2015

# An evaluation of a metric method for sex estimation using the clavicle, humerus, radius, and ulna

BOSTON UNIVERSITY

SCHOOL OF MEDICINE

Thesis

# AN EVALUATION OF A METRIC METHOD FOR SEX ESTIMATION USING THE CLAVICLE, HUMERUS, RADIUS, AND ULNA

by

**AISLING KEARNS**

B.A., Boston University, 2015

Submitted in partial fulfillment of the

requirements for the degree of

Master of Science

2015

Approved by

First Reader ______________________________

Donald Siwek, Ph.D.
Assistant Professor
Department of Anatomy and Neurobiology
Program in Forensic Anthropology

Second Reader ______________________________

James Pokines, Ph.D.
Assistant Professor
Department of Anatomy and Neurobiology
Program in Forensic Anthropology

## ACKNOWLEDGMENTS

I would like to express my gratitude and appreciation to my committee, Dr. Siwek and Dr. Pokines, for all of their advice and help in the completion of my thesis. Your mentoring has been of tremendous help in both the research and writing processes of this project. I would also like to thank Dr. Dawnie Steadman and the Anthropology Department at the University of Tennessee for permitting me access to the William M. Bass Donated Skeletal Collection for research purposes. A special thanks goes to Dr. Albanese, whose previous research facilitated my interest in my particular thesis topic, and to Dr. Bethard, who encouraged me in my research endeavors and offered invaluable advice.

**AN EVALUATION OF A METRIC METHOD FOR SEX ESTIMATION USING THE CLAVICLE, HUMERUS, RADIUS, AND ULNA**

**AISLING KEARNS**

ABSTRACT

Sex estimation is important in both forensic and bioarchaeological contexts for the construction of a biological profile, which might aid in the identification process in forensic cases or answer demographic questions in archaeological contexts. The os coxa is generally considered the best indicator of sex, given its reproductive functionality in females, although it is not always available for analysis, thus presenting a need for alternative methods of sex estimation. The present research aims to validate the previous study by Albanese (2013), which examined the use of the clavicle, humerus, radius, and ulna. Albanese (2013) applied logistic regression analysis to the osteometric data and achieved allocation accuracies between 87.4% and 97.5%. A sample size of 400, comprised of American Whites and American Blacks from the William M. Bass Donated Skeletal Collection, was utilized in the present study.

The present study applies both discriminant function analysis and logistic regression analysis to a total of 20 measurements collected from the clavicle, humerus, radius, and ulna, including three variant measurements that were proposed by Albanese (2013), and a set discriminant functions and logistic regression equations were produced to classify individuals as male or female. Allocation accuracies as high as 100% were produced by the logistic regression equation that utilized all measurements. Discriminant analysis was applied to each of the bones individually, and the results indicated that the humerus exhibited the most sexual dimorphism and had the highest allocation accuracies (95.0% for males and 97.0% for females). Measurements that exhibited the greatest degree of sexual dimorphism were those representative of joint size such as the maximum diameter of the radial head, the vertical diameter of the humeral head, and the epicondylar breadth of the humerus. A set of equations were produced through discriminant function analysis, which are representative of various recovery scenarios and are meant to provide the examiner with sets of equations that might be applicable to a particular case. Because of its high allocation accuracies and its applicability to contemporary American White and Black populations, the methodology should be useful in forensic contexts within the United States.

## TABLE OF CONTENTS

## LIST OF TABLES

## LIST OF FIGURES

# CHAPTER 1: INTRODUCTION

Sex estimation is necessary in both forensic contexts and archaeological contexts for its addition to the construction of a biological profile. The biological profile can aid in the identification of individuals and, in archaeological contexts, sex estimation can provide researchers with important demographic information about specific archaeological populations (Berg, 2013; Moore, 2012). While there have been numerous studies conducted utilizing the os coxa due to its clear sexual dimorphism (Anastasiou & Chamberlain, 2012; Bruzek, 2002; Bytheway & Ross, 2010; Dar & Hershkovitz, 2006; Phenice, 1969), there has not been a large amount of research conducted using alternative methods that can be applied to geographically varied populations.

It is generally accepted that metric standards vary between populations due to variations in the development of sexual dimorphism (Barrier & L'Abbé, 2008; Frayer & Wolpoff, 1985; İşcan, 2005; Mall *et al*., 1999; Steyn & İşcan, 1999). Humans exhibit sexual dimorphism in morphology, size, and also occasionally in behavior, though the present study will focus specifically on sexual dimorphism exhibited through size and morphology. Bones are extremely plastic and therefore, throughout life, the human skeleton is constantly changing in response to extrinsic factors that act upon bone (Moore, 2012). Population differences in sexual dimorphism have been attributed to a variety of factors, such as genetics, environment, and social conditions (Barrier & L'Abbé, 2008; Frayer & Wolpoff, 1985; İşcan, 2005; Steyn & İşcan, 1999). There are two main hypotheses that have been proposed for the evolution of sexual dimorphism, which are sexual selection and intraspecific niche divergence. The sexual selection hypothesis states that the differences in the relationship between body size and reproductive success is the result of a selection favoring different adult body sizes between males and females. The sexual selection hypothesis argues, for instance, that the larger male size can be attributed to the selection processes associated with male to male combat and competition (Frayer & Wolpoff, 1985; Shine, 1989; Slatkin, 1984).

The alternative explanation for sexual dimorphism is that differences between size and morphology in males and females have evolved due to ecological causes (Shine, 1989; Slatkin, 1984). Sexual differences become more ambiguous as normal development is affected by extrinsic factors. For example, the muscular differences between males and females might become less defined when comparing a particularly athletic female with a less active male, or malnutrition might affect the stature of developing males (Frayer & Wolpoff, 1985). Humans have primary and secondary sexual characteristics. Primary sexual characteristics, or the human genitalia, develop *in utero*, while secondary characteristics develop at puberty. As the human body develops, bone is affected by various intrinsic factors, such as hormones. Secondary sexual characteristics include variations in body size and morphology and are more susceptible to being changed by the environment (Frayer and Wolpoff, 1985; Moore, 2012). The extent of sexual dimorphism varies between populations, although regionally the extent of variation does not tend to be extreme (Frayer & Wolpoff, 1985; Nakahashi & Nagai 1986). Non-genetic factors, or extrinsic factors, such as nutritional stress, might account for secular trends in sexual dimorphism (Frayer & Wolpoff, 1985; Moore, 2012). Studies have shown decreases in sexual dimorphism associated with stature correlate with conditions of nutritional stress, and alternatively increases in sexual dimorphism often occur with an improved diet (Brauer, 1982; Gray & Wolfe, 1980; Liebermann, 1982; Stini, 1969). Males are affected by nutritional deficiencies in the environment to a greater extent than females, which results in a decrease in sexual dimorphism (Bogin, 1999; Ross *et al.*, 2003; Stini, 1975). The reason for which females tend to be buffered against effects of nutritional deficiencies is unknown, but it is presumed to be associated with the requirements of female pregnancy (Moore, 2012).

Frayer and Wolpoff (1985) discuss the hypotheses used to explain sexual dimorphism. The authors categorize the hypotheses for the evolution of sexual dimorphism into proximate and ultimate causation models. The proximate causation model focuses more on the environmental factors and how they affect the development of sexual dimorphism. The ultimate causation model, however, assumes that environmental factors have little effect on body size but, rather, that sexual dimorphism is the result of various selection forces operating on males and females and biological factors (Frayer and Wolpoff, 1985).

Due to the sexual dimorphism present in human skeletal remains, sex estimation is necessary in forensic contexts for the identification of individuals and the construction of a biological profile. Sex estimation is also important in bioarchaeological contexts, as it can provide important demographic information about specific archaeological populations or answer cultural questions regarding gender roles and differential access to resources (Berg, 2013; Moore, 2012). However, the terms sex assessment, which involves a visual assessment of nonmetric traits, and sex estimation, which typically involves metric with estimable error rates, must be distinguished from one another (Moore 2012; Spradley & Jantz, 2011).

Because of the varying degrees of human variation between geographical populations, there has been a focus in forensic anthropology on developing group-specific methods, which is useful for the identification of individuals who can be allocated to a geographic and temporal group (Albanese, 2003; Charisi et al., 2011; Cowal & Pastor, 2008; İşcan, 2005; İşcan *et al.,* 1998; Kranioti & Michalodimitrikis, 2009; Macho, 1990; Purkait, 2005; Siegel *et al.,* 2000; Spradley *et al.,* 2008; Tise *et al.,* 2013). However, in bioarchaeological and forensic contexts it may not be possible for group membership to be easily ascertained, and, as such, group-specific methods may not necessarily be useful in these situations. Although there has been significant research exploring different methodologies for estimating sex, there still remains a need for a thoroughly tested metric method for assessing sex that is not population-specific.

Because of its reproductive function in women, the os coxa is generally considered the best indicator of sex (Anastasiou & Chamberlain, 2012; Bruzek, 2002; Bytheway & Ross, 2010; Dar & Hershkovitz, 2006; Klales *et al.,* 2012; Phenice, 1969). Despite its sexual dimorphism, the os coxa is often damaged, particularly in archaeological contexts due to taphonomic processes (Albanese, 2013; Ortner, 2003). Because of the susceptibility of the os coxa to damage, alternative methods must be devised to determine sex from skeletal remains (Albanese, 2013; Ortner, 2003; Phenice, 1969). Typically, following the os coxa, the cranium has been previously considered the next best element for analysis, however, Spradley and Jantz (2011) showed that postcranial elements are actually better indicators of sex than cranial elements. Previous research has also shown that the arm bones may be good discriminators of sex, and generally have high allocation accuracies (Albanese, 2013; Charisi *et al.,* 2011; Cowal & Pastor, 2008; Frutos, 2004; Holman & Bennett, 1991; İşcan *et al.*, 1998; Kranioti & Michalodimitrakis, 2009; Mall *et al.*, 2001; Papaioannou *et al.,* 2012; Rogers, 2009; Steyn & İşcan, 1999; Vance *et al*., 2011). Therefore, more research must be conducted to examine the use of the upper limb in sex estimation, as it may be a potential avenue for the development of universal methodologies given the particularly high allocation accuracies the upper limb has shown in the past.

The aim of the present research is to validate a previous study by Albanese (2013), which presented a new method of sex estimation using the clavicle, humerus, radius, and ulna. Albanese (2013) formed a series of equations employing logistic regression which used measurements collected from the clavicle, humerus, radius and ulna in order to allocate individuals as either male or female based upon a p-value. Albanese found that allocation accuracies ranged between 87.4% and 97.5% when he employed his methodology and tested it on four skeletal collections including the Terry collection at the Smithsonian, the Coimbra collection in Portugal, the Grant collection at the University of Toronto, and the Lisbon collection in Portugal.

The present research attempts to validate Albanese (2013), which produced high allocation accuracies and is suggested to be a universal methodology. In the present study, measurements were collected from the clavicle, humerus, radius, and ulna using 400 individuals, consisting of both American Blacks and American Whites, from the William M. Bass Donated Skeletal Collection. Measurements collected from the four bones included the standard measurements as laid out by Buikstra and Ubelaker (1994), and three additional measurements developed by Albanese (2013).

Unlike Albanese (2013), the present study applies both discriminant function analysis and logistic regression in order to develop functions that will discriminate sex depending on the bone or the combinations of bones that are available for analysis. The importance of the current study derives from its potential applicability as a universal method that can be applied across populations. Universal methodologies for estimating sex are required for cases in which the individual under analysis cannot be applied to a specific geographic-temporal group. The ability of examiners to apply sex estimation methods universally would be essential for forensic cases, particularly when individuals are recovered from areas in which are occupied by more than one variant group. Furthermore, a variety of sex estimation methods must be developed in order to provide examiners with different options depending on the recovery scenarios. The current study aims to provide examiners with a various equations for sex estimation that might suit their needs in different recovery scenarios.

# CHAPTER 2: PREVIOUS RESEARCH

The majority of early methods of sex estimation were conducted through visual assessment, generally avoiding the use of osteometrics, which was often thought to be more a tedious and time-consuming process (Phenice, 1969; Stewart, 1979; Walker 2008). In fact, Stewart (1979) suggested that metric sex estimation might be useful as a validation method only in addition to visual assessments of sex. However, metric methods of sex estimation have recently received more attention in research and are now considered less subjective, as they result in lower inter- and intra-observer error rates than those inherent in visual assessments (Adams & Byrd, 2002; Spradley & Jantz, 2011). Adams and Byrd (2002) examined thirteen standard measurements, well-known in forensic anthropology, and nine nonstandard measurements, which were unfamiliar to most observers. Sixty-eight forensic anthropologists with varying levels of experience were asked to perform each of these measurements, and the results were examined for interobserver variation. The authors found that the interobserver error of the standard postcranial measurements was generally low, revealing their usefulness in the development of methodologies for sex and age estimation (Adams & Byrd, 2002).

Correlating with the development of sex estimation methods utilizing osteometrics, there also developed a need for statistical analysis of measurements. Discriminant function analysis has become the most popular statistical method used in sex estimation, given its usefulness at discriminating between two or more groups (İşcan, 2005). Discriminant function analysis allows researchers to classify individuals into specific groups, whether it be sex, ancestry, or another dependent variable. However, discriminant function analysis makes the assumption that the sample being analyzed is normally distributed, which leads some researchers to use logistic regression as a statistical method instead since it makes less assumptions (Albanese, 2013; Albanese, 2003; Moore, 2012). In discriminant function analysis, posterior probabilities and typicality probabilities are applied to data in order to calculate the classification probabilities (Albanese *et al.*, 2008), which is useful in predicting sex from osteometric data. The development of sex estimation methods within the field of physical anthropology have followed this trend of moving from simple forms of visual sex assessment to more reliable methods grounded in statistical analyses.

While there have been numerous studies conducted utilizing the os coxa due to its clear sexual dimorphism (Anastasiou & Chamberlain, 2012; Bruzek, 2002; Bytheway & Ross, 2010; Dar & Hershkovitz, 2006; Klales *et al.,* 2012; Phenice, 1969), there has not been a large amount of research conducted using alternative methods which can be applied to geographically varied populations. In general, the os coxa is considered optimal in estimating sex, because of the sexual dimorphism created through the reproductive functionality of the bone in females. To enable a relatively large infant to pass through the pelvic canal during birth, the shape of the female os coxa is much longer and rounder than that of the male os coxa. Therefore, there is clear sexual dimorphism in an undamaged os coxa, and visual assessments of the os coxa are typically applicable across varied populations (Berg, 2013; Ortner, 2003; Phenice, 1969; Volk & Ubelaker, 2002).

Phenice (1969) developed a visual method for estimating sex using the os coxa. Phenice stated that the ventral arc, the subpubic concavity, and the medial aspect of the ischio-pubic ramus could be used in conjunction accurately to allocate individuals as either male or female with an accuracy of 95% or greater. The methodology is simple and objective enough to allow novice researchers to estimate sex accurately. The visual traits of the pubis have been used extensively by anthropologists in the estimation of sex from human remains when the os coxa was present (Phenice, 1969).

The Phenice (1969) method was tested further by Ubelaker and Volk (2004) on 198 individuals of known sex from the Terry Collection. An examiner trained in the technique, but with no further forensic anthropology training, was able to attain allocation accuracies of 88.4%. The authors found that if other non-metric pelvic indicators were used in addition to the Phenice traits, allocation accuracies were raised to 96.5%. Other features of the os coxa utilized by Ubelaker and Volk (2004) included the morphology of the sciatic notch, subpubic angle, auricular area, preauricular sulcus, acetabulum, and dorsal pubic pitting. The authors suggest that the experience of the observer significantly contributes to the accuracy of the method (Ubelaker and Volk, 2004).

Klales *et al.* (2012) reevaluated the Phenice (1969) method and scored the various aspects of the pubis on a five-point ordinal scale. When all three traits were used to evaluate sex in conjunction, the allocation accuracy for Klales *et al.*'s (2012) revised method was 94.5% when performed by experienced observers. The authors asserted that there was a need for a revision of the Phenice (1969) methodology, because scoring the extremes of a particular trait fail to reflect the range of variation that exists in the os coxa. In general, the authors admitted that non-metric techniques tended to force observers to characterize traits into one of only a few phases which do not always accommodate the range of variation. Furthermore, the traits were often weighted equally, although some may be more sexually dimorphic and better predictors of sex than others (Klales *et al.*, 2012).

Bruzek (2002) also developed a visual method for assessing of sex using the os coxa. The methodology was tested on a sample of 402 French and Portuguese adults of known sex and age. The author evaluated five traits of the os coxa and found that when they were applied in conjunction, the allocation accuracy was 95%. The five characteristics of the os coxa that were assessed include the preauricular sulcus, the greater sciatic notch, the composite arch, the morphology of the inferior os coxa, and the ischiopubic proportions. According to Bruzek (2002), the first three characteristics are sex-specific adaptations to bipedal locomotion, while the last two characteristics are the result of an adaptation of the female pelvic canal for reproduction. The developed method of sex determination is advantageous, according to the author, because it reduces the subjectivity involved in previous methods utilizing the os coxa, and also increases the probability of correct allocation of fragmented remains (Bruzek, 2002).

The traditional metric method for determining sex using the os coxa often results in relatively high intra-observer error (Albanese, 2003). Albanese (2003) demonstrated that the standard measurement of the length of the pubic bone results in higher rates of intra-observer error due to an ambiguous landmark, specifically the acetabular margin, used in the measurement. The acetabular margin, or the area where the ischium and ilium meet, is difficult to locate on adult individuals, because the area fuses during the individual's mid-to-late teens. The difficulty in locating the acetabular margin, therefore, leads to problems replicating measurements (Albanese, 2003). In fact, *FORDISC 3.1* no longer allows examiners to input these measurements due to high error-rates. Because the os coxa is often damaged or missing, and due to the unreliability of the traditional metric measurement associated with the acetabular margin, new methods for estimating sex must be devised and tested on various populations.

