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REVIEW

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Advances in Biomedical Engineering for Understanding and Managing Metabolic Syndrome: A Comprehensive Review

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Abstract: Metabolic syndrome (MetS) is a complex disorder characterized by a set of interrelated metabolic abnormalities, such as central obesity, hypertension, dyslipidemia, and insulin resistance. It constitutes a major public health problem worldwide due to its association with an increased risk of cardiovascular disease, type 2 diabetes mellitus (T2DM) and other chronic diseases. Biomedical engineering (BME), through its interdisciplinary nature, has contributed significantly to the understanding, diagnosis, and treatment of MetS. The aim of this review article is to provide a comprehensive overview of the current state of research and advances in BME approaches to the study and management of MetS. The article will delve into diverse approaches, including computational and omics models, that have been used to improve our understanding of MetS. In addition, it will provide an overview of specialized devices that have been designed for the non-invasive assessment of individuals with MetS.

Keywords: Metabolic syndrome; Diabetes; Obesity; Biomedical

Introduction

Metabolic syndrome (MetS) is a complex and increasingly prevalent disease that encompasses a set of interconnected metabolic risk factors[1]. This multisystem syndrome significantly increases the risk of developing severe health complications, such as cardiovascular disease (CVD)[2,3], type 2 diabetes mellitus (T2DM)[4] and even

certain types of cancer[5,6]. The diagnostic criteria for MetS typically include abdominal obesity, as defined by waist circumference measurements, combined with specific thresholds for other components such as elevated blood pressure, altered glucose metabolism (e.g., elevated fasting glucose or insulin resistance (IR), and abnormal lipid levels (e.g., elevated triglycerides and low HDL-cholesterol)[7]. Specific cut-off values for each component may vary slightly depending on the guidelines used, including those provided by organizations such as the National Cholesterol Education Program Adult Treatment Panel III (NCEP ATP III) or the International Diabetes Federation (IDF) (**Table 1**)[7]. The increasing global prevalence of MetS has become a major public health problem, primarily promoted by sedentary lifestyles, unhealthy dietary habits and genetic predisposition[8].

Biomedical engineering (BME) has a profound impact on MetS by revolutionizing the diagnosis, treatment, and understanding of this complex condition. Through the development of advanced imaging techniques, such as magnetic resonance imaging (MRI) and computed tomography (CT), biomedical engineers enable accurate and non-invasive assessment of MetS components Overall, BME advancements have the potential to transform the understanding, diagnosis, and management of MetS, leading to more effective and personalized healthcare strategies for individuals affected by this condition[9-11]. Understanding the underlying mechanisms, risk factors and potential interventions against MetS is crucial to address this burgeoning public health problem and promote global wellness.

Table 1. Diagnostic criteria for metabolic syndrome (MetS)

Criteria	NCEP ATP III	IDF
Abdominal obesity	Waist circumference Men: ≥ 102 cm (> 40 in) Women: ≥ 88 cm (> 35 in)	Waist circumference Men: ≥ 94 cm Women: ≥ 80 cm
Elevated blood pressure	≥ 130 mmHg systolic or ≥ 85 mmHg diastolic Or Pharmacological treatment	≥ 130 mmHg systolic or ≥ 85 mmHg diastolic Or Pharmacological treatment
Altered glucose metabolism	Fasting glucose ≥ 100 mg/dL Or Pharmacological treatment	Fastin glucose ≥ 100 mg/dl
Abnormal lipid levels	Triglycerides > 150 mg/dL Or Pharmacological treatment HDL cholesterol Men: < 40 mg/dL Women: < 50 mg/dL Or Pharmacological treatment	Triglycerides > 150 mg/dl Or Pharmacological treatment HDL cholesterol Men: < 40 mg/dl Women: < 50 mg/dl Or Pharmacological treatment
Required criteria	Any three of the five criteria	Abdominal obesity plus any two of the four criteria

Recent reviews in the field of BME have highlighted innovative data integration approaches that hold great promise for advancing our understanding of MetS. These reviews highlight the importance of integrating data from diverse sources, such as genomics, metabolomics, proteomics, and clinical parameters, to gain a comprehensive view of the complex interactions underlying the MetS. Using advanced computational techniques, machine learning algorithms, and systems biology approaches, these studies highlight the potential to unravel intricate metabolic pathways and identify new biomarkers that could improve early detection and personalized treatment strategies for MetS (**Table 2**)[9,10,12-15].

