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REVIEW

Chronic Diseases® and Translational Medicine

Application of wearable devices for monitoring cardiometabolic dysfunction under the exposome paradigm

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Abstract

Environmental factors, including chemical/physical pollutants, as well as lifestyle and psychological factors, contribute greatly to the pathways leading to cardiometabolic diseases with a heavy disease burden and economic loss. The concept of exposomes provides a novel paradigm for combining all exposure characteristics to evaluate disease risk. A solution-like exposome requires technological support to provide continuous data to monitor vital signs and detect abnormal fluctuations. Wearable devices allow people to conveniently monitor signals during their daily routines. These new technologies empower users to more actively prevent and manage cardiometabolic disease by reviewing risk factors of the disease, especially lifestyle factors, such as sleeping time, screen time, and mental health condition. Devices with multiple sensors can monitor electrocardiography data, oxygen saturation, intraocular pressure, respiratory rate, and heart rate to enhance the exposome study and provide precise suggestions for disease prevention and management.

KEYWORDS

cardiometabolic disease, environmental factors, wearable device

Key points

- Screen time, sleep duration, and mental health condition can be used to evaluate cardiometabolic disease risk.
- Wearable/portable devices capture environmental exposure and vital signs for monitoring health conditions.
- Novel wearable devices can monitor eye pressure, electrocardiography data, and oxygen saturation, contributing to health management.

1 | INTRODUCTION

Cardiometabolic diseases, including cardiovascular conditions and metabolic dysfunction, caused more than 17.9 million deaths worldwide in 2019.[1] Cardiometabolic dysfunction refers to a group of common co-occurring disorders that affect the cardiovascular system, metabolism, and other body systems, such as diabetes, hypertension, obesity, and dyslipidemia.[2] These diseases are often linked to lifestyle factors, such as poor diet, physical inactivity, and smoking. The relationship between metabolic dysfunction and cardiometabolic diseases is complex, but the prevention strategy could be the same.

The prevention and monitoring of disease progression, especially vital signs, have garnered the interest of both public health policymakers and clinicians. Environmental factors are usually the source of oxidative stress and the driving force of metabolic diseases, leading to increased blood pressure and heart rate, and sleep rhythm alterations. However, because environmental factors are usually hidden and require long exposure periods to manifest, the cumulative health effects of such damage usually draw attention only after the appearance of disease symptoms, resulting in their impact often being underestimated and warning signs lacking.

An exposome is a novel paradigm for people to understand how the overall environment stimulates the etiological change from chronic conditions to cardiometabolic diseases.[3] Hazardous environmental component detection methods available to date mainly focused on epidemiological studies, which have limited ability to achieve long-term continuous ambulatory monitoring of dynamic changes in health conditions. Such expositions are unsatisfactory because they provide little evidence of personal preventive suggestions to avoid adverse outcomes.

Several studies have suggested that wearable devices can provide more reliable, detailed data on human activities and exposure characteristics,[4,5] providing an effective way to assess health risks and facilitate further interventions.[6,7] For example, wearable devices can monitor health indicators such as weight, fat, blood sugar, and blood pressure to detect the risks of metabolic diseases early and help patients effectively control their condition. Moreover, these devices can deliver real-time condition data of patient changes and identify potential risks in a timely manner to provide clinical doctors with customized treatment plans to effectively improve their patients' health. Wearable devices provide a comprehensive disease-monitoring solution.

This review focuses on the elements that require a cardiometabolic disease process and attempts to pinpoint the overlapping usage of environmental hazardous factors and early signs of diseases, which could provide a list of the main and novel concerns for evaluating disease risk. The first section of this thesis reviews the main and emerging risk factors for cardiometabolic diseases worth considering within the scope of the wearable side while outlining and summarizing the characteristics or vital signs that could be used to evaluate preclinical conditions or deserve further consideration. We then explore how wearable devices or materials can monitor these physiological signals and extend our knowledge of the usage of novel technologies.

2 | CARDIOMETABOLIC DISEASE-RELATED FACTORS

Exposome refers to the totality of environmental exposures that an individual experiences throughout their lifetime from conception to death. Exposomics is the study of exposomes focusing on identifying and quantifying the various environmental exposures that individuals encounter and understanding how these exposures interact with each other and with genetic and epigenetic factors to influence an individual's health outcomes.