When the os coxa is unavailable for analysis, the cranium has traditionally been considered the next best element for sex estimation (Giles & Elliot, 1963; Ortner, 2003; Spradley & Jantz, 2011; Walker, 2008). Followers of this belief, Giles and Elliot (1963) developed an early method of sex estimation using the cranium. A sample size of 408 crania were used in their 1963 study, including individuals of both Black and White ancestry. Nine measurements of the crania were selected for their accessibility and potential predictive power in estimating sex. Discriminant function analysis was applied to the collected measurements, forming 21 combinations of the measurements that were used to develop discriminant functions, which achieved accuracies between 82% and 89%. Giles and Elliot (1963) proved that measurements of the cranium were useful in sex estimation, but that the sectioning points may need to be adjusted based upon the population under study (Giles and Elliot, 1963).

Walker (2008) developed a method of estimating sex based upon a scoring system for cranial traits including the nuchal crest, mastoid process, orbital margin, glabella supraorbital ridge, and the mental eminence. The study revealed that the accuracy of using discriminant functions, which incorporate the visually assessed scores of the aforementioned cranial traits, is comparable to other studies that use craniometrics to determine sex. Walker (2008) stated that the scores perform extremely well as independent variables in sex estimation. Allocation accuracies for the methodology ranged between 84% and 88%. The disadvantage to using visually assessed cranial trait scores, as opposed to craniometrics, is the subjectivity associated with the method. He suggests using caution when applying the methodology across populations, as the discriminant functions may produce high error rates and sex determination biases when applied to other populations (Walker, 2008).

Ogawa *et al.* (2013) used osteometrics instead of visually assessed traits of crania and generated a set of discriminant functions to estimate sex in individuals of Japanese origin. The authors used a sample of 113 individuals comprised of 73 males and 40 females. A total of ten measurements were collected from the skull including maximum cranial length, cranial base length, maximum cranial breadth, maximum frontal breadth, basion-bregmatic height, upper facial breadth, bizygomatic breadth, bicondylar breadth, bigonial breadth, and ramal height. The measurements were selected for their repeatability and their utility in fragmentary crania. From these measurements, nine discriminant functions were developed, which had classification accuracies that ranged between 77.8% and 88.1%. When the same functions were tested again on a sample of 50 new individuals, the classification accuracies were between 86.7% and 93.0% (Ogawa *et al.,* 2013).

Spradley and Jantz (2011) addressed the notion that the cranium is the second best indicator of sex and examined the utility of postcranial elements for sex estimation. Their study indicated that postcranial elements outperform the cranium in the estimation of sex. They found that measurements which are representative of joint size have the ability to correctly classify 88-90% of individuals, and multivariate functions developed with postcranial bones can correctly allocate 94% of individuals. However, the best methods for sex estimation using the cranium generally will not achieve over 90% accuracy in predicting sex. Therefore, the authors conclude that postcranial elements should be used for sex estimation should the pelvis not be available for analysis (Spradley & Jantz, 2011).

Albanese *et al.* (2005) explored using universal methodology for developing a univariate sex estimation method. The methodology was based on the use of a sectioning point determined through calculating the mean of measurements collected from a sample of unknown individuals, and then the mean is used as a specific sectioning point to differentiate between males and females. The authors conducted experiments using various sample sizes and sex ratios with measurements of the distal humerus collected from the Coimbra Collection to test the accuracy of this procedure. The authors found in their experiment that this methodology could produce allocation accuracies between 83% and 96% when the sample size is greater than 40 individuals and the sex ratio is less than 1.5:1. Univariate measurements were used to emulate archaeological recovery scenarios. The methodology was further tested by the authors on different bones in order to assess whether the method was applicable to a number of different sexually dimorphic measurements, aside from the epicondylar breadth of the humerus. The data that were collected from the Lisbon Collection and Belleville, an archaeological sample, revealed that joint measurements of the long bones provide the highest allocation accuracies. Discriminant function analysis was used for the development of metric sex estimation methods. The overall mean for each subsample was used as the sectioning point. All individuals with a measurement greater than the sectioning point were classified as male, while all individuals whose measurements fell below the sectioning point were classified as female. Individuals with measurements equal to the sectioning point were classified as indeterminate. The total allocation accuracies for the method were between 57% and 100%, and in 92% of the scenarios, allocation accuracies were greater than 80% (Albanese *et al.*, 2005).

Although the methodology developed by Albanese *et al.* (2005) could potentially be used universally, it was also limited, because it requires the sample to include an evenly distributed amount of males and females. The unidentified sample cannot contain only males or only females; for example, the sample cannot be from a battlefield, which would contain mostly, if not all, men. Beyond that, the methodology relies heavily on there being enough variation between males and females to distinguish between the two sexes with a sectioning point. However, if there were semi-ambiguous males or particularly robust females included in the sample, this methodology would not be sufficient in differentiating between the sexes (Albanese *et al.,* 2005). Therefore, more universal methodologies for sex estimation are still needed that may not suffer from the same limitations incurred through the use of sectioning point. Additionally, the method cannot be used on only one individual, as it requires the mean of multiple individuals with approximately equivalent ratios of males and females in order to develop an accurate sectioning point.

A more recent method of determining sex (Anastasiou & Chamberlain, 2012) explored the possibility of using the sexual dimorphism of the sacro-iliac joint through geometric-morphometric techniques. Eight landmarks were recorded from 29 female and 35 male auricular surfaces of the ilium and sacrum. It was revealed that the auricular surface is sexually dimorphic, and that when using the auricular surface of the ilium, it was possible to classify 87.5% of individuals correctly. While using the auricular surface of the sacrum, it was possible to classify 84.4% of individuals correctly. When the auricular surface was employed in conjunction with the sacrum, the probability of correctly allocating individuals increased to 94.5%. The weakness of this methodology is that it lacks an in-field method for sex estimation, as it requires extensive analysis using a digital program (Anastasiou & Chamberlain, 2012).

Some of the previous research on sex estimation has explored the possibility of using the femur to estimate sex (Albanese *et al.,* 2008; Albanese, 2003; Brown *et al.,* 2007; Macho, 1990; Milner & Boldsen, 2012; Purkait, 2005) Dibennardo and Taylor (1983) used discriminant function analysis to develop functions for estimating sex and race using 15 out of 32 measurements collected from femora and innominates. The developed functions were able to correctly classify 95% of the study sample. The measurements used in the function for sex estimation reflected morphological aspects of size and shape, such as joint size, represented by the acetabular and epicondylar diameter of the femur, and shape elements manifested in the form of the greater sciatic notch and the inferomedial aspect of the pubic body (Dibennardo & Taylor, 1983).

Macho (1990) examined the patterns of sexual dimorphism in the femur among different populations. He asserted that even adjacent African tribes exhibit different degrees of sexual dimorphism. Compared to African populations, bicondylar width yielded a higher degree of differentiation in a European population. That author attributed the differences in sexual dimorphism to the variation in the biomechanical demands on the femur in different living conditions; however, there was not a great degree of variation in the femoral length, a surprising outcome considering that femoral length correlates with stature (Macho, 1990). Inadequate nutrition may result in males achieving a lower amount of growth potential than their female counterparts; therefore, sexual dimorphism also fluctuates with environmental factors (Stinson, 1985). As such, the author asserts that there is a need for population specific methods in sex estimation, at least in the case of the femur which is so closely correlated with stature and environmental factors (Macho, 1990).

Alunni-Perret *et al.* (2008) examined the use of the epicondylar breadth measurement of the femur in sex estimation for a contemporary French population. The sample size is fairly small, consisting of only 88 individuals from a donated collection at the Medical School of Nice. The authors confirmed that there is sexual dimorphism present in the bicondylar breadth of the femur, as the mean measurements for the males (84.3 mm) was larger than that of the females in the sample (74.8 mm). Through the use of discriminant function analyses, the authors achieved classification accuracies of 95.4%, and as such, the authors suggested that bicondylar breadth of the femur is the most accurate method of sex estimation in a contemporary French population and insisted that it is even better than the diameter of the femoral head for this population (Alunni-Perret *et al.*, 2008).

Purkait (2005) conducted a study of the proximal femur to estimate sex. Purkait (2005) collected two measurements of the femur, which, when employed together, yielded accuracy results of 86.1%. When using a single variable, the prediction accuracy for males was 85.5% and 81.3% for females. The author stated that one of the benefits of using the proximal end of the femur for sex estimation is that the method can be used on fragmented bone where the shaft or the distal end are missing. The study assumes that most males use muscles more heavily than females. Since the traction epiphysis is a site of muscle insertion, the area would be larger in males than in females if it is true that males use their muscles more heavily than females. Therefore, Purkait (2005) suggested using caution when attempting to estimate sex in an exceptionally active population. Beyond having lower allocation accuracies, the Purkait (2005) study was only tested on one population comprised of middle-class residents of central India. The method also relies heavily on how muscle usage affects the femur. The author recommended using caution when analyzing the sexual dimorphism of the femur in cases of exceptionally athletic or active people. The reliance on muscle usage as an indicator of sexual dimorphism is unreliable (Purkait, 2005).

Brown *et al.* (2007) tested the Purkait (2005) method on 200 Indo-European and African American individuals from the Terry Collection, using discriminant function analysis to determine the validity of the Purkait (2005) methodology. They also compared the usefulness of the triangle method to an assessment of sex through measurement of the maximum diameter of the femoral head. The authors concluded that a single variable from the Purkait (2005) triangle method provided an accuracy rate of 85.5%, while using the maximum head diameter provided an accuracy rate of 87% in the tested sample. When the two methods were used in combination, the allocation accuracy was raised to 90%. The study also evaluated population variability in association with the femur. The authors found that although the measurements overall were smaller than those from the Purkait (2005) study, the results were within one standard deviation and, as such, the biological meaning is ambiguous (Brown *et al.* 2007).

Albanese (2003) also explored the possibility of using the femur in combination with the os coxa to estimate sex. The study had multiple purposes, including testing the reproducibility of an alternative method to the traditional method using the os coxa, which the author claims results in high intra-observer error due to the ambiguity of the acetabular margin used in the measurement process. This study was also conducted to discover the best measurement of the pubis and use it combination with measurements of the os coxa and femur to develop a metric method for assessing the sex of an individual. Albanese (2003) created the metric method so that it could be applied to populations of various geographic origins and time periods. He collected standard and variant measurements of the os coxa and femur. One of the new measurements found to be particularly useful as a sex determinant was the superior pubic ramus length (Albanese, 2003).

The traditional approach of measuring the length of the pubis involves measuring from the superior margin of the pubic symphysis to the acetabular margin of the pubis, which is an ambiguous landmark. In juveniles, the acetabular margin of the pubic symphysis is readily visible, but after fusion of the ischium, ilium, and pubis, the area becomes difficult or impossible to locate (Albanese, 2003; Steward, 1979). Locating the acetabular margin involves using highly subjective methods such as searching for irregularities or notches in the acetabulum or holding the bone up to the light to recognize differences in bone thickness. Albanese (2003) collected several standard measurements of the os coxa and femur and created two new measurements including superior pubic ramus length and acetabular-ischium length. The results of the study conveyed that it is possible to achieve high allocation accuracies with populations derived from different geographical regions. Albanese (2003) claimed that an allocation accuracy of 98% can be achieved from a variety of samples from North America and Europe from the 19th and 20th centuries. He attributed this high allocation accuracy to a new measurement developed using the superior pubic ramus rather than the traditional pelvic length. Accuracy could also have been increased, because measurements from both the femur and the os coxa were used in analysis (Albanese, 2003).

Albanese *et al.* (2008) focused more specifically on the proximal femur and fragmentary os coxa and attempted to recreate a situation which might arise in archaeological and forensic contexts where it would be unlikely to find a bone in its entirety. To test their method on a large range of human variation, the authors comprised their sample of individuals from both the Terry and Grant collections. The authors collected standard measurements of the femur and developed three related variant measurements on the proximal femur. The three new measurements were taken from the sides of a triangle formed on the proximal end of the femur through three separate landmarks: the greater trochanter, fovea capitis, and the lesser trochanter. Because these new measurements form a triangle, it is possible to assess dimorphism in both size and angle of the neck. Using the Law of Cosines, the angles of the formed triangle could be calculated, since the lengths of the sides of the triangle were known. Logistic regression was then used by the authors to allocate individuals as either male or female. A combination of ratios and angles from the triangle located on the proximal femur were found to be consistent predictors of sex. The results of the study revealed high allocation accuracies of 95 to 97%. The authors acknowledged, however, that the study might not be applicable to populations that fall outside the standards of the population used to develop their method, specifically the Terry collection. Although it was not their original intention, the study resulted in a somewhat population-specific method (Albanese *et al.,* 2008).

Milner and Boldsen (2012) explored the possibility of using the humeral and femoral head diameters of White Americans to determine sex. The authors found that male humeral and femoral heads were generally larger than female humeral and femoral heads. It was also determined that the humerus yielded slightly more accurate results than the femoral head did in determining sex. The authors found that when the measurements were used in conjunction rather than independently, no further information was gained (Milner & Boldsen, 2012). Considering that the authors found the humerus yielded more accurate results than the femur in sex estimation, perhaps future research should focus on developing more sex estimation methods from the upper limb.

Studies have also been conducted using other postcranial elements, such as that by Franklin *et al.* (2012), who developed a method of estimating sex in a Western Australian population from MSCT scans (multislice spiral computed tomography) of the sternum. The authors evaluated the sternum using these MSCT scans for 187 individuals. A total of 8 inter-landmark linear measurements were collected and analyzed using descriptive statistics and discriminant function analyses. The authors found that all measurements were statistically significant and the cross-validated classification accuracies were between 72.2% and

84.5%. The measurements that were found to be better predictors of sex include the combined length of the manubrium and body, sternal body length, manubrium width, and corpus sterni width at the first sternebra. The authors concluded that the sternum is also a suitable element for sex estimation. However, the accuracies that this study achieved were not quite as significant or as high as other studies that have evaluated the use of the long bones from the upper limb and lower limb in sex estimation (Franklin *et al.,* 2012).

Frutos (2002) developed a metric method for determining sex utilizing the clavicle and scapula in a contemporary Guatemalan population. Measurements collected included the maximum length of the clavicle, the circumference at midshaft of the clavicle, and the height and width of the glenoid fossa of the scapula. Discriminant function analysis was performed on the collected data, which produced classification rates ranging from 29.4% to 54.9%. The author concluded that these measurements are useful for sex estimation and can be used for exhumation projects in Guatemalan indigenous populations (Frutos, 2002).

Sakaue (2003) developed a sex estimation method using long bones of both the lower limb and upper limb in a contemporary Japanese population. The author collected measurements from the humerus, radius, ulna, femur and tibia from a total of 64 individuals, which were analyzed using stepwise discriminant analysis. The variables that were found to be good discriminators in sex estimation included the width of the articular surface of the distal humerus, the sagittal diameter of the head of the radius, the articular breadth of the ulna, the bicondylar width of the femur, the transverse diameter of the lateral condyle of the femur, and the epiphyseal breadth of the tibia. Allocation accuracies for the method ranged between 91% and 95%. The author found that sexual dimorphism was greater among measurements that were representative of joints (Sakaue, 2003).

A number of studies have been conducted which explore the use of only the upper limb in sex estimation and have found it to be a particularly good discriminator of sex (Albanese, 2013; Charisi *et al.,* 2011; Cowal & Pastor, 2008; Frutos, 2004; Holman & Bennett, 1991; Kranioti & Michalodimitrakis, 2009; Mall *et al.*, 2001; Rogers, 2009; Vance *et al*., 2011). One of the earlier studies to examine the use of the upper limb was Holman and Bennett (1991), which used discriminant function analysis on five measurements of the arm and wrist, which included maximum lengths of the arm bones and two measurements representative of the width of the wrist. The authors selected 302 adult skeletons at random from the Terry Collection including 75 Black females, 75 Black males, 76 White females, and 76 White males. The authors found that the bistyloid breadth of the radius is the most sexually dimorphic of the five measurements that were collected. For individuals of White ancestry, the functions provided accuracy levels of 85% or better, while individuals of Black ancestry had accuracy levels of 80% or better (Holman & Bennett, 1991). Differentiations in accuracy levels between ancestries suggests that population specific methods are required for metric sex estimation.

The head of the radius was determined to be an effective indicator of sex by Berrizbeitia (1989). The author measured the maximum and minimum diameters of the radial head in 1108 radii from Black and White North Americans. Sectioning points were created for the measurements in order to classify individuals as either male or female. Allocation accuracy was 92% using the left radius and 94% using the right radius. When both radii were used in conjunction, the allocation accuracy raised to 96%. Berrizbeitia suggests that the analysis should be extended to other North American populations in order to assess its applicability as a more universal method (Berrizbeitia, 1989).

The sexual dimorphism of the humerus was examined by İşcan *et al.* (1998). The authors stated that the extent of variation among Asian populations had not been quantified through discriminant function analysis. The purpose of their study was to establish metric standards for sex estimation using the humerus in Chinese, Japanese, and Thai populations. Six standard measurements were collected from the humerus including the maximum length, vertical head diameter, minimum midshaft diameter, maximum midshaft diameter, midshaft circumference and epicondylar breadth. The variables selected by stepwise discriminant function analysis that were common to all three populations were the vertical head diameter and epicondylar breadth. The allocation accuracies were as high as 86.8% in a Chinese population, 92.4% in the Japanese population, and 97.1% in a Thai population. A comparison of the populations revealed that the Chinese were the least sexually dimorphic and the largest measurements. The Thai population was generally the smallest but also the most sexually dimorphic. The authors insisted that the classification accuracies decreased when the formula developed for one population was used on another. Although each of these populations is classified as Asian, it is clear that there are significant metric differences that affect sexual dimorphism across regions. Therefore, population specific measurements must be developed for sex estimation (İşcan *et al.*, 1998).

Following İşcan *et al.* (1998), Steyn and İşcan (1999) also developed a metric method for sex estimation using the humerus. Six measurements were collected from the humerus and analyzed using stepwise discriminant function analysis. The results indicated that the humeral head diameter and the epicondylar breadth were the best predictors of sex in a White population; however, in a Black population, the humeral head diameter and the maximum length were better discriminators. Allocation accuracies were as high as 96% in the White population and 95% in the Black population (Steyn & İşcan, 1999).

Mall *et al.* (2001) assessed the possibility of using the long bones of the arm to estimate sex, achieving higher accuracy rates than that of Holman and Bennett (1991). Three measurements each were taken for the humerus, radius, and ulna, and then discriminant analysis was applied to the measurements in order to evaluate the data. The authors found the vertical humeral head diameter to be the best predictor of sex, resulting in an allocation accuracy of 90.41%. When measurements of the radius were applied together, 94.93% of the individuals were classified correctly. The method, however, was tested on a relatively small amount of individuals (n = 143) (Mall *et al.,* 2001).

