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Fingerprints white line counts (fWLC): an unfolding panacea of body composition estimation among students of selected tertiary institution in Kano State Nigeria

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Abstract
The term "fingerprint white lines (fWL)" refers to a region of ridge hypoplasia that appears as white lines in a captured fingerprint, dubbed "white lines". The aim of this work was to see if there is any sexual dimorphism in fingerprint white line count (fWLC) and body composition parameters (BCP), as well as look into the relationship between the two. The study was a cross sectional design with 300 participants. The body composition parameters were measured using a bioelectric impedance machine. The fingerprint was captured using a live scanner to determine the fWLC. Females had considerably higher metabolic age, body fat, and visceral fat. In all ten digits, statistically significant differences in fWLC were found. Females were shown to have a higher fWLC, metabolic age, body fat, and visceral fat than males. Except for percent body fat, the fWLC revealed a significant negative correlation with all body composition indices. The fWLC of the left thumb correlates with percent visceral fat while the left and right middle fWLC showed a significant correlation with metabolic age. All ten digits fWLC had a strong link with percent body fat, percent muscle mass, and resting metabolism, with the left ring and thumb fWLC having a higher correlation. Thumb, index, middle, and little fWLC of the left digit, and middle and ring fWLC of the right digit are used to calculate BMI. The greatest predictors for BMI and percent body fat were found to be the left middle and right little digits fWLC. Left ring and right middle digit fWLC were the best predictors of percentage muscle mass and metabolic ages, respectively. Both resting metabolism and percent visceral fat were best predicted by the left thumb fWLC. Finally, sexual dimorphism in relation to BCP and fWLC was discovered.

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Keywords: Body composition parameters, Fingerprint white line count, Relationship, Sexual dimorphism

INTRODUCTION

The term "fingerprint white lines" refers to a region of ridge hypoplasia that becomes evident as white in a captured fingerprint, dubbed "white lines" (Cummins and Midlo, 1943; Ashburgh, 1999; D' Adamo, 2010). It has been reported that fWLC correspond to depressions on the epidermal ridges, and that this feature may signify the loss of cells and extracellular matrix that make up the skin tissues (Maceo, 2011; Adamu *et al.,* 2019). The fingerprint is a significant biological feature of the human body that provides a lot of information about gender (Qi *et al.,* 2021). A fingerprint is defined by a series of parallel ridge lines that end and intersect (Cummins and Midlo, 1943, Dario and Davide, 1996). Loops, whorls, and arches are the three basic types of human fingerprints (Galton, 1892). White lines are worn off ridges that become evident due to an exceptional quantity of fine secondary wrinkles (D'Adamo, 2010). Body composition is important for calculating stored energy, long-term energy balance, and analyzing fat depots and skeletal muscle (Wang *et al.,* 1992).

At the moment, research on fingerprint gender features is mostly at the conceptual stage, whereas standardization research is scarce (Qi *et al.,* 2021). In the Hausa community, the FWLC asymmetry has potential in gender and left or right of the digit prediction, although index and ring digits were the best digits for expressing dimorphism and discrimination (Taura *et al.,* 2020).

Previous research suggested that fingerprint parameters like ridge count differences between fingers on the same hand could reflect circumstances related to relative caudal growth inhibition, and that an embryo developing under such conditions would accumulate less tissue in the lower body (Terry *et al.,* 1991). The mean differences in ridge count of the fourth and fifth fingertips of the right hand have also been linked to the index of upper body tissue distribution (Seidell, 1992).

Fingerprint gender identification seeks to recognize one's gender information by extracting gender-related elements from an unidentified fingerprint (Qi *et al.,* 2021). It consists of two stages: extraction and classifying, with the former being the most important because the effectiveness of gender identification is largely dependent by the availability of gender-related traits (Shinde and Annadate, 2015; Abdullah *et al.,* 2016a, b; Mishra and Maheshwary, 2017; Wedpathak *et al.,* 2018; Rekha *et al.,* 2019). The accuracy of classifying ridge-related characteristics extracted manually was fairly acceptable, with an overall accuracy of 90% for average (Arun and Sarath, 2011; Badawi *et al.,* 2006; Wedpathak *et al.,* 2018).

Females have more white lines than males (Badawi *et al.,* 2006; Taduran *et al.,* 2016). There is no way to compare WLC in Filipino males and females to WLC in other groups because no other published studies, except Badawi *et al.* (2006), have proven WLC as a significant trait for sexual determination purposes (Taduran *et al.,* 2016).

