PHYSICAL AND MENTAL FATIGUE ASSESSMENT OF CONSTRUCTION WORKERS USING SWEAT-BASED BIOSENSORS

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PhD

The Hong Kong Polytechnic University

2023

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Physical and mental fatigue assessment of construction workers using sweat-based biosensors

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A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

May 2023

CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

_______ __________ (Signed)

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DEDICATION

To my beloved families

For all your unconditional love and encouragements.

ABSTRACT

Fatigue has been identified as a primary cause of construction site accidents in many studies. Owing to the nature of construction tasks, workers have to perform their duties attentively over a long period of time in a harsh environment. Mental and physical fatigue are the dominant risk factors for weakening workers' ability to perform functionally. Recent studies have proposed electroencephalography and eye-tracking based solutions to detect mental fatigue, whereas physiological biomarkers (i.e., heart rate, temperature, and breathing rate) to assess physical fatigue. However, fatigue that construction workers usually experience appears to be complicated and more than one type. Specifically, it usually involves the interactive influences between physical and mental fatigue, therefore, single type of fatigue assessment could result in biased and inaccurate outputs.

This study proposed to develop non-invasive wearable sweat-based biosensors that can measure chemical biomarkers to assess mental and physical fatigue. To achieve this objective, first, a systematic review was conducted to investigate 1) the potential sweat-based biomarkers that are relevant to fatigue; 2) the prevalent sensing technologies in the sweat biosensor domain. Second, an experiment was conducted to model the relationship between sweat biomarkers and fatigue levels during simulated construction rebar tasks using machine learning techniques. Lactate was selected for further investigation due to its high concentration in sweat and its crucial role in supplying energy resources during high-energy consumption activities. Third, an advanced wireless organic electrochemical transistor-based biosensor with high selectivity and sensitivity was developed to measure lactate concentrations from sweat. Fourth, an experiment was conducted to evaluate the reliability of the sweat lactate device in assessing fatigue. This was done by comparing the results obtained from the proposed device with those obtained from a professional

blood lactate meter, and conducting a test-retest experiment to assess its accuracy. Last, an investigation was conducted to validate the usefulness of sweat lactate in assessing physical and mental fatigue during construction manual material handling task and equipment operation task, respectively. Overall this project was the first to develop and validate the feasibility of sweat-based sensors in detecting fatigue levels during construction tasks. The results of this study will provide a comprehensive solution for monitoring and mitigating fatigue of construction workers exposed to prolonged tasks in seemingly harsh environments.

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ACKNOWLEDGEMENTS

Being able to pursue my PhD degree under the guidance of Professor Heng LI is the greatest honor of my life. He is an incredible individual, embodying dignity, compassion, wisdom, and extensive research experience. Professor Li is always interested in exploring research studies. During our weekly meetings, he would discuss the research investigations with us not just as a professor, but as a wise senior who genuinely cared about each individual's progress and inspired us with his knowledge and experience. Whenever we faced difficulties with our research studies, he was always there to offer help and support to the best he can. Under his guidance and encouragement, I was able to discover my passion for research, and this made my PhD studies go through smoothly.

I wish to convey my deepest appreciation to my co-supervisor, Professor Xiaoming TAO, for her unwavering support throughout my research project. Her passion and genuine attitude towards science have had an enormous impact on me. I am grateful for her guidance and advice, which I will undoubtedly benefit from in both my academic and personal life in the future. Additionally, I would like to express my thanks to Professor Feng YAN, whose support for our research project was invaluable. His success in academics will guide me to strive to be a researcher in his footsteps.

I owe a debt of gratitude to Dr. Bo FANG for teaching me how to conduct laboratory experiments, organize a research project, and present the research work in a paper. His words of wisdom have helped me navigate the complexities of research and overcome moments of doubt and panic. Furthermore, I would like to express my sincere appreciation to Zeyu ZHAO for providing me with tremendous assistance during my research work.

I am deeply grateful to Dr. Xinge YU, Dr. Xiaowei LUO, Xingcan HUANG, Muhammad IRFAN, Xiaoying LI, Dr. Anwer SHAHNAWAZ, Imran MEHMOOD, Xin FANG, Qiubin REN, Dr. Shuai

HAN, Dr Haitao WU, Xiujuan JIN, Yi YU, Guo ZHANG, Runhao GUO, Ting Kong, and all the colleagues from Smart Construction Lab for their invaluable supports throughout my research studies. I would also like to express my heartfelt appreciation to my family for always being there for me and helping me navigate the challenges of life. Without their love and support, it would not have been possible for me to complete this journey successfully.

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CHAPTER 1 INTRODUCTION

This chapter serves to illustrate the workforce issue of construction industry and emphasize the importance of investigating fatigue to improve health and safety. To provide context for the research topic, an overview of the technologies used to detect and evaluate fatigue is presented. The study's objectives and aims are subsequently defined, and the structure of the thesis, along with its research significance, is highlighted.

1.1 Research Background

Construction industry is booming and essential in Hong Kong. It is expected to grow at 3.3% in real terms from 2023, as a result of global economic recovery and government's investments in infrastructure projects (RESEARCH AND MARKETS, 2022). However, labour issues stymy the rapid growth, and become the most pressing challenge for the construction industry in the months and years ahead. These include an increasing labour cost, an ageing workforce, and a shortage of skilled workers (Umer, 2022). There has been a 44% increase in labour salaries for construction workers from 2012 to 2015 (Cheung J, 2016). What’s worse, 37.7% of skilled and semi-skilled workers are over 55 years old (CONSTRUCTION INDUSTRY COUNCIL, 2018). Furthermore, a shortage of 10,000 to 15,000 construction workers is forecasted from 2019 to 2023 (CONSTRUCTION INDUSTRY COUNCIL, 2018). Sustain workforce becomes an even bigger challenge as to the nature of construction tasks entails long-hour work, hazardous environment and labor-intensive tasks; this discourages young people to join the workforce.

International Labor Organization (2022) reported that there are at least 60,000 deaths of construction workers every year, making the industry one of the world’s largest and most dangerous work sectors. Serious health and safety problems in the construction industry not only decrease the economic efficiency of enterprises, but also produce a variety of social problems such as loss/injury of family provider and loss of quality life (Elsebaei et al., 2020). Nowadays, nearly 90% of the casualties and accidents that have occurred at construction sites are incurred by workers' improper or wrong operations/behaviors (Suraji et al., 2001), where many such mistakes could be attributed to excessive levels of fatigue suffered by workers. Many studies identified fatigue as a major factor causing construction accidents (Aryal et al., 2017; Esmaeili & Hallowell, 2012; Tixier et al., 2016; M. Zhang et al., 2015). Fatigue refers to the gradual discomfort, decline in work ability and the body's resistance to continue working in the process of labor. While they experience general weakness, physical and mental exhaustion, lack of concentration, sluggishness, construction site workers are in a state of fatigue (Venkata Sai Vardhan et al., 2021). Consequently, this decreases in capability of properly performing tasks and increases the risk of serious accidents.

Construction site workers are prone to fatigue due to prolonged working time (X. Dong, 2005), high physical demanding tasks (Hartmann & Fleischer, 2005), and harsh work environments like high temperature and humid (Yi et al., 2016). Their performance is the primary risk factor to safety. For example, accidents involving rebar bending, cutting, fixing might cause serious injuries due to dangerous working scenarios. Also, accidents involving the use of lifting equipment not only causing injury and death in construction industry, but also affect people in the vicinity (Goldobina et al., 2019). It is thus important to prevent construction site workers from working under excessive stress or fatigue, as this can lead to improper operations and ultimately result in accidents. And this is precisely the primary purpose of this study that will be further elaborated subsequently.

1.2 Research Problem

Fatigue is generally defined as the lassitude or exhaustion of mental and physical strength induced by manual labor or mental activities (M. Zhang et al., 2015). Construction site workers are exposed to unique work settings that often necessitate prolonged physical and/or mental exertion, which can lead to two major types of fatigue: physical and mental. To manage or minimize the ill-effects of fatigue, monitoring and assessing fatigue levels through various methodologies can offer solutions.

