants stated that they had seen before, although they were not among the test images shown to the participants, shown in Picture 1.

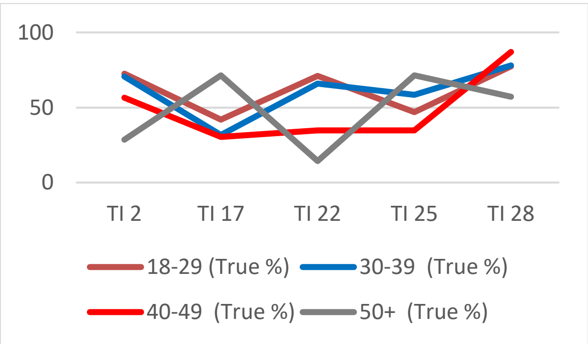
Picture 2. TI 8 (not included in the test images) identified with high rates of accuracy across multiple age groups and both sexes [Published with permission of the participant]

The TI 8, which most of the participants identified with a high rate of accuracy, is shown in Picture 2.

The ratios of true – false distributions of the participants' answers according to age groups are shown in Table 2. The TI 8 had the best accuracy (93,5%) among participants aged 18 to 29, while the TI 21 had the lowest accuracy (38%). The highest accuracy (95,1%) was seen in the TI 8, while the lowest accuracy (31.7%) was observed in the TI 17. The identification made by participants aged 40-49 had the maximum accuracy (95.7%) in the TI 8 and TI 10, and the lowest accuracy (30.4%) in the TI 17. The TI 3, TI 14, TI 30 had the maximum accuracy (100%) among participants aged 50 and over, whereas the TI 1 and TI 22 had the lowest accuracy (14.3%).

Table 2. Distribution of participants' true and false answers according to age groups

Test images	18-29 (N=124)		30-39 (N=41)		40-49 (N=23)		50 and over (N=7)	
	True (%)	False (%)	True (%)	False (%)	True (%)	False (%)	True (%)	False (%)
1	54,8	45,2	51,2	48,8	47,8	52,2	14,3	85,7
2	72,6	27,4	70,7	29,3	56,5	43,5	28,6	71,4
3	75,0	25,0	82,9	17,1	78,3	21,7	100,0	
4	52,4	47,6	36,6	63,4	56,5	43,5	57,1	42,9
5	80,6	19,4	78,0	22,0	78,3	21,7	71,4	28,6
6	82,3	17,7	82,9	17,1	82,6	17,4	85,7	14,3
7	55,6	44,4	48,8	51,2	43,5	56,5	71,4	28,6
8	93,5	6,5	95,1	4,9	95,7	4,3	85,7	14,3
9	79,8	20,2	73,2	26,8	65,2	34,8	71,4	28,6
10	80,6	19,4	78,0	22,0	95,7	4,3	71,4	28,6
11	83,1	16,9	92,7	7,3	78,3	21,7	85,7	14,3
12	75,0	25,0	82,9	17,1	65,2	34,8	57,1	42,9
13	83,9	16,1	75,6	24,4	87,0	13,0	57,1	42,9
14	82,3	17,7	70,7	29,3	78,3	21,7	100,0	
15	75,0	25,0	80,5	19,5	69,6	30,4	57,1	42,9
16	81,5	18,5	75,6	24,4	82,6	17,4	71,4	28,6
17	41,9	58,1	31,7	68,3	30,4	69,6	71,4	28,6
18	78,2	21,8	85,4	14,6	73,9	26,1	71,4	28,6
19	53,2	46,8	48,8	51,2	47,8	52,2	57,1	42,9
20	74,2	25,8	85,4	14,6	69,6	30,4	71,4	28,6
21	38,7	61,3	34,1	65,9	34,8	65,2	28,6	71,4
22	71,0	29,0	65,9	34,1	34,8	65,2	14,3	85,7
23	49,2	50,8	43,9	56,1	52,2	47,8	57,1	42,9
24	74,2	25,8	75,6	24,4	69,6	30,4	42,9	57,1
25	46,8	53,2	58,5	41,5	34,8	65,2	71,4	28,6
26	86,3	13,7	78,0	22,0	65,2	34,8	71,4	28,6
27	67,7	32,3	70,7	29,3	69,6	30,4	57,1	42,9
28	77,4	22,6	78,0	22,0	87,0	13,0	57,1	42,9
29	52,4	47,6	36,6	63,4	47,8	52,2	57,1	42,9
30	75,0	25,0	70,7	29,3	69,6	30,4	100,0	



Graph 1. Correct estimation distributions of test images (TI) with the highest differences according to age groups

The distribution of the minimum 10% difference observed in at least 3 age groups among the true estimation made on the test images according to age groups is shown in Graph 1. Accordingly, the highest differences were observed in TI 2 (18-29: 72,6; 50+: 28,7), TI 17 (40-49: 31,7; 50+: 71,4) and TI 22 (18-29: 71,0; 50+: 14,3).