Table 2. Data integration approaches applied to understand and asses the metabolic syndrome (MetS)

Approach	Summary	Reference
Development of prediction models for MetS based on whole genome sequencing data	The relationship between single nucleotide polymorphism (SNP) of circadian clock genes and the development of MetS was studied. A prediction model for metabolic syndrome was constructed using logistic regression, random forest, adaboost and neural network	16

Continuation Table:

Approach	Summary	Reference
Use of computational models to describe long-term development of MetS in APOE3L. CETP mice fed with a high-fat diet.	Computational modelling of energy balance in individuals with Metabolic Syndrome MINGLeD was utilized in combination with analysis of dynamic adaptations in parameter trajectories. (ADAPT) to achieve a model library describing various phenotypes to analyze energy expenditure and energy balance.	17
Validation of artificial AI-based scores for MetS prediction	Different ML algorithms were trained to predict the MetS status of each subject according to clinical and biochemical data. Subsequently, a module was used to explain the developed models and thus extract new scores for MetS detection.	18
Combination of multi-omics and clinical information to characterize metabolic diseases molecularly and clinically.	Integration of metabolomics, proteomics, peptidomics and clinical information to elucidate latent molecular hallmarks and interrelationships of multiple metabolic diseases, including MetS, hyperglycemia, hypertension and T2DM.	19
Use of genetic and metabolomic analysis to identify metabolite biomarkers of MetS.	Multi-stage metabolomics analysis was used to identify metabolite biomarkers and subsequently construct a metabolite risk score for MetS. Subsequently, two-stage Genome-wide association studies (GWAS)analyses were used to identify SNPs associated with the metabolites.	20

Biomedical Engineering Approaches for Understanding Metabolic Syndrome

BME employs computational modeling and simulation techniques to enhance the understanding of MetS. Through the integration of data from genetics, omics technologies and clinical parameters, computational models can effectively capture the intricate interactions and dynamics occurring in the MetS (**Figure 1**)[21,22]. The development of MetS is characterized by complex interactions and feedback loops encompassing multiple time and space scales, from cellular to organismal levels[14]. Computational modeling techniques, such as constraint-based modeling and kinetic modeling, can be applied to these metabolic networks to simulate and analyze the metabolic perturbations associated with MetS[23]. These models make possible the simulation of the impact of genetic variations, lifestyle modifications and pharmaceutical treatments on MetS-related outcomes.

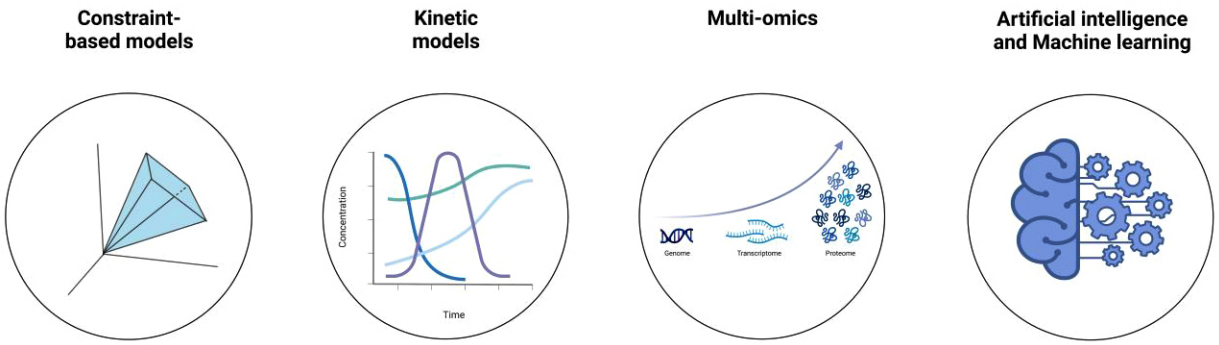

Figure 1. Computational models for the understanding of metabolic syndrome (MetS).

Computational models are promising tools for understanding the complex dynamics underlying metabolic syndrome (MetS). These models employ mathematical and computational techniques to simulate and analyze the intricate interactions between various molecular and physiological components that contribute to the development and progression of MetS.