Frutos (2004), developed population-dependent standards for metric determination of sex using the humerus in a Guatemalan population. Measurements were collected from 118 humeri, including maximum length, maximum diameter of the head, circumference at midshaft, maximum diameter at midshaft, minimum diameter at midshaft, and epicondylar breadth. Discriminant function analysis was used to examine the measurements and determine which measurements are better discriminators of sex. Classification accuracies ranged from 76.8% to 95.5% for the univariate functions. The maximum diameter at midshaft was found to be the least useful in discriminating sex when compared with the other measurements collected from the humerus, while the best predictor was found to be the maximum diameter of the shaft. When multiple variables were applied in conjunction, the classification accuracy raised to 98.2% (Frutos, 2004).

Cowal and Pastor (2008), meanwhile, specifically explored the use of the proximal ulna as a possible indicator of sex. The authors developed a function and selected the notch length and olecranon width as the optimal measurements for estimating sex. With a function using the selected measurements, the authors achieved a classification accuracy of 85.4%. However, the authors suggested caution in using the developed methodology on populations other than Europeans (Cowal & Pastor, 2008). The bones of the forearm were also examined for sexual dimorphism in Barrier and L'Abbé (2008) using discriminant function analysis, specifically for a South African population. The sample was composed of 200 males and 200 females. Sixteen measurements were collected from the radius and ulna. The authors found that the best predictors of sex for the radius are the distal breadth, minimum midshaft diameter, and the maximum diameter of the head. The best discriminators of sex on the ulna were found to be the minimum midshaft diameter and the olecranon breadth. Classification accuracies ranged between 76% and 86%. Because the allocation accuracies using the forearm are not particularly high in a South African population, the authors suggest using additional sex estimation methods in conjunction with their developed method (Barrier & L'Abbé, 2008).

Given the success of the humerus in the sex discrimination of adult populations, Rogers (2009) evaluated the use of the humerus in determining the sex of adolescents. Juveniles are particularly difficult to sex, because most of the sexual dimorphism in the human skeleton develops at the time of puberty. Rogers (2009) investigated the possibility of using the carrying angle in the arm, the degree of lateral angulation allowed at the elbow, to indicate the sex of adolescents. Rogers (2009) used four landmarks on the distal humerus, including trochlear constriction, trochlear symmetry, olecranon fossa shape and depth, and the angle of the medial epicondyle. She then devised a scoring system for examining the morphological traits on the distal humerus determined by majority rule, and in the case of a draw (since there are four landmarks), the olecranon fossa was the deciding factor. The overall accuracy of this method was 81%, and it worked best in individuals under the age of fifteen (Rogers, 2009).

Kranioti and Michalodimitrakis (2009) used standard osteometric techniques to measure the humerus and examined sexual dimorphism specifically in an adult Cretan population. The authors collected measurements from 168 humeri. The humerus was found to be highly sexually dimorphic: when all measurements were applied in combination, about 92.3% of the individuals were allocated correctly. An accuracy rate of 92.9% was produced by applying discriminant stepwise analysis. The vertical head diameter of the humerus was revealed to have the greatest discriminatory power, allocating 89.9% of individuals correctly (Kranioti & Michalodimitrakis, 2009).

Similar to Kranioti and Michalodimitrakis (2009), Charisi *et al.* (2011) examined the use of a metric method for sex estimation using all the long bones of the arm in a modern skeletal population from Greece. Measurements were collected from 204 individuals, which included 111 males and 93 females with age ranges between 19 and 99 years of age. The authors collected maximum length measurements, along with epiphyseal widths, for the humerus, radius and ulna. The authors used discriminant function analysis to develop two functions for each bone, left and right. Wilks' lambda revealed that the discriminant functions had high discriminatory power, and as such, the bones were considered highly sexually dimorphic. The left ulna was the least sexually dimorphic and provided a classification accuracy of 90.3%. The right humerus had the greatest sexual dimorphism, and provided a classification accuracy of 95.7%. While the developed functions provided high allocation accuracies, all above 90%, the methodology is population-specific (Charisi *et al.*, 2011). Albanese (2013) suggested that discriminant functions developed using measurements of the arm bones and the clavicle may be applied across populations, and the potential of a methodology that is not population-specific should be explored.

Papaioannou *et al.* (2012) also developed a methodology for sex estimation in a contemporary Greek population, specifically from the island of Crete, using the scapula and clavicle. Those authors collected eight measurements from the scapula and six measurements from the clavicle using a sample size of 147 individuals, including 66 females and 81 males. Those authors applied both discriminant function analysis and principal component analysis to the data. The results indicate that there is pronounced sexual dimorphism in the bones, mainly attributed to size differences between the two groups. The glenoid cavity of the scapula exhibited the greatest degree of sexual dimorphism, which suggests that the humeral head should also be highly sexually dimorphic (Papaioannou *et al.*, 2012).

Departing from osteometric methods, Vance *et al.* (2011) investigated a visual assessment method of sex estimation using the distal humerus. Their study focused on three features of the posterior and distal humerus: olecranon fossa shape, angle of the medial epicondyle, and trochlear extension. When these characteristics were employed independently, they were not particularly useful in allocating an individual as either male or female. When the variables were employed together, there was a 74% allocation accuracy of males and 77% allocation accuracy of females (Vance *et al.,* 2011). It is clear, especially given the low accuracy rates of Vance *et al.* (2011) compared with recent metric assessments of sex (Albanese, 2013; Charisi *et al.,* 2011; Cowal & Pastor, 2008; Frutos, 2004; Kranioti & Michalodimitrakis, 2009; Mall *et al.*, 2001), that osteometrics of postcranial elements are more useful for sex estimation than visual assessments of sex (Adams & Byrd, 2002).

Ahmed (2013) assessed sexual dimorphism of the upper limb in a contemporary adult Sudanese population. However, instead of developing a sex estimation method that utilizes the bones of the upper limb, that author examined the sexual dimorphism of the upper limb with the soft tissue still intact. Measurements were collected from 240 right-handed Sudanese individuals aged between 25 and 30, which included the upper arm length, ulnar length, wrist breadth, hand length, and hand breadth. Classification rates for the study ranged between 78.5% and 88.5%. Ahmed (2013) found that the ulnar length had the greatest sexual dimorphism, while the least sexually dimorphic measurement was the upper arm length. The developed methodology is particularly useful for the recovery of limbs in medico-legal cases, especially when resources for DNA analysis are limited (Ahmed, 2013).

Tise *et al.* (2013) also examined the use of the clavicle in sex estimation. The authors claimed that when forensic anthropologists attempt to estimate sex in Hispanic populations without applying population-specific methods, males are often misclassified as females. The maximum length of the clavicle was found to be the best univariate indicator of sex, and with a sectioning point of 147 mm, the maximum length of the clavicle resulted in a classification rate of 87.29%. The radius, however, was found to be a better multivariate predictor of sex, with a cross-validated classification rate of 89.43%, using the stepwise selected variables radius maximum length and the radius anterior-posterior diameter at midshaft. The authors also examined the use of the humerus in sex estimation as a multivariate indicator of sex, which provided an overall classification rate of 88.96% using the stepwise selected variables of the humerus maximum length, humeral head diameter and the humerus maximum diameter at midshaft. The authors also ranked the bones based upon their accuracies as discriminators of sex for a given population, and found that the radius and humerus were more accurate for a Hispanic population, while the humerus and clavicle had higher accuracies for American Blacks, and the humerus and ulna provided higher accuracies for American Whites. The authors asserted that researchers must focus on developing population specific standards because the degrees of sexual dimorphism can vary among populations. However, the authors examined the use of the arm bones in sex estimation for three different populations (Hispanics, American Blacks, and American Whites) and found that the arm bones were useful for sex estimation, despite some being more useful in specific populations than others (Tise *et al.,* 2013).

Although many group-specific methods have been developed to estimate the sex of individuals, there are few methods that are considered universal and applicable to various populations. It is generally accepted that metric methods for sex estimation are population-specific and cannot be applied to different geographical and temporal groups, with the exception of the pubic bone (Albanese, 2003; Siegel *et al.,* 2000). Albanese (2013) developed a metric method for estimating sex using the clavicle, humerus, radius and ulna. Albanese (2013) indicated that this metric method could be applied to varied populations. He collected a combination of standard and developed measurements from the clavicle, humerus, radius and ulna, using the Terry, Coimbra, Grant, and Lisbon Collections, and then combinations of these variables were used to increase accuracy of sex estimates in various recovery scenarios. Using a forward stepwise likelihood ratio to select variables for each recovery scenario, and several variables were consistently significant predictors of sex. The useful standard measurements included maximum length of the clavicle, sagittal diameter of the humeral head, epicondylar breadth of the humerus, maximum length of the radius, maximum diameter of the radial head, diameter of the radius at midshaft. Albanese (2013) also found three significantly significant, alternative measurements including cranial-caudal diameter of the clavicle, anterior-posterior diameter of the ulna, and diameter of the ulna at the maximum crest pronouncement (Albanese, 2013).

Albanese developed a set of logistic regression equations from the different variables for each recovery scenario, using the various coefficients and sample sizes. His logistic regression equations provide a p-value, which allocate individuals as either male or female. If the p-value was greater than 0.5, then the individual would be designated as male, and if the p-value was less than 0.5, the individual would be designated as female. The value of p also provides the accuracy of the estimate. For example, if the value of p were 0.93, the individual would be classified as male and there would be a 93% chance that the individual is indeed male. Albanese (2013) found that using this methodology, depending on the various combinations of metrics, an allocation accuracy of greater than 90% could be attained when using at least three measurements from at least two of the bones. Albanese (2013) found that this methodology is accurate, except in cases of extremely small males, but even in those cases, the p-value will indicate that the likelihood of a correct allocation is low. He asserted that this methodology is particularly useful, because it accurately allocates individuals as either male or female and is not population-specific. It is for these reasons that the current study uses the methodology developed by Albanese (2013) and applies it to more modern population, specifically the William M. Bass skeletal collection, and attempts to validate the methodology (Albanese, 2013).

There has been significant research exploring different methodologies for estimating sex, yet there still remains a need for a thoroughly tested metric method for assessing sex that is not population-specific. Most of the previous research has focused on developing population-specific methods (Albanese, 2003; Charisi et al., 2011; Cowal & Pastor, 2008; İşcan, 2005; İşcan *et al.,* 1998; Kranioti & Michalodimitrikis, 2009; Macho, 1990; Purkait, 2005; Siegel *et al.,* 2000; Spradley *et al.,* 2008; Tise *et al.,* 2013), but as Albanese (2013) has demonstrated, future research using metric methods for the bones of the arm may produce sex estimation methods that are more universal. Past research has shown that the arm bones may be good indicators of sex, and generally have high allocation accuracies (Albanese, 2013; Charisi *et al.,* 2011; Cowal & Pastor, 2008; Frutos, 2004; Holman & Bennett, 1991; İşcan *et al.*, 1998; Kranioti & Michalodimitrakis, 2009; Mall *et al.*, 2001; Papaioannou *et al.* 2012; Rogers, 2009; Steyn & İşcan, 1999; Vance *et al*., 2011). Further research of the upper limb in metric sex estimation utilizing statistical methods such as discriminant function analysis and logistic regression may produce improved methods of sex estimation that are universally applicable (Albanese, 2013).

# CHAPTER 3: MATERIALS AND METHODS

## Measurements

The materials and methods are based on the methods outlined in Albanese (2013). A combination of standard measurements, set forth by Buikstra and Ubelaker (1994), and new measurements, developed by Albanese (2013) were collected from the clavicle, humerus, radius and ulna. A sample size of 400 individuals was used for the present study consisting of 202 females (198 American Whites and 4 American Blacks) and 198 males (174 American Whites and 24 American Blacks) from the William M. Bass Donated Skeletal Collection, housed in the Anthropology department of the University of Tennessee in Knoxville, Tennessee. Materials used in the collection of measurements included a standard osteometric board, a sliding caliper, and flexible measuring tape.

Measurements collected from the clavicle were the maximum clavicular length, the cranial-caudal diameter, the superior-inferior clavicular diameter at midshaft, and the anterior-posterior clavicular diameter at midshaft. The cranial-caudal diameter of the clavicle is an alternative measurement proposed by Albanese (2013) and is measured at the clavicular midshaft using the sliding caliper, with the flat surface of the scapular end held parallel to the arms of the caliper. The examiner should take the measurement with the arms of the sliding caliper perpendicular to the midshaft of the clavicle but also with flat surface of scapular end parallel to the arms of the caliper (Albanese, 2013). The other measurements collected from the clavicle are standard measurements described in detail by Buikstra and Ubelaker (1994). The maximum length of the clavicle was measured from the sternal end to the scapular end using an osteometric board. Similar to the cranial caudal diameter, the superior-inferior diameter at midshaft was collected using sliding caliper, measuring from the superior surface of the clavicle to the inferior surface at midshaft. The clavicle anterior-posterior diameter at midshaft measured the distance from the anterior to the posterior surface at midshaft using the sliding caliper (Buikstra & Ubelaker, 1994). The standard measurements for the clavicle are depicted in Figure 3.1. The variant measurement of the cranial-caudal diameter is essentially the same as the measurement labeled 37; however, the examiner needs to be certain that the flat portion of the bone, at the scapular end, is parallel to the caliper arms.

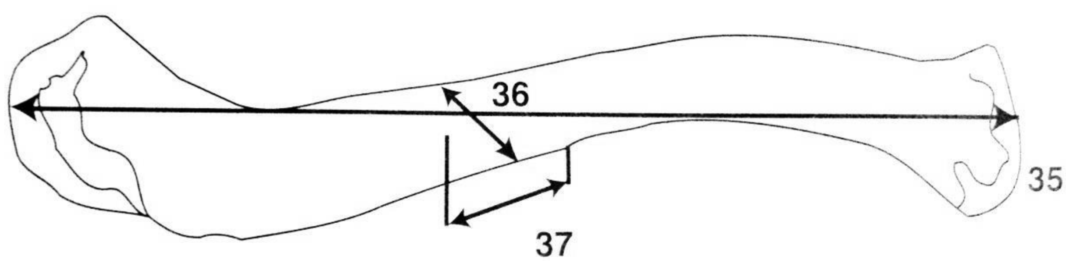


**Figure 3.1: Standard measurements of the clavicle (Buikstra & Ubelaker 1994: 79).**

Measurements collected from the humerus include the humeral maximum length, epicondylar breadth, vertical diameter of the head, maximum diameter at midshaft, and the minimum diameter at midshaft. No variant measurements of the humerus were proposed by Albanese (2013). The maximum length of the humerus measures the distance from the most superior point on the head of the humerus to the most inferior point on the trochlea of the humerus, measured with an osteometric board. The epicondylar breadth is measured with an osteometric board from the most lateral projection of the lateral epicondyle to the most medial projection of the medial epicondyle. The vertical diameter of the humeral head is measured with a sliding caliper from the most superior point on the humeral head to the most inferior point. Both the maximum and minimum diameter at midshaft is measured using a sliding caliper, however, the midpoint of the diaphysis must be determined using an osteometric board. The measurements of the humerus are depicted in Figure 3.2.

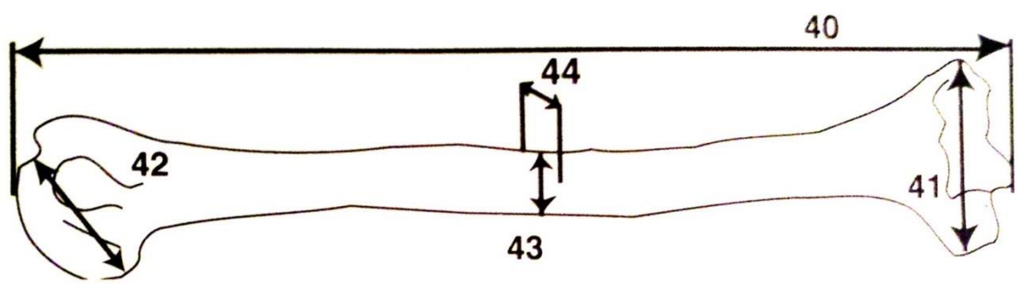


**Figure 3.2: Standard measurements of the humerus (Buikstra & Ubelaker 1994: 80).**

Measurements collected from the radius were the radial maximum length, anterior-posterior diameter at midshaft, medial-lateral diameter at midshaft, and the maximum diameter of the radial head. The maximum length of the radius is measured using an osteometric board from the most proximal point on the head of the radius to the most distal point on the styloid process. The anterior-posterior diameter at midshaft and the medial-lateral diameter at midshaft are measured with a sliding caliper, though an osteometric board should be used to determine the midpoint of the diaphysis. The maximum diameter of the radial head is an alternative measurement proposed by Albanese (2013) and is measured using the sliding calipers. The standard measurements are depicted in Figure 3.3.

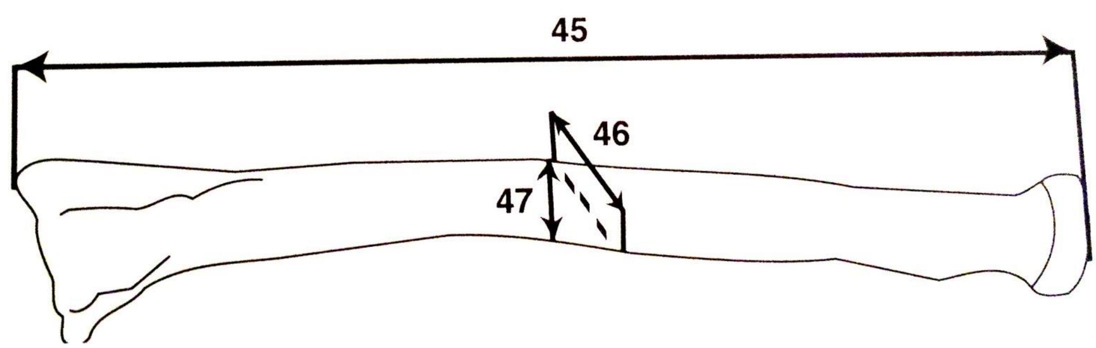


**Figure 3.3: Standard measurements of the radius (Buikstra & Ubelaker 1994: 80).**

A total of seven measurements were collected from the ulna including five standard measurements and two variant measurements developed by Albanese (2013). The collected measurements were the ulnar maximum length, ulnar dorso-volar diameter, physiological length, and the minimum circumference, anterior-posterior diameter, and the diameter at maximum crest pronouncement. The maximum length, measured with an osteometric board, is the distance from the most superior point on the olecranon process to the most inferior point on the styloid process.  The dorso-volar diameter is the maximum diameter measured with a sliding caliper at the greatest crest pronouncement in the anterior-posterior plane.  The medial lateral diameter is the distance between the medial and lateral surfaces at the greatest crest pronouncement, taken perpendicular to the dorso-volar diameter with a sliding caliper.  The physiological length is the distance between the most distal portion of the coronoid process to the distal portion of the ulna, excluding the styloid process.  The minimum circumference is measured at the distal portion of the diaphysis with a measuring tape.