Research Problem of Mental fatigue assessment

Mental fatigue is the temporary incapacity to sustain cognitive and emotional performance, its multidimensional and multicausal characteristics make them exceedingly difficult to be quantified, thereby, it has been previously monitored using questionnaires. However, questionnaire-based mental fatigue monitoring is a manual process that interrupts workers' tasks, motivating researchers to use electroencephalograph (EEG)-based sensor technologies instead (Boksem et al., 2005; Wascher et al., 2016). Placed on the head and forehead, EEG sensors use an array of sensor units to read the electrical activity of various parts of the brain. Although EEG technology can achieve continuous mental fatigue monitoring, it requires multiple sensor units to maintain constant contact with the head/forehead, which may cause irritation and limit long-term use on construction sites. Beside EEG, eye-tracking is also a potential technology to monitor manifestations of mental fatigue (Yamada & Kobayashi, 2018). Recent studies have found wearable eye-tracking technology to be useful in evaluating and classifying various levels of mental fatigue for construction equipment operators (J. Li et al., 2019). Compared to EEGs, eye-tracking technology is more resistant to measurement of signal noise produced by operators' body movements. However, its intrusiveness and susceptibility to light limit its application in a variety of construction scenarios.

Research Problem of Physical fatigue assessment

Physical fatigue is defined biomechanically as a reduction in muscle capacity to produce strength. It refers to elevated distress and is commonly associated with heavy workloads. Although Survey questionaries have been used in the past (Fang et al., 2015; Mitropoulos & Memarian, 2013), smart sensor technologies have become increasingly widespread in recent years. Various technologies have been successfully tested to monitor physiological measures such as heart rate (HR) (Abdelhamid & Everett, 1999), heart-rate variability (HRV) (Tsai, 2016), skin temperature (Chan et al., 2012), electromyography (EMG) (McDonald et al., 2015), and jerk metrics (L. Zhang et al., 2019). Specifically, HR and HRV are the prevalent methods in construction (Anwer et al., 2020; Umer et al., 2022), but they are more relevant to managing the intensity of the activities rather than controlling the individual's fatigue.

Potential fatigue assessment methodology

The majority of recent studies only focus on monitoring single type of fatigue, be it physical or mental. However, once fatigue sets in among construction site workers, in some cases both manual laborers and equipment operators may experience complex fatigue situations. For example, when a rebar worker performs a long-period task, a decrease of muscle strength and an increase of anxiety could happen simultaneously, thus, inducing both physical and mental fatigue. Similarly, operators experience prolonged sitting and sustained concentration, not only induce mental fatigue, but also muscle pain in back or leg which refers to physical fatigue. As such, construction site workers in fact suffer from a complex fatigue situation. Accordingly, our project targeted to explore new, cutting-edge technologies to address the challenge of fatigue surveillance in both physical and mental. To tackle this issue, the measurement of chemical biomarkers might present an opportunity.

Examining the actual mechanisms of fatigue, which entail intricate neuroendocrine and biochemical processes may offer a methodology to assess both physical and mental fatigue (Li et al., 2020; Mehmood et al., 2022; Pau et al., 2016). For example, when a construction worker performs a long-period task, the continuous consumption of physical and mind strength of laborers gradually changes chemical biomarkers in the body. Seshadri et al. (2019) reviewed current wearable monitoring sensors and summarized those chemical biomarkers have strong correlations to mental and physical fatigue of human bodies. However, current professional sensing technologies on measurements of chemical biomarkers are emerging on blood or saliva, their strong intrusive nature hinders further application at the construction site. Among the very latest research in the areas of health and fitness, the sweat-based sensor has drawn tremendous attentions due to its non-intrusiveness, simplicity, and low-cost (Xu et al., 2021). The detection of perspiration is accessible by portable sensors on practically most area of the body with a minimum of discomfort (H. Lee et al., 2017). Besides, human sweat, as a biofluid for noninvasive biosensing, is enormously promising because of its rich distribution (>100 glands/cm^2) (Sonner et al., 2015) and containing abundant biochemicals contents, such as sodium, chlorine, potassium, lactate, calcium, glucose, ammonia, ethanol, and urea (Heikenfeld, 2016). These biochemical compounds within sweat may offer a numerous wealth of information about people's health and fatigue status (Koh et al., 2016). Of course, sweat cannot replace blood completely. However, as previously stated, we are looking at the use of minimally invasive devices/monitors. This necessitates an occasional blood sample to calibrate, a sufficient need for non-invasive evaluation would be a correlation of the states of change between concentrations of metabolites in the excreted fluid and the corresponding values in the blood (Karpova et al., 2020). This necessitates the experimental calibration test on measurements of sweat and blood biomarkers in our study. In summary, the features of non-invasive and rich biochemical contents enable sweat sensor to be a tremendous promising device for construction site workers. But, as of my knowledge, this potentially beneficial technology has not received sufficient attention in its application to the construction industry.

Conclusion

Through the aforementioned study review, four research problems are drawn: (1) there is a lack of non-invasive, accurate and comprehensive tools for monitoring mental and physical fatigue among construction site workers; (2) sweat-based biosensor, as a potential tool to tackle this problem, has not been explored in construction domain; (3) there is a necessity to examine the correlation between sweat and blood biomarkers for calibration analysis; (4) validation of the proposed methodology for implementing construction scenarios is necessary to ensure its feasibility. In order to evaluate the general/broad usefulness of sweat biomarker among construction site workers, this research will study fatigue arising from construction manual workers and equipment operators.

1.3 Aim and Objectives

The primary aim of this research is to develop non-invasive sweat-based wearable sensors that can measure chemical biomarkers to assess mental and physical fatigue.

To achieve this goal, the following specific objectives have been drawn up for this research:

(1) To summarize and evaluate current wearable sweat-based biosensors for monitoring fatigue/stress through measuring chemical biomarkers.

(2) To establish the relationship between potential sweat biomarkers and fatigue development during a simulated construction rebar task, thereby, sorting out the predominant biomarker for further study. In this case it is sweat lactate.

(3) To develop and fabric advanced wireless sweat-based lactate sensors for assessing fatigue.

(4) To validate and evaluate the suggested sweat-based sensors for monitoring fatigue coupled with blood lactate measurements during a simulated construction equipment operation task.

(5) To assess the feasibility of using the sweat lactate biomarker in evaluating physical and mental fatigue coupled with other established fatigue assessment methodologies during manual material handling task and equipment operation task at construction sites, respectively.

1.4 Research Approaches

An explanation of the approach pathways to reach these five objectives is given as follows.

Objective 1

Through literature review on the wearable sweat-based biosensors, valuable biomarkers for monitoring fatigue were thoroughly investigated, then research gaps and limitations of existing methods were summarized.

Objective 2

Through conducting laboratory experiments, the relationship between potential sweat biomarkers and fatigue development was established. Sweat rate, sodium, lactate, and glucose have been chosen for studying fatigue development among construction rebar workers based on an extensive review of existing literature. In this case, Machine learning techniques were employed to model and predict fatigue levels.

Objective 3

An advanced wireless sweat-based lactate biosensor system with high selectivity and sensitivity was fabricated. Lactate was selected because of its high concentrations in sweat and crucial role in supplying energy resource during high-energy consumption activities, both physically and mentally.

Objective 4

The overall accuracy and reliability of the sweat-based lactate sensor for monitoring fatigue was validated against the results of a professional blood lactate meter. This task also verified the effectiveness of the proposed sweat-based sensor through conducting a test-retest experiment.

Objective 5

We have proposed that lactate can serve as an indicator for assessing both physical and mental fatigue. In order to validate this hypothesis, we conducted experiments employing sweat lactate to evaluate physical and mental fatigue, respectively. Our approach involved comparing the results with other established methodologies, such as 1) heart rate, breathing rate, skin temperature, and Borg 6-20 for physical fatigue during construction manual material handling task, and 2) EEG signals and NASA Task Load Index (NASA-TLX) for mental fatigue during construction equipment operation task.

1.5 Research Implication and Significances

Firstly, there is a lack of non-invasive tool proactively monitor mental and physical fatigue of construction site workers. In this regard, sweat-based sensors could provide a breakthrough, opening an avenue for a new generation of sensors to improve the health and safety monitoring of construction workers. As the sweat-based sensors are developed, they could significantly change the way the industry deals with mental and physical fatigue, hence benefiting the industry and the general society as well.

Secondly, this study will lead to a new generation of abundant fatigue-related data from construction site workers. These data could be analyzed using state-of-the-art data analytics to reveal latent patterns and relationships between various variables, paving the path for a better comprehension of workers' fatigue related issues. Also, the results obtained from sweat lactate and glucose measurements could be used to recommend immediate nutrition intake, while the results obtained from sweat sodium and sweat rate measurements could be used to suggest instant electrolytes intake. These could effectively help alleviate the negative effects of fatigue. As a result, evidence-based policies and industry-wide guidance can be formulated and disseminated in the construction industry.

