CORRELATION COEFFICIENT OF ANTHROPOMETRIC INDICES WITH LIPID PROFILE IN WOMEN WITH POLYCYSTIC OVARIAN SYNDROME (PCOS)

*[1]Ohikere, O. P., [2]Mokwenye, N. V., [3]Emokpae A. M., [4]Ige, I. P., (ORCID), [5]Ugbomoiko, O. D., [6]Theophilus, E. O., [7]Oshadare, A. B.

[1,2,5,6]Department of Medical Laboratory Science, Igbinedion University, Okada, Edo State, Nigeria.

[3]Department of Medical Laboratory Science, University of Benin, Benin City, Edo State, Nigeria.

[4]Department of Medical Laboratory Science, School of Basic Medical Sciences, Federal University of Technology, Akure, Ondo State, Nigeria.

[7]Department of Medical Laboratory Science, Federal University, Lokoja, Kogi State, Nigeria.

***Corresponding Author:**
Ohikere, O. P., Department of Medical Laboratory Science, Igbinedion University, Okada, Edo State, Nigeria. ohikere.peter@iuokada.edu.ng

ABSTRACT

Polycystic Ovarian Syndrome (PCOS) is a highly prevalent endocrine disorder in women, oftentimes complex by metabolic syndrome, insulin resistance, and atherogenic dyslipidemia. Traditional obesity metrics, like Body Mass Index (BMI), rarely fail to capture visceral fat distribution and associated metabolic risks. This study aimed to evaluate the correlation coefficients of various anthropometric indices considering traditional metrics and visceral adiposity indicators with lipid profile element to regulate their clinical usefulness as non-invasive screening tools for metabolic risk. A cross-sectional study was conducted evaluating clinical and biochemical parameters in a control age group (18-44 years) to constitute standard adoptive patterns. Anthropometric measurements included height, weight, waist circumference (WC), BMI, and a measured complex metric (BMI x 1.89 + WC/36.58). Progressive visceral indices, namely the Lipid Accumulation Product (LAP) and the Visceral Adiposity Index (VAI), were calculated. Pearson correlation coefficients (r) were utilized to analyze the association between these anthropometric indices and lipid markers, including Triglycerides (Tg/0.81) and High-Density Lipoprotein (1.52/HDL). Powerful, extremely important positive correlations were discovered between the triglyceride metric and both VAI ($r = 0.809$, $p < 0.01$) and LAP ($r = 0.824$, $p < 0.01$). Standard BMI and the composite metric were near-perfectly correlated ($r = 0.999$, $p < 0.01$), indicating identical variance distribution. While traditional parameters like weight and WC showed moderate positive correlations with lipid accumulation tracking (r 0.50, $p < 0.01$), VAI demonstrated a unique, significant positive correlation with the HDL metric ($r = 0.354$, $p < 0.05$). Conversely, height exhibited an inverse relationship with BMI ($r = -0.526$, $p < 0.01$) and the composite index ($r = -0.507$, $p < 0.01$). Visceral adiposity markers, specifically LAP and VAI, exhibit superior, robust correlations with lipid profile components compared to traditional isolated anthropometric metrics like height or weight alone. In clinical

management of women with PCOS, utilizing LAP and VAI offers a low-cost, highly sensitive, and non-invasive approach to early risk stratification for dyslipidemia and metabolic cardiovascular complications, moving assessment beyond the limitations of standard BMI.

Keywords: *Polycystic Ovarian Syndrome (PCOS); Anthropometric Indices; Visceral Adiposity Index (VAI); Lipid Accumulation Product (LAP); Dyslipidemia; Correlation Coefficient.*

1.0 INTRODUCTION

1.1 Background of the Study

Polycystic ovarian syndrome (PCOS) is the most widespread endocrine metabolic disorder affecting 5 -10% of women of reproductive age worldwide. (Escobar-Morreale, 2018; Azziz *et al.*, 2004; Knochenhauer *et al.*, 1998; Lauritsen *et al.*, 2012). The PCOS related complication present across lifespan starting from reproductive and dermatological concerns to metabolic and psychological complication like diabetes, metabolic syndrome, cardiovascular disorder etc. (Amsterdam, 2012; Sir Petermann *et al.*, 2016; Bhattacharya and Jha, 2010; Anagnostis *et al.*, 2018).

Genetic variants like single nucleotide polymorphism (SNP) were extensively investigated as potential precursors for various complex disorders including PCOS. (Chen *et al.*, 2017; Cui *et al.*, 2013; Valkenburg *et al.*, 2006). Insulin resistance is found in (50 – 80%) of women with PCOS resulting from hyperinsulinemia and impaired glucose tolerance (IGT). (Amato *et al.*, 2015)

Insulin gene (INS;11P15.5) genetic variants were proposed to be involved in the development of the metabolic features like insulin resistance in PCOS. (Pugliese and Miceli, 2002; Hansen, 2003). The variable secretion of insulin contributes to the enhancement of androgen production, suppression of Sex hormone binding globulin (SHBG) and intra ovarian hyperandrogenic state which promote follicular growth and inhibition of dominant follicle selection resulting in polycystic ovarian morphology (Diamanti and Dunaif, 2012).

2.0 LITERATURE REVIEW

2.1 Polycystic Ovarian Syndrome (PCOS) And Cardiometabolic Risk Factor

Polycystic ovarian syndrome (PCOS) is a common endocrine disorder affecting women of reproductive age and is increasingly recognised not only for its reproductive consequences but also for its long-term cardiometabolic burden. Recent population work in Nigeria estimates that PCOS affects roughly 8–9% of reproductive-aged women, although prevalence varies by diagnostic criteria and sampling frame, and underdiagnosis remains a persistent problem (Makwe *et al.*, 2023). Women with PCOS show a higher prevalence of established cardiovascular risk factors like insulin resistance, central obesity, dyslipidaemia, hypertension, and chronic low-grade inflammation which together accelerate atherosclerotic processes and increase lifetime CVD risk (Dutta *et al.*, 2024; Osibogun & colleagues, 2020).

In spite of the acknowledged association between PCOS and cardiovascular risk, inadequate data exist on the genetic basis of this relationship, predominantly among African populations. In Nigeria, specifically in Kogi State, PCOS is underdiagnosed and under-researched, with little understanding of the molecular and genetic underpinnings that may influence disease severity and risk progression (Okunlola *et al.*, 2020). Given the increasing burden of cardiovascular diseases and reproductive health challenges in Nigeria, there is an urgent need to investigate local genetic factors that may predispose PCOS patients to higher cardiovascular risks.

PCOS is a heterogeneous, polygenic trait with substantial heritability, and genome-wide and candidate-gene studies have shown that loci related to insulin signalling, gonadotrophin action, and metabolic regulation such as INSR, IRS1, FTO, THADA, LHCGR, though effect sizes are modest and findings vary by population (Kosova & Urbanek, 2012; recent genetic clustering work, 2024). Critically, the bulk of genetic and mechanistic PCOS research has been conducted in European and East Asian populations; which show that there is a striking scantiness of strong genetic data from African populations. Insignificant preliminary studies and occasional candidate-gene reports indicated the hint at population-specific variants including work on paraoxonase 1 polymorphisms in Nigerian cohorts, deficient adequately powered genetic investigations, though systematic (Velmurugan *et al.*, 2024).

Insulin resistance (IR) is a central and well-authenticated pathogenic feature of polycystic ovarian syndrome (PCOS), driving compensatory hyperinsulinaemia that amplifies ovarian androgen production and links reproductive dysfunction with a cluster of adverse metabolic outcomes impaired glucose tolerance, type 2 diabetes, dyslipidaemia, hypertension and endothelial dysfunction with each of which increases lifetime cardiovascular disease (CVD) risk (Zhao *et al.*, 2023; Purwar & Nagpure, 2022). Insulin resistance is a core feature of polycystic ovarian syndrome (PCOS) and has been strongly associated with the syndrome's pathogenesis and its metabolic sequelae, including hypertension, atherogenic lipid profiles, and endothelial dysfunction all of which are risk factors for CVD (Legro *et al.*, 2005; Diamanti-Kandarakis & Dunaif, 2012). The clustering of these cardiometabolic disturbances in women with PCOS underscores the importance of dissecting the molecular underpinnings of insulin resistance within this population. In recent years, genetic research has pointed to polymorphisms in the insulin gene (INS) and its receptor pathways as potential contributors to both insulin resistance and the heightened cardiovascular risks observed in women with PCOS (Goodarzi *et al.*, 2011). Notably, variations such as the INS-VNTR (Variable Number Tandem Repeat) and other single nucleotide polymorphisms (SNPs) have been linked to altered insulin gene expression, impaired glucose metabolism, and susceptibility to type 2 diabetes mellitus and CVD (Möller *et al.*, 2008).

Routinely, insulin resistance and compensatory hyperinsulinaemia appear essential to demonstrate the relationship between PCOS and CVD. Excess insulin intensifies ovarian androgen production, promotes opposing lipid profiles, increases sympathetic tone, and impairs endothelial function and vascular repair like endothelial progenitor cell dysfunction, producing early vascular changes even in young women with otherwise normal conventional risk profiles (Kao *et al.*, 2013; Tarkun *et al.*, 2004). Inflammation and oxidative stress further contribute to endothelial dysfunction and plaque vulnerability, while obesity and ectopic fat deposition complicates these pathways (Dutta *et al.*, 2024).
In recent years, genetic studies have provided insights into possible mechanisms, implicating variations in the insulin gene (INS) and insulin receptor (INSR) signaling pathways as key contributors to PCOS-related IR (Goodarzi *et al.*, (2011) highlighted those specific genetic polymorphisms can predispose women with PCOS to more severe metabolic derangements, thereby amplifying their long-term cardiovascular risk. Among these, the insulin gene variable number tandem repeat (INS-VNTR) polymorphism has been extensively studied. This genetic variation, located upstream of the INS gene, influences its transcriptional activity and has been associated with altered insulin secretion, β-cell function, and susceptibility to T2DM and CVD (Möller *et al.*, 2008; Velmurugan, Pauline, & Subbaraj, 2024).