Constraint-based models

In the 1980s, several data analysis approaches were developed to cope with the increasing amount of biological data available at that time, one of these approaches was the constraint-based models (CBM)[24]. Initially, the CBMs used mathematical algorithms to determine theoretical yields of metabolic pathways

and metabolite overflows[25]. Studies conducted at that time showed a good concordance between CBM predictions and measured cell behavior[26]. Leading the way for predicting phenotypes from a biochemically reconstructed network. Decades later, CBMs started to be used in the analysis of genotype-phenotype relationships, based on the principle that biological organisms function within the limits and constraints imposed by their genetic and environmental components[27]. This approach facilitated the study of the global organization of cellular behavior, such as the structure of metabolic pathways[28] and metabolic fluxes[29]. CBMs can be utilized to study metabolic pathways and analyze how perturbations in these pathways might contribute to metabolic disorders. Several models have been designed to explain the development of metabolic dysfunction in multiple diseases[30-32].

Kinetic models

The kinetic models were designed with the intention of addressing the limitations of CBMs[33]. They provide a distinct advantage in predicting the actions of living organisms under conditions far away from equilibrium. As a result, they extend the computational capacity to encompass cellular physiology, going beyond the steady-state assumption of CBMs[34]. Kinetic models are focused on describing the dynamic behavior of metabolic reactions using detailed mathematical equations that incorporate enzyme kinetics, metabolite concentrations, and regulatory factors[35]. Through simulating the kinetics of specific enzymes and reactions, kinetic models can elucidate the underlying mechanisms that contribute to metabolic dysregulation in MetS[36].

Model INtegrating Glucose and Lipid Dynamics (MINGLeD)

Recently, a new model has been designed, combining both in vivo and in silico models. A new data-driven physiological model called MINGLeD (Model INtegrating Glucose and Lipid Dynamics) has been developed to describe glucose, lipid and cholesterol metabolism. This model allowed the identification of distinct phenotypes inside the MetS and provided information on the underlying metabolic dysregulations by describing the development and long-term progression of the MetS[17,37].

Computational models, including the MINGLeD model, present an innovative approach to understanding MetS, demonstrating several remarkable novelties and advantages in contrast to conventional methods[13,17]. Firstly, these computational models work dynamically and comprehensively, capturing the intricate interplay of diverse metabolic pathways and their effects on the MetS[27,34,36]. Unlike traditional static approaches, these models consider the dynamic nature of metabolic pathways, allowing for a more accurate representation of the underlying physiological dynamics in MetS[27,33]. Furthermore, the MINGLeD model specifically introduces a new dimension by integrating multiple omics data sources, such as genomics, metabolomics and lipidomics. This integration enhances a holistic understanding of MS by elucidating the complex relationships between genetic factors, metabolic intermediates, and lipid profiles. This approach facilitates the identification of previously missed biomarkers, potential therapeutic targets, and mechanisms insights that would be hidden by traditional methods of single data analysis[17,37,38].

Omics

In addition to the previously mentioned models, a new field of research has been added. The omics refers to a set of comprehensive techniques used to study various biological molecules, including genomics (study of genes)[39], transcriptomics (study of gene expression)[40], proteomics (study of proteins)[41], metabolomics (study of small molecules)[42] and epigenomics (study of chemical modifications of DNA)[43]. They provide a holistic view of the molecular alterations and interactions that occur in a biological system, shedding light on the underlying pathophysiology of diseases such as MetS[44]. Scientists have identified numerous genetic variants (FTO, TCF7L2, MC4R, etc.) associated with the development and progression of MetS disease through large-scale genomic studies and advanced sequencing technologies[45]. These gene variants are implicated in the regulation of body weight, energy balance and glucose metabolism. The study of these genetic markers provides a better understanding of the molecular mechanisms underlying MetS and allows researchers to identify potential therapeutic targets[19].

Metabolomics

Another outstanding field that has improved the

understanding of MetS is metabolomics. Metabolomic studies have revealed distinct metabolic profiles in individuals with MetS compared to healthy individuals. These profiles often show alterations in metabolites involved in lipid metabolism, glucose, aminoacids and oxidative stress[46]. One of the objectives of metabolomics is to identify metabolites that could function as biomarkers of MetS. Recently a study identified metabolites associated with MetS, using LysoPC(14:0), LysoPC(15:0), propionyl carnitine, phenylalanine, and docosapentaenoic acid to construct a metabolite risk score to assess the risk of MetS. This score showed to have a dose-response relationship with MetS and metabolic abnormalities[20]. Globally, the use of omics approaches in MetS research provided valuable information on the genetic, molecular, and metabolic fundamentals of this complex disease. Further advancement of these technologies will hold significant potential for improving risk prediction, diagnosis, treatment, and prevention strategies, leading eventually to enhanced health outcomes for people affected by MetS.