Thirdly, apart from the construction industry, other industries could also benefit from this study. For example, the transportation industry also faces the issue of mental and physical fatigue among drivers and port workers. Many transportations related accidents have been attributed to their fatigue. Therefore, by applying the same methodology as proposed in the study, the transportation industry can identify the critical periods of fatigue among its workers and take necessary precautions to ensure their safety.

Lastly, the sweat sensor is a sophisticated biological product that, through this study, will be shared with the construction industry, government institutions, and academia. This will promote the development of commercial sweat-based sensors for construction workers' fatigue management. Once developed, these commercial sensors could significantly change the way the industry deals with fatigue from construction workers, hence enlarging social impact of the study. Additionally, the knowledge gained from this study will be shared with prominent health and safety organizations in Hong Kong, Mainland China, and abroad. The benefits of this dissemination are twofold. First, these organizations will be updated on the achievements of this study; second, research teams will be able to seek advice from domain experts on how to further enhance this work.

1.6 Thesis Structure

The following is the outline of the thesis:

Chapter 1 introduces the background, research problem, aim and objectives, research approaches, contributions, and thesis structure.

Chapter 2 demonstrates a comprehensive review on sweat-based sensors for monitoring fatigue and sorts out the current limitations and research gap.

Chapter 3 establishes the relationship between chemical biomarkers and fatigue level of construction rebar workers, then directs the follow-up research focusing on a specific chemical biomarker, lactate, as a target to be monitored for assessing fatigue.

Chapter 4 presents the development and fabrication of wearable sweat-based lactate sensors.

Chapter 5 conducts validation studies to evaluate the accuracy and reliability of the self-developed device during a simulated construction operation task.

Chapter 6 conducts experiments to assess the feasibility of using sweat lactate in monitoring physical and mental fatigue during construction manual material handling task and equipment operation task.

Chapter 7 concludes the research findings and highlights the contributions, as well as illustrates the future study in this topic.

CHAPTER 2 LITERATURE REVIEW

This section reviews existing research on sweat biomarkers related to stress and fatigue. Then, sweat-based wearable biosensors are summarized. After that, sweat sensing approaches are reviewed. Finally, a conclusion is summarized.

2.1 Introduction

Fatigue is a common symptom among healthy adults. Subjective fatigue affects approximately 14% to 60% of the healthy population (Watanabe et al., 2008). Given that construction work is a physically demanding, labor-intensive, and repetitive task, workers are susceptible to developing fatigue (Darbandy et al., 2020; Ng & Tang, 2010). Nearly 40% of construction workers in the United States have reported experiencing significant fatigue, which can have a negative influence on worker safety, health status, and productiveness (Ricci et al., 2007). Workplaces that are hot and humid and have long hours and heavy workloads have been shown to exacerbate the negative consequences of fatigue (Abdelhamid & Everett, 2002; Hallowell, 2010; Judith K. Sluiter, 2006), resulting in more and more dangerous human actions and mishaps (Judith K. Sluiter, 2006). The incidence of work-related musculoskeletal problems and falls in construction workers may also be increased by excessive fatigue (Umer et al., 2018).

In one of the first theories of fatigue, an unbalanced internal environment is cited as a key cause, with stress as a potential contributor (Kop & Kupper, 2016). Later theories attribute fatigue to a breakdown in one's ability to adjust to stressful situations, rather than to a lack of sleep or some other underlying cause (Siegrist, 1991). Because fatigue is an adaptive response to prolonged stress, it can be viewed as an individual's decision to give up on efforts to reduce a persistent stressor. This means that the behavioral implications of fatigue may be adaptive in the sense that they could reduce the potentially harmful effects of long-term depletion of biological resources (Fink, 2016; Kop & Kupper, 2016). The term "fatigue" refers to a person's inability to perform at their best (Whelan & Porter, 1981). Mental and physical fatigue are two different types of fatigue. A decline in cognitive and behavioral performance is caused by extended cognitive workload (Boksem et al., 2005; Boksem & Tops, 2008), while physical fatigue is caused by prolonged and intense physical workload (Frone & Tidwell, 2015). Occupational fatigue has long been recognized as one of the top five health risks in the construction industry due to its detrimental effects on worker health, safety, and productivity (Lerman et al., 2012; Shortz et al., 2019). Concerns regarding worker safety and health have prompted an increased focus on keeping track of needless physical tasks in order to avoid fatigue, injuries, or accidents in physically demanding workplaces (Hwang et al., 2016). For this reason, workers in the construction industry need regular examinations and early identification of fatigue (Anwer, Li, Antwi-Afari, Umer, & Wong, 2021; Umer et al., 2018).

There are many factors that contribute to fatigue, including sleep deprivation, constant mental activity, and long periods of exertion (Michael et al., 2012). Physical exertion that lasts for a long period of time can lead to fatigue, which can be felt in the peripheral muscles and in the central nervous system (CNS) (Ament & Verkerke, 2009). Ionic imbalances in myocytes are altered as a result of decreased glycogen storage and an accumulation of metabolites in the case of the former (Michael et al., 2012). Although the specific mechanism for the latter is still up for question, it has been established that cytokines and/or neurotransmitters such as interleukin (IL) 1, IL-6, tumor necrosis factor (TNF), serotonin, dopamine, and tyrosine are altered when the CNS is implicated in the experience of exhaustion (Cannon et al., 1989; Cannon & Kluger, 1983; Council, 2009). Autonomic nervous system (ANS) is impacted by prolonged physical activity, resulting in simultaneous withdrawal of the parasympathetic nervous system (PNS) and activation of the parasympathetic nervous system (SNS) (Klein & Corwin, 2002). To eliminate the need for self-reported fatigue, all of these physiological changes might be used as potential objectives for accurately detecting fatigue levels.

Only a handful of objective approaches are available for diagnosing and monitoring fatigue. Fatigue has been measured in the past using questionnaires. Researchers, however, have been seeking to employ more objective, accurate, and non-invasive procedures because of the limitations of existing methods. Chemical biomarkers are regarded as the gold standard for fatigue monitoring among the available options because of their accuracy and objectivity (Seshadri et al., 2019). Construction workers, on the other hand, are exposed to unique work environments that necessitate physically demanding and significant mental effort to complete work tasks, as opposed to athletes and sports people whose jobs entail task specific physical load. It is possible that in this case the underlying metabolic changes are rather distinct. Until recently, the use of chemical biomarkers for real-time fatigue monitoring applications was restricted due to the requirement for taking blood samples and conducting laboratory analysis. Non-invasive tests, such as saliva and sweat analysis, have been made possible by technological advancements. These measurements can also assess changes in biochemical profiles over time. Numerous chemical biomarkers, such as blood lactate, pH, potassium, sodium, and blood glucose concentrations in saliva, could be investigated to determine the development of fatigue in construction workers. For instance, lactate was utilized in a prior study to demonstrate that continuous physical work results in a rise in the body's lactic acid content, which may contribute to feelings of fatigue (Wickens, 2004). Similarly, it has been discovered that mental stress is related to lactate levels (Hermann et al., 2019). Furthermore, pH, potassium, sodium, and glucose levels are associated with a rise in lactic acid (Seshadri et al., 2019), hyper/hypokalemia, hyper/dehydration, energy loss (Gao et al., 2016), drowsiness, irritability, and muscle cramps. As a result, the aim of this systematic review is to offer a complete analysis of numerous sweat-based biomarkers for stress and fatigue assessment, the recent outlook of sweat-based biosensor development, and what methodologies are employed in wearable biosensors for monitoring biomarkers.

2.2 Methods

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist was used to conduct a comprehensive review of the literature. The combination of the terms "biomarkers," OR “Sweat,” OR "Wearable biosensors," and "Fatigue OR Stress" was searched for in electronic databases such as PubMed, Web of Science, and IEEE Explorer (Table 2.1).

Table 2.1 Search Strategies

Keywords (28-12-2022)	PubMed	Web of Science	IEEE Explorer
Sweat biomarkers OR Chemical biomarkers OR Sweat Cortisol OR Sweat electrolytes OR Sweat ammonia OR Sweat glucose OR Sweat Lactate OR Ammonia	10,982	33,622	491
Wearable biosensors OR Wearable sensors OR Wearable biosensing technology OR Wearable electrochemical sensors OR Wearable biochemical Sensors OR Wearable Chemical Sensors	1,488	27,494	14680
Fatigue OR Stress OR Burnout OR Exertion OR Exhaustion	195,506	2,520,421	94150
Combined, Limit (up to 28-12-2022)	48	59	6
Total after duplicates removed	**98**		

The initial step of the review was to analyze the titles and abstracts of the returned publications. The possibly eligible articles must have been published till December 28, 2022. Additionally, the articles were required to focus on the identification of fatigue or stress biomarkers in sweat. Finally, the articles must be written in the English language. The full text of the potentially relevant publications was analyzed in the second step of the review. There has to be a detailed description of the sensors, their properties, and their suitability for human sweat to be provided. Total citations of all included papers were also calculated based on their citations. The Web of Science Core Collection search tool and the Google Scholar search engine were used to determine the number of citations.