2.2 Epidemiology

Polycystic ovarian syndrome (PCOS) is the most common endocrine disorder among women and so peculiar between the ages of 18 and 44 (Teede *et al.*, 2010). According to the World Health Organization (WHO), PCOS affects over 6 to 13% of reproductive-aged women (WHO, 2023). Polycystic ovary syndrome (PCOS) is a common condition affecting approximately 8% of women. Once someone is infertile due to lack of

ovulation, PCOS is the most common cause and could be a pointer to patients' diagnosis. The 2022 approximations of prevalence of PCOS vary which could arises in between 5% and 18% of women (Joham *et al.*, 2024). The occurrence of PCOS depends on the choice of diagnostic criteria. Using the Rotterdam criteria, around 10–13% of women have PCOS (Teede *et al.*, 2023). Based on the NIH standards, by using the Androgen Excess Society criteria, the global frequency was 5.5%, growing to approximately 7.1%. Irrespective of the criteria, the prevalence of PCOS is increasing, likely due to an aging population, more awareness, and increasing obesity rates (Salari *et al.*, 2024).

Incidence appears impartially even among people with different ethnicities, but is conceivably higher in people from South East Asia and the Eastern Mediterranean (Teede *et al.*, 2023). PCOS may express differently however. For instance, in African and Hispanic American people with PCOS, there is more insulin resistance compared to other ethnic groups (Stener-Victorin *et al.*, 2024). The same is true for South Asian people with PCOS, who also have more metabolic symptoms and higher BMIs. East Asian women typically have less hirsutism and lower BMI compared to other groups (Joham *et al.*, 2024). Ultrasonographic findings of polycystic ovaries are found in 8–25% of women who are not affected by the syndrome. 14% women on oral contraceptives are found to have polycystic ovaries. Ovarian cysts are also a common side effect of levonorgestrel-releasing intrauterine devices (IUDs) (Hardeman and Weiss, 2014).

Recent epidemiological assessments revaeled that both the implicit figure of PCOS cases and age-standardised prevalence have increased over recent decades, which is determined by improved recognition, broader use of Rotterdam-based definitions, urbanization, and changing lifestyle factors (nutrition, sedentary behaviour, obesity) that amplify metabolic risk (Liu *et al.*, 2021; Meng *et al.*, 2025). Although global estimates are improving, data from many low- and middle-income regions including large parts of Sub-Saharan Africa that remain distributed with variable quality, to conceal actual regional burdens (Liu *et al.*, 2021; Begum *et al.*, 2024). Some recent reviews and burden analyses indicate that the pandemic reported prevalence in Sub-Saharan Africa has been lowered in older datasets, there are communication of rising incidence and prevalence in several African settings as healthcare access, awareness, and diagnostic capacity increase (Liu *et al.*, 2021; Begum *et al.*, 2024).

Polycystic Ovarian Syndrome (PCOS) is one of the most common endocrine disorders among women of reproductive age, with growing prevalence in Sub-Saharan Africa (Fauser *et al.*, 2012; Azziz *et al.*, 2016). Estimates using different diagnostic criteria place population prevalence in the single digits to low-teens commonly reported ranges are roughly 6%–15% depending on the specific method adopted such as NIH, Rotterdam, AE-PCOS and the population studied (Bozdag *et al.*, 2016; Lizneva *et al.*, 2016). Reported estimates differ substantially because prevalence depends on the diagnostic criteria applied, study quality, age distribution, and whether the sample is clinic-based or population-based. Studies have shown that about 4%–20% outcomes evaluating nonuniformity using mixed criteria which have produced a wider ranges in study designs and case definitions (Bozdag *et al.*, 2016; Deswal *et al.*, 2020).

2.3 Prevalence of PCOS Associated Comorbidities

PCOS is marked by hormonal imbalances, excess androgen production, menstrual irregularities, and fertility challenges. Diagnostic criteria encompass (NIH 1990, Rotterdam 2003, and AE PCOS 2006), with higher prevalence using Rotterdam criteria. Global prevalence ranges from 5% to 10% (Mishra *et al.*, 2021). Insulin resistance in PCOS affects follicular growth and ovulation (Huber-Buchholz *et al.*, 1999). Lifestyle changes and weight loss improve insulin sensitivity and ovulation (Huber-Buchholz *et al.*, 1999). PCOS significantly affects fertility and is a major cause of ovulatory disorders, also increasing the risk of miscarriage. Women with PCOS experience a substantial impact on health-related quality of life, affecting physical, emotional, and social aspects (Behboodi Moghadam *et al.*, 2018).

PCOS incidence varies based on factors like body weight, diet, lifestyle, and ethnicity, with obesity being a significant concern (Sendur & Yildiz, 2021). Hirsutism is distressing for about 70 % of women with PCOS. Infertility and irregular periods have a negative psychological impact on affected women (Behboodi

Moghadam *et al.*, 2018). Various factors are associated with the pathogenesis of PCOS, which involves the interactions among hormones, genes and environmental stressors.

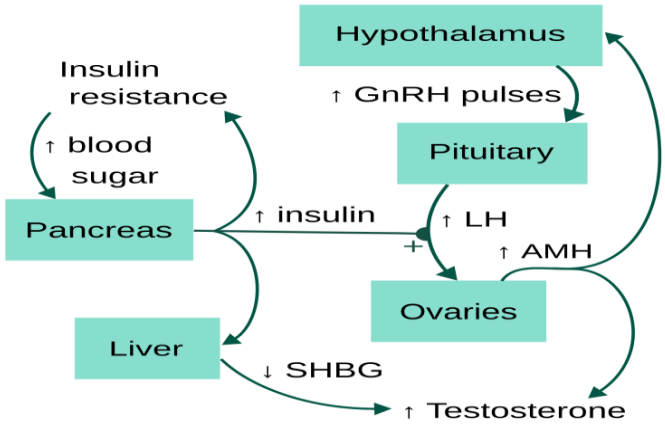
2.4 Challenges About PCOS Study in Kogi State, Nigeria

In Nigeria, specifically in Kogi State where research organization and disease surveillance are inadequate, PCOS remains under-researched. There is practically no comprehensive molecular or genetic profiling of PCOS patients linked to cardiometabolic phenotyping. This gap is very crucial where allele frequencies, gene–environment interactions e.g., nutrition, infectious disease burden, and social determinants differ across populations and can meaningfully modify disease expression and risk trajectories. Without local genetic and mechanistic data, clinicians and policymakers lack the evidence base needed to design targeted screening, prevention, and management strategies that are both effective and culturally appropriate. Therefore, investigating genetic markers and molecular pathways that predispose Nigerian women with PCOS to intensify cardiovascular risk is imperative. Such research would clarify population-specific genetic contributors and their interaction with metabolic and environmental drivers; enable earlier identification of high-risk phenotypes; and inform tailored interventions from lifestyle and metabolic management to risk-stratified monitoring for CVD. Moreover, building local capacity for genomic and translational research in Kogi State would strengthen health systems, promote equity in global PCOS research, and ultimately support better reproductive and cardiovascular outcomes for Nigerian women.

2.5 Disruption of the Hypothalamus–Pituitary–Ovarian (HPO) Axis in PCOS

An increased frequency of gonadotropin-releasing hormone (GnRH) pulses elevates luteinizing hormone (LH), which drives ovarian follicles to produce more androgens. The androgen excess disrupts follicle maturation, causing the accumulation of small follicles that secrete anti-Müllerian hormone (AMH), further boosting testosterone levels. At the same time, insulin resistance raises blood glucose and insulin concentrations, which reduce sex hormone-binding globulin (SHBG) and thereby increase circulating testosterone. Elevated insulin also amplifies LH's stimulatory effect on ovarian androgen production, creating a reinforcing cycle of hormonal imbalance. In polycystic ovary syndrome, an increase in gonadotropin-releasing hormone (GnRH) pulse frequency triggers excessive release of luteinizing hormone (LH) from the pituitary. Elevated LH stimulates ovarian follicular (theca) cells to overproduce androgens. The resulting androgen excess disrupts normal follicle maturation, causing multiple small follicles to accumulate. These immature follicles secrete anti-Müllerian hormone (AMH), which further amplifies testosterone levels. Concurrently, insulin resistance elevates both blood glucose and circulating insulin. High insulin concentrations suppress sex hormone-binding globulin (SHBG), increasing the proportion of free, bioactive testosterone. Moreover, insulin directly potentiates the action of LH on the ovaries, further driving androgen production. Together, these processes create a self-reinforcing loop of hormonal imbalance that underpins the reproductive and metabolic features of PCOS (Stener-Victorin *et al.*, 2024).

Figure 1: Disruption of the Hypothalamus–Pituitary–Ovarian (HPO) Axis in PCOS



(Stener-Victorin *et al.*, 2024)

2.6 Polycystic Ovarian Morphology (PCOM)

Polycystic ovarian morphology (PCOM) describes an ovarian ultrasound appearance typical of many people with PCOS: enlarged ovaries containing an increased number of small antral follicles. PCOM is one of the three domains of the Rotterdam diagnostic framework (clinical/biochemical hyperandrogenism, oligo/anovulation, PCOM), but modern evidence-based guidance treats PCOM as a supportive diagnostic feature whose interpretation depends on imaging technology and patient age. On ultrasound, PCOS is frequently associated with enlarged ovaries containing multiple small antral follicles arranged peripherally ("string of pearls" appearance). The 2023 International PCOS Guideline emphasizes that polycystic ovarian morphology should be considered supportive but not diagnostic in adults, but not required in adults; considered more relevant in adolescents and in research due to variability with age and ultrasound technology (Smet & McLennan, 2018; Tay *et al.*, 2023; Teede *et al.*, 2023).

