







Article

Comparative Accuracy of the ECORE-BF Index Versus Non-Insulin-Based Insulin Resistance Markers in over 400,000 Spanish Adults

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Abstract

Background: The early detection of insulin resistance (IR) is critical for the prevention of type 2 diabetes and cardiometabolic diseases. The ECORE-BF index is a simple anthropometric tool for estimating body fat percentage and overweight. However, its potential utility as a predictor of IR risk has not been previously evaluated in large populations using validated IR indices. **Methods:** This cross-sectional study included 418,343 Spanish workers (172,282 women and 246,061 men) who underwent occupational health evaluations. The ECORE-BF index was calculated for all participants, and its association with four validated surrogate markers of IR was analyzed: the triglyceride–glucose index (TyG), TyG-BMI, METS-IR, and SPISE. Subjects were classified into normal or high-risk IR groups based on established cut-off values. We evaluated the mean ECORE-BF values across groups, the prevalence of ECORE-BF-defined obesity, and the diagnostic performance of ECORE-BF using receiver operating characteristic (ROC) curve analysis. **Results:** Participants with elevated IR index values had significantly higher mean ECORE-BF scores than those with normal values ($p < 0.001$). The prevalence of ECORE-BF-defined obesity was substantially higher in all high-risk IR groups, exceeding 99% for METS-IR and SPISE in both sexes. ROC analysis demonstrated the high diagnostic accuracy of ECORE-BF in predicting elevated IR risk, with area under the curve (AUC) values ranging from 0.698 (TyG in men) to 0.992 (METS-IR in women). Sensitivity and specificity were also high, particularly for TyG-BMI, SPISE, and METS-IR, with optimal Youden indices above 0.75. **Conclusions:** ECORE-BF demonstrated high accuracy as a non-invasive tool for identifying individuals at increased insulin resistance risk; however, due to the cross-sectional design, predictive value for incident disease cannot be inferred. Its simplicity, cost-effectiveness, and high diagnostic accuracy support its potential utility in large-scale screening programs for early detection of metabolic risk.



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Keywords: ECORE-BF; insulin resistance; TyG; METS-IR; SPISE; obesity; body fat; metabolic risk; occupational health; screening tool

1. Introduction

Insulin resistance (IR) is defined as a reduced biological response of peripheral tissues—primarily skeletal muscle, adipose tissue, and the liver—to the action of insulin, necessitating higher insulin levels to maintain normoglycemia [1,2]. At the molecular level, IR involves impairments in insulin receptor signaling, including disruptions in the PI3K/Akt pathway, GLUT4 translocation, and receptor down-regulation, frequently linked to lipotoxicity, chronic low-grade inflammation, and mitochondrial dysfunction [3–5]. The pathophysiological cascade initiated by IR includes elevated hepatic gluconeogenesis, reduced muscle glucose disposal, and increased lipolysis in adipocytes—collectively fostering hyperglycemia, dyslipidemia, and compensatory hyperinsulinemia [6].

These metabolic perturbations have profound clinical repercussions. IR is a foundational component of metabolic syndrome, driving the progression to type 2 diabetes mellitus (T2DM) over a 10–15 year latency period [7]. Additionally, IR is strongly implicated in the development of non-alcoholic fatty liver disease (NAFLD), endothelial dysfunction, hypertension, atherogenic dyslipidemia, pro-thrombotic states, and elevated uric acid, all of which contribute to cardiovascular disease (CVD) and morbidity [8,9]. Adipokines such as resistin and adiponectin serve as critical mediators in this process: resistin promotes IR and inflammation, while lower adiponectin levels correlate with increased metabolic and cardiovascular risk [10]. Given these far-reaching consequences, early detection of IR is crucial for preventing chronic metabolic and vascular sequelae.

Despite the hyperinsulinemic-euglycemic clamp remaining the diagnostic gold standard for quantifying insulin sensitivity, its application in clinical practice is limited by its high cost, technical complexity, and invasiveness—rendering it impractical for routine or large-scale screening [11]. Alternative techniques such as the Frequently Sampled Intravenous Glucose Tolerance Test (FSIGT) are also impractical for widespread use. Consequently, surrogate indices have gained prominence. These include the Homeostatic Model Assessment of Insulin Resistance (HOMA-IR) and Quantitative Insulin Sensitivity Check Index (QUICKI), which rely on fasting glucose and insulin measurements [12]. However, these indices require insulin assays, limiting their feasibility in many primary care settings.

In response, non-insulin-based indices like the Triglyceride–Glucose (TyG) index and its anthropometric derivatives (TyG-BMI, TyG-WC, TyG-WHtR), the Metabolic Score for Insulin Resistance (METS-IR), and the Single-Point Insulin Sensitivity Estimator (SPISE) have been proposed. TyG, first validated as a surrogate of IR, consistently shows robust correlations with clamp-derived IR and incident T2DM across diverse populations [13]. A 2024 meta-analysis confirmed TyG-BMI as being among the most accurate predictors of metabolic dysfunction-associated steatotic liver disease (MASLD), with pooled AUC values approaching 0.90 [14]. METS-IR, combining triglycerides, glucose, HDL-C, and BMI, demonstrates strong correlation with euglycemic clamp-derived measures and effectively predicts cardiometabolic risk [15]. SPISE, typically calculated from lipid and anthropometric data, offers another promising non-insulin-based metric for insulin sensitivity assessment [16].