The first variant measurement of the ulna proposed by Albanese (2013) is the maximum diameter at the maximum crest pronouncement, which is measured using a sliding caliper. This measurement is approximately in the medial-lateral plane, but the examiner should take the measurement wherever the diameter is at its greatest which may not be directly in the medial-lateral plane.  The anterior-posterior diameter of the ulna, which is an alternative measurement to the standard dorso-volar diameter, is measured perpendicular to the diameter of the maximum crest pronouncement with a sliding caliper.  Albanese (2013) asserts that the collecting the anterior-posterior diameter perpendicular to the maximum diameter at the maximum crest pronouncement results in a larger medial-lateral measurement and a smaller anterior-posterior measurement compared to the standard measurement.  A diagram of the standard measurements for the ulna are shown in Figure 3.4.

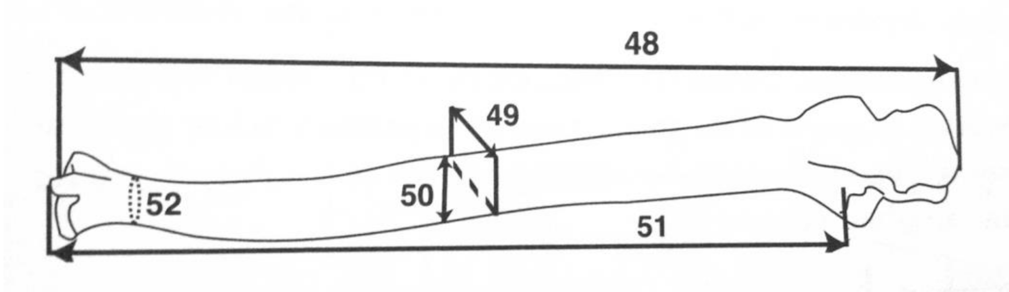


**Figure 3.4: Standard measurements of the ulna (Buikstra & Ubelaker 1994: 81).**

**Statistical Methodology**

In this study, two statistical tests were used to analyze the data: discriminant function analysis and logistic regression analysis. Binary logistic regression analyses were applied to the data using the IBM Statistical Package for Social Sciences (SPSS). Logistic regression provides a p-value that can be used to evaluate the data and allocate individuals as either male or female, along with providing a statement about the probability of that allocation being correct. For this study, a p-value less than 0.5 indicates that the individual is female, whereas a p-value of greater than 0.5 indicates that the individual is male.

The basic format of logistic equations is as follows:

$$P = 1 / (1 + e^{(-z)})$$

In this equation, p represents the probability of individual being male or not male, while (Z) is a linear combination of variables multiplied by a standard coefficient (Albanese, 2013). For the purpose of the present study, all of the data were run together with a binary logistic regression model through SPSS, following which, binary logistic regression was also applied to each of the bones separately to better reflect various recovery scenarios. Logistic regression analyses were also repeated using only the standard measurements of bones, since these are the measurements that would be most understood and utilized the most by forensic anthropologists. Furthermore, Albanese (2013) provided a series of logistic regression equations using various combinations of measurements from all of the bones. These combinations of measurements were repeated in the current study with the new set of data from the William M. Bass Donated Skeletal Collection, and logistic regression analyses were reapplied to these combinations of measurements to produce new equations with more modern data. The current data were also inserted into the logistic regression equations developed by Albanese (2013) to test the validity of those set of equations against the equations produced by the current study.

Discriminant function analyses were also applied to the data in order to develop functions and to determine which variables, or measurements, were better predictors of sex for the data. Although Albanese (2013) did not use discriminant function analyses because of the assumption that the data are normally distributed, it was used in the present study because it shows more clearly which elements have more sexual dimorphism and achieves similar accuracies to logistic regression analyses. Discriminant function analyses produce a set of functions from the data with weighted coefficients for each variable used in the equation. The basic format of the discriminant analysis linear equation is as follows:

$$D = v_1X_1 + v_2X_2 + v_3X_3 \ldots\ldots v_iX_i + a$$

In the above equation, (D) is the discriminant function, (v) is the coefficient of the independent variable, (X) is the examiner's score for that particular variable, (a) is a constant, and (i) is the number of predictor (or independent) variables used in the creation of the function. Good predictors of a particular outcome tend to have larger coefficients. The purpose of this function is to maximize the distance between the categories in order to give the function a stronger discriminatory power. After creating the functions with the existing data set, the functions can then be used to classify new cases (Burns & Burns, 2008). In the present study, the data collected from the William M. Bass Donated Skeletal Collection was used in the creation of a new set of discriminant functions. As with the logistic regression analyses performed, discriminant functions were developed for situations in which all the bones and measurements were present, and also developed for each bone separately. The discriminant analyses were also employed to develop equations using only the standard measurements of the bones, since these are the measurements that are most familiar to forensic anthropologists, and it has been shown that using variant measurements can result in higher inter- and intraobserver error (Adams & Byrd, 2002).

The drawback of using discriminant analyses is that it makes a number of assumptions including that each predictor variable is normally distributed, that all of the allocations of the dependent variable in the original data are correctly classified, there are at least two categories and each category is mutually exclusive, all of the data can be categorized, the categories must be defined before collecting data, the predictive variables should discriminate quite clearly between the groups to ensure that there is little to no overlap, and sample sizes for each category should not be grossly different (Burns & Burns, 2008). Although there are various assumptions that are made by discriminant analyses, it is useful in cases where these assumptions can be met, such as in the current study. Discriminant function analyses have been shown to be effective and useful in the development of sex estimation methodologies (Albanese *et al*. 2005; Alunni-Perret *et al*., 2008; Dibennardo & Taylor, 1983; Franklin *et al*., 2012; Giles & Elliot, 1963; İşcan, 2005; Moore, 2012; Ogawa *et al*., 2013; Walker, 2008).

Stepwise discriminant function analyses were also employed in the study. Stepwise discriminant function analysis essentially attempts to create ideal combinations of measurements for prediction equations by highlighting the better predictive variables, while eliminating the less effective variables. For the purposes of this study, stepwise discriminant function analyses were applied to the various combinations of measurements to produce more robust equations for estimating the sex of individuals.

All sets of equations that were developed for the study have the coefficients provided in various tables in the results section. These sets of coefficients can be placed into their respective equations, whether it be logistic regression, or discriminant function analysis. The examiner should take caution not to mix the coefficients from various equations, as each coefficient is specific to its developed equation. Furthermore, if a specific equation is to be utilized for sex estimation, none of the variables provided by the equation can be excluded from the computation.

To quantify any intra-observer error, the first 30 individuals were measured twice following the data collection, and then paired t-tests were applied to the measurements in order to assess if there was a significant difference between the original measurements and the recollected measurements.

# CHAPTER 4: RESULTS

## Discriminant Function Analysis

Discriminant function analyses were utilized to provide allocation accuracies, along with highlighting which measurements, or independent variables, were most sexually dimorphic. The means and standard deviations of all the measurements collected are provided in Table 4.1 and 4.2 for male and females, respectively. In forensic and archaeological contexts, all four bones might not be recovered; therefore, the measurements of each bone were also analyzed separately to produce discriminant functions for each bone. One of the equations produced for each bone includes only standard measurements, while a second equation includes the variant measurements suggested by Albanese (2013).

A series of discriminant functions were developed using various combinations of the collected measurements. The basic format of the discriminant function is as follows:

$$D = v_1X_1 + v_2X_2 + v_3X_3 \ldots\ldots v_iX_i + a$$

In the discriminant function equation, (D) is the discriminant function, (v) is the coefficient, or weight, of the independent variable, (X) is the examiner's score for that particular variable, (a) is a constant, and (i) is the number of predictor (or independent) variables used in the creation of the function.

**Table 4.1: Means and standard deviation for all male collected measurements**.

| Measurement | Mean | Std. Deviation |
|---|---:|---:|
| Clavicle Maximum Length | 156.688 | 10.364 |
| Clavicle Anterior-Posterior Diameter | 13.538 | 7.161 |
| Clavicle Superior-Inferior Diameter | 11.050 | 1.556 |
| Clavicle Cranial-Caudal Diameter | 11.568 | 1.499 |
| Humerus Maximum Length | 333.357 | 17.859 |
| Humerus Epicondylar Breadth | 63.829 | 3.829 |
| Humerus Vertical Diameter of Head | 49.211 | 2.492 |
| Humerus Maximum Diameter Midshaft | 23.055 | 1.983 |
| Humerus Minimum Diameter Midshaft | 19.035 | 1.759 |
| Radius Maximum Length | 251.990 | 25.375 |
| Radius Anterior-Posterior Diameter | 12.789 | 1.157 |
| Radius Medial-Lateral Diameter | 16.352 | 1.601 |
| Radius Maximum Diameter Head | 24.221 | 1.404 |
| Ulna Maximum Length | 271.402 | 19.980 |
| Ulna Physiological Length | 237.312 | 25.686 |
| Ulna Dorso-Volar Diameter | 15.101 | 1.697 |
| Ulna Medial-Lateral Diameter | 17.131 | 1.495 |
| Ulna Maximum Crest Pronouncement | 18.030 | 1.735 |
| Ulna Anterior-Posterior Diameter | 13.809 | 1.383 |
| Ulna Minimum Circumference | 38.312 | 3.168 |

**Table 4.2: Means and standard deviations for all female collected measurements.**

| Measurement | Mean | Std. Deviation |
|---|---|---|
| Clavicle Maximum Length | 140.309 | 7.435 |
| Clavicle Anterior-Posterior Diameter | 10.836 | 1.280 |
| Clavicle Superior-Inferior Diameter | 9.219 | 1.238 |
| Clavicle Cranial-Caudal Diameter | 9.612 | 1.208 |
| Humerus Maximum Length | 303.721 | 17.629 |
| Humerus Epicondylar Breadth | 54.901 | 2.956 |
| Humerus Vertical Diameter of Head | 42.617 | 2.275 |
| Humerus Maximum Diameter Midshaft | 20.806 | 12.890 |
| Humerus Minimum Diameter Midshaft | 15.597 | 1.511 |
| Radius Maximum Length | 225.756 | 12.211 |
| Radius Anterior-Posterior Diameter | 10.498 | 0.861 |
| Radius Medial-Lateral Diameter | 13.776 | 1.423 |
| Radius Maximum Diameter Head | 20.428 | 1.219 |
| Ulna Maximum Length | 242.463 | 12.409 |
| Ulna Physiological Length | 212.672 | 17.890 |
| Ulna Dorso-Volar Diameter | 12.254 | 1.400 |
| Ulna Medial-Lateral Diameter | 14.358 | 1.253 |
| Ulna Maximum Crest Pronouncement | 15.050 | 1.492 |
| Ulna Anterior-Posterior Diameter | 10.915 | 1.019 |
| Ulna Minimum Circumference | 32.453 | 2.619 |

The canonical discriminant function coefficients provided by the discriminant analyses are used as the weighted coefficients for the developed equation following the above format. The product, (D), is then compared to a sectioning point, which is developed from the group centroids provided by the discriminant analysis. The sectioning points are different for each equation, but if (D) is greater than the provided sectioning point, then the individual is classified as male, and if (D) is below the sectioning point, then the individual is classified as female. For a particular case, the examiner can enter his/her measurements into one of the functions that have been developed. The examiner must be sure to include only measurements used to develop the equation while also not leaving any of measurements out, or the equation will not work properly. For instance, if the equation was developed using all measurements of the humerus, then all the same measurements must be collected by the examiner for new estimations. The coefficients for each of the developed equations, along with the constant of the function, are provided in Tables 4.6 - 4.14. Each table represents a different discriminant function, in which the provided coefficients for each variable are multiplied by the examiner's measurement for that particular variable, and the provided constant is added to classify an individual as male or female.

The allocation accuracies provided by the developed discriminant functions are provided in Table 4.3. The highest allocation accuracy of 96.5% was achieved when all the measurements were applied in conjunction. However, when only the standard measurements of each bone were used, the overall classification rate was 95.5%, and the same amount of males (95.0%) was correctly classified as when all the measurements were used.

**Table 4.3: Allocation accuracies of the developed discriminant function equations.**

| | Correct Male Classifications | Correct Female Classifications | Correct Overall Classifications |
|---|---|---|---|
| **All Measurements** | 95.0% | 98.0% | 96.5% |
| **Standard Measurements** | 95.0% | 96.0% | 95.5% |
| **All Clavicle Measurements** | 88.9% | 89.1% | 89.0% |
| **Clavicle Standard Measurements** | 86.9% | 89.1% | 88.0% |
| **Humerus Measurements** | 95.0% | 97.0% | 96.0% |
| **All Radius Measurements** | 93.1% | 96.0% | 95.5% |
| **Radius Standard Measurements** | 87.9% | 92.5% | 90.2% |
| **Ulna All Measurements** | 90.5% | 95.5% | 93.0% |
| **Ulna Standard Measurements** | 87.9% | 94.5% | 91.2% |

When discriminant function analyses were applied to each of the bones individually, the classification accuracies were lower than when the bones were employed in conjunction. The least effective predictor of sex proved to be the clavicle, with an overall allocation accuracy of 89.0%; while the most effective predictor of sex was the humerus, with an overall classification rate of 96.0%. In the cases where only the standard measurements of the bone were used to develop the equation, the classification accuracies tended to be lower than when all measurements were employed. However, with the exception of the clavicle, which had the lowest classification accuracy of 88%, all of the equations achieved allocation accuracies of greater than 90%.

The canonical correlation values produced by the discriminant function analyses are reported in Table 4.4 for each of the developed equations. The canonical correlation value is a reflection of the variance between males and females which can be explained by the model that is produced. In order to calculate the effect size of the predictor variables, or the percentage of variance explained by the model, the examiner must square the canonical correlation value. For example, the canonical correlation value that was produced from the discriminant analysis of measurements from the clavicle was 0.754. The canonical correlation value is squared and becomes 0.5685, which suggest that the model explains 56.85% of the variation between males and females. The Wilk's lambda value indicates the amount of variance that remains unexplained by the developed model. For instance, in the case of the clavicle, the Wilk's lambda value is 0.439, indicating that 43.9% of the variation is unexplained by the model produced from measurements of the clavicle. These values are also included in Table 4.4.

**Table 4.4: Canonical correlation values and the Wilk's lambda values produced for each model.**

| | Canonical Correlation | Percentage of Model Explained | Wilk's Lambda |
|---|---|---|---|
| **All Measurements** | 0.889 | 79.03% | 0.209 |
| **Standard Measurements** | 0.874 | 76.39% | 0.236 |
| **All Clavicle Measurements** | 0.754 | 56.85% | 0.432 |
| **Clavicle Standard Measurements** | 0.749 | 56.10% | 0.439 |
| **Humerus Measurements** | 0.855 | 73.10% | 0.269 |
| **All Radius Measurements** | 0.839 | 70.39% | 0.296 |
| **Radius Standard Measurements** | 0.787 | 61.94% | 0.380 |
| **Ulna All Measurements** | 0.834 | 69.56% | 0.305 |
| **Ulna Standard Measurements** | 0.810 | 65.61% | 0.343 |

Discriminant function analysis also provides a structure matrix for each equation, which indicates the variables that are the most effective and the least effective discriminators for each case. Table 4.5 shows the structure matrix that was produced when all the measurements were analyzed in conjunction.  Although the values indicating the absolute size of each variable's correlation with the function might vary depending on the function that is produced, the relative rank of a specific variable's effectiveness does not change.  The structure matrix reveals that the most effective predictor of sex is the maximum diameter of the radial head, which is a variant measurement that was suggested by Albanese (2013).  Following the maximum diameter of the radial head, the best discriminators of sex are the vertical diameter of the humeral head and the epicondylar breadth of the humerus.  The best discriminating variable from the ulna was the variant anterior-posterior diameter measurement suggested by Albanese (2013).  The most effective predictor variable from the clavicle, the maximum length of the clavicle, is one of the least effective predictors of sex overall.  The least effective discriminating variable of all the measurements is the maximum diameter at midshaft of the humerus.  The least effective predictor of sex for the radius was the maximum length, while the least effective predictor variable for the ulna is the physiological length.

The equations that were developed for each case are described in Tables 4.6 through 4.14.  These tables include the variable constants that should be applied to each measurement, along with a constant that should be added in place of the variable a from the discriminant function equation.  The sectioning points, calculated from the group centroids, are also provided for each equation.