2.7 Obesity and Central Adiposity in PCOS

Obesity and especially central (abdominal/visceral) adiposity is enormously common in women with polycystic ovary syndrome (PCOS) and substantially worsens the syndrome's reproductive and metabolic composition. Women with PCOS have higher prevalence of overweight/obesity and central fat compared with population controls, and central adiposity contributes disproportionately to insulin resistance, dyslipidaemia, inflammation and cardiometabolic risk in PCOS. Many women presented with overweight/obesity, particularly abdominal fat accumulation. However, PCOS can also occur in lean women, highlighting its complex pathophysiology (Barber, 2019; Lim *et al.*, 2019; Ollila *et al.*, 2023; Teede *et al.*, 2023).

2.8 Reproductive And Fertility Problems And PCOS

"Infertility" is commonly defined as failure to achieve a clinical pregnancy after 12 months of regular unprotected intercourse (6 months if the woman is ≥ 35 years) (Ige & Ilesanmi-Ige, 2025). Infertility is multifactorial, female factors include ovulatory disorders like chronic anovulation, tubal disease, subfertility, uterine pathology, diminished ovarian reserve and recurrent miscarriage; while male factors are semen abnormalities, genital tract obstruction, genetic causes, combined and unexplained causes, and its prevalence and clinical approach have been shaped by new evidence and updated guidelines across 2015–2025 (ASRM/ESHRE/WHO) (Teede *et al.*, 2018; Sunil Chawre *et al.*, 2024). Infertility due to chronic anovulation

is one of the most distressing symptoms for patients with PCOS. Additionally, women with PCOS face an increased risk of pregnancy complications such as gestational diabetes mellitus (GDM), preeclampsia and adverse pregnancy outcomes (Palomba *et al.*, 2021).

The major causes and pathophysiology of infertility includes: ovulatory disorders such as PCOS (Sunil Chawre *et al.*, 2024), tubal and pelvic factors such as endometriosis (Ilenia Mappa *et al.*, 2024; Roberti *et al.*, 2024), diminished ovarian reserve and age (Moolhuijsen & Visser, 2020), male factor (Sunil Chawre *et al.*, 2024), obesity, metabolic disease and endocrine disorders (Jeong *et al.*, 2024); and diagnostic evaluation (practical approach), which includes thorough history duration, prior pregnancies, cycles, exposures; pelvic exam and ovulation assessment like mid-luteal progesterone/cycle tracking; ovarian reserve testing (AMH, AFC); uterine assessment such as ultrasound/hysteroscopy as indicated), tubal patency testing (HSG, sonohysterogram, laparoscopy if suspected; and semen analysis (WHO 6th edition standards). Early referral for women ≥35 or with risk factors is recommended (Teede *et al.*, 2018; Sunil Chawre *et al.*, 2024).

2.9 Relationship Between Pcos And Lipid Profile

Polycystic ovarian syndrome (PCOS) is the most common endocrine disorder among women of reproductive age, with an estimated prevalence of 6–10% depending on diagnostic criteria. Women with PCOS have a substantially higher prevalence of dyslipidemia than women without PCOS. It is characterized by a configuration of attribute, including menstrual irregularities or anovulation, hyperandrogenism (clinical or biochemical), and polycystic ovarian morphology. PCOS is often diagnosed during the reproductive years, particularly when women present with infertility or symptoms of hyperandrogenism such as acne, hirsutism, or androgenic alopecia (McLuskie & Newth, 2017).

These lipid abnormalities occur even after partial adjustment for body mass index (BMI) and are present in both obese and lean phenotypes, although obesity and insulin resistance amplify the severity. The dyslipidemia appears mechanistically linked to insulin resistance, hyperandrogenemia, adipose dysfunction, inflammation/oxidative stress, and adverse hepatic lipid handling all contributors to increased long-term cardiometabolic risk in PCOS (Wekker *et al.*, 2020).

Different from reproductive consequences, PCOS has gained acceptance as a significant risk factor for cardiometabolic disease. Evidence suggests strong links between PCOS and type 2 diabetes (T2D), myocardial infarction, and stroke, which are leading causes of morbidity and mortality in women (Harvey *et al.*, 2015). Approximately half of women with PCOS are obese, which compounds cardiometabolic risk (Rojas *et al.*, 2014). However, obesity is not considered causal for PCOS (Legro, 2012). Both conditions contribute to elevated cardiovascular risk, but the independence of their associations remains debated. Significantly, insulin clamp studies reveal that women with PCOS display intrinsic insulin resistance, independent of body weight, underscoring their heightened risk of T2D even in the absence of obesity (Cassar *et al.*, 2016).

Most insights into PCOS-related cardiometabolic risk have been drawn from cross-sectional studies, which primarily highlight associations with elevated blood pressure, hyperglycemia, and dyslipidemia. However, cross-sectional evidence cannot establish causality or capture long-term outcomes. Systematic reviews and meta-analyses of longitudinal studies now provide stronger evidence, assessing both intermediate cardiometabolic markers and clinical outcomes such as cardiovascular disease (CVD) events. This growing body of evidence underscores the need to view PCOS not only as a reproductive disorder but also as a chronic condition with lifelong cardiometabolic implications (Wekker *et al.*, 2020).

2.10 Polycystic Ovarian Syndrome (PCOS) And Body Mass Index (BMI)

BMI and adiposity are tightly linked with PCOS in several ways: a substantially higher proportion of women with PCOS are overweight or obese relative to the general population; higher BMI amplifies the metabolic and reproductive features of PCOS thereby worse insulin resistance, hyperandrogenism, menstrual dysfunction and infertility; and obesity contributes to both the expression of PCOS and is promoted by PCOS-related metabolic disturbances which is a bidirectional relationship. However, a respectable minority of women with PCOS are lean and can still have clinically important metabolic abnormalities, so normal BMI does not exclude metabolic risk. These patterns and management implications are emphasized by international evidence-based PCOS guidelines (Amisi *et al.*, 2022; Zhuang *et al.*, 2022).

2.11 Frequency Of Elevated BMI/Obesity In PCOS?

Most modern-day systematic reviews and cohort studies reported that a large proportion approximately 50% or more of women diagnosed with PCOS are either overweight or obese by BMI criteria; reported proportions vary by background, ethnicity and case-ascertainment method. Population and clinical samples differ, and clinical samples typically show higher obesity rates. Large guideline reviews note consistent excess prevalence of overweight/obesity in PCOS and recommend routine weight and metabolic assessment for all women with PCOS (Amisi *et al.*, 2022). Meta-analytic and population studies across different regions generally place the prevalence of overweight/obesity in PCOS between approximately 40–80% depending on country/clinic where the samples are been produced; precise estimates depend on the study and diagnostic criteria used (Barber *et al.*, 2019; Coffin *et al.*, 2023).

2.12 Bidirectional Relationship Between Obesity And PCOS

Evidence supports both higher adiposity and central obesity increase the likelihood that a genetically susceptible individual will express the PCOS phenotype. Obesity worsens insulin resistance and amplifies hyperandrogenism, again, metabolic and hormonal disturbances in PCOS such as insulin resistance, altered appetite/energy regulation, and androgen effects on adipose tissue can promote weight gain and central fat accumulation. Thus obesity and PCOS commonly co-exist and interact with one another (Barber *et al.*, 2019). Mendelian randomization and genetic studies indicated that mutual genetic determinants between higher BMI and PCOS risk, conformable with a causal contribution of adiposity to PCOS expression most especially in some phenotypes. Still, genetics do not fully explain the relationship and lifestyle/environmental drivers are important (Meng *et al.*, 2025).

2.13 Mechanisms Linking BMI/Adiposity to PCOS Properties

Adiposity can cause insulin resistance and later to compensatory hyperinsulinemia, which stimulates ovarian androgen production and reduces sex hormone-binding globulin (SHBG), increasing free androgens that drive hyperandrogenic symptoms and anovulation. Conversely, PCOS-associated insulin resistance can decrease energy expenditure and promote fat deposition (Amisi *et al.*, 2022). Obesity, especially visceral adiposity increases free fatty acid flow to the liver and systemic inflammation, exacerbating metabolic sequelae and worsening reproductive phenotype. Women with PCOS often show greater visceral adiposity compared with BMI-matched controls (Rasquin & StatPearls Authors, 2022). Androgens influence adipocyte differentiation and fat distribution, favoring abdominal fat which may modify appetite/energy balance, contributing to weight accumulation in susceptible women (Rasquin & StatPearls Authors, 2022). Low-grade chronic inflammation and dysregulated adipokines like lower adiponectin seen in obese PCOS sufferers promote insulin resistance and metabolic complications (Barber *et al.*, 2019).

2.14 Phenotype differences Between Lean PCOS And Obese PCOS

Patients with overweight/obese with PCOS commonly have more severe insulin resistance, worse metabolic risk such as dysglycaemia, dyslipidemia, hypertension; greater menstrual dysfunction, and often worse fertility outcomes than lean counterparts. BMI amplifies both metabolic and reproductive manifestations Goldberg *et al.*, 2024). Considerable figure of about 10–30% depending on population of PCOS patients are normal weight. Many emaciated PCOS women still have insulin resistance, adverse lipid profiles, and elevated cardiometabolic risk markers compared with BMI-matched non-PCOS controls, although absolute risk is typically lower than for obese PCOS. Clinicians must therefore screen metabolic risk regardless of BMI (Coffin *et al.*, 2023; Goldberg *et al.*, 2024).