Both males and females with fWLC had leftward asymmetry in all digits. Except for the middle digits, all of the digits showed significant sexual dimorphism in fWLC asymmetry. In terms of determining sex and left or right, the coefficients of discrimination of sex and left or right of digit were found to be significant for all digits except the middle ones. For index and ring digits, the variance of sex and left or right of the digits explained by fWLC asymmetry was higher (Taura *et al.,* 2020). Previous research has shown the utility of fingerprint white line counts (fWLC) as a reliable feature for sex inference, with females having more white lines than males (Badawi *et al.,* 2006; Taduran *et al.,* 2016). However, it has been proposed that the incidence of fWLC rises with age or when an individual's subcutaneous body fat changes (Cummins and Midlo, 1943; Ashburgh, 1999).

The link between BCP and fWLC is poorly understood. This relationship is also underrepresented in the literature and the information is needed to serve as a baseline for BCP and fWLC in the Nigerian population. The fWLC could be used in large-scale screening for BCP estimation, resulting in data that can be used to assess the anthropometric body composition status of unidentified person. The objective of this study was to see if there is any sexual dimorphism in fingerprint white line count (fWLC) and body composition parameters (BCP), as well as look into the relationship between the two.

MATERIALS AND METHODS

Study population, area and participants

The study was cross-sectional, with questionnaires used to collect bio-data (sex, age, ethnicity, and birthplace), while bioelectrical impedance analyses (BIA) and live scanners were used to collect anthropometric parameters and fWLC (Digita Persona, China). A total of 300 students from the College of Health Sciences at Bayero University Kano and the Faculty of Basic Medical Sciences at Maitama Sule University participated in the study, with 150 males and 150 females. Any students registered at either of the two institutions, who were in the College of Health Sciences, Faculty of Basic Medical Sciences, and do not have any physical abnormality, notably at the tip of the fingers, and who belong to the Hausa/fulani or Hausa-fulani ethnic group were recruited for the study.

Non-registered students at either of the two universities, students outside the college of health sciences, and people with physical deformities, particularly at the tips of their fingers, as well as non-hausa and Hausa-fulani ethnic groups, were all excluded from the study. Before the study began, ethical clearance was obtaineded from the department of Anatomy, Faculty of Basic Medical Sciences, Bayero University Kano, ethical committee, while informed consent was obtained from the participants.

Measurement of body composition parameters

With the subject wearing light indoor attire, body weight and height were measured to the closest 0.1 kg and 0.5 cm, respectively using a standiometer (RZ-160, China) (Adamu *et al.,* 2019).

Bioelectric Impedance Analysis (Omron HBF-514, China) was used to measure body compostion parameters with participant standing barefooted on the main, with each of his heel placed on a heel electrode, with knees bent and back straight ahead, arms lifted horizontally and elbow extended straight, the display device raised up to the face so that the subject can see it (Adamu *et al.,* 2019).

Fingerprint capture and analysis

The fingerprints of all 10 digits were captured using a direct sensing method [thumbprint in touch with live scan (digital persona) sensor] (Jain *et al.,* 2007; Adamu *et al.* (2018). Each fingerprint was saved using a software (Print analyzer) created using the Microsoft Visual Basic (version 6.0) programming language. A participant was instructed to clean his or her fingers to remove any dirt from the skin ridges. The fingers were then separately put on the fingerprint sensor (digital persona) (Adamu *et al.,* 2019). Following the capture of a plain fingerprint, the participants' gender (male or female), sex (male or female), side of the finger (left or right), and unique code (questionnaire code) were recorded with each fingerprint. The original size image was used for scaling, and an amplified image (at a ratio of 7.74) was used to determine ridge density and thickness for each fingerprint (Adamu *et al.,* 2019).

Fingerprints White-line Counts

The skin folds in the friction fingerprint epidermal ridges that appeared as white lines in fingerprint photographs were defined as the white lines. The number of white lines detected per unit plain fingerprints were used to calculate the fingerprint white line counts (FWLC) for each digit (Taduran *et al.,* 2016; Adamu *et al.,* 2019). The fWLC's dependability and intraobserver error have been previously described (Adamu *et al.,* 2019).