**Table 4.5: The structure matrix when all the variables are run together. Variables are ordered by absolute size of correlation with the function. Variant measurements suggested by Albanese (2013) are marked with an (*).**

| Variable | Function |
|---|---|
| Radius Max Head Diameter* | 0.744 |
| Humerus Head Vertical Diameter | 0.714 |
| Humerus Epicondylar Breadth | 0.673 |
| Ulna Anterior Posterior Diameter* | 0.614 |
| Radius Anterior Posterior Diameter | 0.579 |
| Humerus Min Diameter Midshaft | 0.540 |
| Ulna Min Circumference | 0.520 |
| Ulna Transverse Diameter | 0.518 |
| Ulna Max Crest Pronouncement* | 0.475 |
| Ulna Dorso-Volar Diameter | 0.472 |
| Clavicle Max Length | 0.468 |
| Ulna Max Length | 0.449 |
| Radius Medial Lateral Diameter | 0.438 |
| Humerus Max Length | 0.430 |
| Clavicle Cranial Caudal Diameter* | 0.370 |
| Radius Max Length | 0.340 |
| Clavicle Superior Inferior Diameter | 0.336 |
| Ulna Physiological Length | 0.287 |
| Clavicle Anterior Posterior Diameter | 0.136 |
| Humerus Max Diameter Midshaft | 0.063 |

**Table 4.6: Weighted coefficients of the discriminant equation when all measurements are present for every bone.**

| Predictor Variable | Coefficient |
|---|---|
| Clavicle Maximum Length | 0.022 |
| Clavicle Anterior-Posterior Diameter | 0.008 |
| Clavicle Superior-Inferior Diameter | 0.169 |
| Clavicle Cranial-Caudal Diameter | -0.089 |
| Humerus Maximum Length | -0.007 |
| Humerus Epicondylar Breadth | 0.052 |
| Humerus Vertical Diameter of Head | 0.149 |
| Humerus Maximum Diameter Midshaft | -0.003 |
| Humerus Minimum Diameter Midshaft | -0.014 |
| Radius Maximum Length | -0.005 |
| Radius Anterior-Posterior Diameter | 0.041 |
| Radius Medial-Lateral Diameter | -0.072 |
| Radius Maximum Diameter Head | 0.259 |
| Ulna Maximum Length | 0.012 |
| Ulna Physiological Length | 0.004 |
| Ulna Dorso-Volar Diameter | -0.022 |
| Ulna Medial-Lateral Diameter | 0.051 |
| Ulna Maximum Crest Pronouncement | -0.049 |
| Ulna Anterior-Posterior Diameter | 0.280 |
| Ulna Minimum Circumference | 0.041 |
| **Constant** | -23.988 |
| **Sectioning Point** | 0.01 |

**Table 4.7: Weighted coefficients of the discriminant function produced when all standard measurements are present for every bone (Buikstra & Ubelaker 1994).**

| Predictor Variable | Coefficient |
|---|---|
| Clavicle Maximum Length | 0.024 |
| Clavicle Anterior-Posterior Diameter | 0.006 |
| Clavicle Superior-Inferior Diameter | 0.087 |
| Humerus Maximum Length | -0.006 |
| Humerus Epicondylar Breadth | 0.083 |
| Humerus Vertical Diameter of Head | 0.188 |
| Humerus Maximum Diameter Midshaft | -0.003 |
| Humerus Minimum Diameter Midshaft | 0.046 |
| Radius Maximum Length | -0.006 |
| Radius Anterior-Posterior Diameter | 0.129 |
| Radius Medial-Lateral Diameter | -0.055 |
| Ulna Maximum Length | 0.014 |
| Ulna Physiological Length | 0.006 |
| Ulna Dorso-Volar Diameter | 0.061 |
| Ulna Medial-Lateral Diameter | 0.055 |
| Ulna Minimum Circumference | 0.032 |
| **Constant** | -23.939 |
| **Sectioning Point** | 0.007 |

**Table 4.8: Weighted coefficients of the discriminant function for all measurements of the clavicle.**

| Predictor Variable | Coefficient |
|---|---|
| Clavicle Maximum Length | 0.084 |
| Clavicle Anterior-Posterior Diameter | 0.035 |
| Clavicle Superior-Inferior Diameter | 0.118 |
| Clavicle Cranial-Caudal Diameter | 0.307 |
| **Constant** | -17.371 |
| **Sectioning Point** | 0.006 |

**Table 4.9: Weighted coefficients of the discriminant function for only standard measurements of the clavicle (Buikstra & Ubelaker 1994).**

| Predictor Variable | Coefficient |
|---|---|
| Clavicle Maximum Length | 0.087 |
| Clavicle Anterior-Posterior Diameter | 0.041 |
| Clavicle Superior-Inferior Diameter | 0.392 |
| **Constant** | -17.388 |
| **Sectioning Point** | 0.0055 |

**Table 4.10: Weighted coefficients of the discriminant equation for all measurements of the humerus.**

| Predictor Variable | Coefficient |
|---|---|
| Humerus Maximum Length | 0.009 |
| Humerus Epicondylar Breadth | 0.112 |
| Humerus Vertical Diameter of Head | 0.215 |
| Humerus Maximum Diameter Midshaft | -0.002 |
| Humerus Minimum Diameter Midshaft | 0.182 |
| **Constant** | -22.311 |
| **Sectioning Point** | 0.0085 |

**Table 4.11: Weighted coefficients of the discriminant function for all measurements of the radius.**

| Predictor Variable | Coefficient |
|---|---|
| Radius Maximum Length | 0.009 |
| Radius Anterior-Posterior Diameter | 0.380 |
| Radius Medial-Lateral Diameter | 0.051 |
| Radius Maximum Diameter Head | 0.524 |
| **Constant** | -19.055 |
| **Sectioning Point** | 0.008 |

**Table 4.12: Weighted coefficients of the discriminant function for only standard measurements of the radius (Buikstra & Ubelaker 1994).**

| Predictor Variable | Coefficient |
|---|---|
| Radius Maximum Length | 0.020 |
| Radius Anterior-Posterior Diameter | 0.638 |
| Radius Medial-Lateral Diameter | 0.215 |
| **Constant** | -15.512 |
| **Sectioning Point** | 0.02 |

**Table 4.13: Weighted coefficients of the discriminant function for all measurements of the ulna.**

| Predictor Variable | Coefficient |
|---|---|
| Ulna Maximum Length | 0.022 |
| Ulna Physiological Length | 0.006 |
| Ulna Dorso-Volar Diameter | -0.026 |
| Ulna Medial-Lateral Diameter | 0.147 |
| Ulna Maximum Crest Pronouncement | 0.013 |
| Ulna Anterior-Posterior Diameter | 0.434 |
| Ulna Minimum Circumference | 0.103 |
| **Constant** | -18.168 |
| **Sectioning Point** | 0.015 |

**Table 4.14: Weighted coefficients of the discriminant function only standard measurements of the ulna (Buikstra & Ubelaker 1994).**

| Predictor Variable | Coefficient |
| --- | --- |
| Ulna Maximum Length | 0.023 |
| Ulna Physiological Length | 0.008 |
| Ulna Dorso-Volar Diameter | 0.149 |
| Ulna Medial-Lateral Diameter | 0.237 |
| Ulna Minimum Circumference | 0.138 |
| **Constant** | -18.409 |
| **Sectioning Point** | 0.0065 |

### Stepwise Discriminant Function Analysis

Stepwise discriminant function analysis was also applied to the collected measurements, which produces a function by eliminating the superfluous variables and by including only variables that contribute most significantly to the model. The allocation accuracies for the equations created through discriminant function analysis are reported in Table 4.15. The highest overall classification accuracy was 96.8%, when all the measurements were employed together. All measurements had an overall allocation accuracy of greater than 89.0%. The bone that produced the highest allocation accuracy was the humerus, while the clavicle proved to be the least effective discriminator of all the bones.

**Table 4.15: Allocation accuracies of the developed discriminant function equations produced through stepwise discriminant function analysis.**

| | Correct Male Classifications | Correct Female Classifications | Correct Overall Classifications |
|---|---|---|---|
| **All Measurements** | 96.0% | 97.5% | 96.8% |
| **Standard Measurements** | 95.5% | 96.5% | 96.0% |
| **All Clavicle Measurements** | 88.9% | 89.6% | 89.3% |
| **Humerus Measurements** | 95.0% | 97.0% | 96.0% |
| **All Radius Measurements** | 93.5% | 96.0% | 94.8% |
| **Ulna All Measurements** | 90.5% | 95.0% | 92.8% |

The canonical correlation values and the Wilk's lambda values for each equation produced using stepwise discriminant function analysis are reported in Table 4.16. Each of the values was close to the original values produced through regular discriminant function analysis, generally showing only 1-2% decrease from the values of the original equations. The coefficients, constants, and sectioning points for the developed stepwise equations are reported in Tables 4.17 - 4.22.

**Table 4.16: Canonical correlation values and the Wilk's lambda values produced for each stepwise model.**

| | Canonical Correlation | Percentage of Model Explained | Wilk's Lambda |
|---|---|---|---|
| **All Measurements** | 0.884 | 78.15% | 0.218 |
| **Standard Measurements** | 0.870 | 75.69% | 0.244 |
| **All Clavicle Measurements** | 0.753 | 56.70% | 0.433 |
| **Humerus Measurements** | 0.855 | 73.10% | 0.269 |
| **All Radius Measurements** | 0.850 | 72.25% | 0.277 |
| **Ulna All Measurements** | 0.832 | 69.22% | 0.307 |

**Table 4.17: Weighted coefficients of the stepwise discriminant function for all measurements of all bones.**

| Predictor Variable | Coefficient |
|---|---|
| Clavicle Maximum Length | 0.024 |
| Clavicle Superior-Inferior Diameter | 0.100 |
| Humerus Epicondylar Breadth | 0.055 |
| Humerus Vertical Diameter of Head | 0.142 |
| Radius Maximum Diameter Head | 0.245 |
| Ulna Anterior-Posterior Diameter | 0.292 |
| **Constant** | -23.449 |
| **Sectioning Point** | 0.0095 |

**Table 4.18: Weighted coefficients of the stepwise discriminant function for only standard measurements of all bones (Buikstra & Ubelaker 1994).**

| Predictor Variable | Coefficient |
|---|---|
| Clavicle Maximum Length | 0.022 |
| Clavicle Superior-Inferior Diameter | 0.102 |
| Humerus Epicondylar Breadth | 0.091 |
| Humerus Vertical Diameter of Head | 0.180 |
| Radius Anterior-Posterior Diameter | 0.196 |
| Ulna Maximum Length | 0.009 |
| Ulna Dorso-Volar Diameter | 0.086 |
| **Constant** | -23.855 |
| **Sectioning Point** | 0.0085 |

**Table 4.19: Weighted coefficients of the stepwise discriminant function for all measurements of the clavicle.**

| Predictor Variable | Coefficient |
|---|---|
| Clavicle Maximum Length | 0.084 |
| Clavicle Anterior-Posterior Diameter | 0.033 |
| Clavicle Cranial-Caudal Diameter | 0.419 |
| **Constant** | -17.308 |
| **Sectioning Point** | 0.006 |

**Table 4.20: Weighted coefficients of the stepwise discriminant function for all measurements of the humerus.**

| Predictor Variable | Coefficient |
|---|---|
| Humerus Maximum Length | 0.009 |
| Humerus Epicondylar Breadth | 0.111 |
| Humerus Vertical Diameter of Head | 0.214 |
| Humerus Minimum Diameter Midshaft | 0.182 |
| **Constant** | -22.322 |
| **Sectioning Point** | 0.0085 |

**Table 4.21: Weighted coefficients of the stepwise discriminant function for all measurements of the radius.**

| Predictor Variable | Coefficient |
|---|---|
| Radius Max Length | 0.009 |
| Radius Anterior-Posterior Diameter | 0.415 |
| Radius Maximum Diameter Head | 0.538 |
| **Constant** | -18.923 |
| **Sectioning Point** | 0.008 |

**Table 4.22: Weighted coefficients of the stepwise discriminant function for all measurements of the ulna.**

| Predictor Variable | Coefficient |
|---|---|
| Ulna Maximum Length | 0.026 |
| Ulna Medial-Lateral Diameter | 0.154 |
| Ulna Anterior-Posterior Diameter* | 0.429 |
| Ulna Minimum Circumference | 0.099 |
| **Constant** | -17.845 |
| **Sectioning Point** | 0.0075 |

### Binary Logistic Regression Analysis

Similar to the discriminant function analyses that were performed, Binary logistic regression analyses were also applied to each of the bones in conjunction, and then to all of the bones individually. The basic format of the logistic equation is:

$$P = 1 / (1+e^{-z})$$

Where (P) is the probability of a particular outcome, and (z) is the linear set of coefficients multiplied by their observed measurement with the addition of some constant. In the equation, if p is less than 0.5, then the individual is female, and if it is above 0.5, then the individual is male.

The classification rates produced from the developed binary logistic regression equations are reported in Table 4.23. When all the measurements were employed in conjunction, the classification accuracy was 100.0%. When only the standard measurements were used, the overall classification accuracy decreased to 98.3%. Unlike with the discriminant function analyses, the lowest allocation accuracy of 89.5% was associated with the equation developed using only the standard measurements of the radius.

**Table 4.23: Allocation accuracies of the developed binary logistic regression equations.**

| | Correct Male Classifications | Correct Female Classifications | Correct Overall Classifications |
|---|---|---|---|
| **All Measurements** | 100.0% | 100.0% | 100.0% |
| **Standard Measurements** | 98.0% | 98.5% | 98.3% |
| **All Clavicle Measurements** | 90.5% | 92.5% | 91.5% |
| **Clavicle Standard Measurements** | 89.9% | 92.5% | 91.3% |
| **Humerus Measurements** | 96.5% | 96.0% | 96.3% |
| **All Radius Measurements** | 95.5% | 93.5% | 94.5% |
| **Radius Standard Measurements** | 88.9% | 90.0% | 89.5% |
| **Ulna All Measurements** | 94.0% | 94.0% | 94.0% |
| **Ulna Standard Measurements** | 91.0% | 93.0% | 92.0% |

However, the equations developed using measurements of the clavicle were greater than 91.0% using the binary logistic regression. The humerus was the best individual indicator of sex, achieving an allocation accuracy of 96.3%. Each of the bones produced high allocation accuracies of 89.5% or greater, and the female allocation accuracies are all greater than 90.0%.

**Table 4.24: Nagelkerke R square values for produced logistic regression equations**.

| | Nagelkerke R Square Value | % Correlation between Variables and Outcome |
|---|---|---|
| **All Measurements** | 1.000 | 100.0% |
| **Standard Measurements** | 0.965 | 96.5% |
| **All Clavicle Measurements** | 0.800 | 80.0% |
| **Clavicle Standard Measurements** | 0.798 | 79.8% |
| **Humerus Measurements** | 0.911 | 91.1% |
| **All Radius Measurements** | 0.911 | 91.1% |
| **Radius Standard Measurements** | 0.799 | 79.9% |
| **Ulna All Measurements** | 0.888 | 88.8% |
| **Ulna Standard Measurements** | 0.839 | 83.9% |

The Nagelkerke R square values for each equation are reported in 4.24. These values reflect the correlation between the independent variables and the predictive outcome. The higher the Nagelkerke R square value, the stronger the relationship is between the predictive outcome and the independent variables.

Each of constants and variable coefficients of the binary equations are reported in the following Tables 4.25 - 4.33. The variable coefficients are multiplied by the examiner's measurements, added together, along with the added constant, and then input for z in the basic logistic regression equation. If the output, P, of the logistic equation is greater than 0.5, then the individual is male, of if it is less than 0.5, then the individual is female. Furthermore, the output, P, also provides the actual probability of that particular outcome being correct. For example, if P comes out to be 0.95, then the individual is classified as male, and there is a 95.0% chance that the provided allocation is actually correct. If P equals 0.15, then the unknown individual is classified as female, and there is an 85.0% chance of that particular classification being correct.

**Table 4.25: Weighted coefficients of the logistic regression equation for all measurements for all bones.**

| Predictor Variable | Coefficient |
|---|---|
| Clavicle Maximum Length | 22.681 |
| Clavicle Anterior-Posterior Diameter | 110.408 |
| Clavicle Superior-Inferior Diameter | 451.886 |
| Clavicle Cranial-Caudal Diameter | -363.631 |
| Humerus Maximum Length | -9.752 |
| Humerus Epicondylar Breadth | 9.551 |
| Humerus Vertical Diameter of Head | 6.905 |
| Humerus Maximum Diameter Midshaft | -73.084 |
| Humerus Minimum Diameter Midshaft | -21.841 |
| Radius Maximum Length | 3.908 |
| Radius Anterior-Posterior Diameter | 176.094 |
| Radius Medial-Lateral Diameter | 96.312 |
| Radius Maximum Diameter Head | 355.292 |
| Ulna Maximum Length | 1.731 |
| Ulna Physiological Length | 6.901 |
| Ulna Dorso-Volar Diameter | 127.635 |
| Ulna Medial-Lateral Diameter | 213.277 |
| Ulna Maximum Crest Pronouncement* | -177.758 |
| Ulna Anterior-Posterior Diameter* | -87.735 |
| Ulna Minimum Circumference | 41.202 |
| **Constant** | -17988.154 |

**Table 4.26: Weighted coefficients of the logistic regression equation for only standard measurements of all bones (Buikstra & Ubelaker 1994).**

| Predictor Variable | Coefficient |
|---|---|
| Clavicle Maximum Length | 0.209 |
| Clavicle Anterior-Posterior Diameter | 0.571 |
| Clavicle Superior-Inferior Diameter | 0.455 |
| Humerus Maximum Length | -0.036 |
| Humerus Epicondylar Breadth | 1.069 |
| Humerus Vertical Diameter of Head | 0.529 |
| Humerus Maximum Diameter Midshaft | -1.030 |
| Humerus Minimum Diameter Midshaft | -0.805 |
| Radius Maximum Length | -0.008 |
| Radius Anterior-Posterior Diameter | 1.336 |
| Radius Medial-Lateral Diameter | 0.309 |
| Ulna Maximum Length | -0.019 |
| Ulna Physiological Length | 0.072 |
| Ulna Dorso-Volar Diameter | 1.000 |
| Ulna Medial-Lateral Diameter | 0.648 |
| Ulna Minimum Circumference | 1.469 |
| **Constant** | -153.115 |

**Table 4.27: Weighted coefficients of the logistic regression equation for all measurements of the clavicle.**

| Predictor Variable | Coefficient |
|---|---|
| Clavicle Maximum Length | 0.192 |
| Clavicle Anterior-Posterior Diameter | 0.841 |
| Clavicle Superior-Inferior Diameter | 0.350 |
| Clavicle Cranial-Caudal Diameter | 0.426 |
| **Constant** | -46.466 |

**Table 4.28: Weighted coefficients of the logistic regression equation for only standard measurements of the clavicle (Buikstra & Ubelaker 1994).**

| Predictor Variable | Coefficient |
|---|---|
| Clavicle Maximum Length | 0.194 |
| Clavicle Anterior-Posterior Diameter | 0.885 |
| Clavicle Superior-Inferior Diameter | 0.703 |
| **Constant** | -46.278 |