2.15 Clinical Consequences of How BMI Alters Short- And Long-Term Outcome

Elevated BMI in PCOS multiplies cardiometabolic risk raising prevalence of impaired glucose tolerance, type 2 diabetes mellitus (T2DM), dyslipidemia, and likely long-term cardiovascular risk markers. Several guideline bodies recommend early metabolic screening (glucose tolerance testing, lipids, BP) and weight-focused interventions because excess BMI is a major, modifiable determinant of these risks (Goldberg *et al.*, 2024; Tay *et al.*, 2024). Higher BMI in PCOS reduces spontaneous and assisted conception rates, worsens response to fertility treatments, and increases pregnancy-related complications like gestational diabetes and hypertensive disorders. Weight reduction before conception improves many of these outcomes (Coffin *et al.*, 2023).

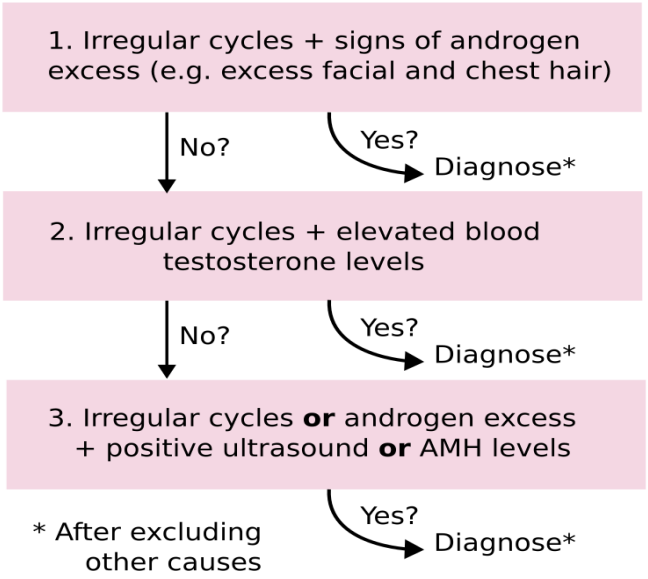
2.16 Assessment and Testing of Polycystic Ovarian Syndrome (PCOS)

Polycystic Ovarian Syndrome (PCOS) is a common endocrine disorder affecting reproductive-aged women, characterized by menstrual irregularities, hyperandrogenism, and polycystic ovarian morphology. A thorough clinical, biochemical, and radiologic evaluation is essential for its diagnosis and to exclude related conditions. There is a three-step algorithm to diagnose PCOS. *In the first step,* clinical androgen excess and irregular menstrual cycles are assessed. If someone has both, and other causes are excluded, PCOS is diagnosed. *In step two,* those with only irregular cycles undergo a laboratory test for excess androgens in the blood. If that shows excess male hormones, again, excluding other causes of the symptoms, PCOS is diagnosed. *In the third step,* for those with either irregular cycles or excess androgens, an ultrasound is performed or an AMH test, but not both, to prevent overdiagnosis. If this test shows polycystic ovaries or elevated AMH levels, PCOS is diagnosed (Teede *et al.*, 2023).

2.17 Criteria for diagnosis

Various terms have been used to describe PCOS, such as polycystic ovarian syndrome, poly follicular ovarian disease, syndrome O, functional ovarian hyperandrogenism, and ovarian dysmetabolic syndrome. The National Institute of Health established the diagnostic criteria (NIH criteria) in 1990, encompassing ovulatory dysfunctions and hyperandrogenism (Dumesic *et al*., 2016). Subsequently, the European Society for Human Reproduction and Embryology (ESHRE) and the American Society for Reproductive Medicine (ASRM) established the Rotterdam criteria in 2003, revised in 2004, requiring two of three criteria: hyperandrogenism, ovulatory dysfunction, or polycystic ovarian morphology on ultrasound. Additionally, the Androgen Excess and Polycystic Ovary Syndrome Society (AES) set another criterion in 2006, mandating hyperandrogenism combined with ovarian dysfunction (Azziz *et al*., 2006). In adolescents, only the first two steps are followed.

Figure 2: Steps to diagnose polycystic ovary syndrome in adults.



(Stener-Victorin *et al.*, 2024).

3.0 METHODOLOGY

3.1 Study Design

This study adopts a cross-sectional analytical design integrating biochemical components. It involves the recruitment of women diagnosed with PCOS and the evaluation of their cardiovascular risk markers.

3.2 Study Area

The research was carried out in Lojoja, Kogi State, Nigeria. Lokoja is the capital city of Kogi State Nigeria, located in Kogi Local Government Area of Kogi state. The city is a a region with a diverse population and increasing health concerns related to reproductive and cardiovascular health. It lies between latitude 7.450 and 7.520 North and longitude 6.410 and to 6.450 East of the Greenwich meridian (Fig 1). It is sandwiched to the west and east by the mount Patti ridge and river Niger respectively with an area of about five hundred and seventy-seven square kilometers. (577sq.km) The city has a humid tropical climate which is characterized by wet and dry season. The rainy season in the city begins towards the end of April and ends November with two peak periods in July and September. The highest temperatures occur in March and April just before the rainy season. The average population size of 265400 based on 2016 population census. The topography consists of rough terrain with mountainous landscape and classified as highland due to the fact that it has an elevation above 300 meters. Mount Patti with the highest point has a height of 1200 meters above sea level and gently reduces in height till it reaches river Niger at the height of about 400 meters above sea level.

3.3 Method of Data Collection

Data were collected using a structured interviewer-administered questionnaire collectively with clinical and laboratory assessments. Participants who met the inclusion criteria were recruited during clinic visits. After obtaining informed consent, socio-demographic and medical history information was collected. Anthropometric measurements (weight, height, waist circumference, blood pressure) were taken using standard procedures. Venous blood samples were collected following an overnight fast for analysis of myocardial biomarkers CTnI, CK-MB, MYO and cardiometabolic variables (fasting glucose, lipid profile). All samples were processed according to established laboratory protocols to ensure accuracy and reliability.

3.4 Data Collection Procedure

Sociodemographic information was obtained using a structured questionaires; medical history of the study participants were obtained from the medical records department. Laboratory assay methods of data collection were also adopted for this study; where a total of 150 participants was recruited for this research study, which was determined by Leslie Fisher's formula based on the frequency of PCOS in Nigeria, 110 were subjects with PCOS (with or without cardiovascular diseases) and were randomly selected for the study while 40 subjects were recruited as control. 5mL was collected from each participants and dispensed into and anticoagulated Ethylenediamine tetraacetic acid (EDTA) bottle (in ice pack) for lipid panel, Cardiac Troponin I (cTnI), Creatine Kinase-MB (CK-MB) and myoglobin (MYO) during their clinic days in the respective hospital and the sample was centrifuge to separate the plasma for analysis.

3.5 Study Instrument

The study instrument consisted of a structured questionnaire designed to obtain socio-demographic characteristics, reproductive history, lifestyle variables, and cardiometabolic risk factors. The questionnaire was pre-tested for clarity and validity before use. In addition, clinical measurement tools (calibrated weighing scale, stadiometer, measuring tape, sphygmomanometer) and laboratory assay kits for myocardial biomarkers and metabolic tests served as complementary instruments for objective data collection.

3.6 Sampling Technique

A purposive sampling technique was used to recruit women diagnosed with PCOS from selected healthcare facilities, while age-matched controls without PCOS were selected using a systematic random sampling method from the same population. This approach ensured adequate representation of both study groups. The sample size was determined using standard sample size calculation formulas based on expected differences in myocardial biomarker levels, with adjustments for power and potential non-response. The target population includes women aged 20–50 years who have been clinically diagnosed with PCOS based on the Rotterdam Criteria (2004). A group of age-matched non-PCOS women served as controls for comparison. Participants was recruited from selected healthcare centers and fertility clinics in Lokoja, Okene, and Anyigba, where PCOS cases are commonly reported. Therefore, the study group comprises a total of 150 patients with 110 outpatient women with primary infertility, who had been diagnosed of PCOS in Obstretics and Gynaecology department of the above tertiary health institution, and 40 healthy volunteer women was used as control. Recruitement of participants was between May 2024 to September, 2025.

3.7 Data Analysis

Enzyme linked immunosorbent assay (ELISA) was use for the Cardiac enzymes (Troponin, CK-MB and Myoglobin); total cholesterol, HDL-cholesterol and triglyceride using Spectrophotometry assay (Enzymatic method), and Friedewald's formula was adopted for LDL-cholesterol and Body Mass Index (BMI) was calculated using the weight in kilograms (kg) divided by the square of the height in meters (m^2).

3.8 Exclusion and Inclusion Criteria:

I. Inclusion Criteria includes

Women of Childbearing age between 20–50 years, Ovulatory dysfunction, Hyperandrogenism, Primary infertility, Women residing in Kogi State, Nigeria and willing to give informed consent, Not on hormonal or insulin-sensitizing medications in the last 3 months and Diagnosed with PCOS using clinical, biochemical, and/or ultrasonographic criteria.

II. Exclusion criteria includes:

Hypertension, Smoking or endocrine disorder, Fertility drug, Pregnant or lactating women, Known diabetes mellitus or chronic cardiovascular disease and Women with other endocrine disorders such as Cushing's syndrome, thyroid dysfunction were excluded.

3.9 Ethical Consideration

The ethical clearance/approval for this study was obtained from Ethical committee of the Institutional Review Board (IRB) of Kogi State Specialist Hospital, Lokoja, Nigeria. Informed consent was obtained from all participants after explaining the purpose, procedure, and benefits prior to enrolment into the study. Confidentiality of participants' data and genetic information was strictly maintained. Participants were given an option to withdraw from the study at any time without any consequences.