It was tested whether sex, age and education level affected the participants' identification skills, based on a total of 30 answers (Table 3). As a result, there was a statistically significant ($p<0.05$) difference in correct identification between sexes in the **TI 11, TI 15, and TI 30**, it was observed in the **TI 1, TI 3, TI 9, TI 10, TI 22, TI 24** according to age, and in the **TI 20 and TI 23** according to education level.

Table 3. Effect of sex, age, and education levels on participants' estimation

	Sex			Age			Education		
	Unstandardized coefficients		Sig.	Unstandardized coefficients		Sig.	Unstandardized coefficients		Sig.
Test images	**B***	**Std. error**		**B**	**Std. error**		**B**	**Std. error**	
1	0,118	0,066	0,074	2,885	1,417	**0,043**	0,292	0,155	0,061
2	0,020	0,076	0,789	1,623	1,644	0,325	0,049	0,180	0,785
3	-0,005	0,080	0,952	-5,353	1,711	**0,002**	-0,300	0,187	0,111
4	-0,139	0,072	0,055	0,542	1,542	0,726	-0,017	0,169	0,919
5	-0,027	0,091	0,767	-1,955	1,952	0,318	-0,304	0,213	0,156
6	0,029	0,090	0,751	-0,915	1,944	0,638	0,012	0,213	0,956
7	0,058	0,072	0,421	-0,922	1,545	0,551	0,157	0,169	0,355
8	-0,114	0,157	0,470	-0,811	3,376	0,810	0,113	0,369	0,759
9	0,097	0,080	0,227	3,991	1,717	**0,021**	0,071	0,188	0,707
10	-0,056	0,094	0,554	-4,366	2,022	**0,032**	-0,163	0,221	0,462
11	-0,215	0,106	**0,044**	-0,208	2,274	0,927	-0,195	0,249	0,435
12	0,088	0,083	0,292	1,079	1,793	0,548	0,167	0,196	0,397
13	-0,082	0,093	0,383	2,004	2,004	0,319	0,031	0,219	0,886
14	0,092	0,091	0,313	-0,308	1,949	0,874	-0,154	0,213	0,472
15	0,262	0,084	**0,002**	-1,071	1,801	0,553	-0,123	0,197	0,532
16	0,103	0,085	0,231	-0,547	1,836	0,766	0,004	0,201	0,983
17	-0,061	0,069	0,380	1,245	1,494	0,406	0,298	0,163	0,070
18	0,054	0,091	0,553	-0,425	1,954	0,828	-0,248	0,214	0,247
19	-0,072	0,069	0,300	-0,845	1,480	0,569	-0,159	0,162	0,326
20	-0,002	0,089	0,978	-1,752	1,908	0,360	-0,416	0,209	**0,048**
21	0,061	0,071	0,391	1,834	1,518	0,229	0,223	0,166	0,181
22	0,072	0,073	0,321	6,585	1,561	**0,000**	0,154	0,171	0,368
23	0,055	0,066	0,406	0,509	1,429	0,722	-0,315	0,156	**0,046**
24	-0,138	0,086	0,108	3,951	1,844	**0,034**	0,230	0,202	0,255
25	-0,078	0,069	0,264	-1,663	1,491	0,266	-0,244	0,163	0,136
26	0,114	0,092	0,217	3,094	1,986	0,121	0,196	0,217	0,367
27	0,102	0,075	0,177	-0,905	1,622	0,577	-0,006	0,177	0,973
28	0,013	0,086	0,879	0,478	1,846	0,796	-0,118	0,202	0,559
29	0,062	0,070	0,377	0,372	1,506	0,805	-0,263	0,165	0,112
30	-0,224	0,081	**0,007**	-1,155	1,749	0,510	-0,104	0,191	0,588

*B: It refers to the change in the dependent variable based on the change in the independent variable.

Participants were first shown medical masked faces and asked to identify unmasked faces. Then, unmasked faces were shown, and the medical masked faces were asked to be identified. How successfully participants could identify unmasked faces compared to medical masked faces was analyzed with the Wilcoxon Signed Rank Test (Table 4). According to the results of this test, it is seen that the identification of medical masked images gives statistically better performance than the identification of unmasked face ($p<0.05$).