Several studies have attempted to build connections and quantify the impact of exposure to cardiometabolic diseases, including metabolic syndrome (MetS), type 2 diabetes (T2D), and cardiovascular disease. The varied concept of the exposome made it a great challenge to disentangle the effects of single components,[8] while wearable and portable devices facilitated new solutions to these questions. Exposome monitors include external and internal components. The measurement process of external components is similar to "personal exposure monitoring," which is widely used in occupational and environmental epidemiology studies.[9] The main advantage of this method is that specific exposures can be measured directly. In contrast, wearable devices have limited solutions for internal exposure. However, these technologies can capture sequential physiological changes for early disease detection, providing a vision that links the initial events to the exposure element in a PRECEDE–PROCEED model application.[10] A promising theoretical contribution involves simultaneously strengthening the causal inference of exposure and outcomes.

This section reviews the recent literature summarizing the evidence that links different categories of exposure and adverse health outcomes. The involved complexity has led researchers to array a list of these joint exposure elements and distinguish their importance. The main exposures included here were measurable elements, such as environmental pollutants, lifestyle elements, psychological factors, and living environment (Figure 1).

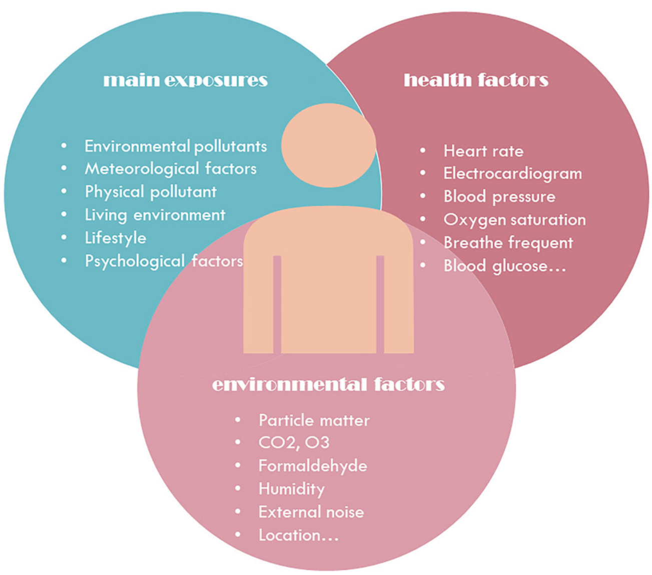

FIGURE 1 Exposome and health factors.

TABLE 1 Exposure components and wearable devices.

Category	Exposure elements	Latest measured wearable device	Method	Future of application	References
Environmental pollutants	$PM_{2.5}$, PM_{10} (particle matter)	EnviroSensor 2.0/ micropem	The infrared light-emitting diodes and photosensitive transistors in Sharp Dust Sensor GP2Y101 are arranged diagonally to detect particles of reflected light in the air.	It could have a smaller size and longer working time in the future.	[49]
	O_3	EnviroSensor 2.0	When ozone diffuses into the sensor, a small current is formed between the electricity price and the working electrode. This current is proportional to the ozone concentration entering the sensor within a certain range. Finally, the circuit system processes and calculates the ozone content.	Precisely measured the real-time personal exposure levels.	[49]
	Formaldehyde	LSCM-loaded SnO_2 fiber-in-tubes (FITs)	LSCM-loaded as-spun Sn precursor/polymer composite fibers have a porous FIT SnO_2 structure with high surface area, high oxygen vacancy concentration, and a large work function. Therefore, LSCM-loaded SnO_2 FITs (LSCM@SnO_2 FITs) show an extremely high response to formaldehyde and excellent selectivity for interfering gases.	Real-time monitoring of indoor formaldehyde level.	[50]
	Humidity	Breathable nanomesh humidity sensor	The humidity sensor utilizes the properties of water-absorbing polymer nanofibers and discontinuous metal layers to create a porous structure that shows excellent gas or sweat permeability and functions as a true biocompatible device with a breathable design.	The sensor will be used to reveal the correlation between exercise status or skin afflictions and sweat emissions.	[51]
	Atmospheric pressure	Smartphones that are equipped with a pressure sensor.	A set of four identical Samsung Galaxy S4 smartphones, using piezoresistive technology pressure-sensing sensors measuring 5×5 mm, were used to measure atmospheric tides.	It will enhance the ability to monitor and study atmospheric processes in the future.	[52]
	External noise	MOSFET devices	Low-Frequency Noise was measured using MOSFET devices with Easy-to-Use and Programmable Source-Measuring Unit. This work was conducted to design a programmable biasing and amplification system with very low noise, able to measure current noise. And the instrument has been integrated into a complete wafer-level device characterization system.	The measurement was limited to lab, and it will be used in daily lives.	[53]
	Ultraviolet (UV) light	A novel self-powered p-CuZnS/n-TiO_2 UV photodetector	By effectively replacing the Ti foil with a thin Ti wire for the anodization process, they made a fiber-shaped flexible and wearable device, which could easily be integrated with commercial electronics to function as a real-time monitor system.	It hopes to provide a real-time wearable UV radiation monitor and transmits data to smartphones via wifi.	[54]
	Radiation	G-CSF wearable system	This device designed a system consisting of a commercial microchip, a temperature sensor, a γ-ray detection sensor, a flexible heater, and a G-CSF temperature-sensitive microneedle patch. And it can detect γ radiation and immediately release G-CSF into the human body.	It will be beneficial against unexpected ionizing radiation-induced injury.	[55]