**Table 4.29: Weighted coefficients of the logistic regression equation for all measurements of the humerus.**

| Predictor Variable | Coefficient |
|---|---|
| Humerus Maximum Length | 0.028 |
| Humerus Epicondylar Breadth | 0.584 |
| Humerus Vertical Diameter of Head | 0.556 |
| Humerus Maximum Diameter Midshaft | -0.054 |
| Humerus Minimum Diameter Midshaft | 0.652 |
| **Constant** | -78.786 |

**Table 4.30: Weighted coefficients of the logistic regression equation for all measurements of the radius.**

| Predictor Variable | Coefficient |
|---|---|
| Radius Maximum Length | 0.019 |
| Radius Anterior-Posterior Diameter | 1.462 |
| Radius Medial-Lateral Diameter | 0.417 |
| Radius Maximum Diameter Head | 2.043 |
| **Constant** | -72.993 |

**Table 4.31: Weighted coefficients of the logistic regression equation for only standard measurements of the radius (Buikstra & Ubelaker 1994).**

| Predictor Variable | Coefficient |
|---|---|
| Radius Maximum Length | 0.050 |
| Radius Anterior-Posterior Diameter | 1.650 |
| Radius Medial-Lateral Diameter | 0.592 |
| **Constant** | -39.867 |

**Table 4.32: Weighted coefficients of the logistic regression equation for all measurements of the ulna.**

| Predictor Variable | Coefficient |
|---|---|
| Ulna Maximum Length | 0.058 |
| Ulna Physiological Length | 0.037 |
| Ulna Dorso-Volar Diameter | -0.153 |
| Ulna Medial-Lateral Diameter | 0.177 |
| Ulna Maximum Crest Pronouncement | 0.485 |
| Ulna Anterior-Posterior Diameter | 1.610 |
| Ulna Minimum Circumference | 0.385 |
| **Constant** | -64.935 |

**Table 4.33: Weighted coefficients of the logistic regression equation for only standard measurements of the ulna (Buikstra & Ubelaker 1994).**

| Predictor Variable | Coefficient |
|---|---|
| Ulna Maximum Length | 0.055 |
| Ulna Physiological Length | 0.029 |
| Ulna Dorso-Volar Diameter | 0.452 |
| Ulna Medial-Lateral Diameter | 0.740 |
| Ulna Minimum Circumference | 0.413 |
| **Constant** | -52.842 |

## Logistic Equations Developed by Albanese (2013)

In the present study, logistic equations were developed for each bone, one equation using only standard measurements, as defined by Buikstra and Ubelaker (1994), and one equation with the inclusion of the more variant measurements proposed by Albanese (2013). The purpose of developing separate equations for each bone was to mimic various recovery scenarios, in which only one of the bones might be available for analysis. However, Albanese (2013) produced a set of fifteen different equations that use combinations of variables from multiple bones in conjunction. Therefore, logistic regression analyses were also run on the various combinations of bones suggested by Albanese (2013) to compare the classification accuracies of Albanese (2013) to the classification accuracies produced by the equations developed using the newly collected data, which are reported in Table 4.34. All combinations of measurements used in the following fifteen equations were proposed by Albanese (2013), and the original coefficients developed by Albanese (2013) are provided, along with the newly reproduced coefficients in Tables 4.35 - 4.49. Each of the equations are numbered the same as they were in the Albanese (2013) study. All of the allocation accuracies are higher in the present study than they were for the Albanese (2013) study.

**Table 4.34: Allocation accuracies provided by the Albanese (2013) developed equations and the allocation accuracies produced by the present study for the combination of variables suggest by Albanese (2013).**

| | Classification Accuracy Albanese (2013) | Classification Accuracy Present Study |
|---|---|---|
| **Equation 1** | 92.3% | 96.8% |
| **Equation 2** | 93.0% | 97.3% |
| **Equation 3** | 90.6% | 96.3% |
| **Equation 4** | 92.5% | 97.0% |
| **Equation 5** | 94.2% | 97.8% |
| **Equation 6** | 92.4% | 96.0% |
| **Equation 7** | 91.9% | 95.5% |
| **Equation 8** | 90.7% | 95.8% |
| **Equation 9** | 90.9% | 92.3% |
| **Equation 10** | 89.2% | 94.8.% |
| **Equation 11** | 90.6% | 95.8% |
| **Equation 12** | 91.4% | 96.0% |
| **Equation 13** | 90.7% | 95.8% |
| **Equation 14** | 90.0% | 95.3% |
| **Equation 15** | 91.8% | 96.5% |

**Table 4.35: Coefficients of logistic regression equations developed by Albanese (2013), and reproduced coefficients of the present study (Equation 1).**

| Predictive Variables | Albanese (2013) Coefficients | Reproduced Coefficients |
|---|---|---|
| Clavicle Max Length | 0.042 | 0.119 |
| Clavicle Cranial-Caudal | 0.595 | 0.330 |
| Humerus Head Diameter | 0.346 | 0.503 |
| Humerus Epicondylar Br. | 0.193 | 0.703 |
| Ulna Anterior-Posterior | 0.825 | 1.425 |
| **Constant** | -48.806 | -103.145 |

**Table 4.36: Coefficients of logistic regression equations developed by Albanese (2013), and reproduced coefficients of the present study (Equation 2).**

| Predictive Variables | Albanese (2013) Coefficients | Reproduced Coefficients |
|---|---|---|
| Clavicle Max Length | 0.051 | 0.083 |
| Clavicle Cranial-Caudal | 0.684 | 1.011 |
| Humerus Head Diameter | 0.315 | 0.384 |
| Humerus Epicondylar Br. | 0.282 | 0.562 |
| Radius Head Diameter | 0.363 | 1.645 |
| **Constant** | -52.753 | -110.595 |

**Table 4.37: Coefficients of logistic regression equations developed by Albanese (2013), and reproduced coefficients of the present study (Equation 3).**

| Predictive Variables | Albanese (2013) Coefficients | Reproduced Coefficients |
|---|---|---|
| Clavicle Max Length | 0.066 | 0.108 |
| Clavicle Cranial-Caudal | 0.689 | 0.885 |
| Humerus Head Diameter | 0.414 | 0.571 |
| Humerus Epicondylar Br. | 0.262 | 0.787 |
| **Constant** | -49.855 | -97.911 |

**Table 4.38: Coefficients of logistic regression equations developed by Albanese (2013), and reproduced coefficients of the present study (Equation 4).**

| Predictive Variables | Albanese (2013) Coefficients | Reproduced Coefficients |
|---|---|---|
| Humerus Head Diameter | 0.294 | 0.472 |
| Humerus Epicondylar Br. | 0.273 | 0.510 |
| Ulna Anterior-Posterior | 1.162 | 1.440 |
| Radius Head Diameter | 0.300 | 1.204 |
| **Constant** | -50.367 | -96.324 |

**Table 4.39: Coefficients of logistic regression equations developed by Albanese (2013), and reproduced coefficients of the present study (Equation 5).**

| Predictive Variables | Albanese (2013) Coefficients | Reproduced Coefficients |
|---|---|---|
| Clavicle Cranial-Caudal | 0.551 | 0.633 |
| Humerus Head Diameter | 0.267 | 0.392 |
| Humerus Epicondylar Br. | 0.262 | 0.500 |
| Ulna Anterior-Posterior | 1.153 | 1.064 |
| Radius Head Diameter | 0.294 | 1.455 |
| **Constant** | -53.830 | -99.853 |

**Table 4.40: Coefficients of logistic regression equations developed by Albanese (2013), and reproduced coefficients of the present study (Equation 6).**

| Predictive Variables | Albanese (2013) Coefficients | Reproduced Coefficients |
|---|---|---|
| Clavicle Max Length | 0.109 | 0.071 |
| Clavicle Cranial-Caudal | 0.613 | 0.759 |
| Ulna Anterior-Posterior | 1.040 | 1.152 |
| Ulna Max Crest Diameter | 0.524 | -0.011 |
| Radius Max Length | -0.062 | 0.013 |
| Radius Head Diameter | 0.863 | 2.035 |
| **Constant** | -48.207 | -80.656 |

**Table 4.41: Coefficients of logistic regression equations developed by Albanese (2013), and reproduced coefficients of the present study (Equation 7).**

| Predictive Variables | Albanese (2013) Coefficients | Reproduced Coefficients |
|---|---|---|
| Ulna Anterior-Posterior | 1.180 | 1.388 |
| Ulna Max Crest Diameter | 0.487 | 0.208 |
| Radius Head Diameter | 0.830 | 2.034 |
| **Constant** | -41.309 | -65.594 |

**Table 4.42: Coefficients of logistic regression equations developed by Albanese (2013), and reproduced coefficients of the present study (Equation 8).**

| Predictive Variables | Albanese (2013) Coefficients | Reproduced Coefficients |
|---|---|---|
| Clavicle Max Length | 0.126 | 0.038 |
| Clavicle Cranial-Caudal | 0.637 | 0.978 |
| Radius Max Length | -0.059 | 0.014 |
| Radius Anterior-Posterior | 1.083 | 1.424 |
| Radius Head Diameter | 0.958 | 2.241 |
| **Constant** | -44.338 | -85.420 |

**Table 4.43: Coefficients of logistic regression equations developed by Albanese (2013), and reproduced coefficients of the present study (Equation 9).**

| Predictive Variables | Albanese (2013) Coefficients | Reproduced Coefficients |
|---|---|---|
| Clavicle Max Length | 0.098 | 0.120 |
| Clavicle Cranial-Caudal | 0.618 | 0.599 |
| Ulna Anterior-Posterior | 0.889 | 1.429 |
| Ulna Max Crest Diameter | 0.468 | 0.527 |
| **Constant** | -39.164 | -49.983 |

**Table 4.44: Coefficients of logistic regression equations developed by Albanese (2013), and reproduced coefficients of the present study (Equation 10).**

| Predictive Variables | Albanese (2013) Coefficients | Reproduced Coefficients |
|---|---|---|
| Humerus Head Diameter | 0.409 | 0.597 |
| Humerus Epicondylar Br. | 0.290 | 0.567 |
| Radius Anterior-Posterior | 0.802 | 1.335 |
| **Constant** | -43.852 | -76.307 |

**Table 4.45: Coefficients of logistic regression equations developed by Albanese (2013), and reproduced coefficients of the present study (Equation 11).**

| Predictive Variables | Albanese (2013) Coefficients | Reproduced Coefficients |
|---|---|---|
| Humerus Head Diameter | 0.363 | 0.670 |
| Humerus Epicondylar Br. | 0.272 | 0.591 |
| Ulna Anterior-Posterior | 0.943 | 1.554 |
| **Constant** | -43.508 | -84.670 |

**Table 4.46: Coefficients of logistic regression equations developed by Albanese (2013), and reproduced coefficients of the present study (Equation 12).**

| Predictive Variables | Albanese (2013) Coefficients | Reproduced Coefficients |
|---|---|---|
| Clavicle Cranial-Caudal | 0.582 | 0.326 |
| Humerus Head Diameter | 0.361 | 0.627 |
| Humerus Epicondylar Br. | 0.230 | 0.595 |
| Ulna Anterior-Posterior | 0.911 | 1.347 |
| **Constant** | -46.413 | -83.874 |

**Table 4.47: Coefficients of logistic regression equations developed by Albanese (2013), and reproduced coefficients of the present study (Equation 13).**

| Predictive Variables | Albanese (2013) Coefficients | Reproduced Coefficients |
|---|---|---|
| Clavicle Cranial-Caudal | 0.676 | 0.781 |
| Humerus Head Diameter | 0.459 | 0.697 |
| Humerus Epicondylar Br. | 0.328 | 0.697 |
| **Constant** | -45.865 | -81.328 |

**Table 4.48: Coefficients of logistic regression equations developed by Albanese (2013), and reproduced coefficients of the present study (Equation 14).**

| Predictive Variables | Albanese (2013) Coefficients | Reproduced Coefficients |
|---|---|---|
| Clavicle Cranial-Caudal | 0.565 | 0.647 |
| Humerus Head Diameter | 0.396 | 0.562 |
| Humerus Epicondylar Br. | 0.267 | 0.613 |
| Radius Anterior-Posterior | 0.655 | 1.124 |
| **Constant** | -45.936 | -81.711 |

**Table 4.49: Coefficients of logistic regression equations developed by Albanese (2013), and reproduced coefficients of the present study (Equation 15).**

| Predictive Variables | Albanese (2013) Coefficients | Reproduced Coefficients |
|---|---|---|
| Clavicle Max Length | 0.055 | 0.085 |
| Clavicle Cranial-Caudal | 0.585 | 0.782 |
| Humerus Head Diameter | 0.370 | 0.472 |
| Humerus Epicondylar Br. | 0.220 | 0.748 |
| Radius Anterior-Posterior | 0.579 | 0.837 |
| **Constant** | -49.399 | -96.025 |

In order to test the accuracy of equations, 10% of the sample in the present study were chosen at random to input into both the equations developed by Albanese (2013) and the equations that were reproduced in the present study. Classification accuracies were calculated from the sample of individuals that were input into each equation, and are reported in Table 4.50. All of the classification accuracies were high for both sets of equations, but the reproduced equations had better allocation accuracies overall. Also the individual probabilities produced by each equation tended to be better for the reproduced equations.

**Table 4.50: Classification accuracies calculated from 10% of the sample.**

| | Accuracy of Albanese (2013) Equations | Accuracy of Reproduced Equations |
|---|---|---|
| **Equation 1** | 100.0% | 100.0% |
| **Equation 2** | 100.0% | 100.0% |
| **Equation 3** | 96.25% | 100.0% |
| **Equation 4** | 98.75% | 100.0% |
| **Equation 5** | 100.0% | 100.0% |
| **Equation 6** | 97.5% | 100.0% |
| **Equation 7** | 97.5% | 100.0% |
| **Equation 8** | 100.0% | 100.0% |
| **Equation 9** | 97.5% | 97.5% |
| **Equation 10** | 95.0% | 100.0% |
| **Equation 11** | 100.0% | 100.0% |
| **Equation 12** | 95.0% | 97.5% |
| **Equation 13** | 95.0% | 97.5% |
| **Equation 14** | 95.0% | 100.0% |
| **Equation 15** | 97.5% | 100.0% |

## Intra-observer Error

For a set of 30 individuals, chosen at random, all of the measurements were recollected twice in order to calculate the intra-observer error rates. The intra-observer error was calculated by performing a paired sample t-test from the first measurement and the last measurement that was taken. The calculated p-values from the t-tests of each measurement are reported in Table 4.51. Almost all of the p-values were insignificant, meaning that there was no significant intra-observer error. However, the cranial-caudal diameter, the radius maximum length, and radius medial-lateral diameter did have p-values less than 0.05, meaning that there was significant intra-observer error for those three measurements. In examining the data points themselves, there was never more than a 3 mm difference between the first and last measurement, and the majority of measurements had only a 1 mm difference, if not the same exact measurement. The significant p-values may be a reflection of the small sample size individuals selected for the recollection of measurements.

**Table 4.51: The p-values provided by the T-Tests performed for each measurement. Variant measurements proposed by Albanese (2013) are marked by an (*).**

| Measurement | P-Value of T-Test |
|---|---|
| Clavicle Maximum Length | 0.0504 |
| Clavicle Anterior Posterior Diameter | 0.1100 |
| Clavicle Superior-Inferior Diameter | 0.2842 |
| Clavicle Cranial-Caudal Diameter* | 0.0314 |
| Humerus Maximum Length | 0.3237 |
| Humerus Epicondylar Breadth | 0.4654 |
| Humerus Head Vertical Diameter | 1.0000 |
| Humerus Maximum Diameter Midshaft | 0.0620 |
| Humerus Minimum Diameter Midshaft | 0.6043 |
| Radius Maximum Length | 0.0014 |
| Radius Anterior Posterior Diameter | 0.7868 |
| Radius Medial-Lateral Diameter | 0.0314 |
| Radius Head Maximum Diameter* | 0.0563 |
| Ulna Maximum Length | 0.7216 |
| Ulna Physiological Length | 0.3311 |
| Ulna Dorso-Volar Diameter | 0.2966 |
| Ulna Transverse Diameter | 0.1340 |
| Ulna Maximum Crest Pronouncement* | 0.1841 |
| Ulna Anterior Posterior Diameter* | 0.0620 |
| Ulna Minimum Circumference | 0.5725 |

# CHAPTER 5: DISCUSSION

Allocation accuracies proved to be particularly high when more measurements were employed in conjunction, especially with the inclusion of some of the variant measurements proposed by Albanese (2013), such as the maximum diameter of the radial head. The logistic regression equation (Table 4.32) that utilized all the collected measurements, in particular, was able to correctly classify 100.00% of individuals in the sample used to develop the equation. Further research might be conducted by collecting all measurements, including variant measurements, from a different ancestral population in order evaluate if the logistic regression equation developed is equally as effective when applied to a different population.

Considering the vast amount of research citing the variation of human remains over geographical regions (Albanese, 2003; Charisi et al., 2011; Cowal & Pastor, 2008; İşcan, 2005; İşcan *et al.,* 1998; Kranioti & Michalodimitrikis, 2009; Macho, 1990; Purkait, 2005; Siegel *et al.,* 2000; Spradley *et al.,* 2008; Tise *et al.,* 2013), it would be expected that the allocation accuracy would decrease when the specific equation is applied to a different ancestral population. However, the present study suggests that perhaps a universal methodology of sex estimation can be developed, or that it may, at least, be possible to apply one equation to multiple populations if it cannot be used completely universally. In the present study, measurements were collected from two different ancestral populations, American Blacks and Whites. The equations developed from the measurements provided by both of these populations were able to accurately estimate sex in individuals, despite their ancestry. Albanese (2013) insists that with these suggested standard and variant measurements of the upper limb, examiners can accurately estimate sex universally, though further testing will be required to state that definitively.