Biomedical Engineering Tools for Assessing Metabolic Syndrome

BME tools have a crucial role in the assessment of MetS. They cover a wide range of technologies and techniques designed to measure and assess various parameters associated with MetS. For example, body composition analyzers (BCAs), such as bioelectrical impedance analysis (BIA)[47] and dual-energy X-ray absorptiometry (DEXA)[48], provide information on body fat percentage, muscle mass and visceral fat levels. Furthermore, continuous glucose monitoring (CGM)[49] systems allow blood glucose levels to be monitored over time, providing valuable data on glucose metabolism and diabetes risk. Beyond glucose monitoring, blood pressure monitoring devices and cholesterol analysis tools support the assessment of hypertension and lipid abnormalities[50]. Finally, metabolic rate measurement tools, such as indirect calorimetry devices, estimate energy expenditure and metabolic rate[51]. These BME tools contribute to the early detection, diagnosis and management of MetS, allowing healthcare professionals making more informed decisions and providing personalized care to individuals at risk.

Body Composition Analyzers

During weight gain, body composition undergoes a transformation characterized by a higher accumulation of fat compared to lean mass. This composition change is linked to an increase in insulin resistance and the onset of MetS. Nevertheless, excessive fat accumulation is not the main metabolic risk factor, the location where fat is stored determines the risk[52]. Abdominal adiposity is a pivotal component of MetS because it contributes to the development of insulin resistance and cardiometabolic diseases through visceral adipose tissue (VAT) dysfunction and adipokine dysregulation. Anthropometric measurements do not accurately reflect visceral adiposity and cannot differentiate between subcutaneous and visceral obesity. In the last few decades, new technologies have been developed to accurately determine the internal composition of the body. BCAs provide a comprehensive body composition analysis, including measurements of fat mass, muscle mass, bone density and hydration levels[53].

One of the most used methods is BIA. Through the measurement of the impedance of electrical currents passing through the body, BIA provides valuable information on the distribution of body fat, muscle mass and water content[54]. BIA devices send a harmless electrical signal through the body and measure the resistance encountered. Using algorithms and mathematical models, these devices can estimate body fat percentage, muscle mass and other relevant parameters[55]. Multiple studies have evaluated the use of BIA in MetS assessment. These studies have demonstrated that the measurement of VAT using BIA is a useful method for predicting the risk of MetS. In addition, it has been observed that total body fat and visceral fat levels are higher in subjects with MetS[47,53,56,57]. BIA offers a convenient and accessible way to monitor changes in body composition over time, making it a valuable tool for people who want to improve their health and fitness.

Individuals with MetS are at increased risk for osteoporosis and fractures because this condition is commonly associated with hormonal imbalances, reduced physical activity and vitamin D deficiencies[58]. DEXA a non-invasive imaging technique has proven to be valuable in assessing body composition and bone density. DEXA scans can detect changes in bone

density, which can help in identifying individuals who may require intervention for preventing fractures and maintaining bone health[59]. While initially utilized for measuring bone mineral density, DEXA has increasingly become recognized for its role in the assessment of MetS[60]. DEXA provides accurate measurements of total body fat, lean mass, regional fat distribution and VAT quantification, factors that have been strongly associated with IR and metabolic abnormalities of MetS[61]. In addition, DEXA scanners provide an assessment of sarcopenia, an important feature of individuals with MetS, through the measurement of appendicular lean mass[62].

Glucose sensing devices

Abnormalities in glucose metabolism play a key role in the development and progression of MetS. One of the main abnormalities is insulin resistance, in individuals with IR, the cells are less responsive to the effects of insulin, resulting in elevated levels of glucose in the bloodstream. This condition typically preludes the development of T2DM[63]. IR is strongly related to another key abnormality of glucose metabolism observed in MetS: glucose intolerance. Glucose intolerance is the inability of the body to effectively metabolize glucose after consuming a meal. This leads to elevated blood glucose levels, but not high enough to fulfill the criteria for T2DM[64]. In addition to IR and glucose intolerance, individuals with MetS often have elevated fasting blood glucose levels, commonly described as hyperglycemia. Chronic elevated blood glucose levels contribute to the development of oxidative stress, inflammation and endothelial dysfunction, factors involved in the pathogenesis of CVD[65].