TABLE 1 (Continued)

Category	Exposure elements	Latest measured wearable device	Method	Future of application	References
	Screen time	Phillips Actiwatch Spectrum	This wrist uses an integrated color sensor IC (Hamamatsu S11059-02DT), which can measure four spectral bands: blue (400–540 nm), green (455–630 nm), red (575–660 nm), and infrared (785–885 nm). The work showed that it is possible to detect screen time by using an optical color sensor and demonstrates that wearable color measurement can enable a new dimension for machine-learning analysis.	Authors are optimistic about advancing the ability to activity recognition in the real world.	[56]
Lifestyle	Physical activity	Wearable sensor and algorithm for automated measurement of screen time	The work showed that it is possible to detect screen time by using an optical color sensor and demonstrates that wearable color measurement can enable a new dimension for machine-learning analysis.	The human use of electronic displays has been linked with a wide variety of pathologies, including obesity, circadian disruption, sleeping disorders, cardiometabolic disease, and socioemotional behavior disorders in children.	
	Sleeping time/daily routine	Algorithm based on heart rate (HR) data	The sleeping time is measured by HR recorded through a wearable device and a personalized phase-response curve of circadian rhythm in HR (CRHR) through the Social Rhythms app. This work introduces a statistical method to extract and track six key physiological parameters and estimate a personalized phase-response curve of CRHR.	Future population-based studies usage.	[57]
Living envir-onment	Real-time location	Wearable cameras and Computer Vision Application Programming Interface (API)	This study analyzed 8598 volunteers' wearable camera images by using manual image identification, image recognition with Computer Vision API, and color calculation in Matlab to demonstrate the volunteer's behavior, time use, movement path, and experiencing scenes to gather individual activities and spatiotemporal information.	It will head on to promote a continuous, multidimensional collection of individual behavioral data.	[58]

Abbreviation: LSCM, perovskite La0.75Sr0.25Cr0.5Mn0.5O3-δ.

2.1 | Environmental pollutants

Air pollution, including ambient particulate matter (PM) gas pollutants, is known to increase the burden of death worldwide[11] and may disproportionately damage the health of ethnic minorities.[12] Long- and short-term exposure can increase the risk of MetS in most populations. A meta-analysis suggested that 12.28% of the risk of MetS could be attributed to PM 2.5 μm or smaller[13]; this influence could harm adolescents and children at increased concentrations.[14] Evidence of ozone-induced alterations of lipid metabolites and glucose intolerance remains unclear based on the existing toxicology and epidemiology research.[15,16] Physical activity has a joint effect or interaction with air pollution, and according to recent research, activity intensity can lessen the adverse impact of pollutants.[17]