2.3 Results

A preliminary search of electronic databases yielded 113 hits. 15 duplicate studies were eliminated from the total, bringing the total to 98. Another 17 publications were omitted because they were not human research, and two more were omitted because they were not written in English. The remaining 79 abstracts were analyzed further, and 32 unrelated research studies were removed. A total of 47 articles remained for full-text examination. Another 34 articles were omitted from this review because they made no relevance to the primary issue. As a result, the current review comprised a total of 13 publications. The complete selection algorithm is illustrated in Fig. 2.1.

Detailed information about the final selected articles is provided in Table 2.2, including the names of the authors and the names of the publishers as well as information about the biomarkers evaluated, the participants and their demographics, the types of sensors and wearables used, the time it took for the sensor to begin recording, and the number of citations. Sweat biomarkers such as metabolites (i.e., lactate and glucose), amino acids & Hormones and electrolytes were discovered (Bariya et al., 2018) (Fig. 2.2). Potentiometric and amperometric biosensors are widely used to detect sweat-based biomarkers in real time. Wearable biosensors, such as an epidermal patch or a sweatband, have received a great deal of validation in scientific publications. The bio-signals collected by these wearable sensors could take anywhere from 1 to 20 minutes to begin recording.

Table 2.3 has a detailed list of all eligible publications, which includes the validation techniques, experiments, findings, and conclusions of each paper. Most of the included studies used laboratory trials for validation of wearable biosensors for monitoring sweat-based biomarkers. The majority of the research included in this review used a stationary cycling program to evaluate the concentrations of sweat biomarkers under a variety of physiological circumstances.

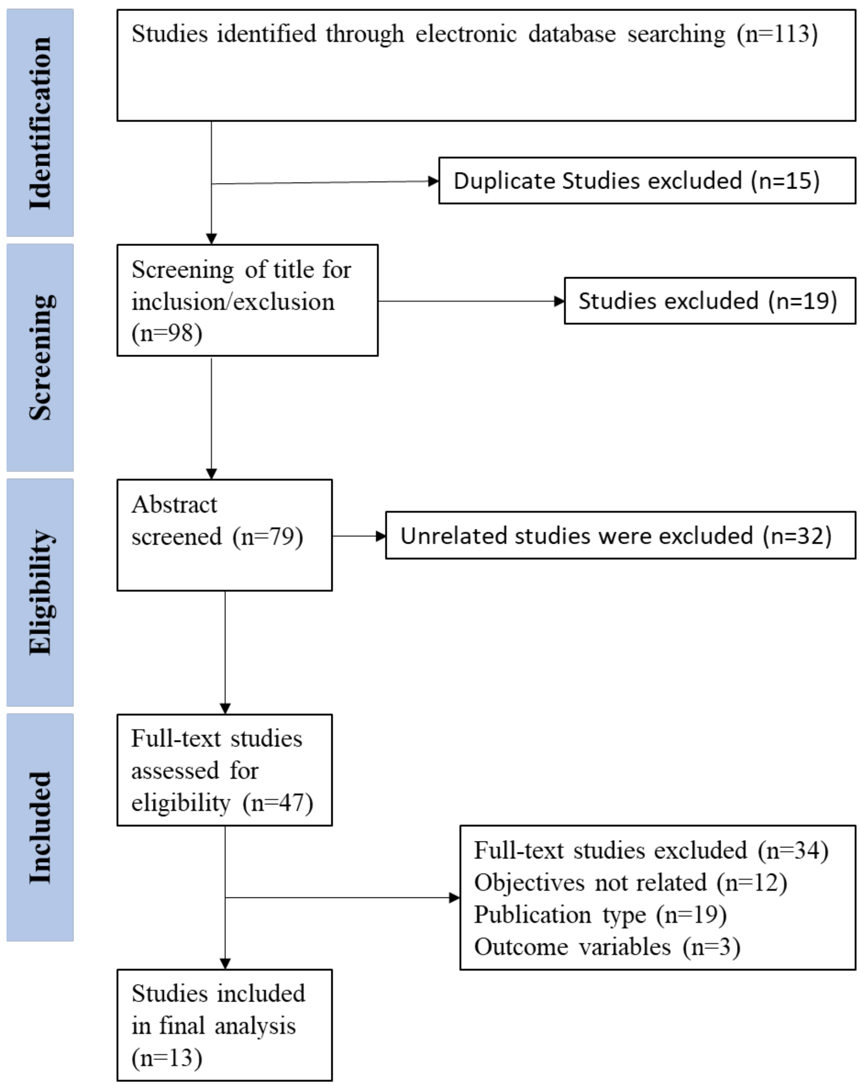


Fig. 2.1 The process of selecting research studies and the outcomes of the literature (PRISMA flow chart)

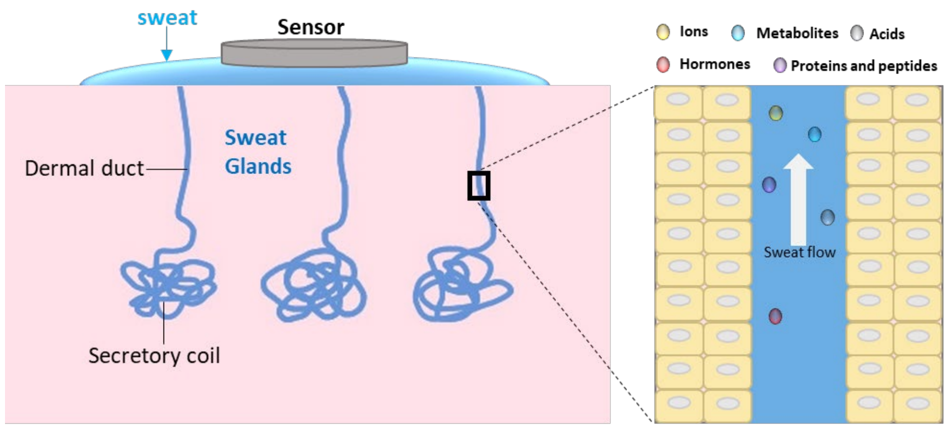


Fig. 2.2 Schematic drawing of sweat gland structure and biomarkers (Bariya et al., 2018)

2.4 Discussion

Sweat-based biomarkers have been discovered to have considerable promise for stress and fatigue evaluation in the current review. This review also found that the use of sweat-based biosensors to detect stress and fatigue has grown in popularity in recent years.

2.4.1 Sweat biomarkers for stress and fatigue

Earlier research has concentrated on the detection of fatigue by physiological signs, visual tasks, and biomarkers (Xu et al., 2018). Changes in electroencephalogram (EEG) theta (θ) waves, high-frequency (HF) EEG, pulse signals, and the ratio of low- and high-frequency components (LF/HF ratio) are used to detect physiological signals (Li et al., 2017). Glare conditions and frequencies, mouth movements, and head positions are all examples of vision tasks (Cyganek & Gruszczyński, 2014). Creatine kinase (Hecksteden et al., 2016; Wiewelhove et al., 2015), blood interleukin (IL)-8 (Dutheil et al., 2013), and α-amylase (Yamaguchi et al., 2006) are all examples of chemical biomarkers that can be detected. While some of these metrics have been used in clinical practice to quantify fatigue, the majority is invasive diagnostic tests that require blood samples and hence cannot be utilized for rapid, on-site, and accurate fatigue identification. When compared to blood and urine, which can be influenced by kidneys and other causes, sweat biofluid is more stable and easier to sample (Xu et al., 2019). There has been a lot of interest in sweat component analysis for fatigue detection in China and other nations (Calderón-Santiago et al., 2014; Zhang, 2017).