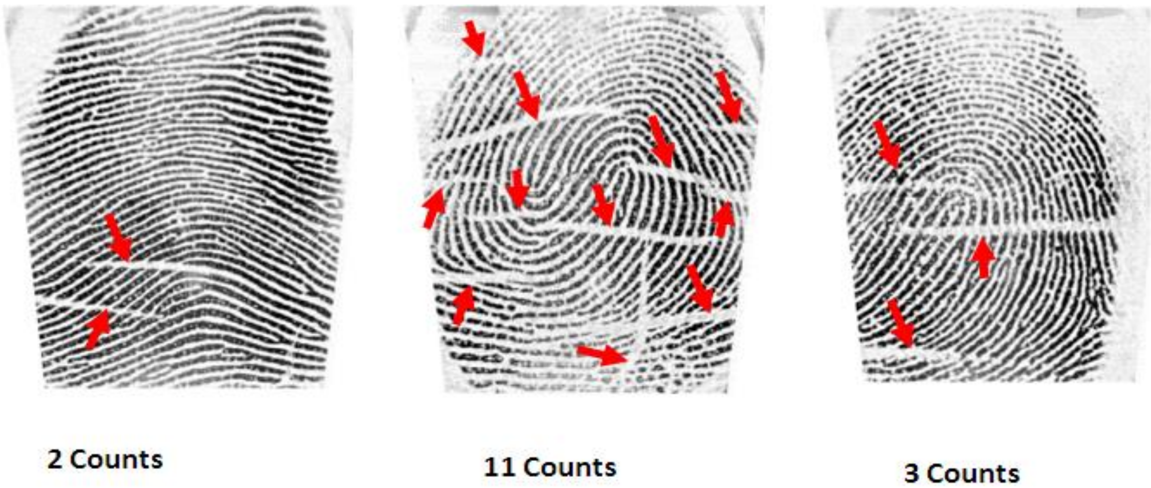

Figure 1: White lines counts of a fingerprint (Arrows showing specific white line on a fingerprints)

Statistical Analyses

IBM Corporation's SPSS version 20 (for Windows) was used for data analysis. The result was presented as mean±standard deviation, and quartiles. To compare differences in fingerprint and body composition measures, Mann Whitney test was done and the association between fingerprints and body composition was determined using the Pearson correlation test. To create a model for

RESULTS

Measurement Error

The Cronbach's Alpha (reliability coefficient) readings varied from 0 to 1, with 0 indicating "no reliability," 0.2 to 0.4 indicating "good reliability," 0.4 to 0.6 indicating "moderate reliability," 0.6 to 0.8 indicating "considerable reliability," and 1 indicating "nearly perfect reliability" (Shrout and Fleiss, 1979). The white line counts of the ten digits have a Cronbach's Alpha of 0.98-1.00. Repeated measurements was done on 30 subjects.

Table 1, shows descriptive statistics and percentiles of white lines count in male and female participants. A significant different was observed in height, weight, muscle mass and resting metabolism which shows that males had higher values than females. A significantly higher metabolic age, body fat and visceral fat were found in females. Statistically significant differences were observed in fWLC in all the ten digits. Females were observed to have higher fWLC compared to males.

Table 1: Descriptive statistics and percentiles body composition parameters and fingerprint white line count (fWLC) among the study population

	Male			Female			
Variables	Mean ± SD	Min-Max	Median (IQR)	Mean ± SD	Min-Max	Median (IQR)	Z value
Height (cm)	169.67± 6.69	157-196	169.75(165-73.5)	158.62±5.66	143.50-172.00	158.25(155-162.63)	-12.07**
Weight (Kg)	58.45±8.55	44.30 - 104.60	57.60(52.75-61.88)	52.11± 10.74	37.60-99.60	48.95(45.4-55.1)	-7.56**
BMI (Kg/m^2)	20.30± 2.18	17.20 - 30.90	19.90(18.68-21.3)	20.62± 3.88	14.40-36.60	19.90(18.2-21.95)	-0.82
%Body Fat	13.15±5.79	5 - 38.20	11.95(8.98-16.2)	28.66± 7.83	10.10-53.30	27.35(23.2-33.13)	-13.52**
%Muscle Mass	43.84±3.66	28.50 -49.90	44.30(42.08-46.4)	27.34±3.15	20.10- 43.00	27(25.2-28.7)	-14.78**
Resting Met.	1487.87± 119.62	1153 -2058	1474.5(1409.75-1555.25)	1223.80± 120.86	1034-1783	1186(1146-1263.5)	-13.13**
Met. age (years)	20.20± 6.57	18 -69	18.00(18-18)	22.85±8.97	18.00-61.00	18(18,23)	-3.46**
%Visceral fat	2.75± 1.95	1 -12	2.00(1-4)	3.03±1.68	1.00-14.00	3(2-4)	-2.45*
R. Thumb fWLC	1.03±1.13	0 -6	1(0-2)	2.13±1.66	0 -8	2(1-3)	-6.31**
L. Thumb fWLC	1.24±1.29	0 -5	1(0-1)	2.71±1.90	0 -12	2(1-4)	-7.61**
R. Index fWLC	0.47±0.92	0 -8	0(0-1)	1.43±1.78	0 -11	1(0-2)	-5.65**
L. Index fWLC	0.85±1.29	0 -9	0(0-1)	2.24±2.03	0 -11	2(1-3)	-7.07**
R. Middle fWLC	0.56±0.94	0 -5	0(0-1)	1.87±2.06	0 -9	1(0-3)	-6.74**
L. Middle fWLC	0.92±1.38	0 -7	0(0-0)	2.53±2.54	0 -15	2(1-4)	-6.84**
R. Ring fWLC	0.58±1.22	0 -10	0(0-1)	2.35±2.81	0 -17	1.5(0-3)	-7.42**
L. Ring fWLC	0.93±1.47	0 -7	0(0-2)	3.31±2.99	0 -17	3(1-5)	-8.49**
R. Little fWLC	0.49±1.20	0 -10	0(0-0.25)	2.03±2.40	0 -11	1(0-3)	-7.28**
L. Little fWLC	0.66±1.15	0 -5	0(0-1)	2.77±2.89	0 -12	2(0-4)	-8.02**