Chemical pollutants, which can be categorized as synthetic chemicals, natural mixtures, heavy metals, and endocrine-disrupting chemicals, increase the risk of metabolic diseases and T2D.[18] These chemical pollutants can be produced or found in food processing, drinking water, and agricultural production,[19] and appear more frequently in modern life. Previous research has established that exposure to low levels of multiple chemicals triggers metabolic disturbances[18] and that exposure occurring in early life may have a more profound effect.[19] Meanwhile, the meta-analysis suggested that plasma hexachlorobenzene (persistent organic pollutants) concentration was positively associated with incident T2D.[20]

Noise has received increasing attention in recent years, and the impact of noise exposure has been increasingly recognized.[21] Noise exposure includes chronic noise and traffic-related noise, which may cause several health outcomes, such as stress, hearing loss, and annoyance.[22] Furthermore, studies have also found that a 11.6 dB increase in noise increased the risk of developing MetS by 17%,[23] and lifelong environmental noise exposure could have cumulative effects on diabetes.[24]

Light exposure has been linked to an increased risk of developing T2D and MetS. Light exposure may decrease melatonin secretion and disrupt the biological clock, leading to an increased risk of diabetes.[25]

Radiation exposure has been linked to an increased risk of MetS. Research has found that exposure of the hypothalamic–pituitary–adrenal axis to radiation can lead to increased visceral fat mass and a high prevalence of growth hormone deficiency and MetS.[26] Additionally, survivors of nephroblastoma and neuroblastoma who have undergone abdominal irradiation are at increased risk of developing components of MetS.[27]

Temperature is an exposure that can be visibly felt, and it can be classified as body temperature and environmental temperature, or cold and hot. Several studies have suggested that exertional heat stroke, anthropogenic heat emissions, and high outdoor temperatures may increase the risk of MetS and T2D.[28–30] Age also has a joint effect or interaction with heat exposure, according to the results of recent research, but further investigations into the mechanisms of these effects are needed.[29] Interestingly, previous studies have explored the relationship between cold exposure and diabetes and found that cold exposure may be a potential therapy for diabetes by increasing brown adipose tissue mass and activity.[31]

2.2 | Lifestyle

Unhealthy lifestyle habits, such as physical inactivity and smoking, can cause adverse events in many diseases. Previous research has established that physical inactivity accounts for 7% of the burden of T2D,[32] and smoking may cause a range of physiological side

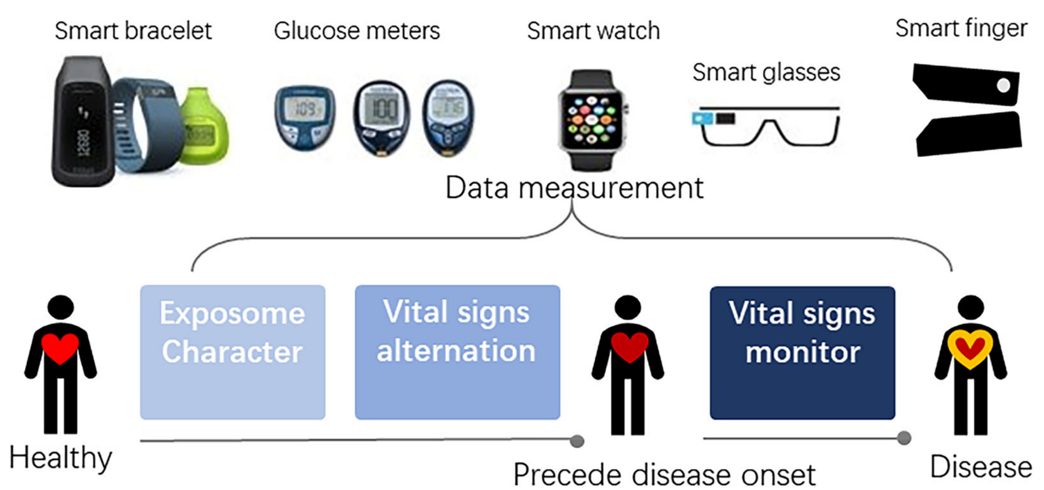

FIGURE 2 Exposome and vital signs monitor.

TABLE 2 Vital signs of cardiometabolic disease monitored by wearable devices.