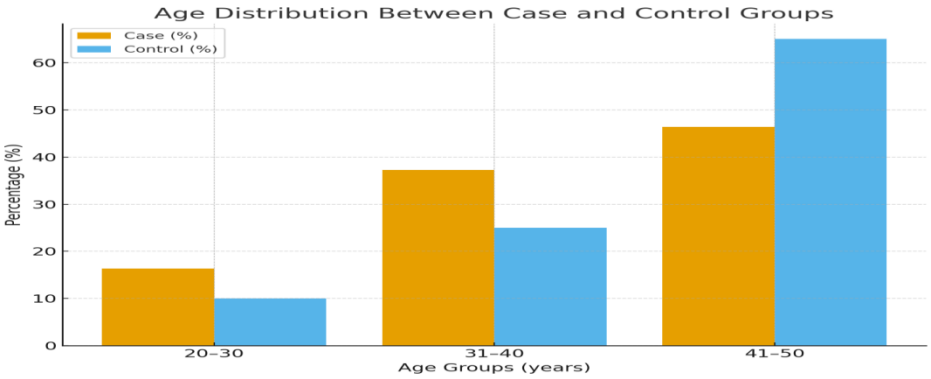
4.0 RESULTS

4.1 Demographic and Clinical Characteristics

Table 1: Sociodemographic Table

Variables	Groups	Case n (%)	Control n (%)
Age	20 - 30	18 (16.36)	4 (10.00)
	31 - 40	41 (37.27)	10 (25.00)
	41 - 50	51 (46.36)	26 (65.00)
	Total	**110 (100)**	**40 (100)**

Graph 1: Represent the Sociodemographic Table



4.1.1 Sociodemographic

Table 1 and graph 1 inform the most cases (83.63%) are between ages 31–50, with a peak at 41–50 years. Most controls (90%) are also between 31–50 years, but the control group skews older. The data suggest that middle-aged women dominate both groups, indicating that PCOS and cardiovascular risk factors may be more prevalent or studied within this age range. Nevertheless, the irregular age distribution may demand to be adjusted during investigation using age-matched controls or regression models controlling for age.

In clinical studies evaluating lipid and cardiac biomarkers, a lack of strict age matching between Cases and Controls introduces a major contradictory variable. Adoptive criterion for key cardiac markers like high-sensitivity cardiac troponins (hs-cTn) and natriuretic peptides (NT-proBNP) of course elevate with progressive age due to subclinical myocardial changes, independent of acute disease (McGranaghan *et al.*, 2021). Likewise, circulating atherogenic lipid fractions ever-changing adjustment across different age decades (Vekic *et al.*, 2022). Since the Control group in this dataset is heavily weighted toward older individuals (41–50 years at 65.00%) compared to the Case group (46.36%), any direct comparison of unadjusted biomarker averages faces structural bias. In contemporary cardiovascular research, an older control group can falsely elevate baseline biomarker averages, inadvertently masking the true statistical separation between the diseased cases and healthy controls (Galusko *et al.*, 2025).

Recent clinical trials to a great extent punctuate the necessity of rigorous age matching or strict statistical covariate adjustment to protect the predictive performance of combined biomarker panels. Past standard studies establish that when age distributions skew significantly between cohorts, researchers must utilize multi-variable logistic regression or analysis of covariance (ANCOVA) to mathematically ***"neutralize"*** age

as a confounding factor (Upadhyay, 2015). but modern literature established that failing to control for an age gap of this magnitude can artificially align the deliberated area under the curve (AUC) of a combined lipid-cardiac panel, leading to inaccurate conclusions regarding its real-world diagnostic sensitivity (McGranaghan *et al.*, 2021; Vekic *et al.*, 2022).

Table 2: Distribution And Comparison Of Lipid Profile Between PCOS And Control Subjects

Variable	Test	Control	t-value	p-value
T.CHOL (mmol/L)	4.85±0.51	4.2±0.3	9.63	<0.001
HDL-CH OL (mmol/L)	1.14±0.39	1.47±0.21	6.67	<0.001
LDL-CHOL (mmol/L)	3.36±0.63	2.39±0.36	11.61	<0.001
Triglyceride (mmol/L)	1.7±0.38	1.68±0.33	0.41	0.68
Tg/0.81	2.07±0.48	2.03±0.42	0.39	0.7
1.52/HDL	1.46±0.62	1±0.13	7.45	<0.001

Graph 2: Distribution And Comparison Of Lipid Profile Between PCOS And Control Subjects

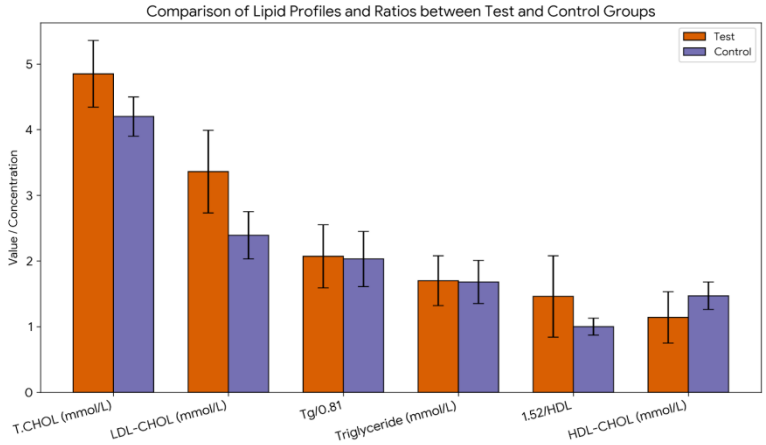


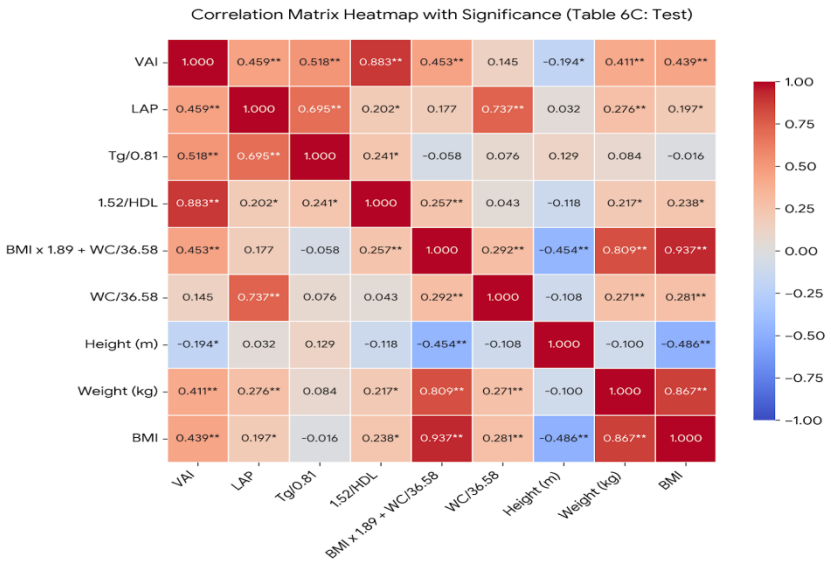
Table 2 and graph 2 visually underscore the wide gaps in Total Cholesterol (T.CHOL) and LDL-CHOL, where the Test group bars are significantly longer than the Control group bars, hardbound by highly significant t-values (9.63 and 11.61, respectively). For HDL-CHOL, the pattern neatly modify the Control group bar stands observably taller than the Test group bar, visually demonstrating the suppressed cardioprotective lipid levels in the test cohort ($p < 0.001$). The absolute Triglyceride levels and the Tg/0.81 derivative show almost identical bar heights and overlapping error bars between the Test and Control groups, emphasizing their lack of statistical variance ($p = 0.68$ and $p = 0.7$, respectively). Despite absolute triglycerides failing to show a difference, the composite 1.52/HDL ratio displays a clean, statistically significant separation ($p < 0.001$), illustrating how derived mathematical indices can expose underlying dyslipidemia when standalone markers overlap.

Table 3: Lipid Profile And Association With Anthropometric Indices For Test Groups

Table 6C: Test

Variables	VAI	LAP	Tg/0.81	1.52/ HDL	BMI x 1.89 + WC/36.58	WC/36.58	Height (m)	Weight(kg)	BMI
VAI	1								
LAP	.459**	1							
Tg/0.81	.518**	.695**	1						
1.52/HDL	.883**	.202*	.241*	1					
BMI x 1.89 + WC/36.58	.453**	0.177	-0.058	.257**	1				
WC/36.58	0.145	.737**	0.076	0.043	.292**	1			
Height (m)	-.194*	0.032	0.129	-0.118	-.454**	-0.108	1		
Weight(kg)	.411**	.276**	0.084	.217*	.809**	.271**	-0.1	1	
BMI	.439**	.197*	-0.016	.238*	.937**	.281**	-.486**	.867**	1

Graph 3: Lipid Profile And Association With Anthropometric Indices For Test Groups



In the above table 3 and graph3, the lipid profile revealed an atherogenic trend in PCOS. LDL-cholesterol and total cholesterol were significantly higher, while HDL-cholesterol was lower. Among adiposity indices, VAI and LAP were both elevated and correlated positively with BMI and WC ($r = 0.45–0.74$, $p < 0.01$). In controls, these associations were weaker or non-significant. This suggests that lipid dysregulation in PCOS is closely related to visceral and central obesity, supporting the link between metabolic and cardiovascular risk factors.