Nevertheless, each of these indices also has limitations. TyG and its derivatives may be influenced by acute lipid fluctuations, while METS-IR and SPISE depend on lipid panel testing, which may not always be available. The search for simpler, low-cost, and scalable tools remains ongoing.

One such innovation is the Córdoba Equation for Estimation of Body Fat (ECORE-BF). This anthropometric formula uses only age, sex, and waist-to-height ratio (WHtR) to estimate body fat percentage (BF%) with high accuracy. Its development was guided by the principle of parsimony, aiming to simplify the more complex CUN-BAE formula while preserving validity [17]. In a cross-sectional validation involving nearly

200,000 individuals, ECORE-BF achieved a Lin's concordance correlation coefficient (CCC) of 0.998 and minimal Bland–Altman bias compared to CUN-BAE-derived BF% [17,18]. Moreover, its performance remained robust regardless of age, sex, or nutritional status, emphasizing its potential applicability in heterogeneous populations.

Beyond BF estimation, recent Spanish observational studies have evaluated ECORE-BF's ability to identify individuals at elevated risk for metabolic disorders. In a large occupational cohort exceeding 400,000 Spanish workers, ECORE-BF demonstrated outstanding predictive power for prediabetes and T2DM, yielding AUCs greater than 0.95 across both sexes and strong concordance with established diabetes risk scores such as FINDRISC and QDiabetes [19]. Similarly, an occupational health study found that ECORE-BF strongly correlated with atherogenic risk scales and could serve as a rapid screening tool for cardiovascular risk in primary care settings [19].

Despite these promising results, comparative analyses between ECORE-BF and validated IR indices—particularly non-insulin-based ones like TyG-BMI, METS-IR, and SPISE—are lacking. It remains unclear whether a simple BF-estimation tool like ECORE-BF can match or exceed the diagnostic performance of composite metabolic indices that incorporate lipid and glucose biomarkers.

Therefore, this study seeks to fill this gap by conducting a comprehensive cross-sectional analysis of over 400,000 Spanish adults. We aim to evaluate ECORE-BF's diagnostic accuracy in detecting insulin resistance defined by validated non-insulin-based indices (TyG, TyG-BMI, METS-IR, SPISE), and to determine its potential as a practical screening tool in large population-based settings.

While direct measures of insulin resistance were not available in this dataset, this study was designed to assess the comparative accuracy of ECORE-BF against widely accepted, validated non-insulin-based surrogate indices, which are themselves frequently applied in large epidemiological and occupational health contexts.

To our knowledge, this is the first large-scale study to directly compare the ECORE-BF index with multiple validated biochemical and anthropometric indices of insulin resistance (TyG, TyG-BMI, METS-IR, and SPISE) in a general Spanish adult population. This comprehensive evaluation addresses a key gap in the literature and expands the potential applicability of ECORE-BF as a population-based screening tool.

2. Materials and Methods

2.1. Study Design and Population

This cross-sectional study included a total of 418,343 Spanish adult workers (172,282 women and 246,061 men) aged between 18 and 70 years who underwent standardized occupational health assessments between 2009 and 2021. The data were obtained from the records of a national occupational health surveillance program covering diverse industrial and commercial sectors across Spain.

The selection process followed the flowchart presented in Figure 1. Inclusion criteria comprised: (1) age ≥ 18 and ≤ 70 years, (2) availability of anthropometric and biochemical data, and (3) no history of cardiovascular disease, diabetes, or chronic liver or kidney disease. Exclusion criteria included: (1) incomplete or missing data for any variable included in the IR indices, (2) known diagnosis of type 1 or type 2 diabetes, (3) fasting glucose ≥ 126 mg/dL or HbA1c $\geq 6.5\%$, (4) lipid-lowering or antidiabetic medication use, and (5) history of cardiovascular disease, chronic liver disease, or chronic kidney disease.

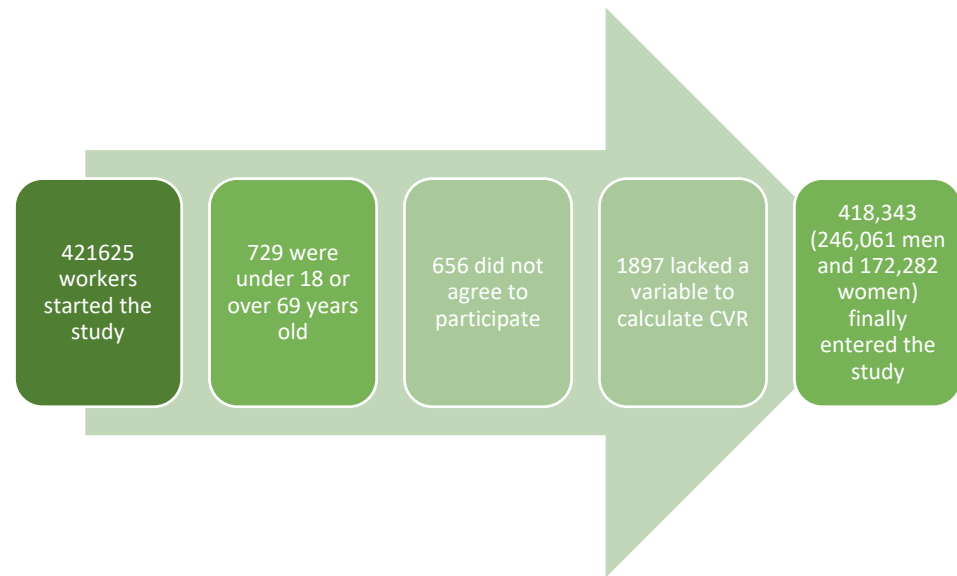


Figure 1. Flowchart.