As mentioned previously, alterations in glucose metabolism have a major impact on the health of individuals with MetS. CGM devices provide valuable real-time information on blood glucose levels, CGM systems consist in a small sensor that is inserted under the skin and measures glucose levels in the interstitial fluid. These devices provide real-time glucose readings at regular time intervals, usually every few minutes, allowing users to monitor their glucose levels continuously throughout the day[66]. The continuous monitorization of glucose levels is particularly useful for controlling IR. Individuals with IR frequently report fluctuations in their blood glucose levels, making it difficult to achieve stable glycemic control. CGM devices provide real-time information, allowing individuals to quickly identify and effectively manage episodes of hyperglycemia or hypoglycemia[67]. The use of CGM devices must be performed in collaboration with healthcare professionals to guarantee proper interpretation of glucose readings and adequate adaptations of treatment regimens.

Non-invasive blood pressure monitoring

The IR is a key factor in the development of other components of the MetS. An example is the development of alterations in blood pressure. IR triggers impaired nitric oxide production and endothelial dysfunction. Resulting in a reduction of vasodilation and an increase in peripheral vascular resistance, contributing to elevated blood pressure levels. Furthermore, the abnormal lipid profile and abdominal obesity also contribute to these alterations by activating proinflammatory pathways, oxidative stress and release of adipokines and inflammatory mediators, respectively[65,68]. Additionally, the renin-angiotensin-aldosterone system (RAAS) is commonly dysregulated in MetS, contributing to hypertension. Activation of the RAAS pathway leads to increased production of angiotensin II and aldosterone, which promotes sodium and water retention. These mechanisms further elevate blood pressure levels in individuals with MetS[69,70].

The presence of hypertension in MetS increases considerably the risk of cardiovascular complications, such as cardiopathies, strokes and renal diseases. Therefore, it is essential to effectively control blood pressure in individuals with MetS to minimize these risks. Continuous blood pressure monitoring with noninvasive devices supports healthcare professionals in the assessment and control of blood pressure fluctuations[71]. The most commonly used methods include automatic arm cuff devices, wrist monitors and ambulatory blood pressure monitoring (ABPM). Automated arm cuff devices are frequently used in clinics and health centers. They consist in placing an inflatable cuff around the arm, which is connected to an electronic device. The cuff inflates and deflates automatically, while sensors detect blood pressure oscillations. The devices provide accurate and reliable measurements of systolic and diastolic blood pressure[72-74]. On the other side, wrist blood pressure

monitors use an inflatable cuff placed over the radial artery that automatically inflates and deflates to measure blood pressure. Although wrist blood pressure monitors are convenient, it is important to consider that their accuracy can be compromised by body position, movement and individual variations[75-77]. Ultimately, ABPM is a useful tool for assessing blood pressure variations over a 24-hour period. ABPM consists of wearing a portable device that automatically measures blood pressure at regular intervals throughout the day and night. This method provides a complete profile of blood pressure variations during daily activities, sleep, and a variety of conditions, enabling a more accurate assessment of blood pressure control in individuals with MetS[78,79]. Through the periodical monitoring of blood pressure levels, healthcare professionals are able to detect and follow-up changes in blood pressure, determine the effectiveness of lifestyle modifications and medications, and take informed decisions about treatment[71].

The role of wearables in real-time

In the last decade, wearable devices have become powerful tools in healthcare, enabling real-time monitoring and assessment of various physiological parameters. These devices, which range from fitness trackers to advanced health monitoring wearables, offer several key advantages in assessing MetS[80]. The first advantage is that wearables allow continuous monitoring of essential parameters such as physical activity levels, heart rate, blood pressure, glucose levels and sleep patterns. This real-time data provides a complete and dynamic view of an individual's metabolic health, allowing for a more accurate assessment compared to a one-time measurement[81]. Moving further into MetS treatment, wearables generate personalized data profiles based on each individual's unique physiological responses. This information enables personalized interventions and lifestyle modifications, which are the cornerstone of MetS treatment[82,83]. It is noteworthy that the information obtained with these devices should be analyzed in conjunction with the clinical information of each individual[84]. Nevertheless, in order to widespread and effectively use wearables for MetS assessment, a number of challenges need to be addressed. These include ensuring the accuracy and reliability of the data, by conducting larger studies. Additionally, privacy and security issues must be addressed, and data generated by wearables must be integrated into existing healthcare systems[85,86].