Table 2.2. Overview of wearable biosensors for monitoring sweat-based biomarkers

Citations	Publishers	Biomarkers	Subjects	Demographics	Types of sensors	Types of wearables	Time taken start recording	Cited by
Guinovart et al. (2013)	The Royal Society of Chemistry	Electrolytes (Ammonia)	Not reported	Not reported	Potentiometric sensor	Tattooed sensor	Not reported	231
Rose et al. (2015)	IEEE	Electrolytes (Na+)	Seven healthy volunteers	Not reported	Potentiometric electrolyte sensors	Epidermal patch	4 min	364
Imani et al. (2016)	Nature	Lactate	3 healthy males	Not reported	Amperometric lactate biosensor	Epidermal patch	Not reported	546
Matzeu et al. (2016)	The Royal Society of Chemistry	Electrolytes (Na+)	Four Healthy active male athletes	Not reported	Potentiometric electrolyte sensors	Sweatband	20 min	64
Emaminejad et al. (2017)	National Academy Sciences	Electrolytes (Na^+/Cl^-) Glucose	Six healthy volunteers and three Cystic Fibrosis patients	Not reported	Potentiometric electrolyte sensors Amperometric glucose sensors	Sweatband	20 min	435
Alizadeh et al. (2018)	The Royal Society of Chemistry	Electrolytes (Na+and K+)	One healthy male	Not reported	Potentiometric electrolyte sensors	Epidermal patch	Not reported	92
McCaul et al. (2018)	Wiley	Electrolytes (Na+)	One healthy male	26 Y	Potentiometric electrolyte sensors	Wristband	8 min	32
Bariya et al. (2018)	American Chemical Society	pH	Not reported	Not reported	Potentiometric electrolyte sensors	Wristband	14 min	166

Choi et al. (2019)	Elsevier	Electrolytes (Cl^{-})	10 individuals with Cystic Fibrosis (CF) and 10 healthy subjects	CF: male = 4, female = 6, age = 28.9 ± 7.4 years; healthy individuals: male = 1, female = 9, age = 35.0 ± 12.1 years	Colorimetric sensors	Epidermal patch	15 min	41
Renner et al. (2020)	IEEE	Electrolytes (Ammonia)	35 male and 5 female	Age 39.9 ± 12.5 years Height 180.3 ± 7.9 cm, Weight 80.9 ± 12.7 kg	A screen-printed electrolyte sensor	Polystyrene tubes	Not reported	4
Saha et al. (2021)	MDPI	Lactate	Eight healthy subjects	5 females and 3 males, aged 20–28	Polydimethylsiloxane (PDMS)-based hydrogels	Wearable patch	Not reported	1
Seki et al. (2021)	Nature	Lactate	23 healthy 42 patients (CVDs)	Age 20 Y (healthy) 63 Y (patients) Male 21 (healthy), 32 (patients) Height 171 cm (healthy), 165 cm (patients) BMI 22 (healthy), 23 (patients)	Amperometric lactate biosensor	Sensor chips	Not reported	5
Huang et al. (2021)	Springer	Glucose Lactate	Not reported	Not reported	Polydimethylsiloxane (PDMS)-based enzymatic biofuel cells	Epidermal patch	1 min	5

Table 2.3. Validation experiment for continuous monitoring of sweat-based biomarkers using wearable biosensors

Citations	Sweat Biomarkers	Validation methods	Experiment	Findings	Conclusions
Guinovart et al. (2013)	Electrolytes (Ammonia)	Laboratory trials	A 30-minute stationary cycling regimen with three-minute cool-down periods and another three-minute rest period was employed in the study. To achieve an anaerobic state, each volunteer drank mineral water the entire time and cycled and ran alternately every five minutes.	High Noise signal at the beginning. Low Noise signal (< 0.5 mV) when sweat begins. Amount of NH4+ = 0.1 to 1 mM (range). NH4+ levels increased with the increased load of cycling without sprinting. Sensor signals increased with increased speed of cycling.	Solid-state tattoo potentiometric cells that can detect ammonium (NH4 +) in sweat have been developed and are currently being tested. It combines screen-printed technology with a temporary transfer tattoo. NH4+ may be detected at physiological levels in sweat using this new potentiometric sensor, which is identical to ordinary potentiometric electrodes. Preliminary findings indicate that this ion selective electrode-tattoo can sense the transition of subjects doing intense exercise from an aerobic to anaerobic state. The new epidermal ammonium sensor will require more testing before it can be fully used and validated, but it has already opened up new possibilities for evaluating athletic performance, healthcare, and other fields. Electrolyte concentrations in sweat can be monitored non-invasively using a mix of epidermal integration, screen-printed technology, and potentiometric sensors.
Rose et al. (2015)	Electrolytes (Na+)	Laboratory trials	To determine the radio-frequency ID (RFID) Na+ sensor's accuracy, they repeatedly measured 50mM NaCl, which should provide 185mV according to the calibration curve. To further investigate the possibility of continuous	The sensor output *rose* as the analyte concentration *increased*. The sensor responded fast to each concentration change, with a response time of around *30 seconds*. The correlation coefficient = *0.99*. Sensor sensitivity = *0.3 mV/mM*. *Sensor*	For basic sweat sensing at physiologically relevant levels, the current patch works well and accurately and would perform even better with a higher sampling frequency, improved power management, sensor signal conditioning, and analog sensor input conversion efficiency. When it comes to collecting real-time data on people's

			monitoring in sweat, the concentration of NaCl was adjusted every 4 minutes for 45 minutes, ranging from 20mM to 70mM.	*accuracy = 96%. Sensor precision = 28%. Average value for high concentration = 255mV.* CV = 0.1%. *Average value for low concentration = 237mV.* CV = 0.8%.	health, wearable and wireless gadgets fill a huge gap in the technology needed.
Imani et al. (2016)	Lactate	enzyme-free amperometric sensor	The Chem–Phys hybrid patch was created and applied to the fourth intercostal area of three healthy male volunteers in order to evaluate performance under realistic conditions. Sweat-lactate levels and ECG signals were regularly measured during 15–30 minutes of intense cycling exertion. While pedaling difficulty was increased intermittently, participants were instructed to maintain a steady riding cadence on a stationary cycle.	Heart rate (HR) was 60 to 120 beats per minute and low current response was recorded by the lactate biosensor at the start of the cycling activity HR and sweat production increased as individuals increased amount of effort. LOx-based biosensor recorded lactate from the epidermis at the commencement of perspiration. Perspiration rate, HR, lactate levels increased as riding intensity increased. The HR returned to a level close to normal resting HR after cooldown session. Simultaneously, the lactate concentration decreased.	This technology was a vital first step in the research and development of multimodal wearable sensors, which integrate chemical, electrophysiological, and physical sensors to provide a more comprehensive view of human physiology. Human studies have demonstrated that it is possible to monitor physiochemistry and electrophysiology at the same time with minimal cross-talk, paving the way for the creation of a new class of hybrid sensing devices.
Matzeu et al. (2016)	Electrolytes (Na+)	Laboratory trials	Using stationary bikes and a cycle ergometer at an effort level that elicited sweating, a group of healthy, active	Linear relationship between the sensors and a PEDOT solid-contact layer (R2 > 0.98), with an average	Results show that the sensor is capable of displaying changes in Na+ concentrations in real time throughout workout sessions. Due to the fact that variations in Na+ levels could be

			male athletes was tested in an indoor environment. The PotMicroChip was attached to the upper left arm using a Velcro® strap (after cleaning the sampling region with alcohol swabs and deionised water). The external forearm was selected as the primary sampling location. When the athlete was unable to keep up with the set intensity load, the trials were halted.	slope and offset of 55.5 mV/log Na+ and 474.8 mV, respectively. The slope and offset standard deviations = 4.9 mV/log Na+ and 23.1 mV. Sensors with a PEDOT/PB film as the SC layer demonstrated excellent linear calibration ($R2 > 0.98$). The slope and offset values = 53.4 ± 3.0 mV/log Na+ and 524.1 ± 14.4 mV. When the PotMicroChips began harvesting perspiration, Na+ levels increased for 2 and 5 minutes, respectively. Na+ levels then stabilized at an average of 10.3 ± 0.2 mM and 24.2 ± 2.7 mM. The average interpolated sodium concentration at the end of cycling sessions was found to be 18.2 ± 8.9 mM.	followed from the point of first sweat contact with the sensor to the point of final sweat contact with the sensor, it was possible to obtain distinct "over time sodium profiles" for each individual athlete.
Emaminejad et al. (2017)	Electrolytes ($Na+/Cl^-$) Glucose	Blood glucose	To assess the wearable platform's efficacy for noninvasive glucose monitoring, they performed real-time sweat stimulation and glucose sensing measurements of a	The results of this experiment demonstrate that the sweat and blood glucose levels before and after 30 g oral glucose consumption follow a similar pattern. The off-body measurements	Cystic fibrosis diagnosis and blood/sweat glucose correlation investigations were carried out using human subjects to establish the wearable platform' clinical efficacy. They used this technology to detect an increased electrolyte content in the perspiration of cystic fibrosis patients compared to healthy control volunteers.