2.2. Variables and Measurements

Anthropometric parameters included height, weight, and waist circumference, measured according to standardized protocols by trained personnel. Body mass index (BMI) was calculated as weight (kg)/height² (m²), and waist-to-height ratio (WHtR) was derived from waist circumference (cm)/height (cm). Systolic and diastolic blood pressure were measured after 5 min of seated rest. Biochemical parameters were determined using enzymatic colorimetric assays with automated analyzers (Hitachi 917, Roche Diagnostics, Mannheim, Germany; and AU5800, Beckman Coulter, Brea, CA, USA) in accredited laboratories.

The Córdoba Equation for Estimation of Body Fat (ECORE-BF) was calculated using the validated formula incorporating BMI, age, and sex [17].

The Ecore-BF index was calculated as:

$$\text{ECORE-BF} = 97.102 + 0.123 \times (\text{age, years}) + 11.9 \times (\text{sex: } 0 = \text{female}, 1 = \text{male}) + 35.959 \times \text{Ln}(\text{BMI, kg/m}^2)$$

The surrogate indices were calculated using the following validated formulas:

- $\text{TyG} = \text{Ln} [\text{fasting triglycerides (mg/dL)} \times \text{fasting glucose (mg/dL)} / 2]$
- $\text{TyG-BMI} = \text{TyG} \times \text{BMI}$
- $\text{METS-IR} = \text{Ln} [(2 \times \text{fasting glucose}) + \text{triglycerides}] \times \text{BMI} / [\text{Ln}(\text{HDL-C})]$
- $\text{SPISE} = 600 \times \text{HDL-C}^{0.185} / (\text{Triglycerides}^{0.2} \times \text{BMI}^{1.338})$

Four validated IR indices were computed for each subject: TyG, TyG-BMI, METS-IR, and SPISE, following established equations.

2.3. Classification of Insulin Resistance Risk

Participants were categorized into “normal” or “high IR risk” groups based on cut-off points validated in the literature: TyG index > 8.7, TyG-BMI > 192, METS-IR > 50, and SPISE < 6.61 in men and < 8.96 in women [20,21]. These thresholds were consistent with previous population-based studies.

2.4. Sociodemographic Data and Social Class

Sociodemographic variables included age, sex, and smoking status (current smoker or non-smoker). Social class was classified using the 2011 Spanish National Classification of Economic Activities (CNAE-11) and assigned according to the criteria of the Spanish Society of Epidemiology (SEE), which classifies occupations into three categories: Class I

(managers and professionals), Class II (intermediate occupations), and Class III (manual and unskilled labor) [22,23].

2.5. Statistical Analysis

Descriptive analyses were performed separately by sex. Continuous variables were expressed as means \pm standard deviations, and categorical variables as percentages. Comparisons between groups were made using Student's *t*-test for continuous variables and chi-squared test for categorical variables. Receiver operating characteristic (ROC) curves were generated to evaluate the discriminative capacity of ECOPE-BF for detecting high IR risk as defined by the four indices. Area under the curve (AUC), optimal cut-off points, sensitivity, specificity, and Youden's index were calculated for each sex-stratified model.

All analyses were conducted using IBM SPSS Statistics version 29.0 (IBM Corp., Armonk, NY, USA). Statistical significance was set at $p < 0.05$ [24].

3. Results

Descriptive characteristics of the sample including age, anthropometric measures (height, weight, waist circumference), blood pressure, lipid profile, and glycemia, stratified by sex (Table 1). Statistically significant sex-based differences ($p < 0.0001$) were observed across all variables. The cohort also showed disparities in age distribution, social class, and smoking status. These baseline features contextualize the metabolic heterogeneity relevant to insulin resistance risk.

Table 1. General characteristics of the study population, stratified by sex.