Biomedical Engineering Interventions for Managing Metabolic Syndrome

Previously we have discussed how BME contributed to enrich the understanding of the pathophysiology and assessment of MetS. Nevertheless, BME interventions have emerged as promising approaches for the management of MetS. For instance, we have previously discussed that the development of wearable devices equipped with sensors can continuously monitor physiological parameters such as blood glucose levels, heart rate and physical activity. These devices provide real-time data that can aid in personalized management and facilitate timely interventions.

Targeted drug delivery systems have emerged as a promising approach to treat MetS by taking a more comprehensive approach and directly addressing the underlying molecular pathways and mechanisms involved in the development and progression of MetS. Targeted drug delivery systems refer to methods or technologies designed to deliver drugs specifically to the affected tissues or cells while minimizing their exposure to healthy tissues. This approach allows for higher drug concentrations at the target site, which can lead to improved therapeutic outcomes and reduced adverse effect. One of the most widely studied strategies for the targeted delivery of drugs against MetS is nanoparticles[10]. Several types of nanoparticles have been explored for targeted drug delivery in MetS, including liposomes. Liposomes, a unique type of nanodrug delivery system, are spherical vesicles composed of one or more concentric phospholipid bilayers enclosing an aqueous core. There are several advantages of liposomes, such as reduced drug toxicity compared to free drugs and enhancement of immune system of the organism[87]. One of the key advantages of liposomes in the context of MetS is their ability to improve the solubility and stability of drugs. Many drugs used in the treatment of MetS, such as anti-inflammatory drugs or lipid-lowering drugs, often have low water solubility. By encapsulating these drugs within liposomes, their solubility can be enhanced, resulting in improved drug delivery and bioavailability[88-90]. Nevertheless, it has been observed that other types of nanoparticles can also

be useful in the treatment of MetS, such as polymeric nanoparticles[91], exosomes[90,92], nanoemulsion[93], and others. Nanoparticles have demonstrated a great potential for targeted drug delivery systems in the treatment of MetS. With the continued advances in nanotechnology, these innovative approaches may revolutionize the treatment of MetS and improve patient outcomes. Continuous research and investment in this field is crucial to unlock the full potential of nanoparticles in the fight against MetS and its associated complications.

The Use of Artificial Intelligence and Machine Learning

In recent years, the integration of technological advancements, particularly artificial intelligence (AI) and machine learning (ML), has emerged as a promising approach for understanding and managing MetS[16,94]. AI refers to the use of computers and technology to stimulate intelligent behavior and critical thinking comparable to a human being[95], while ML is an implementation of AI and computer science, employing algorithms that refine accuracy through experiential learning[96]. ML approaches have been noted for their use in MetS risk assessment, where anthropometric, clinical and histological data are used to construct risk models[53,97,98].These models have demonstrated efficient performance in predicting MetS and have facilitated the evaluation of how lifestyle changes, genetics and environmental factors impact such prediction[16,18,99,100].

The future perspectives regarding the use of AI and ML for the assessment and treatment of MetS are immensely promising and herald a transformative era in healthcare. As these technologies move forward, they are primed to transform the way MetS is understood, diagnosed, and treated, offering a multitude of exciting possibilities[101,102]. AI and ML algorithms can be exploited to predict an individual's risk of developing MetS based on a constellation of factors. These predictions enable healthcare professionals to implement targeted preventive measures, allowing individuals to make informed lifestyle changes before the onset of MetS[103,104]. Going beyond MetS prediction, AI-based simulations can accelerate the discovery and development of new pharmaceutical interventions for MetS. By modeling interactions between potential drug candidates and metabolic pathways, AI can identify promising compounds for further exploration. This could lead to the creation of innovative treatments that target specific components of MetS more effectively[105,106].