Measured feature	Description	Main technological advantages	Applications for diseases prevention	References
Heart rate	The blood pressure (BP), respiration rate, and heart rate (HR) are continuously monitored by an earphone-type device based on a single photoplethysmography sensor.	**(1)** Long short-term memory was used to extract features. **(2)** BP regression models and RR measurements were used to monitor BP and RR.	Continuous monitoring of vital signs through the changes in blood vessels.	[64]
Heart rate	Hitoe 1, a composite of conductive polymer PEDOT:PSS and nanofibers, was developed as a fabric-type bioelectrode for collecting vital data, such as HR and ECG measurements.	**(1)** Clothing monitor. **(2)** Including conductive polymers on nanofiber fabrics. **(3)** Compatible with skin and stable signal of ECG waveform provider.	Health measurement on heart load and the detection of vital signs to prevent health crisis outcomes.	[65]
Electrocardiogram (ECG)	The heart-rate variability (HRV) from the ECG accelerated the filtering and feature extraction by the system-on-Chip (SoC).	**(1)** Noise removement of signal. **(2)** Extended usage HRV: When combined with Beck depression inventory, it can display the individual's mental state on a smartphone/other.	Monitoring the HRV from the ECG enables the speculation of mental state and early diagnosis.	[66]
Blood pressure	The BP is measured by Shuzo's wearable Sensor.	**(1)** The algorithm advantage: the system is based on the pulse wave velocity method so that the systolic BP value is calculated according to the pulse wave propagation time. **(2)** Great user-wearing experience. **(3)** Easily attached to other portable devices.	BP to hypertension surveillance.	[67]
Oxygen saturation	The cerebral oxygen saturation can be recorded by the WORTH band.	**(1)** Brain oxygenation based on near-infrared spectroscopy. **(2)** The hardware/material advantage: a highly integrated central block is embedded, which comprises several advanced modules.	Brain circulation could be assessed at a higher spatial resolution.	[68]
Breathe frequent	The tongue-based motion is monitored by an field programmable gate arrary (FPGA)-based 16 channels array surface ultrasonic system.	**(1)** Algorithm advantage: the FPGA receives the digitized echo signal and calculates the curve of interest by a linear interpolation algorithm. **(2)** Hardware/material advantage: the system contains a custom-designed 3.5-MHz ultrasonic array transducer, an ultrasound pulser/receiver, a high-speed analog-to-digital converter, and so forth.	Tongue-based motion can be monitored clinically by this ultrasonography system.	[69]
Blood glucose	Blood glucose can be measured by a nonenzymatic fluorescent glucose sensor.	The sensor calculates the glucose concentration of the sample by using the characteristic that UV emission decreases linearly with increasing glucose concentration on ZnO NTs.	The application of ZnO NTs in the sensor can measure blood glucose noninvasively.	[70]

(Continues)

TABLE 2 (Continued)

Measured feature	Description	Main technological advantages	Applications for diseases prevention	References
Intraocular pressure (IOP)	The IOP can be monitored by a wearable contact lens.	(1) Strain gauge: the structure of Wheatstone bridge could help improve the measurement sensitivity. (2) Strain gauge's output voltage: consistently related to physiological IOP changes.	The noninvasive intraocular pressure sensor can play a potential role in continuous intraocular pressure monitoring.	[71]
CO_2	Transcutaneous blood CO_2 is monitored by miniaturized nondispersive infrared (NDIR) sensor-based wearable wristband device.	(1) NDIR sensor detects CO_2 by measuring the IR absorption fingerprint of CO_2 molecules at the wavelength of 4.26 μm. (2) Using Beer–Lambert's law to quantify the CO_2 concentration in the gas sample.	A self-contained percutaneous wristband can monitor CO_2 clinically and at home.	[72]

Abbreviations: PEDOT, Poly(3,4-ethylenedioxythiophene); PSS, poly(styrene sulfonate).

effects, including insulin resistance.[33] Recently, new findings among smokers have provided further evidence that the average total cholesterol in smokers is significantly greater than that in nonsmokers, and the mean high-density lipoprotein level in nonsmokers is significantly higher than smokers.[34] These findings shed light on the mechanisms of action of smoking, MetS, and T2D.