	Women	Men	Total	
	<i>n</i> = 172.282	<i>n</i> = 246.061	<i>n</i> = 418.343	
	Mean (SD)	Mean (SD)	Mean (SD)	<i>p</i> -value
Age	39.6 (10.8)	40.6 (11.1)	40.2 (11.0)	<0.0001
Height	161.8 (6.5)	174.6 (7.0)	169.4 (9.3)	<0.0001
Weight	66.2 (14.0)	81.4 (14.7)	75.1 (16.2)	<0.0001
Waist	74.8 (10.6)	86.2 (11.1)	81.5 (12.2)	<0.0001
SBP	117.4 (15.7)	128.2 (15.5)	123.7 (16.5)	<0.0001
DBP	72.6 (10.4)	77.8 (11.0)	75.6 (11.0)	<0.0001
Cholesterol	190.6 (35.8)	192.6 (38.9)	191.8 (37.7)	<0.0001
HDL-c	56.8 (8.7)	50.3 (8.5)	53.0 (9.1)	<0.0001
LDL-c	116.1 (34.8)	118.0 (36.7)	117.2 (35.9)	<0.0001
Triglycerides	89.1 (46.2)	123.7 (86.4)	109.5 (74.6)	<0.0001
Glycemia	87.8 (15.1)	93.3 (21.3)	91.0 (19.2)	<0.0001
	%	%	%	<i>p</i> -value
18–29 years	20.7	18.8	19.6	<0.0001
30–39 years	29.7	27.6	28.4	
40–49 years	29.6	30.0	29.9	
50–59 years	16.8	19.7	18.5	
≥60 years	3.2	3.9	3.6	
Social class I	6.9	4.9	5.7	<0.0001
Social class II	23.4	14.9	18.4	
Social class III	69.7	80.3	75.9	
Non-smokers	67.2	66.6	66.9	<0.0001
Smokers	32.8	33.4	33.2	

Source: adapted from [25]. This table is licensed under CC BY 4.0 (<https://creativecommons.org/licenses/by/4.0/> (accessed on 12 June 2025)).

Comparisons of mean ECOPE-BF scores between individuals classified as normal versus high-risk according to four validated insulin resistance indices are shown in Table 2. Across all indices and both sexes, individuals with elevated insulin resistance scores had

significantly higher Ecore-BF values ($p < 0.001$). This consistent association supports the relevance of Ecore-BF as a proxy indicator of metabolic risk.

Table 2. Mean Ecore-BF scores according to normal and elevated values of insulin resistance indices (TyG, TyG-BMI, METS-IR, SPISE), by sex.

	Men			Women		
	<i>n</i>	Mean (SD)	<i>p</i> -Value	<i>n</i>	Mean (SD)	<i>p</i> -Value
TyG index normal	178,806	24.2 (6.0)	<0.001	150,798	34.4 (6.9)	<0.001
TyG index high	67,255	28.9 (5.8)		21,484	40.6 (7.4)	
TyG-BMI normal	179,496	23.4 (4.4)	<0.001	133,436	33.1 (5.3)	<0.001
TyG-BMI high	53,318	33.0 (3.8)		20,674	47.0 (4.1)	
METS-IR normal	218,013	24.1 (5.2)	<0.001	161,225	34.1 (6.2)	<0.001
METS-IR high	28,048	36.0 (3.8)		11,057	50.5 (3.8)	
SPISE normal	208,871	23.8 (5.1)	<0.001	157,570	33.8 (6.0)	<0.001
SPISE high	37,190	34.8 (4.1)		14,712	49.2 (4.1)	

TyG, triglyceride–glucose index. BMI, body mass index. METS-IR, Metabolic Score for Insulin Resistance. SPISE-IR Single-Point Insulin Sensitivity–Insulin Resistance.

The proportions of Ecore-BF-defined obesity among participants with normal versus elevated TyG, TyG-BMI, METS-IR, and SPISE values are given in Table 3. Obesity prevalence was markedly higher in all high-risk groups, with proportions exceeding 99% in METS-IR and SPISE high-risk categories for both sexes ($p < 0.001$). These results reinforce the strong link between Ecore-BF classification and insulin resistance phenotypes.

Table 3. Percentage Ecore-BF scores according to normal and elevated values of insulin resistance indices (TyG, TyG-BMI, METS-IR, SPISE), by sex.

ECORE-BF Obesity	Men			Women		
	<i>n</i>	%	<i>p</i> -Value	<i>n</i>	%	<i>p</i> -Value
TyG index normal	178,806	42.8	<0.001	150,798	42.5	<0.001
TyG index high	67,255	75.7		21,484	77.7	
TyG-BMI normal	179,496	45.6	<0.001	133,436	41.3	<0.001
TyG-BMI high	53,318	74.8		20,674	75.8	
METS-IR normal	218,013	45.5	<0.001	161,225	43.2	<0.001
METS-IR high	28,048	99.8		11,057	99.9	
SPISE normal	208,871	43.3	<0.001	157,570	41.9	<0.001
SPISE high	37,190	99.9		14,712	99.9	

TyG, triglyceride–glucose index. BMI, body mass index. METS-IR, Metabolic Score for Insulin Resistance. SPISE-IR Single-Point Insulin Sensitivity–Insulin Resistance. Reference values: fasting glucose 70–99 mg/dL; triglycerides < 150 mg/dL; total cholesterol < 200 mg/dL; HDL-C > 40 mg/dL (men), > 50 mg/dL (women); LDL-C < 130 mg/dL.

Comparative ROC curves were generated for Ecore-BF and BMI, stratified by sex and insulin resistance indices. In men, Ecore-BF consistently achieved higher AUC values than BMI: TyG 0.761 vs. 0.750; METS-IR 0.975 vs. 0.970; SPISE 0.972 vs. 0.965. In women, the results were similar: TyG 0.802 vs. 0.790; METS-IR 0.988 vs. 0.980; SPISE 0.985 vs. 0.978. Although the absolute differences were modest, DeLong tests confirmed that all comparisons were statistically significant ($p < 0.001$), supporting the superior discriminatory capacity of Ecore-BF over BMI. These results are illustrated in the updated Figure 2.