Conclusions

Throughout this review we have discussed the role that BME plays in the understanding and assessment of MetS (**Figure 2**). Starting with the introduction of CBMs in the 1980s and continuing into modern era with the use of AI and ML, BME has evolved along with our understanding of the MetS. Furthermore, progress has been reflected in the introduction of devices that allow continuous assessment of individuals with MetS, and have also proven useful in assessing the risk of other MetS-associated diseases. Although BME interventions offer great potential for treating MetS, several challenges need to be addressed to maximize their potential and drive future advances in this field. One of the main challenges is the complexity and heterogeneity of MetS itself. MetS encompasses a wide range of interconnected metabolic abnormalities, each with its own characteristics and underlying mechanisms. The development of interventions that can effectively address multiple aspects of MetS simultaneously remains a major challenge. Another challenge is the translation of BME innovations from the laboratory to clinical practice. While there have been exciting developments in diagnostics and drug delivery systems, many of these advancements are still in the early stages of research or limited to preclinical studies. By addressing the challenges and focusing on personalized approaches, targeted therapies, digital health integration, collaboration, and long-term assessment, BME can pave the way for transformative interventions that enhance the lives of individuals affected by MetS.

Advances in biomedical engineering (BME) have facilitated the development of powerful tools for understanding metabolic syndrome (MetS), providing a comprehensive view of the intricate processes that contribute to this condition. This has enabled the creation of new diagnostic and therapeutic approaches intended to enhance the lives of individuals affected by MetS. BCAs: body composition analyzers, CGM: continuous glucose monitoring, MetS: metabolic syndrome.

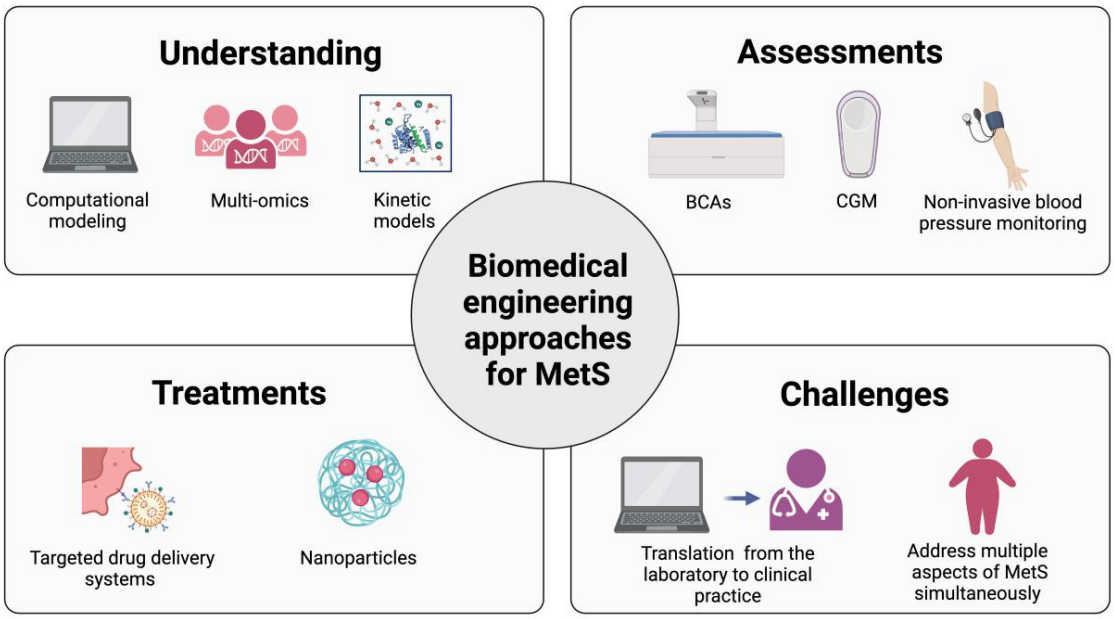

Figure 2. Biomedical engineering (BME) approaches addressing metabolic syndrome (MetS).

Conflict of Interest

None

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Appendix A. Abbreviations

ABPM: ambulatory blood pressure monitoring;
AI: artificial intelligence;
BCAs: body composition analyzers;
BIA: bioelectrical impedance analysis;
BME: biomedical engineering;
CBM: constrained-based models;
CGM: continuous glucose monitoring;
CT: computed tomography;
CVD: cardiovascular disease;
DEXA: dual-energy X-ray absorptiometry;
GWAS: genome-wide association studies;
IDF: International Diabetes Federation;
IR: insulin resistance;
MetS: metabolic syndrome;
ML: machine learning;
MRI: magnetic resonance imaging;
NCEP ATP III: National Cholesterol Education Program Adult Treatment Panel III;
RAAS: renin-angiotensin-aldosterone system;
T2DM: type 2 diabetes mellitus.