*P<0.05, **P<0.01, R; right, L; left, SD; standard deviation, min; minimum, max; maximum, IQR; inter quartile range (25th -75th percentile), BMI; body mass index, met; metabolism/metabolic

Table 2, shows Pearson's correlation for the association between body composition, fingerprint indices, and fWLC. It was discovered that fingerprint indices had no correlation with body composition. Except for percent body fat, the fWLC revealed a significant negative correlation with all body composition indices. Only the fWLC of the left thumb correlated with percent visceral fat. The left and right middle fWLC showed a significant correlation with metabolic age. All ten digit fWLC correlated with percent body fat, percent muscle mass, and resting metabolism, with the left ring and thumb fWLC having a stronger association. The thumb, index, middle, and little finger fWLC of the left digits, as well as the middle and ring fWLC of the right digits, revealed a significant correlation with BMI.

Table 2: Correlation of body composition with fingerprint indices and white lines count

Variables	BMI (Kg/m²)	%Body Fat	%Muscle Mass	Resting Met.	Metabolic age (years)	%Visceral fat
Right Thumb fWLC	-0.088	0.236**	-0.331**	-0.304**	-0.045	-0.080
Left Thumb fWLC	-0.159**	0.250**	-0.390**	-0.398**	-0.087	-0.127*
Right Index fWLC	-0.005	0.270**	-0.312**	-0.222**	-0.017	-0.001
Left Index fWLC	-0.121*	0.234**	-0.352**	-0.301**	-0.084	-0.058
Right Middle fWLC	-0.126*	0.238**	-0.349**	-0.309**	-0.119*	-0.069
Left Middle fWLC	-0.161**	0.214**	-0.351**	-0.311**	-0.113*	-0.092
Right Ring fWLC	-0.135*	0.206**	-0.328**	-0.312**	-0.113	-0.089
Left Ring Fwlc	-0.097	0.309**	-0.428**	-0.373**	-0.076	-0.031
Right Little Fwlc	-0.094	0.257**	-0.369**	-0.299**	-0.083	-0.010
Left Little Fwlc	-0.117*	0.273**	-0.416**	-0.366**	-0.058	-0.061

*P <0.05, **P< 0.01, fWLC; fingerprint white line count, Resting met (resting metabolism)

Table 3, illustrates a linear regression model for predicting body composition from fingerprint indices and the number of white lines. The best predictor for BMI was the middle left digit fWLC, and the best predictor for body fat was the right little digit fWLC. Left ring and right middle digit fWLC were the strongest predictors of percentage muscle mass and metabolic ages, respectively. The fWRC of the left thumb was the strongest predictor of resting metabolism and visceral fat percentage.

Table 3: Step wise multiple linear regression for prediction of body composition from fingerprint indices and white lines count

Body composition prediction models	R	R²	SEE	F	P -Value
Body mass index=(-0.231)left middle digit WLC+20.860	0.161	0.026	3.107	7.931	0.005
% Body fat =(1.215) left ring digit fWLC +18.328	0.309	0.095	09.886	31.384	0.000
% Body fat =(0.903) left ring digit fWLC +(0.943) right index digit WLC +18.098	0.328	0.107	9.836	17.862	0.000
% Muscle mass =(-1.450) left ring fWLC+38.665	0.428	0.183	8.095	66.645	0.000
Resting metabolism =(-39.884)left thumb digit fWLC+1434.674	0.398	0.158	164.147	56.017	0.000
Resting metabolism =(-27.874) left thumb digit fWLC+(-14.261) left little fWLC+1435.370	0.426	0.182	162.115	32.973	0.000
Metabolic age =(-0.547) right middle digit fWLC+22.192	0.119	0.014	7.917	4.275	0.040
% Viscral fat=(-0.129) left thumb digit fWLC +3.146	0.127	0.016	1.809	4.853	0.028

SEE; standard error of estimate, fWLC; fingerprint white line count

DISCUSSION

The amount of energy expended while resting quietly in a supine position is known as resting metabolism (Kaur and Deol, 2021). The resting metabolic rate is generally, but not entirely, utilised (Bursztein *et al.,* 1989). Adult men have a higher resting metabolism (RM) than adult women (Bursztein et al., 1989; Bogert *et al.,* 1973; Kaur and Deol, 2021).