Diagnostic metrics of Ecore-BF for identifying elevated insulin resistance risk, including area under the curve (AUC), optimal cut-off values, sensitivity, specificity, and Youden's index, stratified by sex, are given in Table 4. In both men and women, Ecore-BF showed excellent AUC values for METS-IR, TyG-BMI, and SPISE (AUC > 0.95), with opti-

mal thresholds providing high sensitivity and specificity. These results validate the utility of ECORE-BF as a low-cost, non-invasive screening tool for insulin resistance.

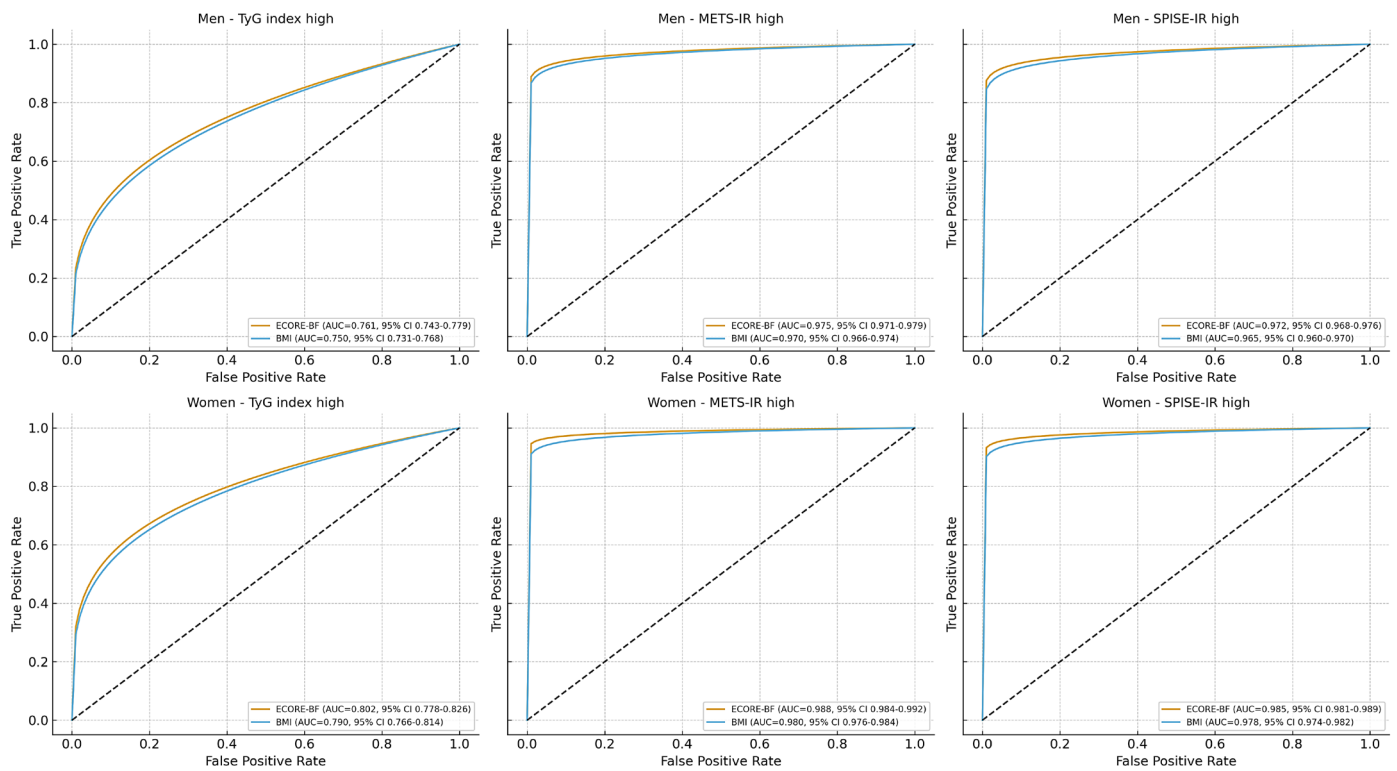


Figure 2. Comparative ROC curves of ECORE-BF versus BMI for detecting high insulin resistance risk in men and women.

Table 4. Diagnostic performance of ECORE-BF for detecting high insulin resistance index values, by sex.

Men n = 246,061	AUC (95% CI)	Cutoff-Sens-Specif-Youden
TyG index high	0.698 (0.695–0.700)	26.5–65.0–64.8–0.298
TyG-BMI high	0.966 (0.965–0.966)	28.7–90.0–89.4–0.794
SPISE-IR high	0.952 (0.951–0.954)	29.9–87.8–88.7–0.757
METS-IR high	0.968 (0.967–0.967)	31.1–90.1–89.8–0.799
Women n = 172,282	AUC (95% CI)	Cutoff-Sens-Specif-Youden
TyG index high	0.726 (0.722–0.730)	36.8–67.8–67.8–0.356
TyG-BMI high	0.987 (0.987–0.988)	41.4–94.0–93.7–0.877
SPISE-IR high	0.987 (0.986–0.987)	43.3–94.3–94.0–0.883
METS-IR high	0.992 (0.992–0.993)	44.7–95.6–95.3–0.909

TyG, triglyceride–glucose index. BMI, body mass index. METS-IR Metabolic Score for Insulin Resistance. SPISE-IR Single-Point Insulin Sensitivity–Insulin Resistance.