			group of subjects participating in fasting and post-glucose ingestion experiments. A commercially accessible glucometer was used to conduct the blood glucose analysis.	obtained from the sweat sample created by the wearable device reveal that oral glucose consumption in fasting people typically leads to a rise in both sweat and blood glucose levels.	Additionally, there is a correlation between a rise in blood and sweat glucose levels following the ingestion of oral glucose during fasting. Their technology enables a diverse variety of noninvasive diagnostic and population health monitoring applications.
Alizadeh et al. (2018)	Electrolytes (Na + and K+)	Laboratory trials	A healthy male volunteer underwent on-body testing of the fully integrated sweat sensors while undergoing high intensity activity on a bicycle on a roller trainer and treadmill running trials. The patches were applied to the back of the individual, around the latissimus dorsi muscle and/or the thoracolumbar fascia in the upper lumbar vertebrae region. Averaging 26 to 29 mph, the bike's top speed during the session, which typically lasts 30 to 60 minutes, caused the person being tested to perspire profusely.	The sensitivity of the Na+ and K+ = 55.7 mV per log a Na+ and 53.9 mV per log a K+ per decade. The results in the Na+ concentration demonstrate the expected rise in voltage associated with the introduction of eutonic sweat to the ISE (from a dry baseline), with minor noise aberrations.	Briefly stated, this research demonstrated the viability of a wireless sweat monitoring device that provides good accuracy while also providing continuous and unobtrusive sweat electrolyte monitoring over a prolonged period of time while maintaining user comfort. The microfluidics and overall system design principles learnt by this device were likely applicable to a wide variety of analytes, despite the fact that it was designed for electrolyte analysis during vigorous perspiration only.
McCaul et al. (2018)	Electrolytes (Na+)	Laboratory trials	A watch-type sweat sampling and analysis platform was used during on-body trials using exercise-induced	Within 8 minutes, the signal at the electrodes begins to rapidly grow as the perspiration replaces	With a relatively short delay (5 minutes) between the point of sweat emergence on the skin surface and the detection of the electrodes, it appears that the watch-type sweat sampling and analysis platform is

			perspiration. VO2Max (absolute oxygen consumption per minute) and relative oxygen consumption per kilogram of body weight (relative oxygen consumption per kilogram of body weight) were measured before the volunteer participated in the trial. In this experiment, the sweat sensor was attached to the volunteer's wrist. A 10-minute warm-up was followed by a 5-minute ramp-up before the subject completed a 50-minute cycling period at 120 W followed by a 10-minute cool-down period.	the conditioning fluid (0.13 mM NaCl). After 12 minutes, the signal began to settle and remained stable until 50 minutes had passed. The concentration of sweat NaCl increases to a high of 17.0 to 17.5 mM (11–13 minutes) and then progressively declines to 11.0 to 11.5% (30–50 minutes). Following that, the Na+ concentration appears to decrease at a faster rate, eventually falling below 6.0 mM near the end of the trial.	working satisfactorily in terms of sweat sampling and analysis as well. The findings demonstrate that there was no statistically significant change in the response characteristics of the system, and as a result of these findings, the trial data can be considered reasonably accurate.
Bariya et al. (2018)	Electrolytes (Ammonia)	Blood ammonia, blood lactate, and heart rate	An electromagnetically braked cycle ergometer was used to test the subjects' maximum load capacity. It was constantly monitored for changes in heart rate and breathing gas levels. The subjects were at rest when the baseline data was obtained. A 25 W increase in exertion was	The data indicate that the HR increases approximately linearly as the effort increases. Lactate concentrations were measured throughout the program, ranging from 0.5 mmol/l at the start to 16.3 mmol/l at the conclusion. Blood ammonium concentrations have been	Using a screen-printed electrolyte sensor that is suited for application in wearable electronic devices, the results presented here show that sweat ammonium concentration may be detected directly from skin samples. As a result of these observations, ammonium content in sweat decreases as a function of increased exertion. But the rate of sweat ammonium production must be taken into account in order to make sweat ammonium practical to use and

			made every three minutes after the first three minutes. If a participant felt they had expended all of their energy, they were allowed to stop the activity. 375 W was the maximum load that could be applied. At the end of each procedure step, 5 ml round-bottom clear polystyrene tubes were used to collect sweat samples from the upper body. The upper arms, shoulders, and back were the preferred locations to gather sweat because they are hairless.	measured to range between 15 and 193 µmol/l. In comparison, following a modest plateau between 150 and 200 W, the sweat ammonium concentration decreases with effort. The content of ammonium in sweat was found to range between 0.12 and 2.17 mmol/l. Sweat ammonium concentration is decreasing, contradicting the other three values. Similar to the other observed characteristics, the sweat ammonium curve exhibits a shift in concentration at 300 W.	meaningful to understand data collected in sweat as compared to blood.
Choi et al. (2019)	Electrolytes (Cl^-)	Standard laboratory test	Pilocarpine iontophoresis was used to generate sweat on both forearms of ten persons with Cystic Fibrosis and ten healthy volunteers. On one arm, a Macroduct sweat collection device was mounted, and perspiration was collected for 30 minutes before being transported to the laboratory for analysis. In the other	The wearable sensor was able to collect steady sweat chloride levels within 15 minutes of starting to sweat. The sensor measured a sweat volume of 13.1 ± 11.4 L (SD) at detection time (5 minutes), which was typically less than the minimum sweat volume of 15 L required for conventional testing. Chloride concentration differences	When utilized in conjunction with a wearable sensor, real-time measurements of sweat chloride can be obtained within 15 minutes of sweat induction. This method requires only a little quantity of sweat volume and provides excellent agreement with standard methods in the process.

			arm, a sensor was attached, and the concentration of chloride ions was monitored in real time for 30 minutes.	between the sensor and typical laboratory practice were 6.2 ± 9.5 mEq/L (SD), which was comparde to the arm-to-arm variability of roughly 3 mEq/L. It was discovered that the two measurements had a Pearson correlation coefficient of 0.97.	
Renner et al. (2020)	Electrolytes (Ammonia)	Blood ammonia, blood lactate, and heart rate	An electromagnetically braked cycle ergometer was used to test the subjects' maximum load capacity. It was constantly monitored for changes in heart rate and breathing gas levels. The subjects were at rest when the baseline data was obtained. A 25 W increase in exertion was made every three minutes after the first three minutes. If a participant felt they had expended all of their energy, they were allowed to stop the activity. 375 W was the maximum load that could be applied. At the end of each procedure step, 5 ml round-bottom clear polystyrene tubes	The data indicate that the HR increases approximately linearly as the effort increases. Lactate concentrations were measured throughout the program, ranging from 0.5 mmol/l at the start to 16.3 mmol/l at the conclusion. Blood ammonium concentrations have been measured to range between 15 and 193 µmol/l. In comparison, following a modest plateau between 150 and 200 W, the sweat ammonium concentration decreases with effort. The content of ammonium in sweat was found to range between 0.12 and 2.17 mmol/l. Sweat ammonium concentration	Using a screen-printed electrolyte sensor that is suited for application in wearable electronic devices, the results presented here show that sweat ammonium concentration may be detected directly from skin samples. As a result of these observations, ammonium content in sweat decreases as a function of increased exertion. But the rate of sweat ammonium production must be taken into account in order to make sweat ammonium practical to use and meaningful to understand data collected in sweat as compared to blood.