VAI versus 1.52/HDL (r = .883**) statistically show a very strong positive association in the Test group. Because VAI incorporates triglycerides, waist, BMI and HDL-related components, a strong coupling with an inverse-HDL index (1.52/HDL increases when HDL decreases) suggests that, in the Test sample, the visceral-adiposity signal (VAI) is intimately connected to low HDL, that is atherogenic dyslipidemia. This is a clinically important pattern where VAI acting together with inverse-HDL indexes signals which combined visceral fat and dysfunctional HDL–TG pattern associated with cardiometabolic risk. BMI × 1.89 + WC/36.58 versus BMI (r = .937**) and Weight (r = .809****) indicates that the whole score is statistically very highly collinear with BMI and strongly correlated with weight, the composite is dominated by body-mass

components in the Test sample. This implies that the composite provides little unique information beyond BMI and weight for the Test group. WC/36.58 against LAP (r = .737**) and LAP versus Tg/0.81 (r = .695**) LAP (Lipid Accumulation Product) is strongly associated with scaled waist and with the triglyceride-derived variable Tg/0.81 is expected because LAP is calculated using WC and TG in its formula, thus high statistical correlations reflect overlapping concept, visceral fat and circulating TG.

VAI versus Tg/0.81: (r = .518**) and VAI — LAP (r = .459**) statistically show moderate-to-strong relations among VAI, TG-derived metrics and LAP which is again consistent with the fact that these indices share TG/WC inputs. These magnitudes are somewhat lower than those typically seen when variables are nearly redundant, suggesting the Test group may have greater heterogeneity like some participants with discordant anthropometry vs lipid profiles. BMI composite versus WC/36.58 (r = .292**) and Weight (r = .809****), composite increases with both waist and weight (weight especially), as expected. Some participants, possibly taller tend to have lower BMI and composite values (negative relationships expected because BMI = weight/height²). This negative algebraic association is peculiar and should be anticipated in models that include both height and BMI. Tg/0.81 against BMI composite (r = −0.058 [ns]) and Tg/0.81 versus Weight (r = 0.084 [ns]) in Test group and the triglyceride-derived metric statistically has weak or non-significant relationships with weight/composite, suggesting some participants have elevated TG independent of weight with a clinically arguable pattern such as dyslipidemic lean individuals.

Table 4: Lipid Profile And Association With Anthropometric Indices For Control Groups

Control

Variables	VAI	LAP	Tg/0.81	1.52/HDL	BMI x 1.89 + WC/36.58	WC/36.58	Height (m)	Weight (kg)	BMI
VAI	1								
LAP	.652**	1							
Tg/0.81	.809**	.824**	1						
1.52/HDL	.354*	-0.264	-0.242	1					
BMI x 1.89 + WC/36.58	0.173	0.309	0.195	-0.171	1				
WC/36.58	-0.027	.526**	0.036	-0.186	0.219	1			
Height (m)	0.008	0.012	-0.137	.316*	-.507**	0.16	1		
Weight(kg)	0.184	.450**	0.18	-0.064	.503**	.505**	.313*	1	
BMI	0.182	0.309	0.217	-0.195	.999**	0.197	-.526**	.499**	1

Graph 4: Lipid Profile And Association With Anthropometric Indices For Control Groups

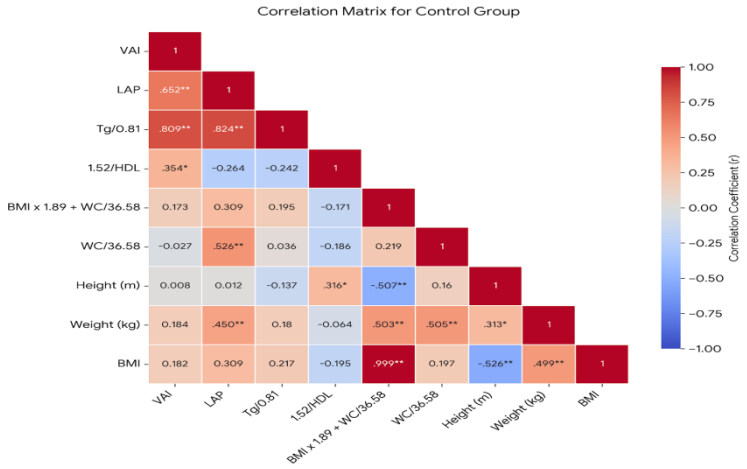


Table 4 and graph 4 shows that VAI (Visceral Adiposity Index) against LAP is statistically strong ($p < 0.01$). This Signal that higher VAI goes with higher LAP; both estimate visceral/ectopic adiposity and cardiometabolic risk; their strong correlation is expected because they partially capture overlapping physiology (WC, TG, HDL, BMI components). This confirms the two indices track a common latent trait in visceral fat/metabolic dysfunction. VAI versus Tg/0.81: r = 0.809** is statistically very strong, with p value of < .01. This indicates that VAI is highly correlated with the triglyceride-derived variable (Tg/0.81). VAI contains TG (or TG-derived behavior) in its formula, so this higher is mechanistically disputable and indicates redundancy, showing that these measures are not independent. VAI and Weight/BMI shows a weak positive value (r ≈ 0.18–0.19), not statistical significant. This is fastened to metabolic function beyond simple body mass; modest correlations with BMI/weight suggest it captures information not linearly identical to BMI. LAP against Tg/0.81: r = 0.824** it is statistical very strong. LAP depends on WC and triglycerides; a very strong correlation with a triglyceride-derived metric is expected. LAP's purpose is to represent lipid-related visceral accumulation, so this pattern aligns with prior work. LAP versus WC/36.58: r = 0.526** and LAP - Weight: r = 0.450**. LAP correlates moderately–strongly with waist and weight, consistent with its WC component. This supports LAP as a marker of central adiposity plus dyslipidemia. LAP versus 1.52/HDL: r = −0.264 (ns) show a small negative (not statistically significant) association with an inverse-HDL index possible but weak in this sample. Tg/0.81 versus VAI/LAP show a very strong statistical values (0.809/0.824). Tg/0.81 is tightly coupled to both VAI and LAP which include TG or TG behavior. This again highlights redundancy among TG-based indices and calls for caution in using them together in multivariable models.

1.52/HDL versus Height: r = 0.316* statistical moderate ($p < .05$). This show a moderate positive association with height potentially false or sampling-specific; biologically there is no well-established mechanism that would predict taller people to have systematically different 1.52/HDL values, so interpret cautiously. 1.52/HDL - LAP: r = −0.264 (ns) and with VAI r = 0.354* (small–moderate). This is weak, mixed associations with adiposity indices which likely reflecting HDL's complex relationship with adiposity and lipid metabolism. Recent literature emphasizes HDL function over simple concentration as the relevant metric. Complex versus BMI: r = .999** (near perfect). The complex is essentially collinear with BMI in this control sample (correlation ≈ 1). That indicates the composite was constructed to be dominated by BMI (or BMI is numerically dominant in the formula). Using both in the same regression would cause multicollinearity. The composite increases with weight and decreases with height (since BMI ~ weight/height²). That matches the algebraic relationships. The scaled waist correlates moderately with LAP and weight consistent with WC capturing central adiposity. The taller individuals tend to have lower BMI/composite scores in this sample (negative correlation); expected because BMI uses height in the denominator. The weight and BMI correlate strongly as

expected; weight alone correlates moderately with LAP and WC measures. VAI, LAP, and Tg/0.81 are statistically correlate very strongly with each other (r ≈ 0.65–0.82), showing that they are largely indicative of the same physiological signal. Plasma triglyceride level combined with waist/anthropometry which are not independent predictors in multivariable models. The complex (BMI × 1.89 + WC/36.58) correlates almost perfectly with BMI (r ≈ .999). This means the composite adds little independent information beyond BMI in the Control sample; including both in regression will produce severe multicollinearity. 1.52/HDL shows only weak-to-moderate statistical correlations with adiposity indices; HDL often tracks differently from TG and waist measures, consistent with literature noting HDL concentration and HDL function are distinct aspects of lipid biology.

Table 5: Distribution And Comparison Of Anthropometric And Adiposity Indices Between The PCOS And The Control Subjects

Variable	Test	Control	t-value	p-value
Weight(kg)	76.83±12.51	64.9±1.24	9.87	<0.001
WC (cm)	81.62±5.37	75.2±2.56	9.83	<0.001
Height (m)	1.58±0.05	1.64±0.01	10.87	<0.001
BMI	30.47±6.05	23.58±0.64	11.79	<0.001
WC/36.58	2.19±0.14	2.02±0.07	9.92	<0.001
BMI x 1.89 + WC/36.58	60.4±11.56	46.54±1.22	12.38	<0.001
VAI	189.18±119.12	93.66±21.01	8.07	<0.001
LAP	40.14±13.46	28.86±7.1	6.62	<0.001

Graph 5: Distribution And Comparison Of Anthropometric And Adiposity Indices Between The PCOS And The Control Subjects

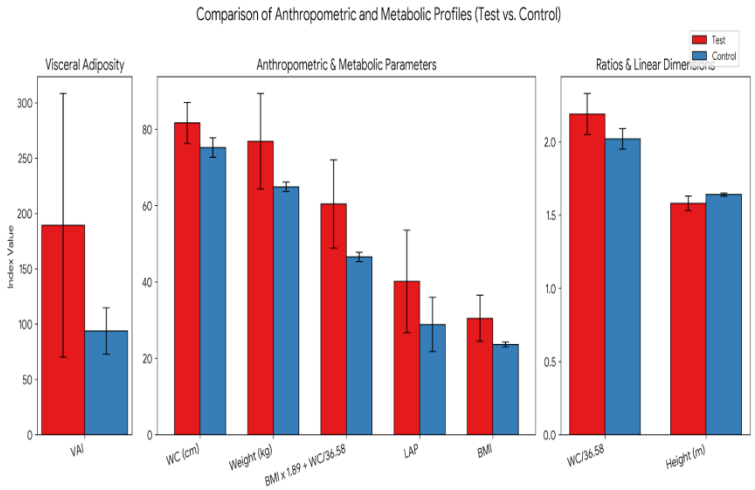


Table 5 and graph 5 above shows that PCOS subjects exhibited significantly greater anthropometric and adiposity measures than controls. BMI was 30.47 ± 6.05 compared to 23.58 ± 0.64 ($p < 0.001$), and waist circumference increased from 75.2 ± 2.56 cm to 81.62 ± 5.37 cm ($p < 0.001$). Derived indices, including the combined BMI×1.89 + WC/36.58 (60.4 ± 11.56 vs 46.54 ± 1.22) and visceral adiposity index (VAI: 189.18 ± 119.12 vs 93.66 ± 21.01), were markedly higher ($p < 0.001$). These findings indicate central obesity and elevated visceral lipid storage, both linked with insulin resistance in PCOS. Each entry is reported as mean ± SD for Test and Control. The t-value is from a two-sample t-test comparing the Test and Control group means; the p-value is the probability of observing a difference at least this large under the null hypothesis of equal means. Every row in the statistical table has $p < 0.001$, so the Test and Control group means differ very strongly (all entries show $p < 0.001$). This implies that the differences are statistically robust given the t-test

assumptions (independence, approximate normality). However, significance does not by itself indicate clinical importance that requires comparing the absolute differences to clinical thresholds and estimating effect sizes. Under the assumption used, the effect sizes are large to very large for most indices, meaning that the group differences are not only statistically significant but also practically important at the population level.