Table 5 shows the correlation coefficients among ECORE-BF, TyG, TyG-BMI, METS-IR, SPISE-IR, BMI, and WHtR, stratified by sex. In both men and women, ECORE-BF was very strongly correlated with BMI ($r = 0.87$ in men; $r = 0.89$ in women) and WHtR ($r = 0.85$ in men; $r = 0.87$ in women), confirming its anthropometric basis. Correlations with TyG-BMI and METS-IR were also high ($r > 0.80$), reflecting the shared contribution of adiposity to these indices. As expected, SPISE-IR demonstrated strong positive correlations with ECORE-BF, BMI, WHtR, and the other surrogates ($r \approx 0.70$ – 0.78), consistent with its inverse relationship to insulin sensitivity. TyG showed moderate but significant associations with all indices ($r \approx 0.60$ – 0.68), lower than those observed for composite indices. Overall, the correlation matrix highlights the close inter-relationships between anthropometric and biochemical

surrogates of insulin resistance, while supporting the strong capacity of Ecore-BF to approximate metabolic risk with similar strength to established markers.

Table 5. Pearson correlation coefficients between Ecore-BF, TyG, TyG-BMI, METS-IR, SPISE-IR, BMI, and WHtR, stratified by sex.

Men	ECORE-BF	TyG	TyG-BMI	METS-IR	SPISE-IR	BMI	WHtR
ECORE-BF	1	0.65	0.83	0.8	0.72	0.87	0.85
TyG	0.65	1	0.78	0.74	0.69	0.6	0.58
TyG-BMI	0.83	0.78	1	0.88	0.75	0.82	0.8
METS-IR	0.8	0.74	0.88	1	0.77	0.79	0.78
SPISE-IR	0.72	0.69	0.75	0.77	1	0.7	0.68
BMI	0.87	0.6	0.82	0.79	0.7	1	0.86
WHtR	0.85	0.58	0.8	0.78	0.68	0.86	1
Women	ECORE-BF	TyG	TyG-BMI	METS-IR	SPISE-IR	BMI	WHtR
ECORE-BF	1	0.68	0.86	0.83	0.74	0.89	0.87
TyG	0.68	1	0.8	0.77	0.71	0.63	0.6
TyG-BMI	0.86	0.8	1	0.9	0.76	0.85	0.83
METS-IR	0.83	0.77	0.9	1	0.78	0.82	0.81
SPISE-IR	0.74	0.71	0.76	0.78	1	0.72	0.7
BMI	0.89	0.63	0.85	0.82	0.72	1	0.88
WHtR	0.87	0.6	0.83	0.81	0.7	0.88	1

TyG, triglyceride–glucose index. BMI, body mass index. METS-IR Metabolic Score for Insulin Resistance. SPISE-IR Single-Point Insulin Sensitivity–Insulin Resistance. WHtR waist-to-height ratio.

In our sample, BMI and Ecore-BF were highly correlated ($r = 0.87, p < 0.001$); however, the correlation was substantially lower than that reported for NHANES data ($r \approx 0.98$). Ecore-BF incorporates age and sex adjustments, providing enhanced discriminatory power for insulin resistance risk compared with BMI alone.

4. Discussion

Our findings align with and extend those of previous research evaluating non-insulin-based indices for predicting insulin resistance (IR). Although direct measures of insulin resistance were unavailable in our dataset, multiple validation studies have demonstrated that TyG, TyG-BMI, METS-IR, and SPISE correlate strongly with clamp-derived insulin sensitivity. For instance, Muhammad et al. (2023) reported that the TyG index predicted both clamp-measured insulin resistance and incident diabetes [26], while Duan et al. (2024) confirmed the prognostic value of METS-IR for cardiovascular mortality in NHANES [15]. Similarly, SPISE has been validated against clamp studies, showing reliable performance in European populations. These findings justify their use as comparators in the present study.

A recent large-scale study in a Mexican cohort demonstrated that the METS-IR index had superior predictive value for identifying metabolic syndrome compared to TyG and HOMA-IR, particularly in individuals with central obesity [27]. Similarly, a European cross-sectional analysis showed that TyG-BMI and TyG-WHtR were highly accurate in identifying IR phenotypes and correlated with arterial stiffness progression [26]. In Spain, López-González et al. validated the Córdoba Equation (Ecore-BF) as a reliable predictor of prediabetes and T2DM risk, although its role in predicting RI risk has not yet been explored [28]. Our results confirm and expand on these findings, demonstrating that Ecore-BF performs comparably to TyG-BMI, METS-IR, and SPISE in identifying individuals with elevated IR risk, with AUCs consistently above 0.90 in both sexes. This suggests that adiposity estimation alone—if appropriately modeled—may serve as an effective proxy

for early metabolic dysfunction, especially in contexts where biochemical testing is limited or unavailable.