			were used to collect sweat samples from the upper body. The upper arms, shoulders, and back were the preferred locations to gather sweat because they are hairless.	is decreasing, contradicting the other three values. Similar to the other observed characteristics, the sweat ammonium curve exhibits a shift in concentration at 300 W.	
Saha et al. (2021)	Lactate	Blood lactate	Using a lactate paper sample, researchers were able to determine the amount of lactate in the blood under five different physiological conditions: rest, moderate exercise (60–70% of maximal heart rate), post-medium-intensity exercise, and post-high intensity exercise. All of the experiments were conducted at 22 degrees Celsius and 45 percent RH (relative humidity).	The hydrogel disc can take fluid from the skin and transmit it to the paper via osmosis while the user is sleeping or otherwise resting. Even without the hydrogel patch, the paper can still collect perspiration during periods of intense sweating (for example, exercise). Inversely proportional to sweating rate is the total amount of lactate moles measured in the experiments. High-intensity exercise has the best association between perspiration and blood lactate concentrations.	Overall, this wearable osmotic sweat sampling patch looks to have significant potential in terms of permitting the continuous sweat collection for hours at a time while also providing valuable health information regarding human lactate patterns under a variety of physiological circumstances. For reliable estimation of lactate concentration in sweat notwithstanding the skin tests, this patch needs additional post-processing processes. To determine lactate levels, a rectangular strip from the sample must be cut off and tested. The existing patch was not the best answer for device operation because an ideal wearable should enable continuous monitoring and real-time data output.
Seki et al. (2021)	Lactate	Blood lactate, and ventilatory threshold	The RAMP protocol ergometer was used to conduct exercise testing on healthy volunteers, while a wearable lactate sensor measured changes in sweat lactate. Lactate levels in the	At the start of the cycling activity, the lactate biosensor registered a negligible current response due to a lack of sweat. As the riding continued to volitional exhaustion, a dramatic	It was the first study to establish real-time monitoring of sweat lactate readings during progressive exercise in both patients with cardiovascular disease (CVD) and healthy individuals. Increasing the detection of ventilatory threshold through the monitoring of lactate levels in sweat may be useful,

		blood were monitored every two minutes using a sensor attached to the upper arm of healthy individuals. The subjects performed the test in an upright position on an electrically braked ergometer. Subjects began by pedaling for 2 minutes at 50 W for healthy males and 0 W for healthy females, then increased the intensity of their exercise until they were no longer able to maintain the pedaling rate (volitional exhaustion). Every minute, the intensity was stepped up by 20 W. (RAMP protocol). At 60 rotations per minute, the pedaling speed was set. According to the subject's exercise capacity, the incremental exercise testing lasted between 10 and 20 minutes. Individuals were instructed to stop cycling immediately and remain on the ergometer for three minutes after	increase in sweat lactate levels was noticed. At the conclusion of the workout period, sweat lactate readings continued to decline slowly in comparison to the heart rate decrease. The correlations between sweat lactate and blood lactate were excellent ($r=0.92$, $P<0.001$). The least-product regression analysis revealed no evidence of a fixed bias or a proportionate bias (95 percent confidence intervals (CIs) for the y-intercept ranged from 9.16 to 19.1; CIs for the slope ranged from 0.854 to 1.020). Similarly, a strong association between the sweat lactate and ventilatory threshold was seen ($r=0.71$, $P<0.001$). Between each threshold, least-product regression analysis revealed a fixed bias (y-intercept, 22.7) and a proportionate bias (slope, 0.57).	which was particularly significant given the difficult circumstances of identifying ventilatory threshold.

			the exercise tests were completed.		
Huang et al. (2021)	Glucose Lactate	Laboratory trials	The lactate and glucose concentrations of a cyclist were monitored in real time as he or she cycled at a steady load. Sensors implanted in the subject's back measured glucose and lactate concentrations during a period of 1200 seconds of activity. The lactate and glucose concentrations in three independent body regions were also measured after 0.5 hours of continuous activity. After that, the sensors were attached to the backs of three volunteers and the changes in lactate and glucose levels in sweat were measured.	Throughout the exercise, the glucose and lactate concentrations gradually reduced due to the dilution impact of the increased sweat rate. Lactate and glucose concentrations were nearly same across all test locations, and a significant drop was observed after 0.5 hours of perspiration. A determination coefficient (R2) of 0.98 and a sensitivity of 2.48 mV/mM was noted for lactate detection, and a determination coefficient (R2) of 0.96 and a sensitivity of 0.11 mV/mM for glucose detection.	A newly invented epidermal, stretchable, self-powered biosensor is demonstrated in this work and may be used to monitor in real time the levels of lactate and glucose in human sweat. Biofuel cells functioning as precise sensing components can work without the use of external power supplies due to the careful selection of materials and device designs. Results from the studies show that the suggested biosensor has the potential to be used in sweat sensing and healthcare monitoring scenarios where sensors on volunteers react in real time to changes in lactate and glucose levels.

Sweating is a physiological response to a variety of factors, including ambient conditions, physical activity, and an individual's emotional state. In addition to salivary biomarkers, other less intrusive approaches such as sweat analysis are becoming increasingly popular for continuous health monitoring (Corrie et al., 2015). Sweat glands, which are classified as either apocrine, apoeccrine, or eccrine, are responsible for the production of sweat (Sato et al., 1989). Apocrine sweat glands are the most common kind of sweat gland found in humans (Sato et al., 1989). Eccrine sweat glands, which are found throughout the body and cover the majority of the surface area, are the primary cause of thermoregulatory sweating (Sato et al., 1987). They produce a fluid that is predominantly composed of water, salts, and a diverse spectrum of biological metabolites (Montain et al., 2006).

Using sweat as an analysis fluid allows for non-invasive samples to be taken for both early and continuing diagnosis (Nunes et al., 2021). Depending on the analytical techniques, sweat samples and preparation may be easier and faster than other biological fluids, such as blood (Calderón-Santiago et al., 2014; Zhang, 2017). Due to its low invasiveness and high protein and peptide content, sweat is an excellent source of chemical biomarkers (Raiszadeh et al., 2012).

Sweat Lactate (sLa)

Several studies have looked at the elements of sweat to determine if they can reflect the physiological state of the individuals. Sweat is a good alternative for biosensing than other potential biomarkers since it is readily available and contains a variety of essential electrolytes, metabolites, amino acids, proteins, and hormones. The determination of lactate in sweat has a number of clinical uses that are currently being explored. One early notion was that because lactate is a result of anaerobic metabolism, it may be utilized to monitor parameters such as physical performance. It was stated that the assessment of sweat lactate would give a non-invasive alternative to blood lactate measurements; and a positive correlation of blood and sweat lactate was found in studies (Karpova et al., 2020; Sakharov et al., 2010a). There are also certain advantages of using sweat lactate (sLa) measurement over other methods, such as the ease of use, non-invasiveness, and ability to measure continuously. New information can be gained from continuous monitoring of sweat gland activity by using an algorithm known as the sLa curve (Katsumata et al., 2021), even though some researchers have concluded that it only provides information about sweat gland metabolism and does not provide insight into clinical use of sLa (Baker et al., 2020). Some scholars looked at how sweat lactate is formed and its relationship to skin temperature, sweat rate, and sweat duration (van Heyningen & Weiner, 1952). It has been previously discovered that when sweat begins, lactate is liberated from the epidermis (Imani et al., 2016). As the resistance of cycling exercise increases, the sweat-lactate concentration increases as well, demonstrating a relationship between physical exertion, heart rate, and, after a physiologic time delay, lactate formation during the experiment (Imani et al., 2016). When exercising at moderate intensity, the concentration of lactate was shown to be substantially higher than when resting ($p < 0.05$) (Saha et al., 2021). This is because (a) exercise produces anaerobic metabolism, which results in the formation of lactate in sweat, and (b) activity generates a larger sweat release, which generates more lactate (Saha et al., 2021). Recent studies have also suggested that lactate serves as a significant energy source to support muscle and brain functions during physical and mental activities (Brooks et al., 2022). Therefore, variations in lactate levels may occur during high-energy activities, both physically and mentally. Accordingly, we believe that sweat lactate might be highly relevant to fatigue development.

Sweat Glucose

Controlling fatigue levels requires constant monitoring of glucose levels (Seshadri et al., 2016). The amount of glucose in human sweat ranges from 10 to 200 μM (Bariya et al., 2018), and studies have investigated the association between sweat glucose and blood glucose levels (Olarte et al., 2013; Wang, 2008). It was revealed that the transit of sweat glucose and critical electrolyte concentrations were similar to those in blood (La Count et al., 2019). Sweat obtained using iontophoresis has also been proven to contain glucose levels that are comparable to those found in blood (Moyer et al., 2012). According to a more recent study, Huang et al. (2022) discovered that when perspiration rate rose, glucose levels decreased gradually during exercise because of the diluting effect and consumption of energy sources withing the bodies (Sonner et al., 2015; Gao et al., 2016). Develop biosensors that reliably measure analytes like glucose, which alter health status when exercising, requires knowledge of lag periods and transport kinetics (Seshadri et al., 2019).