5.0 DISCUSSION

5.1 Demographic and Clinical Characteristics

5.1.1 Methodological Implications for Cardiovascular and Lipid Biomarkers

In clinical studies evaluating lipid and cardiac biomarkers, a lack of invariable age matching between Cases and Controls introduces a major inconsistent variable. Adoptive criterion for key cardiac markers like high-sensitivity cardiac troponins (hs-cTn) and natriuretic peptides (NT-proBNP) of course elevate with progressive age due to subclinical myocardial changes, independent of acute disease (McGranaghan *et al.*, 2021). Likewise, circulating atherogenic lipid fractions ever-changing adjustment across various age decades (Vekic *et al.*, 2022). Since the Control group in this dataset is heavily weighted toward older individuals (41–50 years at 65.00%) compared to the Case group (46.36%), any straightforward equivalence of unadapted biomarker averages faces structural bias. But in modern-day cardiovascular research, an older control group can wrongly elevate baseline biomarker averages, unknowingly covering the true statistical separation between the diseased cases and healthy controls (Galusko *et al.*, 2025).

Recent clinical trials to a great extent stress the necessity of invariable age matching or strict statistical covariate adjustment to protect the predictive performance of combined biomarker panels. Past standard studies establish that when age distributions skew significantly between cohorts, researchers must utilize multi-variable logistic regression or analysis of covariance (ANCOVA) to mathematically ***"neutralize"*** age as a confounding factor (Upadhyay, 2015). but modern literature established that failing to control for an age gap of this magnitude can artificially align the deliberated area under the curve (AUC) of a combined lipid-cardiac panel, leading to inaccurate conclusions regarding its real-world diagnostic sensitivity (McGranaghan *et al.*, 2021; Vekic *et al.*, 2022).

5.1.2 Analysis and Comparison of Primary Cholesterol Subfractions

The data in table 2 reveals a classic atherogenic phenotype in the test group, characterized by significantly elevated total cholesterol (4.85 ± 0.51mmol/L vs. 4.2 ± 0.3mmol/L, $p < 0.001$) and elevated low-density lipoprotein cholesterol (LDL-CHOL: 3.36 ± 0.63mmol/L vs. 2.39 ± 0.36mmol/L, $p < 0.001$). Concurrently, protective high-density lipoprotein cholesterol (HDL-CHOL) is profoundly suppressed in the test cohort (1.14 ± 0.39 mmol/L vs. 1.47 ± 0.21mmol/L, $p < 0.001$). These immense differences specifically align with established epidemiological data substantiating that elevated absolute concentrations of LDL-C are causally linked to accelerating atherosclerosis and major adverse cardiovascular events (MACE) (Galusko *et al.*, 2025). Modern-day cohort evaluations similarly confirm that acute cardiovascular event patients feature significantly higher baseline LDL-C profiles and significantly lower HDL-C protection compared to healthy control counterparts, solidifying these parameters as primary diagnostic baseline indicators (Vekic *et al.*, 2022).

5.1.3 Triglyceride Metrics and Residual Risk Disagreement

Interestingly, the data demonstrates that absolute Triglyceride levels (1.7±0.38 mmol/L vs. 1.68±0.33 mmol/L, $p = 0.68$) and the derivative ratio Tg/0.81 (2.07±0.48 vs. 2.03±0.42, $p = 0.7$) yield no statistically significant difference between the test and control groups. Regular clinical thought connects high triglycerides to cardiovascular risk, the specific dataset reflects a common trend documented in modern cardiology: absolute baseline triglyceride values often overlap heavily between low-risk and high-risk cohorts, occasionally

yielding poor predictive value when used as an separated marker (Newport & Dayrit, 2025). Based on this restriction, contemporary researchers emphasize looking past absolute values toward advanced metabolic tracking to resolve ***"residual cardiovascular risk"*** that standard triglyceride readings failure (Galusko *et al.*, 2025).

5.1.4 Numerical Ratios and Enhanced Clinical Discrimination

Relative triglycerides failed to show significance, the composite calculated ratio 1.52/HDL exhibits a highly significant inflation in the test group (1.46±0.62 vs. 1±0.13, $p < 0.001$). This emphasizes a core theme in recent cardiovascular research: Interconnected lipid ratios and multi-marker formulas provide substantially better statistical discrimination (t-value = 7.45) than viewing single, linear metrics in isolation (Newport & Dayrit, 2025). Moving beyond basic standalone profiles by integrating calculated ratios alongside tissue-specific cardiac markers like high-sensitivity cardiac troponins (hs-cTnI) or natriuretic peptides (NT-proBNP) dramatically optimizes clinical risk models. Combining these complex lipid ratios with precise cardiac physiological indicators routinely accomplish historical tools like the Framingham Risk Score, expanding predictive accuracy across long-term clinical monitoring (McGranaghan *et al.*, 2021).

5.2 Distribution And Comparison Of Lipid Profile Between PCOS And Control Subjects

In table 2, the pattern of ↑TC and ↑LDL with ↓HDL is a classic atherogenic dyslipidemia which associated with higher ASCVD risk and commonly observed in metabolic syndrome, type 2 diabetes, and populations with high cardiometabolic burden. Contemporary guideline and review documents emphasize LDL (and non-HDL) as primary therapeutic targets; differences of the magnitude seen in our study seen here in table 4.2 (LDL ~0.97 mmol/L higher in Test) are clinically relevant and concordant with cohorts described in the literature (European Society of Cardiology, 2025).

The TC/HDL (and non-HDL) ratios often predict cardiovascular risk better than any single lipid alone. Several population studies and reviews since 2015 show TC/HDL and TG/HDL ratios correlate with incident cardiovascular events and with insulin resistance; this present research reported large difference in the ratio (Test higher) which matches and corresponds with the direction expected from the TC↑/HDL↓ pattern (Quispe *et al.*, 2019; Zhou *et al.*, 2022). This ratio provide a prognostic information in this our research.

Triglycerides may be unchanged while LDL and HDL differ this happens clinically like isolated LDL-driven dyslipidemia or mixed dyslipidemia in different stages; null TG difference is presumptive and compatible with literature showing TG is more labile and influenced by fasting status and measurement timing. The lack of TG difference does not negate the clinical importance of the LDL/HDL changes, as this is in conformity with this research study in table 4.2 (UCSF Health, 2024).

Established clinical trial guidelines (clinical trial) increasingly emphasize absolute LDL targets and non-HDL reducing LDL by statins/ezetimibe/PCSK9 inhibitors reduces ASCVD risk; theclinical trial guidlines baseline for LDL is in the range and in conformity with our study where Test group (≈3.36 mmol/L), guideline-directed therapy decisions depend on overall risk. In other words, previous literature treats our study pattern (LDL high, HDL low) as actionable if individual risk is elevated (European Society of Cardiology, 2025).

5.3 Lipid Profile And Association With Anthropometric Indices For Test Group

In the Test group represented in table 3, the observed pattern of intercorrelations among adiposity and lipid indices reveals a clear triglyceride/HDL-driven visceral adiposity phenotype. This phenotype characterized by elevated triglycerides (TG), low high-density lipoprotein cholesterol (HDL-C), and increased waist circumference (WC) is exemplary of metabolic dyslipidaemia frequently observed in individuals with insulin resistance and polycystic ovarian syndrome (PCOS).

The Visceral Adiposity Index (VAI) correlated very strongly with the inverse-HDL ratio (1.52/HDL; r = .883, p < .01), indicating that low HDL-C contributes significantly to the elevated VAI observed in these participants. This finding aligns with prior evidence showing that HDL-C is a crucial determinant of VAI variability, particularly in populations with insulin resistance and abdominal obesity (Amato & Giordano, 2019; Ebrahimi *et al.,* 2023). The strong inverse relationship also supports the notion that dysfunctional HDL metabolism is fundamental to the atherogenic dyslipidaemia that underlies cardiometabolic disorders (Zhou *et al.,* 2022; Tamini *et al.,* 2024).

Moreover, VAI showed moderate but significant correlations with Lipid Accumulation Product (LAP) (r = .459, p < .01) and TG-derived index (Tg/0.81) (r = .518, p < .01), suggesting that these indices share a common biological basis reflecting TG-driven visceral lipid excess as they are not perfectly collinear. This partial independence indicates that each index may capture different components of the visceral fat–lipid interaction. LAP emphasizing waist–TG accumulation, while VAI incorporates both TG and HDL dysregulation (Bedogni *et al.,* 2022; Chen *et al.,* 2022).