Albanese (2013) tested the developed equations from data collected from two different collections (the Terry Collection and the Coimbra Collection), in order to include a large range of human variation within the study. The equations were then tested on data collected from the Grant and Lisbon collections, through which he was able to achieve allocation accuracies greater than 90% with the developed equations. The present study aimed to examine the use of this methodology on a more modern population, and the study was validated using the William M. Bass Donated Skeletal Collection, in Knoxville, Tennessee. The combinations of measurements that were proposed by Albanese (2013) for their higher allocation accuracies were reevaluated in the present study using data collected from the William M. Bass collection. Logistic regression analyses, as used in the original study, were reapplied to the combinations of measurements in order to develop a new set of equations for a more modern population. The redeveloped logistic regression equations (Table 4.35 - Table 4.49) generally achieved higher allocation accuracies overall than the allocation accuracies reported by Albanese (2013). These classification accuracies are reported in Table 4.34. The accuracy of each of the equations was tested in using 10% of the sample collected from the William M. Bass collection. The classification accuracies developed from this sample are reported in Table 4.50, which also reveals that the reproduced equations have higher allocation accuracies overall. The reason for these greater allocation accuracies in the present study may simply be that there were varying degrees of sexual dimorphism between the samples that were used by Albanese (2013) and the present study. In other words, if the William M. Bass Donated Skeletal Collection includes individuals who exhibit greater sexual dimorphism than the individuals included in the Terry and Coimbra collections, then we can expect that individuals from the sample could be classified more easily in the present study. Additionally, if there was a wider range of variation between populations included in the measurements used by Albanese (2013) to develop the equations, it may result in more difficulty allocating an individual to a particular group if each group is based on the same set of coefficients. It should also be noted, that when the equations were tested using data collected from the William M. Bass, the reproduced equations were developed from that same set of data, increasing the likelihood that the equations produced by the present study will allocate the individuals more accurately than the equations produced by Albanese (2013).

Unfortunately, no online database could be used to test the set of equations reported by Albanese (2013), because of his inclusion of variant measurements in the equations. Since online databases generally included only the standard measurements, the data from such sources cannot be utilized for the equations developed by Albanese (2013). It is for this reason that the present study has produced equations that include only standard measurements in addition to the equations with variant measurements. Furthermore, some of the developed equations target individual bones, for scenarios in which only one bone is available for analysis.

The redeveloped equations, given their higher allocation accuracies for modern American populations, might be more useful for forensic contexts than the equations developed by Albanese (2013). However, their usefulness depends entirely on the recovery scenario. While these combinations of measurements, proposed by Albanese (2013), provide high allocation accuracies, they are also limited, because these equations require recovery of more than one bone from the upper limb. As such, new equations were developed in the present study in order to accommodate examiners by providing sex estimation equations requiring only one bone of the upper limb to be available for analysis. It is also possible that if more than one bone were recovered, more than one equation could be employed to ensure that the provided classification is also supported by the other elements present. The present study, however, requires that all the measurements of a particular bone are collected for the developed equations to work, which is a limitation if a particular recovery scenario involves highly fragmented bones. Further research endeavors might include examining the possibility of developing logistic regression equations or discriminant functions that would be useful in the recovery of fragmentary bones.

Specific equations were also developed which excluded the variant measurements proposed by Albanese (2013). It has been shown that inter- and intra-observer error may increase in cases where unfamiliar measurements are used (Adams & Byrd, 2002). Therefore, an equation was developed for each bone which utilized only the standard measurements for the bone. While generally, the allocation accuracies decreased after the exclusion of certain useful variant measurements, such as the maximum diameter of the radial head, all of the logistic regression equations developed from standard measurements produced overall classification accuracies greater than 89.5%.

For the measurements alone, the means and standard deviations are listed in Tables 4.1 and 4.2 for each sex. The standard deviations were generally higher for the male measurements, which suggests that there is perhaps more variation in the size and shape of male bones than there is in female bones. Overall, the allocation accuracies produced by both the discriminant functions and the logistic regression equations were generally higher in females than they were in males. Thus, there appears to be a general trend that females, at least from the Bass Collection, are more easily classified than males. However, this may be attributed to the fact that there are relatively fewer females in the William M. Bass Donated Skeletal Collection who are not of American White ancestry. The limited availability of the American Black females in the William M. Bass skeletal collection is an impediment for the present study, which may explain why the allocation accuracies were higher for females than males. Considering that the sample size of American Black females included in the present study is so small (n = 8), and that the majority of the data comes from American White female individuals, the female equations have mostly been developed from one population. However, the American Black male sample size is larger (n = 24), and therefore would contribute to the development of the sex estimation equations to a greater extent. As such, the equations were developed from two different ancestral male populations, and to a large extent, only one female population. This speculation reasserts the fact that there is variation in human remains between populations, yet the allocation accuracies are still high, greater than 90%, in most cases, for the equations developed from two different populations. Therefore, the assumption that researchers need to create population-specific methods of sex estimation (Macho, 1990; İşcan *et al.,* 1998; Siegel *et al.,* 2000; Albanese, 2003; İşcan, 2005; Purkait, 2005; Cowal & Pastor, 2008; Spradley *et al.,* 2008; Kranioti & Michalodimitrikis, 2009; Charisi et al., 2011; Tise *et al.,* 2013) may not necessarily be true. Considering the fact that the present study and Albanese (2013) developed the metric equations of the upper limb to include a range of human variation, it may be that this methodology can in fact be used universally. However, this theory needs further testing on less sexually dimorphic populations, such as those with Asian-derived ancestry.

Aside from producing effective discriminant functions for sex estimation, the discriminant function analyses also revealed which bones and measurements were the most effective predictors of sex. The humerus consistently proved to be the most accurate individual bone in sex estimation. Discriminant function analysis of the humerus provided a classification rate of 95.0% for males and 97.0% for females, and a stepwise discriminant function analysis produced similar results. The logistic regression equation for the humerus correctly classified 96.5% of males and 96.0% of females, and provided an overall classification rate of 96.3%. Furthermore, when discriminant function analysis was applied to all measurements that were collected for every bone of the upper limb, it was revealed that the vertical diameter of the humeral head and the humeral epicondylar breadth were among the most effective discriminators of sex. However, the least effective discriminator of sex was found to be the maximum diameter of the humerus at midshaft. These results suggest that the humerus is perhaps the most sexually dimorphic bone of the upper limb. Spradley and Jantz (2011) also stated that there is significant sexual dimorphism in the humerus, particularly in an American Black population.

The most effective discriminator of sex in the upper limb following the humerus is the radius, which when all measurements were employed jointly, produced an allocation accuracy of 93.1% for males and 96.0% for females, and an overall allocation accuracy of 94.5%. When only standard measurements of the radius were employed, allocation accuracies dropped to 87.9% for males and

92.5% for females, with an overall classification rate of 90.2%. The decrease in classification rates of the radius is explained by the exclusion of the variant maximum diameter of the radial head measurement, which was actually the most sexually dimorphic of all the measurements. While Spradley and Jantz (2011) found the maximum length to be an effective univariate indicator of sex, the maximum length in the present study proved not to be as effective a predictor as the other variables in the equations (Table 4.5). In fact, when only the standard measurements of the radius were employed, the maximum length of the radius proved to be the least effective discriminator of sex, which means that it is also the least sexually dimorphic of all the measurements. The maximum length of the radius was also one of the few measurements that showed significant intra-observer error ($p=0.0014$). Although the largest difference between the retaken measurements was 3 mm, and only in one case, the intra-observer error is significant and may have contributed to it being a less effective predictor of sex. The logistic regression analysis of the radius produced an overall allocation accuracy of 94.5% including all measurements, and an overall allocation accuracy of 89.5% when only standard measurements were employed. Classification accuracies produced through logistic regression analysis also indicated that the radius was the next best indicator of sex from the upper limb, following the humerus, suggesting that the radius is more sexually dimorphic than the ulna and clavicle, but less sexually dimorphic than the humerus.

The classification rates produced by the ulna indicate that the ulna is more sexually dimorphic and a more effective discriminator of sex than the clavicle. Discriminant function analyses of all measurements of the ulna produced classification accuracies 90.5% for the males and 95.5% for females. When only standard measurements were used classification accuracies decreased to 87.9% for the males and 94.5% for females. The decrease is, of course, due to the fact that the variant anterior-posterior diameter measurement was found to be an effective discriminator of sex, but it was excluded from the analyses run on the standard measurements of the ulna. Logistic regression analysis of all measurements of the ulna produced an overall allocation accuracy of 94.0%, which was reduced to 92.0% with the exclusion of the variant measurements.

The clavicle was the least effective discriminator of sex of all the bones in the upper limb. When discriminant function analysis was employed using all measurements of the clavicle, 88.9% of the males and 89.1% of the females were classified correctly. Meanwhile, when employing only standard measurements of the clavicle, the allocation accuracy of the males reduced to 86.9% and the allocation accuracy of females was 89.1%. Stepwise analyses of the clavicle indicated that the least effective measurement was the superior-inferior diameter. Logistic regression analysis, employing all measurements of the clavicle, produced an overall classification rate of 91.5%. With the exclusion of variant measurements, logistic regression analysis produced an overall classification rate of 91.3%. Because there was not a significant difference between the two developed logistic equations in terms of accuracy, the variant measurement of the cranial-caudal diameter does not have a significant impact on the development of the equations.

Interestingly, the measurements that were highlighted as the most effective predictors of sex, through discriminant function analysis utilizing all the measurements, were measurements that reflect joint size, such as the maximum diameter of the radial head, the vertical diameter of the humeral head, and the epicondylar breadth of the humerus. Spradley and Jantz (2011) also suggest that measurements of joint surfaces of the femur, tibia and humerus were among the most sexually dimorphic measurements in American Black and White populations. The use of joint size and shape as an effective indicator of sex is also supported by other studies examining the use of postcranial elements in sex estimation (Albanese, 2013; Albanese *et al.* 2005, Spradley & Jantz; 2011).

As clearly indicated by the present results, the upper limb is particularly useful for metric sex estimation, as it provides high allocation accuracies and is applicable to various populations. The development of the various equations in the present study is particularly useful in forensic and bioarchaeological contexts, as they represent different plausible recovery scenarios.

# CHAPTER 6: CONCLUSION

The results of the present study indicate that, not only are postcranial metrics of the upper limb particularly useful in sex estimation, but also that equations developed from metrics of the upper limb, in particular, may be applicable across populations, as suggested by Albanese (2013). The current study was able to achieve high allocation accuracies from equations developed using measurements collected from both American Whites and American Blacks. Allocation accuracies were as high as 97%, employing measurements of the humerus alone, and 100.0% when all measurements of each bone were employed together. Further research will involve applying these equations to various ancestral and geographic populations to assess their robusticity when challenged by the extremes human variation in sexual dimorphism. The equations will need to be tested further against populations known to be less sexually dimorphic, such as Asian-derived populations.

The development of more metric methods of sex estimation is particularly important to produce statistically robust data for sex estimation that can be tested and retested. Adams and Byrd (2002) suggest that metric data are more reliable than visually assessed traits in sex estimation and can even be employed reliably by more inexperienced examiners. Furthermore, Spradley and Jantz (2011) suggest that postcranial elements are more reliable indicators in metric sex estimation than cranial elements. The present study provides a metric method of sex estimation that is simple and can be easily reproduced. The importance of this study derives from the development of equations that can be used for sex estimation in a variety of recovery scenarios. Better sex estimates can be achieved if all measurements of the upper limb and clavicle are available for analysis.

However, in certain scenarios it is not always possible to recover all bones, and therefore, for these situations a number of equations were developed specifically tailored to the measurements of each individual bone. The survivorship of osseous materials may be affected by a number of taphonomic processes, such as a specific burial context, scavenger activity, fluvial transport, deliberate fragmentation, weathering, and trampling (Morlan, 1994). Differences in the soil conditions of a burial site and biological activity can significantly affect the state of the remains that are recovered along with which remains are ultimately recovered (Pokines and Baker, 2014). The survivability of bone is also affected by intrinsic factors inherent in the composition of bone. Bone hardness and rigidity is created by the inorganic mineral component, while the organic collagen component affects bone flexibility. As collagen leaches out of the bone overtime, the bone become brittle and breaks and crumbles more easily. The loss of the organic collagen is a common occurrence in archaeological assemblages, which can significantly affect preservation rates (White, 2000).

Bone density also contributes to the differential survivorship of skeletal elements (Brain, 1967; Lam *et al.*, 1998; Lyman, 2014). Bones which are less dense, or areas of bones that have a lower density, are more likely to be missing or damaged (Evans, 2014; Lyman, 2014). Henderson (1987) found that bones that have irregular shapes, such as the os coxa are more susceptible to breakage than other bones (Henderson, 1987). In general the long bones have been found to have better preservation rates than the os coxa (Stojanowski *et al.*, 2002). Carnivore scavenging and preservational issues may make it impossible to determine sex using the os coxa, and in such cases the bones of the upper limb may be utilized. Development of equations for the multiple bones allows the examiner to choose which bone has the best preservation and can be used in a sex estimation method. The logistic regression equations proposed by Albanese (2013) include various measurements of various bones together, which may be applicable if only one portion of a bone is available for analysis.

Further research should be done to develop equations that reflect fragmented portions of bone. For instance, if only the proximal portion of the humerus is recovered, and it is the best bone available for a sex estimate, an equation might be developed using only metrics on the proximal portion of the humerus. These types of equations are likely to be less effective as there will be less measurements to contribute to the coefficients, but they may be useful in some circumstances if nothing else is available for analysis, such as in instances of highly fragmented and commingled remains. Equations, such as these, might be helpful in the pair-matching process of sorting commingled remains prior to DNA analysis. However, further research would need to be conducted to assess whether equations for fragmented bones will have any usability based on their classification accuracies.

Some of the equations were developed to accommodate researchers who are uncomfortable using unfamiliar variant measurements. These equations include only the standard measurements, as defined by Buikstra and Ubelaker (1994), which are familiar to most forensic anthropologists. Logistic regression equations based on the equations developed by Albanese (2013), to represent a variety of recovery scenarios, were also produced with a more modern collection. The allocation accuracies provided by the new equations are all higher than those reported by Albanese (2013). As such, the newly developed equations might be more relevant in forensic contexts, as they were produced from measurements of a more contemporary population.

Furthermore, the equations were produced from both American Black and American White populations, and might be particularly applicable to forensic contexts in the United States. One reason that the logistic regression equations are particularly useful in terms of sex estimation is that the p-value provided by the equation indicates the probability of that particular classification being correct in addition to the classification itself. For example, if the individual was classified as being male using one of the equations, and the p-value for that individual was 0.95, then there would be 95% chance of that classification being correct. This is useful, because if the result of the classification was closer to 0.5, then the examiner may understand classification is not necessarily accurate and might employ other sex estimation methods or another equation to validate the allocation.  As such, the examiner should proceed with caution when considering classifications with p-values closer to the sectioning point of 0.5.

Most previous sex estimation methods require examiners to assign individuals to a specific population, often based upon racial categories, before an assessment of sex can be made (Macho, 1990; İşcan *et al.,* 1998; Siegel *et al.,* 2000; Albanese, 2003; İşcan, 2005; Purkait, 2005; Cowal & Pastor, 2008; Spradley *et al.,* 2008; Kranioti & Michalodimitrikis, 2009; Charisi et al., 2011; Tise *et al.,* 2013).  There are limitations to assigning individuals to a specific group before sex can be determined, and the topic of ancestry and race within the fields of forensic anthropology and archaeology are contentious issues today (Albanese and Saunders, 2006; Komar and Buikstra, 2008; Sauer, 1992).  Using the present methods, sex is considered an independent category and is, therefore, not dependent on estimates of race or ancestry.  In forensic cases, where an estimate of ancestry might be required for identification purposes, the ancestry can be assessed separately and will not affect the outcome of the sex estimate.

While group-specific methods have been proven to be useful when working with known and specific boundaries (Macho, 1990; İşcan *et al.,* 1998; Siegel *et al.,* 2000; Albanese, 2003; İşcan, 2005; Purkait, 2005; Cowal & Pastor, 2008; Spradley *et al.,* 2008; Kranioti & Michalodimitrikis, 2009; Charisi et al., 2011; Tise *et al.,* 2013), they become more problematic when dealing with an individual from an unknown group. When limited to postcranial elements, *FORDISC 3.1* (Jantz and Ousley, 2005) provides ancestry estimates based upon only two populations (Black and White), which is problematic if an individual does not belong to one of those specific ancestral groups. Hefner (2009), who utilized cranial traits to estimate ancestry, noted that many of the traits overlap and it is difficult to deliver a definitive ancestry assessment. In such forensic cases, it is not effective to use population-specific sex estimation methods. In bioarchaeological scenarios, it may be more feasible to allocate individuals to a specific population based upon a geographical location. However, even in cases where an individual can be assigned to a specific archaeological population, examiners are limited by available comparative data sets.

The most sexually dimorphic bones of the upper limb were found to be the humerus and the radius, while the bones that were least effective at predicting sex were the clavicle and the ulna. However, all individual bones achieved allocation accuracies of at least 88.9% or greater, and most allocation accuracies were above 90%. The most effective discriminatory measurements were found to be the maximum diameter of the radial head, the vertical diameter of the humeral head, and the epicondylar breadth of the humerus, all of which suggest that joint size significantly contributes to sexual dimorphism. Previous research has also shown that measurements that are representative of joints tend to be the most effective predictors of sex, while the length and midshaft measurements of bones tend to be the least effective predictors (Albanese, 2013; Albanese et al., 2005; Spradley and Jantz, 2011). Future research might involve examining measurements that are representative of joint size and seeing if these measurements are all effective discriminators of sex. Geometric-morphometric techniques might also be a useful method of distinguishing how significantly joint size and shape contribute to sexual dimorphism.

In particular, however, more research should be conducted to assess the applicability of equations, such as those produced in this study, to geographic and temporal populations worldwide. It is important to start developing methods that can be applied across populations in forensic contexts, particularly as communities grow more and more diverse, it will become even more difficult to allocate and individual to a specific group. Therefore, it is essential that we look towards developing more universal methodologies of sex estimation, and that our methods be applicable to a variety of situations.

## LIST OF JOURNAL ABBREVIATIONS

| | |
|---|---|
| Am J Foren Med Path | American Journal of Forensic Medicine and Pathology |
| Am J Phys Anthropol | American Journal of Physical Anthropology |
| Annu Rev Anthropol | Annual Review of Anthropology |
| Anthropol Sci | Anthropological Science |
| Forensic Sci Int | Forensic Science International |
| J Anthropol Soc Nip | Journal of the Anthropological Society of Nippon |
| J Archaeol Sci | Journal of Archaeological Science |
| J Forensic Leg Med | Journal of Forensic and Legal Medicine |
| J Forensic Sci | Journal of Forensic Sciences |
| J Wash Acad Sci | Journal of Washington Academy of Sciences |
| Soc Sci Med | Social Science and Medicine |
| Q Rev Biol | The Quarterly Review of Biology |
| Z Morphol Anthropol | Zeitschrift für Morphologie und Anthropologie |

## REFERENCES

Adams BJ, Byrd JE. 2002. Interobserver variation of selected postcranial skeletal measurements. J Forensic Sci 47(6):1193-1202.