Table 4. Comparison of successful identification rates of medical masked and unmasked images

	Negative ranks			Positive ranks			Test statistics		
	N	**Mean rank**	**Sum of ranks**	**N**	**Mean rank**	**Sum of ranks**	**Ties**	**Z**	**P**
Masked-Unmasked	11	8,73	96,00	4	6,00	24,00	0	-2,046	0,041

4. DISCUSSION AND CONCLUSION

It is much well understood that covering some parts of the human face impacts people's recognition, particularly during the current pandemic. This difficult condition, which impacts human ability to recognize one another, also has an impact on how facial biometric devices work.

Many studies mention that women's facial recognition performance is better than men [32, 33, 34]. Some researchers have stated that, in general, women are more exposed to faces than men because they tend to socialize one-on-one during childhood and adulthood, and therefore they can make better identifications [35, 36]. However, Ryan and Gauthier (2016) stated that women are more successful than men in recognizing dolls, and men are more successful than women in recognizing toys such as robots and cars. For this reason, it was thought that they identified faces with which they had experience more successfully [37]. In this study, overall successful face identification performances do not show any significant differences according to sex. The sex distribution in the facial images used in the study is quite close to each other. On the other hand, the number of women participating in the test is significantly higher than men. In this regard, although it does not seem possible to make a similar comment based on the examples in the literature, it may be possible to reach a more accurate conclusion about this situation by ensuring a conscious inequality in the sex distribution in the test images (or using only female or male images) and ensuring equality in the sexes of the participants.

Picture 3. Facial images of 2 separate individuals thought to be confused with each other [Published with permission of the participants]

Participants stated that they had seen the people in the 17th and 21st images among the test images before, although they were not among the test images. It is thought that another individual (Picture 3a), among the test images presented without a medical mask, may have been confused with the person in the 17th image (Picture 3b) due to her headscarf. Among the people whose facial images were used, the number of women wearing headscarves was quite low. For this reason, it is estimated that the headscarf attracted the attention of the participants more.

Damer et al. (2020) in their study on the recognition of masked faces, they observed a significant difference in the recognition performance of masked faces compared to unmasked ones [38]. In another study, it was stated that human performance was low in identifying masked faces [4]. In a study by Noyes et al. (2021), which investigated the effect of sunglasses and masks on identification, it was stated that a decrease in performance was observed with a relatively small difference compared to the results of Damer's study. In addition, while glasses and masks were observed to reduce performance in identifying unfamiliar faces, glasses did not affect the identification of familiar faces, but it was observed that the mask reduced accuracy [3]. In this study, identification performance of medical masked faces was found to be more successful than unmasked ones. It is thought that the reason for this situation is that the images are included without interfering with the details of people's clothes, accessories, etc., so the participants may have focused on details other than facial features to keep the people in mind. However, it is also thought that the focus may have been on the eyes as one of the important indicators in defining the face.

The decline in face recognition accuracy with aging is thought to affect young faces but not older faces. Young adults tend to be able to discriminate equally well between target and distractor faces, regardless of age, whereas older adults recognize younger faces less well than older adults [39]. In another investigation, younger participants regularly outperformed older ones in terms of facial recognition accuracy. The reverse trend has been observed among older individuals [40, 41]. In this study, there was no significant variation in accurate answers based on age group. It is believed that making an obvious judgment about these rates would be incorrect because the distribution of groups is not consistent and there is an important difference in numbers, particularly among the 18-29 age group.

The reliability of eyewitness testimony and algorithms created for automated recognition are two commonly tested concerns in the field of face recognition. Making wearing of medical masks a must for an extended period around the world during the pandemic has provided a new viewpoint on the issue. It is a known difficulty that people cannot be distinguished when faces are even partially covered by medical masks, glasses, piercings, etc.

Clothing, hairstyle, accessories, etc. not considered in the facial images presented to the participants. This may have caused participants to pay more attention to other factors to keep medical faces in mind when identifying them. This statement is consistent with medical masked faces being identified more successfully. Although the level of education is not thought to have a significant effect on face recognition, it is also seen that age has the biggest effect.

It is thought that more comprehensive results will be achieved in future studies by increasing the number of test images, standardizing facial images (images containing only the face and eliminating external factors), and ensuring homogeneity in sex and age group distribution.

Ethical Considerations

Kütahya Health Sciences University Non-invasive Clinical Research Ethics Committee approved the study ethic protocol. This work has been carried out in accordance with the Helsinki Declaration.

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Conflict of interest

I wish to confirm that there is no competing interest associated with this publication.

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