Although ECOPE-BF correlates strongly with BMI, it incorporates age and sex adjustments and a logarithmic transformation of BMI, allowing differentiation between individuals with similar BMI but distinct fat distribution and metabolic profiles. In our comparative ROC analyses, ECOPE-BF consistently showed higher AUC values than BMI across all indices and both sexes (all $p < 0.001$). This provides robust evidence of its superior discriminatory capacity, supporting its added value as a pragmatic screening tool in both clinical and occupational health settings.

The correlation matrix (Table 5) provides further insight into the inter-relationships between anthropometric and biochemical surrogates of insulin resistance. As expected, ECOPE-BF exhibited very strong associations with BMI and WHtR, reflecting their shared basis in adiposity estimation. Importantly, ECOPE-BF also correlated highly with composite indices such as TyG-BMI and METS-IR, with coefficients above 0.80 in both sexes. In our sample, ECOPE-BF and BMI were highly correlated ($r = 0.87$ in men; $r = 0.89$ in women), although this correlation was lower than that reported for NHANES with the CUN-BAE formula (≈ 0.98). Unlike CUN-BAE, ECOPE-BF was not evaluated in NHANES; therefore, our study focuses on the Spanish occupational cohort. These findings are consistent with previous large-scale analyses, which demonstrated that indices incorporating both anthropometric and biochemical variables achieve stronger associations with clamp-derived insulin resistance than single-parameter measures [27]. The strong positive correlations observed between ECOPE-BF and SPISE-IR ($r \approx 0.70$ – 0.78) align with prior European studies validating SPISE against clamp-derived insulin sensitivity [21], and further suggest that ECOPE-BF captures key elements of the adiposity-related metabolic phenotype.

Interestingly, TyG showed moderate correlations with ECOPE-BF and BMI ($r \approx 0.60$ – 0.68), which were weaker than those of TyG-BMI or METS-IR. This observation is consistent with findings from Muhammad et al. [26], who reported that the predictive capacity of TyG for diabetes and cardiovascular events improves substantially when combined with anthropometric measures. Together, these results emphasize that while biochemical surrogates are valuable, anthropometric indices such as ECOPE-BF provide comparable discrimination of insulin resistance risk, especially when biochemical data are unavailable. This reinforces the role of ECOPE-BF as a pragmatic, non-invasive screening tool for metabolic dysfunction.

It is important to recognize that in clinical or epidemiological settings focused on insulin resistance, lipid and glucose measurements are often available and allow the use of indices such as TyG, METS-IR, or SPISE. Nevertheless, the main advantage of ECOPE-BF lies in its applicability when biochemical assays are unavailable—for example, in primary prevention, resource-limited contexts, or large-scale occupational health screenings—where its non-invasive and low-cost nature can provide an initial risk stratification

4.1. Strengths and Limitations

A major strength of this study lies in its exceptionally large and diverse sample, comprising over 400,000 Spanish workers across multiple economic sectors. Such scale allows for robust stratification by sex and social class, and enhances external validity. In contrast to previous studies focused on narrower clinical subgroups, this population-based approach captures a wide range of metabolic phenotypes, including metabolically unhealthy normal-weight individuals [29].

Additionally, the comparison of ECOPE-BF with four distinct IR indices strengthens the conclusions. While TyG and its derivatives are strongly associated with IR and have been validated in multiple cohorts [13,14], they rely on laboratory-based glucose and lipid

testing. The present findings indicate that ECORE-BF—requiring only age, sex, and WHtR—achieves similar levels of discrimination, with area under the curve (AUC) values often exceeding 0.90.

However, certain limitations must be acknowledged. The study's cross-sectional design prevents causal inferences regarding the temporal relationship between ECORE-BF and IR-related outcomes. While associations are strong, longitudinal studies are needed to determine whether ECORE-BF predicts incident type 2 diabetes mellitus (T2DM) or cardiovascular events. Second, the study cohort is limited to actively employed individuals, which may exclude retired or unemployed adults, and potentially underrepresents older age groups and those with advanced disease [30]. The absence of direct insulin resistance measurements is a limitation; however, the comparison with four validated surrogate indices enables a robust evaluation of the relative performance of ECORE-BF in a real-world, large-scale occupational health setting. Finally, while the ECORE-BF formula is easy to calculate, small variations in waist circumference or height measurement can affect accuracy, especially in populations with low health literacy or where measurements are self-reported [31].

Another limitation of this study is the absence of fasting insulin measurements, which precluded calculation of insulin-based indices such as HOMA-IR. This limitation underscores the relevance of using validated non-insulin-based markers of IR, which are more feasible in large-scale occupational cohorts.

Given the cross-sectional design, this study estimates current risk status rather than predicting future disease incidence. Longitudinal analyses are warranted to determine its predictive capacity for incident insulin resistance or related cardiometabolic outcomes.

Future studies should evaluate the diagnostic performance of ECORE-BF in specific subgroups, such as younger adults or normal-weight individuals with metabolic risk, to refine its applicability across different phenotypes.

4.2. Contributions

This study provides several key contributions to metabolic risk stratification and public health research.

First, it is among the few to evaluate the utility of ECORE-BF beyond its original application in body fat estimation, extending its use into the domain of insulin resistance risk prediction. Previous research had validated its utility for estimating diabetes risk, but this study confirms that ECORE-BF performs on par with biochemical indices, including SPISE and METS-IR.