According to Arciero *et al.* (1993), men have a higher absolute resting metabolic rate than women due to their bigger amount of fat-free mass. As was reported that the main source of variation in resting metabolic rate in people is the fat-free mass. Males had higher resting metabolism, muscle mass, height and weight than females in this study. However, muscle mass, had a considerable impact on resting metabolic rate (Nosslinger *et al.,* 2021). Several studies have found that the expression of obesity-related genes may predetermine the fingerprint pattern in obese people in utero (Cummins and Midlo, 1943).

The greater metabolic age, body fat, and visceral fat reported in females in this study could be due to the fact that women in the Hausa community rarely engage in physical activity and are more accustomed to a sedentary lifestyle whereas men in the community engage in physical activity. Sedentary daily life, according to Kaur and Deol (2021), is a type of lifestyle that involves no physical activity or exercise. A sedentary lifestyle or life is defined as spending most of the day sitting, lying down, or in a prone or supine position while engaging in activities such as reading, watching television, playing video games, or using the computer (Sedentary Lifestyle, 2018).

The BMI and resting metabolism changes with age, according to Kaur and Deol (2021). According to the findings of Kaur and Deol (2021), people who engaged in moderate to vigorous physical activity have higher body mass and higher resting metabolism. The experiment used the OMRON body composition monitor (BCM) with rulers to assess body mass index, skeletal muscle mass, and body fats. There were substantial variances when the examination was conducted based on sex (Sudarma and Halim, 2017).

This study agrees with Taura *et al.* (2020), who found statistically significant changes in fWLC in all 10 digits. Females were shown to have a higher fWLC than males. Females had more white lines than males because white lines are linked to body fat, and females had higher body fat composition than males. This research was also consistent with another study that found that counting white lines on a fingerprint is a reliable approach for determining sex, with females having more white lines than males (Badawi *et al.,* 2006). This was because white lines on fingerprints were discovered to be strongly related with body fat, and females have been reported to have greater body fat than males. The fWLC was discovered to be a potential predictor of sex among adult Hausa Nigerians (Taura *et al.,* 2019).

According to Taura *et al.* (2020), the left or right of digit should be predetermined before sex discrimination utilizing fingerprint traits like fWLC. In the same note, when statistically significant asymmetry exists between the left and right hand, stature estimation from the limbs or bones may be erroneous or invalid. As a result, the left or right of the bone or limb must be given prior to assessment, and corresponding equations for the left or right must be used (Krishan *et al.,* 2010).

FWLC asymmetry showed good potential for sex and left or right prediction among the Hausa community in Kano, Nigeria. For both sex and left or right prediction, the index and ring fingers had the best accuracy in group membership classification and prediction. The classification of group membership was in favor of males over females in all digits, and right over left (Taura *et al.,* 2020).

Taura *et al.* (2019) found that the difference between right second and fourth digit (dR2,4) and difference between left second and fourth digit (dL2,4) for right and left hands, respectively, exhibited a sexual dimorphism phenomenon that can be used in sex prediction among Hausa population of Kano state, Nigeria. The DFWLCD is a useful index for assessing caudal growth inhibition along the body axis, which is a well-known sexually dimorphic feature in humans. However, the literature on the potential functions of differences in nearby fWLC in sex inference is lacking, particularly among the Hausa community. Only a few research reported the potential relevance of fWLC in sex determination in the other populations (Badawi *et al.,* 2006; Taduran *et al.,* 2016) including the Hausa population (Adamu *et al.,* 2019).

This present findings agrees with the study of Bonnet *et al.,* (1998) where, dimorphism in organ, system, and body composition results from differences in reproductive roles and females have more body fat than males to assist in offspring generation while males have more muscular mass than female. The current study discovered a link between body composition and fWLC.

CONCLUSION

Sex differences in white line count were discovered, with females having more white lines than males. Body composition measures showed sexual dimorphism, with females having higher body fat with more fingerprint white line counts and visceral fat than males, and males having higher muscle mass, weight, height, and resting metabolism than females.

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