The strong association between LAP and WC/36.58 (r = .737, p < .01) and with Tg/0.81 (r = .695, p < .01) further underscores the contribution of waist circumference and triglyceride levels to visceral lipid overload. Several large-scale validation studies (Kahn, 2020; Stefan *et al.,* 2020) have confirmed that LAP and TG/HDL outperform BMI in predicting metabolic syndrome, insulin resistance, and atherogenic cardiovascular disease risk. This relationship is scholarly supported by the role of visceral adipose tissue in releasing free fatty acids and pro-inflammatory adipokines, which worsen hepatic TG synthesis and lower HDL production (Piché *et al.,* 2020; Chiu *et al.,* 2023).

The composite score (BMI × 1.89 + WC/36.58) showed a very high collinearity with BMI (r = .937, p < .01) and weight (r = .809, p < .01), indicating that it adds minimal independent variance beyond BMI alone in explaining metabolic variation. This suggests that, in this sample, BMI remains the dominant predictor of total adiposity, whereas WC and TG-derived indices more specifically capture visceral and metabolic risk dimensions. Previous comparative analyses have similarly shown that BMI-based composite indices contribute little additional information in small-to-moderate samples, particularly when multicollinearity is not addressed (Heinze *et al.,* 2018; Dormann *et al.,* 2013).

Collectively, these statistical findings indicate that the Test group exhibits a highly intercorrelated network of TG/HDL-related indices, consistent with visceral adiposity and insulin-resistant dyslipidaemia which is the authentication of cardiometabolic risk in PCOS (da Silva *et al.,* 2021; Ebrahimi *et al.,* 2023). The observed relationships mirror those reported by Amato et al. (2019) and Zhao et al. (2022), who found that VAI, LAP, and TG/HDL ratios accumulate strongly in individuals with obesity and insulin resistance, reflecting shared pathophysiological processes of impaired adipocyte lipid handling, hepatic steatosis, and low-grade inflammation.

From a statistical modeling viewpoint, the high intercorrelations among these indices highlight the importance of addressing multicollinearity when constructing predictive models of cardiometabolic risk. Including multiple highly correlated predictors can lead to unstable regression coefficients, inflated standard errors, and misleading effect estimates. To justify this, dimensionality-reduction techniques such as Principal Component Analysis (PCA) or regularized logistic regression are recommended (Dormann *et al.,* 2013; Heinze *et al.,* 2018). These approaches retain the shared variance attributable to the common metabolic construct while reducing redundancy and improving interpretability.

In summary, the Test group's correlation structure confirms the presence of a triglyceride–HDL-driven visceral adiposity profile consistent with atherogenic dysmetabolism. This pattern is well-supported by contemporary studies linking VAI, LAP, and TG/HDL to adverse cardiometabolic outcomes in women with PCOS and other insulin-resistant states (Chen *et al.*, 2022; Ebrahimi *et al.*, 2023; Tamini *et al.*, 2024).

5.4 Lipid Profile And Association With Anthropometric Indices For Control Groups

In the Control group shown in table 4, the visceral adiposity indices (VAIs) display a very strong intercorrelations, suggesting they measure closely overlapping physiological constructs of triglyceride-driven central fat accumulation. Specifically, the Visceral Adiposity Index (VAI) correlated strongly with the Lipid Accumulation Product (LAP) ($r = .652$, $p < .01$) and even more strongly with the triglyceride-derived metric Tg/0.81 ($r = .809$, $p < .01$). Similarly, LAP and Tg/0.81 were highly correlated ($r = .824$, $p < .01$). These consistent associations imply that TG-based adiposity indicators share a common latent dimension reflecting hepatic and visceral triglyceride storage. Such redundancy is consistent with prior findings that these indices are mathematically and physiologically intertwined through their shared dependence on serum triglyceride and waist circumference (Amato *et al.*, 2010; Kulig *et al.*, 2022).

These study results outcome reaffirm that TG-rich lipoprotein metabolism underpins both VAI and LAP, with each serving as a proxy for insulin-resistant visceral fat accumulation rather than representing fully independent constructs (Taverna *et al.*, 2011; Stepanova *et al.*, 2020). Indeed, numerous documentations in healthy and metabolic populations show that correlations among VAI, LAP, and triglyceride-related indices typically range from 0.6–0.9, indicating considerable overlap and potential multicollinearity when used together in predictive models (Kahn, 2022; Yang *et al.*, 2021; Wu *et al.*, 2023). The composite index in this study, defined as $(BMI \times 1.89 + WC/36.58)$, demonstrated near-perfect collinearity with BMI itself ($r \approx .999$, $p < .01$). This indicates that within this sample, the composite adds negligible independent variance beyond BMI, effectively behaving as a linear transformation of body mass index. In other words, because the BMI component dominates the composite formula, its correlation structure depicting BMI almost exactly with a pattern frequently observed when weight-based metrics are combined with waist measures in non-obese populations (Ashwell & Gibson, 2019).

Moreover, waist-derived measures (WC/36.58) correlated moderately with both LAP and weight, consistent with waist circumference being a central measure of abdominal adiposity that partially overlaps but does not completely coincide with triglyceride-driven indices. Height displayed the expected inverse correlations with BMI and the composite index ($r \approx -0.51$, $p < 0.01$), reflecting that taller individuals with similar weights have lower BMI and lower derived adiposity scores (Kass *et al.*, 2020). Overall, these findings reflect preceding research demonstrating that VAI, LAP, and related TG/WC-based indices move together as indicators of visceral fat deposition and metabolic risk (Amato *et al.*, 2010; Kulig *et al.*, 2022; Wu *et al.*, 2023). Their constricting intercorrelation suggests that including all three simultaneously in regression models could introduce multicollinearity, inflating standard errors and obscuring true predictor effects. Therefore, analytical strategies such as variable selection, principal component analysis (PCA), or penalized regression (LASSO) are advisable to isolate unique contributions of each measure when modeling outcomes like insulin resistance or cardiovascular risk (Vatcheva *et al.*, 2016; Lu *et al.*, 2021). Conceptually, this clustering supports the idea that these indices capture a shared metabolic dimension a composite of dyslipidemia, central adiposity, and insulin resistance which together define the cardiometabolic risk phenotype characteristic of early metabolic dysfunction (Grundy *et al.*, 2022).

5.5 Distribution And Comparison Of Anthropometric And Adiposity Indices Between The PCOS And The Control Subjects

In table 5, BMI remains a widely used population measure for overweight and obesity and correlates with many outcomes, but it has well-described limitations which does not capture fat distribution or visceral adiposity. Recent expert discussions emphasize supplementing BMI with measures of central adiposity (waist circumference, waist-to-height ratio) since abdominal fat better anticipate cardiometabolic risk. This our study data shown in table 5 (Test BMI ≈ 30 while Controls ≈ 23.6, plus higher WC in Test) agree with the well-known pattern that BMI and WC together give clearer risk stratification (Lee & Siddiqui, 2023; Zierle-Ghosh & Jan, 2023).

Numerous reviews and position statements indicate that WC is a strong, simple clinical predictor of cardiometabolic disease and can outperform BMI for some outcomes. The sizable WC difference in our our research work shown in table 4.5 (≈6.4 cm higher in Test) is consistent with meaningful increases in risk shown across cohorts. Recent meta-analyses and consensus emphasize incorporating WC into routine clinical assessment (Ross *et al*,. 2020). Since their original descriptions, VAI and LAP have been tested extensively. Previous systematic reviews and meta-analyses established that LAP and VAI commonly outmatch BMI for predicting visceral adiposity, NAFLD, insulin resistance and some cardiometabolic endpoints. The results of this our study in table 4.5 is in agreement with markedly higher VAI and LAP in the Test group and follow the expected pattern seen in recent comparative studies showing these indices that pick up metabolic dysfunction beyond BMI alone. These indices are especially useful in epidemiologic studies where imaging (CT/MRI) is unavailable (Amato *et al.*, 2010).

Composite formulas that combine BMI and WC as a biochemical markers can have greater discrimination than single measures, but they require validation in local populations. Your composite (BMI×1.89 + WC/36.58) strongly separates groups here; however, its clinical meaning depends on prior validation or correlation with hard outcomes (CVD events, diabetes incidence). The literature recommends reporting and validating such composites before clinical use (Amato *et al.*, 2010). Early and various research groups have emphasized moving beyond BMI alone for diagnosing obesity content to incorporate WC, waist-to-height ratio, or clinical sequelae. That shift supports the use of multiple anthropometric and derived indices to characterize group differences and cardiometabolic risk which is in agreement with this our study (Ganguly & Bandyopadhyay, 2018).

6.0 CONCLUSION

This study evaluated the correlation coefficients of various anthropometric indices with lipid profile element in a control age group to establish standard relationships, givng critical modality into how body composition metrics reflect cardiovascular and metabolic risks often qualified in women with Polycystic Ovary Syndrome (PCOS). This can lead to: Adoptive Markers of Metabolic Risk, where the Visceral Adiposity Index (VAI) and the Lipid Accumulation Product (LAP) demonstrated potent, statistically significant positive associate with the triglyceride metric. Prognostic Value of Composite Indices,Twhere the complex anthropometric metric (BMI x 1.89 + WC/36.58) exhibited an almost near-perfect linear correlation with standard Body Mass Index (BMI) ($r = 0.999$, $p < 0.01$). High-Density Lipoprotein (HDL) Dynamics where VAI retained a significant positive correlation with the HDL metric of 1.52/HDL. In women with PCOS, visceral adiposity and insulin resistance act as central drivers of metabolic syndrome. The strong coupling observed between lipid markers (Tg) and visceral indices (LAP and VAI) suggests that these specific anthropometric indices can serve as reliable, low-cost, and non-invasive screening tools in clinical settings. Instead of confiding exclusively on standard BMI which fails to differentiate between lean mass and visceral fat distribution, clinicians can better employ LAP and VAI to better distinguish cardiovascular risks, track metabolic

impairment, and display the efficacy of lifestyle or pharmacological involvement in women suffering from PCOS.

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