Insufficient sleep, defined as a curtailed sleep pattern that has persisted most days of the week for at least 3 months,[35] and screen time can also have strong graded associations with insulin resistance or glucose metabolism toward a higher risk of T2D.[36,37]

2.3 | Psychological factors

In addition to external exposure, the importance of internal exposure has been increasingly recognized by researchers. The concept of exposomes is rapidly evolving; thus, the interactions between social determinants and biological factors require attention. The primary concern regarding internal exposure is psychological factors, including depression, stress, hostility, anxiety, and anger, which may increase the risk of MetS.[38] In particular, a meta-analysis suggested that adults in a high-stress group had a 45% higher chance of developing MetS than adults in a low-stress group.[39] A further meta-analysis reported that the link between longer working hours and T2D was apparent in the low socioeconomic status group but null in the high socioeconomic status group.[40]

2.4 | Living environment

The living environment comprises human-made structures and networks that surround us,[41] including food, crime, walkability, and green spaces. The importance of the food environment is indisputable. Research in this area has shown that a shortened distance to food outlets/bars increases the risk of transitioning from a body mass index in the normal range (18.5–22.9 kg/m^2) to one in the obese range (≥25.0 kg/m^2),[42] and adults living in neighborhoods with fewer vegetable and fruit stores or that are closer to fast food restaurants, compared with those with better neighborhood resources, have a significantly increased risk of T2D.[43–45]

Several studies reported an association between walkability, green spaces, and T2D, and a meta-analysis suggested that higher walkability and green spaces tended to be associated with a lower T2D risk.[46,47] Interestingly, as part of the human-made environment, perceived neighborhood crime may cause unfavorable environmental and area disadvantages, ultimately increasing the risk of T2D.[48]

3 | WEARABLE DEVICE APPLICATION FOR MONITORING ENVIRONMENTAL AND PHYSIOLOGICAL CHARACTERISTICS RELATED TO CARDIOMETABOLIC DYSFUNCTION

3.1 | Environmental exposome and wearable/portable devices

External environmental exposure interrupts immune balance and causes oxidative stress, accelerating cardiometabolic diseases. As summarized above, physical and chemical pollutants, climatic factors, and living environment were associated with adverse outcomes in intensive epidemiological studies. Accumulated exposure is a reliable estimate of molecular changes in intermediate chronic disease status that requires proper measurement and calculation. Table 1 summarizes the latest innovations in environmental factor tracking, the employed theories/algorithms, and where contributions will occur in the future.

3.2 | Health indicators and wearable devices

Human vital signs are not typically part of the exposome, but the data provided by novel technologies could contribute to health assessments and the early detection of cardiometabolic diseases. Advancements in fitness trackers equipped with sensors provide reliable data to strengthen the causality between environmental exposure and early physiological deterioration.[59] For example, continuous monitoring of heart rate variability[60] can reflect the short-term toxicity of air pollution,[61] ozone,[62] and geomagnetic disturbances. This paper also listed features related to cardiometabolic diseases that incorporate multiple sensors with a novel intelligent processing method for health providers and outpatient medical surveillance. For instance, the noninvasive measurement of intraocular pressure is an early step in the evaluation of diabetes using portable devices. In addition, electrocardiography is replacing the heart rate used to infer the long-term risk of cardiac symptoms with a 24-h real-time monitoring solution, even for children.[63] As shown in Figure 2, there are two different settings for monitoring vital signs: observing alternations in vital signs in the preceding disease and avoiding disease-related lesions (Table 2).

4 | CONCLUSION

The main strength of this study is that it summarized the latest technologies and algorithms applied to examine outpatients and healthy people with a higher risk of cardiometabolic diseases based on the existing literature. The adoption of biotechnology to combat natural pressures is a strategy for human survival and evolution. Owing to technological constraints, this study cannot provide a comprehensive review of all factors summarized above but lists relatively novel evidence for further usage. With rapid improvements in battery technology alongside smartphones, wearable devices have broad application prospects.

AUTHOR CONTRIBUTIONS

This review was designed and drafted by Haodong Zhang and Pai Zheng. The manuscript was revised by Lingming Hu and Guang Jia. All authors approved the final manuscript.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

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None.

ETHICS STATEMENT

None.

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