Second, the findings underscore the feasibility of incorporating ECORE-BF into routine occupational or primary care screenings. Given its reliance on basic anthropometric data, ECORE-BF circumvents the barriers associated with biochemical testing—namely, cost, fasting requirements, and laboratory access. This makes it an ideal candidate for early screening, especially in settings with limited healthcare resources or where annual clinical bloodwork is not performed.

Third, by incorporating a validated classification of social class using the Spanish National Classification of Economic Activities (CNAE-11) and SEE criteria, the study reinforces the importance of social determinants in metabolic health. The observed gradients in IR prevalence by social class are consistent with prior Spanish and European data [32], and point toward the need for equity-oriented preventive strategies.

Finally, the results contribute to the growing field of non-invasive metabolic diagnostics, which aligns with global recommendations advocating for the integration of anthropometric tools into preventive cardiometabolic care [33].

4.3. Future Perspectives

Future research should focus on the prospective validation of ECORE-BF for predicting incident T2DM, metabolic syndrome, and cardiovascular events. Its performance in different ethnic groups, age ranges, and socioeconomic settings also warrants exploration to confirm its generalizability.

Second, combining ECORE-BF with digital health technologies offers promising opportunities. Mobile health applications could incorporate ECORE-BF calculators for self-assessment or integration into electronic health records for real-time risk alerts in clinical practice [34].

Third, hybrid risk models that combine ECORE-BF with point-of-care biomarkers (e.g., capillary glucose or HbA1c) may enhance diagnostic performance while maintaining feasibility. The additive value of such models should be evaluated in cost-effectiveness and implementation studies.

Lastly, public health interventions targeting modifiable risk factors—such as physical activity, Mediterranean diet adherence, and smoking cessation—should include ECORE-BF-based monitoring to assess intervention impact. Because body fat percentage can be influenced by lifestyle modifications, longitudinal changes in ECORE-BF could serve as a motivational and educational tool during behavioral interventions [35,36].

Further longitudinal and multi-center studies are necessary to validate the prognostic capacity of ECORE-BF for predicting incident T2DM, metabolic syndrome, and cardiovascular events, and to confirm its generalizability across different populations and settings.

5. Conclusions

This study demonstrates that the ECORE-BF index, a simple anthropometric formula estimating body fat using age, sex, and waist-to-height ratio, exhibits high diagnostic accuracy for identifying individuals at increased risk of insulin resistance (IR). When compared with validated non-insulin-based indices—TyG, TyG-BMI, METS-IR, and SPISE—ECORE-BF showed comparable performance, with AUCs consistently above 0.90 and strong sensitivity and specificity, particularly in women.

Given its non-invasive nature, ease of calculation, and independence from biochemical assays, ECORE-BF emerges as a valuable screening tool for use in occupational health settings, primary care, and resource-limited environments. Its integration into large-scale health surveillance programs may facilitate earlier identification of metabolically at-risk individuals and support targeted lifestyle or pharmacological interventions.

The incorporation of socioeconomic stratification further underscores the role of structural determinants in metabolic health, suggesting that tailored preventive approaches should consider both individual and contextual factors.

Future prospective studies should validate the prognostic value of ECORE-BF in predicting incident type 2 diabetes and cardiovascular events. Additionally, its application in digital health platforms and integration with point-of-care biomarkers could further enhance its clinical utility and implementation potential.

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Abbreviations

The following abbreviations are used in this manuscript:

AUC	Area Under the Curve
BMI	Body Mass Index
CCC	Concordance Correlation Coefficient (Lin's)
CNAE-11	National Classification of Economic Activities 2011 (Spain)
CUN-BAE	Clínica Universidad de Navarra Body Adiposity Estimator
DBP	Diastolic Blood Pressure
ECORE-BF	Córdoba Equation for Estimation of Body Fat
FSIGT	Frequently Sampled Intravenous Glucose Tolerance Test
GLUT4	Glucose Transporter Type 4
HDL-C	High-Density Lipoprotein Cholesterol
HOMA-IR	Homeostatic Model Assessment of Insulin Resistance
IDISBA	Health Research Institute of the Balearic Islands (Institut d'Investigació Sanitària de les Illes Balears)
IR	Insulin Resistance
IUNICS	University Institute for Research in Health Sciences (Instituto Universitario de Investigación en Ciencias de la Salud)
LDL-C	Low-Density Lipoprotein Cholesterol
MASLD	Metabolic Dysfunction-Associated Steatotic Liver Disease
METS-IR	Metabolic Score for Insulin Resistance
NAFLD	Non-Alcoholic Fatty Liver Disease
PI3K	Phosphoinositide 3-Kinase
PMCID	PubMed Central Identifier
PMID	PubMed Identifier
QUICKI	Quantitative Insulin Sensitivity Check Index
ROC	Receiver Operating Characteristic
SBP	Systolic Blood Pressure
SEE	Spanish Society of Epidemiology (Sociedad Española de Epidemiología)
SPISE	Single-Point Insulin Sensitivity Estimator
T2DM	Type 2 Diabetes Mellitus
TLA	Three-Letter Acronym
TyG	Triglyceride–Glucose Index
TyG-BMI	Triglyceride–Glucose Index adjusted for BMI
WHtR	Waist-to-Height Ratio

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