Ahmed AA. 2013. Estimation of sex from the upper limb measurements of Sudanese adults. J Forensic Leg Med 20(8):1041-1047.

Albanese J. 2013. A Method for estimating sex using the clavicle, humerus, radius, and ulna. J Forensic Sci 58(6):1413-1419.

Albanese J. 2003. A metric method for sex determination using the hipbone and the femur. J Forensic Sci 48(2):263-273.

Albanese J, Cardoso HFV, Saunders SR. 2005. Universal methodology for developing univariate sample-specific sex determination methods: An example using the epicondylar breadth of the humerus. J Archaeol Sci 32(1): 143-152.

Albanese J, Eklics G, Tuck A. 2008. A metric method for sex determination using the proximal femur and fragmentary hipbone. J Forensic Sci 53(6):283-1288.

Albanese J, Saunders SR. 2006. Is it possible to escape racial typology in forensic identification? In: Schmitt A, Cunha E, Pinheiro J, editors. Forensic anthropology and medicine: complementary science from recovery to cause of death. Clifton, NJ: Humana Press. pp. 289-296.

Alunni-Perret V, Staccini P, Quatrehomme G. 2008. Sex determination from the distal part of the femur in a French contemporary population. Forensic Sci Int 175(2):113-117.

Anastasiou E., Chamberlain AT. 2012. The sexual dimorphism of the sacro-iliac joint: An investigation using geometric morphometric techniques. J Forensic Sci doi: 10.1111/j.1556-4029.2012.02282.x.

Barrier ILO, L'Abbé EN. 2008. Sex determination from the radius and ulna in a modern South African sample. Forensic Sci Int 179(1):85.e1-85.e7.

Berg, GE. 2013. Determining the sex of unknown human skeletal remains. In: Tersigni-Tarrant MA, Shirley NR, editors. Forensic anthropology: An introduction. (ed). Florida: CRC Press. pp 139-160.

Berrizbeitia EL. 1989. Sex determination with the head of the radius. J Forensic Sci 34(5):1206-1213.

Bogin B. 1999. Patterns of human growth. Cambridge: Cambridge University Press.

Brain, CK. 1967. Hottentot food remains and their bearing on the interpretation of fossil bone assemblages. Scientific Papers of the Namib Research Station, 32:1-7.

Brauer GW. 1982. Size sexual dimorphism and secular trend: Indicators of subclinical malnutrition? In: Hall RL. editor. Sexual dimorphism in Homo sapiens: A question of size. New York: Praeger. pp. 245-259.

Brown RP, Ubelaker DH, Schanfield MS. 2007. Evaluation of Purkait's triangle method for determining sexual dimorphism*. J Forensic Sci 52(3):553-556.

Bruzek J. 2002. A method for visual determination of sex, using the human hip bone. Am J Phys Anthropol 117(2):157-168.

Buikstra JE, Ubelaker DH. 1994. Standards for data collection from human skeletal remains. Arkansas Archeological Survey Research Series No. 44, Fayetteville, AR.

Burns RB, Burns RA. 2008. Business research methods and statistics using SPSS. London: Sage Publications Ltd.

Bytheway JA, Ross AH. 2010. A geometric morphometric approach to sex determination of the human adult os coxa. J Forensic Sci 55(4):859-864.

Charisi D, Eliopoulos C, Vanna V, Koilias CG, Manolis SK. 2011. Sexual dimorphism of the arm bones in a modern Greek population. J Forensic Sci 56(1):10-18.

Cowal LS, Pastor RF. 2008. Dimensional variation in the proximal ulna: evaluation of a metric method for sex assessment. Am J Phys Anthropol 135(4):469-478.

Dar G, Hershkovitz I. 2006. Sacroiliac joint bridging: simple and reliable criteria for sexing the skeleton. J Forensic Sci 51(3):480-483.

Dibennardo R, Taylor JV. 1983. Multiple discriminant function analysis of sex and race in the postcranial skeleton. Am J Phys Anthropol 61(3):305-314.

Evans, T. 2014. Fluvial transport. In: Pokines, JT and Symes, SA, editors. Manual of Forensic Taphonomy. Boca Raton: CRC Press. pp. 201-48.

Franklin D, Flavel A, Kuliukas A, Cardini A, Marks MK, Oxnard C, O’Higgin, P. 2012. Estimation of sex from sternal measurements in a Western Australian population. Forensic Sci Int 217(1):230.e1 - 230.e5.

Frayer DW, Wolpoff MH. 1985. Sexual dimorphism. Annu Rev Anthropol 14:429-473.

Frutos LR. 2005. Metric determination of sex from the humerus in a Guatemalan forensic sample. Forensic Sci Int 147(2):153-157.

Frutos LR. 2002. Determination of sex from the clavicle and scapula in a Guatemalan contemporary rural indigenous population. Am J Foren Med Path 23(3):284-288.

Giles E, Elliot O. 1963. Sex determination by discriminant function analysis of crania. Am J Phys Anthropol 21(1):53-68.

Gray JP, Wolfe LD. 1980. Height and sexual dimorphism of stature among human societies. Am J Phys Anthropol 53(3):441-56.

Hefner JT. 2009. Cranial nonmetric variation and estimating ancestry. J Forensic Sci 54:985-995.

Henderson J. 1987. Factors determining the state of preservation of human remains. In: Boddington A, editor. Death, Decay, and Reconstruction: Approaches to Archaeology and Forensic Science. Manchester, United Kingdom. Manchester University Press, pp.43–54.

Holman DJ, Bennett KA. 1991. Determination of sex from arm bone measurements. Am J Phys Anthropol 84(4):421-426.

İşcan MY. 2005. Forensic anthropology of sex and body size. Forensic Sci Int 147(2):107-112.

İşcan MY, Loth SR, King CA, Shihai D, Yoshino M. 1998. Sexual dimorphism in the humerus: A comparative analysis of Chinese, Japanese and Thais. Forensic Sci Int 98(1):17-29.

Jantz R, Ousley S. 2005. FORDISC 3.1. University of Tennessee Press, Knoxville, TN.

Keen JA. 1950. A study of the differences between male and female skulls. Am J Phys Anthropol 8(1):65-80.

Klales AR, Ousley SD, Vollner JM. 2012. A revised method of sexing the human innominate using Phenice's nonmetric traits and statistical methods. Am J Phys Anthropol 149(1):104-114.

Komar DA, Buikstra JE. 2008. Forensic anthropology: Contemporary theory and methods. New York, NY: Oxford University Press.

Kranioti EF, Michalodimitrakis M. 2009. Sexual dimorphism of the humerus in contemporary Cretans—A population-specific study and a review of the literature*. J Forensic Sci 54(5):996-1000.

Lam YM, Chen X, Marean CW, Frey CJ. 1998. Bone density and long bone representation in archaeological faunas: comparing results from CT and photon densitometry. J Archaeo Sci 25:559-570.

Lieberman LS. 1982. Normal and abnormal sexual dimorphic patterns of growth and development. In: Hall RL. editor. Sexual dimorphism in Homo sapiens: A question of size. New York: Praeger. pp. 263-316.

Lyman RL. 2014. Bone density and bone attrition. In: Pokines, JT and Symes, SA, editors. Manual of Forensic Taphonomy. Boca Raton: CRC Press. pp. 201-48.

Macho GA. 1990. Is sexual dimorphism in the femur a" population specific phenomenon”?. Z Morphol Anthropol 78:229-242.

Mall G, Hubig M, Büttner A, Kuznik J, Penning R, Graw M. 2001. Sex determination and estimation of stature from the long bones of the arm. Forensic Sci Int 117(1):23-30.

May S, Cox M. 2000. Sex determination in skeletal remains. In: May S, Cox M. editors. Human osteology in archaeology and forensic science. Cambridge: Cambridge University Press. pp. 117-130.

Milner GR, Boldsen JL. 2012. Humeral and femoral head diameters in recent white American skeletons. J Forensic Sci 57(1):35-40.

Moore MK. 2012. Sex estimation and assessment. In: DiGangi EA, Moore MK, editors. Research methods in human skeletal biology. London: Elsevier Academic. pp. 91-112.

Morlan RE. 1994. Bison bone fragmentation and survivorship: a comparative method. J Archaeo Sci 21(6):797-807.

Nakahashi T, Nagai M. 1986. Sex assessment of fragmentary skeletal remains, J. Anthropol. Soc. Nip. 94(3):289–305.

Ogawa Y, Imaizumi K, Miyasaka S, Yoshino M. 2013. Discriminant functions for sex estimation of modern Japanese skulls. J Forensic Leg Med 20(4):234-238.

Ortner DJ. 2003. Background data in paleopathology. In: Ortner DJ. editor. Identification of Pathological Conditions in Human Skeletal Remains. 2nd ed. San Diego, CA: Elsevier Academic Press. pp. 37-44.

Papaioannou VA, Kranioti EF, Joveneaux P, Nathena D, Michalodimitrakis M. 2012. Sexual dimorphism of the scapula and the clavicle in a contemporary

Greek population: Applications in forensic identification. Forensic Sci Int 217(1):231.e1-231.e7.

Phenice TW. 1969. A newly developed visual method of sexing the os pubis. Am J Phys Anthropol 30(2):297-301.

Pokines JT. 2014. Faunal dispersal, reconcentration, and gnawing damage to bone in terrestrial environments. In: Pokines, JT and Symes, SA, editors. Manual of Forensic Taphonomy. Boca Raton: CRC Press. pp. 201-48.

Pokines JT, Baker JE. 2014. Effects of burial environment on osseous remains. In: Pokines, JT and Symes, SA, editors. Manual of Forensic Taphonomy. Boca Raton: CRC Press. pp. 201-48.

Purkait R. 2005. Triangle identified at the proximal end of femur: a new sex determinant. Forensic Sci Int. 147(2):135-139.

Rogers T. 2009. Sex determination of adolescent skeletons using the distal humerus. Am J Phys Anthropol 140(1):143-148.

Ross AH, Baker LE, Falsetti A. 2003. Sexual dimorphism a proxy for environmental sensitivity? A multi-temporal view. J Wash Acad Sci 89(1-2):1-12.

Sakaue K. 2004. Sexual determination of long bones in recent Japanese. Anthropol Sci 112(1):75-81.

Sauer, NJ. Forensic anthropology and the concept of race: if races don’t exist, why are forensic anthropologists so good at identifying them? Soe Sci Med 40:797-800.

Shine R. 1989. Ecological causes for the evolution of sexual dimorphism: a review of the evidence. Q Rev Biol 64(4):419-461.

Siegel JA, Saukko PJ, Knupfer GC. 2000. Encyclopedia of forensic sciences. 1st ed. San Diego: Academic.

Slatkin M. 1984. Ecological causes of sexual dimorphism. Evolution 38(3):622-630.

Spradley MK, Jantz RL. 2011. Sex estimation in forensic anthropology: Skull versus postcranial elements. J Forensic Sci 56(2):289-296.

Spradley MK, Jantz RL, Robinson A, Peccerelli F. 2008. Demographic change and forensic identification: Problems in metric identification of Hispanic skeletons*. J Forensic Sci 53(1):21-28.

Stewart TD, Kerley ER. 1979. Essentials of forensic anthropology: Especially as developed in the United States. Springfield, IL: Charles C. Thomas.

Steyn M, İşcan MY. 1999. Osteometric variation in the humerus: Sexual dimorphism in South Africans. Forensic Sci Int 106(2):77-85.

Stini WA. 1969. Nutritional stress and growth: Sex difference in adaptive response. Am J Phys Anthropol 31(3):417-426.

Stini WA. 1975. Adaptive strategies of human populations under nutritional stress. In: Watts ES, Johnston FE, Lasker GW. editors. Biosocial interrelations in population adaptation. Chicago: Mouton. pp. 19-41.

Stinson S. 1985. Sex differences in environmental sensitivity during growth and development. Am J Phys Anthropol 28(S6):123-147.

Stojanowski CM, Seidemann RM, Doran GH. 2002. Differential skeletal preservation at Windover Pond: Causes and consequences. Am J Phys Anthropol 119:15-26.

Tise ML, Spradley MK, Anderson BE. 2013. Postcranial sex estimation of individuals considered Hispanic. J Forensic Sci 58(S1):S9-S14. doi:10.1111/1556-4029.12006

Ubelaker DH, Volk CG. 2002. A test of the phenice method for the estimation of sex. J Forensic Sci 47(1):19-24.

Vance VL, Steyn M, L'Abbe EN. 2011. Nonmetric sex determination from the distal and posterior humerus in black and white South Africans. J Forensic Sci 56(3):710-714.

Volk C., Ubelaker DH. 2002. A test of the Phenice method for the estimation of sex. J Forensic Sci 47(1):19–24.

Walker PL. 1995. Problems of preservation and sexism in sexing: some lessons from historical collections for palaeodemographers. In: Saunders SR, Herring A. editors. Grave Reflections. 1st ed. Toronto: Canadian Scholar's Press. pp.31-47.

Walker PL. 2008. Sexing skulls using discriminant function analysis of visually assessed traits. Am J Phys Anthropol 136(1):39-50.

White TD. 2000. Human Osteology. San Diego, California: Academic Press.

**CURRICULUM VITAE**
**Aisling Kearns**

23 Elm Ct.
Cohasset, MA 02025
(781) 385-9460
Year of birth: 1990
aibkearns@gmail.com
kearnsa@bu.edu

## EDUCATION

Boston University, Boston, MA
Masters of Science, Major Forensic Anthropology, May 2015
Overall GPA: 3.58
Thesis Project: "An Evaluation of a Metric Method for Estimating Sex Using the Clavicle, Humerus, Radius, and Ulna"
Thesis Advisors: Dr. Donald Siwek, Dr. James Pokines

Union College, Schenectady, NY
Bachelor of Arts, Major Anthropology, June 2013
Overall GPA: 3.552
Undergraduate Thesis: "Irish Travellers and the Transformative Nature of Media Representation"
Thesis Advisor: Dr. Linda Cool

## PROFESSIONAL EXPERIENCE/TRAINING

Teaching Assistant, Boston University, Boston, MA
September 2014 - Present

> Teaching Assistant for FA 718: Special Topics in Forensic Anthropology: Outdoor Crime Scene Awareness.

Maceration Training, Boston University, Boston, MA
September 2014

> Training with the department of Forensic Anthropology at Boston University in the process of macerating donated human remains for the anatomical collection at the University.

Archaeotek Archaeological Field School, Romania
July 2014

> Gained training in archaeological excavation techniques particularly in dealing with skeletal remains. A month was spent excavating the site of a medieval church in Romania.

Harvard Museum of Natural History Intern, Cambridge, MA
July 2012 - August 2012

Created an independent project that would benefit the museum visitor experience. Worked as a gallery guide on the museum floor, engaging with visitors and answering questions.

Schenectady Museum of Science and Technology Intern, Schenectady, NY
March 2012 - June 2012

Helped put together the Schenectady Erie Canal tour through research efforts. Developed an exhibit proposal for changing one of the exhibits in the museum through the use of museum collections.

Union College Summer Research Fellowship, Union College, Schenectady NY and Co. Cork, Ireland
Research Assistant
June 2011 - August 2011

Documented field notes, pictures, transcriptions, and conducted archival research to support two Union College professors in their ethnographic research on Irish Travellers.

**COURSEWORK**

FA 704: Bioarchaeology
FA 716: Expert Witness Testimony
FA 800: Field Methods in Forensic Anthropology
FA 802: Applied Forensic Anthropology
FA 807: Taphonomy
FA 810: Mortuary Archaeology
FA 805: Advanced Crime Scene Investigation
FA 712: Human Anatomy and Osteology
FA 790: History, Methods and Theory in Biological Anthropology
FA 700: Professional Skills and Thesis Research Development
FA 718: Special Topics in Forensic Anthropology: Outdoor Crime Scene Awareness
FA 705: Forensic Anthropology Techniques
FA 703: Zooarchaeology
FA 806: Advanced Osteology
FA 711: Forensic Pathology
ANT 182: Anthropology of Mediterranean Europe
CLS 278: Ancient World Mythology
HST 260: Medieval Britain
ANT 110: Introduction to Cultural Anthropology
ANT 183: Peoples and Cultures of Latin America
ANT 114: Language and Culture

ANT 363: Research Methods and Design
CLS 129: History of the Roman Empire
GRK 332: Ancient Greek Religion
GRK 334: Ethnography of Greece
HST 344: Ancient Greek Civilization
TAB 361: Archaeology of Athens
ANT 265: Museum Theory and Practice
HST 154: Russia in the Imperial Age
HST 211: American Indian History

## SCHOLARLY PROJECTS AND PRESENTATIONS

Master's Thesis Research

Thesis research is focused on examining a metric method for sex estimation using the clavicle, humerus, radius and ulna that is based upon the method developed by Albanese (2013). The current study uses measurements collected from 400 individuals in the William T. Bass Skeletal Collection at the University of Tennessee.

Current Rodent Gnawing Taphonomy Project

Research is focused on distinguishing between the gnawing patterns of various species of rodent common to the New England area by the size of their incisors.

Current Marine Taphonomy Project

Research on marine taphonomy versus fresh water taphonomy. The project is currently in its second year of study.

Steinmetz Symposium, Union College, Schenectady, NY (May 2013)

Formal oral presentation on cultural representations of Irish Travelers in the media

Undergraduate Thesis Research (June 2011 - March 2013)

Research was on the cultural implications of the transformative nature of the media and its influence on the perceptions and identity of Irish Travelers as a cultural entity.

Union College Summer Research Fellowship, Co. Cork, Ireland (June 2011 - August 2011)

Assisted two professors of Union College in their anthropological research on the culture of the Irish Travelers.

## RESEARCH AND TRAVEL GRANTS

Boston University Graduate Thesis Research Grant ($1,150)
Union College Summer Research Fellowship ($3,000)