Sweat Electrolytes

There is a high concentration of electrolytes such as sodium (Na^+), chloride (Cl^-), potassium (K^+), and ammonia ($NH4^+$) in sweat. Maintaining electrolyte balance necessitates replenishing Na^+ and Cl^- levels following a period of high-intensity exercise (Baker, 2017). Sweating rate and concentration (Na^+) influence total Na^+ loss from sweat, hence calculating sweat Na^+ loss is critical for speeding up fatigue recovery and reducing soft tissue damage caused by dehydration (Allan & Wilson, 1971). Sweating rate and total body sweating loss can be calculated using the equations published in elsewhere (Baker, 2017). Additionally, Baker and colleagues devised a methodology to quantify the Na^+ content in sweat from the forearm using absorbent patches taken from the forearm. Based on their findings, Matzeu et al. (2016) hypothesized that athletes' "over time sodium profiles" could be generated by monitoring changes in Na^+ levels as sweat made its way into contact with the sensor.

Likewise, muscle activity is predicted by potassium (K^+) concentrations in plasma, which can be used as a biomarker to detect muscle fatigue (Medbø & Sejersted, 1990). The electrical activity of the muscles involved in the exercise can explain the increase in K^+ concentration during exercise (Medbø & Sejersted, 1990). The rate at which K^+ is excreted is directly related to the intensity of activity. In order to remove K^+ from the circulation, this proportional regulator, which may be a sodium–potassium pump in the exercising muscle, is responsible. The rate of absorption of extracellular K^+ related to the pump stimulus, and the rate of extracellular accumulation in the extracellular space is related to the rate of absorption. A correlation between sweat K^+ loss and the rate of sweat flow has been established, but its underlying mechanism is still unknown and needs additional investigation (Sato et al., 1987). Despite this, final sweat often has a K^+ that is similar to, albeit with a slightly greater range (~ 2–8 mmol/L), that of blood plasma, which has been recorded (Baker, 2017). In order to quantify and assess the intensity of the workload and the level of fatigue, the measurement of K^+ levels could be quite beneficial (Seshadri et al., 2019).

Other Biomarkers

Given that ammonium is formed in the blood as a result of the breakdown of proteins (Sato et al., 1989), measuring plasma ammonium levels can provide extremely valuable physiological information. During exercise, for example, the concentration of ammonium changes when the body transitions from an aerobic to anaerobic state. However, ammonium in plasma can only be monitored by taking blood samples, which is a major drawback when exercising or engaging in other physical activity. There are several studies showing that ammonium concentrations in sweat can be strongly associated with ammonium levels in plasma (Brusilow & Gordes, 1968; Czarnowski & Gorski, 1991), which is why sweating is a good way to monitor ammonium levels. Czarnowski and Gorski (1991) investigated the association between ammonia levels in plasma and ammonium concentrations in sweat. They believe that ammonia in plasma is the primary source of ammonium in sweat. Ammonium production via sweating during physical activity such as jogging has been studied and the researchers concluded that the difference in nitrogen loss between the two mechanisms was negligible. It has been shown that ammonium is secreted through sweat after short-term activity at the commencement of sweating (Czarnowski & Gorski, 1991). An investigation by Yuan and Chan (2004) found that a one-year training program had a unique effect on the ammonia threshold, which was associated with endurance time. Also, research on rugby players found that ammonium levels in their sweat rose significantly while they were playing the game (Alvear-Ordenes et al., 2005). This was also linked to an increase in blood ammonia levels of roughly three times greater than before. Another study found that when a participant increases the load after beginning to sweat, the levels of ammonium in the sweat rise (Guinovart et al., 2013). As a result, the production of ammonium in sweat can be employed as a biomarker, providing incredibly useful information in a wide range of conditions, such as the transition from aerobic to anaerobic exercise while measuring physical performance, among others.

2.4.2 Sweat-based wearable biosensors

The general population is becoming interested in smartwatches, wearable fitness trackers, and smart, at-home health services. Photoplethysmography is one of the most widely used techniques for measuring real-time stress and fatigue (O. Parlak et al., 2018). Other techniques include heart rate variability (Mohan et al., 2016), as well as respiratory signal and ECG data (Chen et al., 2016). These signals are linked to a stress response, but they do not generate it; rather, they represent the physiological impact of stress and fatigue biomarkers released in the body. As a result, biomarker detection could be a more precise means of detecting stress and fatigue. Efforts are being made to develop devices that can offer valuable, concrete data by detecting specific stress and fatigue biomarkers for the purposes of stress and fatigue monitoring, so that stress and fatigue can be quantified more accurately.

Innovative, non-invasive, sweat-based sensors for stress and fatigue biomarker monitoring have been developed. Wearable sweat sensors have seen a tenfold rise in development and research in the last few years. Medical researchers are still attempting to find out how biomarkers in sweat may be used to monitor our health, but their potential is undeniable. The amount of several molecular markers in sweat has been found to be comparable to the amount seen in human blood plasma (Marques-Deak et al., 2006)

Biosensors for sweat lactate

Likewise, Lactate concentrations in the blood closely resemble those in the sweat, which indicates the level of physical exertion and the intensity of the exercise (Jia et al., 2013). For example, screen printed lactate biosensors with three electrodes and two electrodes for ECG were used to make a hybrid epidermal wearable device that could simultaneously monitor lactate and heart activity at the same time (Imani et al., 2016). Between the two sensor groups, a hydrophobic coating was used to improve the impedance between the amperometric electrodes and ECG, preventing sensor crosstalk. Physicochemical and electrophysiological measurements were made possible with this wearable gadget thanks to the inclusion of both types of sensors on the same piece of equipment. The simultaneous lactate detection of the ECG had no effect, according to real-time monitoring, as compared to current wearable technologies. As the intensity of the activity grew, so did the lactate level record by the biosensor, which matched the estimated sweat-lactate profile. Continuous monitoring of stress and fatigue may be substantially enhanced by converting this device into a wearable. Lactate was measured using a flexible and wearable patch in another investigation (Seki et al., 2021). Sweat was transported using a microfluidic tube equipped with an array of microneedle-type sensors (50 µm in diameter). For the amperometric-based lactate sensor, enzymes were doped and placed on top of a semipermeable copolymer membrane with an outer polyurethane layer on top. The 180 µm thick patch was attached to the skin of six healthy volunteers before to cycling and running using a double-layered adhesive. As a result of thermoregulation, sweating began 10–15 minutes into the warm-up phase. Exercise-induced rises in lactate show a shift toward anaerobic metabolism. In Recently, Saha et al. (2021) created an innovative sweat sampling patch that uses hydrogel discs and paper microfluidic channels to extract sweat over an extended period of time. During periods of inactivity, the hydrogel disc can collect moisture from the skin by osmosis and transmit it to the paper. Even without the hydrogel patch, the paper can collect sweat during active sweating (e.g., exercise). Colorimetric assays are used to measure lactate in the collected fluid. Sweating rate was connected to the amount of lactate excreted in the sweat. High-intensity exercise improves the correlation between sweat and blood lactate concentrations. In addition, the in-situ detection of lactate content in human sweat was accomplished by Huang et al. (2021) using a newly invented epidermal, stretchable self-powered biosensor. Stretchable electronics, a microfluidic system, and biosensors work together in harmony to give the self-powered sweat sensing instrument remarkable sweat collecting and sensing accuracy even when stretched to their limits. Individuals' measurements of lactate levels suggest that the proposed biosensor can be used in wearable sweat sensing and healthcare monitoring scenarios, indicating the potential of the sensor

Biosensors for sweat glucose

It is critical to keep an eye on blood glucose levels when exercising in order to avoid becoming overly fatigued (Seshadri et al., 2016). Abellan Llobregat et al. (2017) described the development of a sweat glucose detecting sensor based on printable and highly stretchy platinum (Pt)-decorated graphite. Glucose oxidase immobilized on Pt-decorated graphite was used to monitor the reduction of hydrogen peroxide using chronoamperometry. Based on results obtained with commercial glucose meters, this sensor worked well with human sweat samples to show a high link between sweat glucose concentrations and blood concentrations. Sensors for glucose monitoring were printed using flexible, tattoo-based sensors (Bandodkar et al., 2015). Interstitial glucose was extracted through reverse iontophoretic extraction and an enzyme-based amperometric biosensor was used. Glucose and lactate can be detected using a microfluidic epidermal device developed by Martn et al. (2017). Adhesive on both sides of the double-sided polydimethylsiloxane layers make up the structure of the biosensor. Microfluidic passages (inlets and outlets), as well as a reservoir for the detection process, were contained in both layers of polydimethylsiloxane. As the wearer repeatedly deformed the biosensor, the sweat was sent to the electrochemical sensor, and the biosensor remained attached to the skin sweat pores. During a 20-minute bout of indoor cycling, the sweat glucose levels of two healthy human individuals were monitored in real time on their bodies. An increase in the current signal was observed when a sweat sample entered and filled the reservoir of the glucose oxidase-modified flow detector during the continuous monitoring of the amperometric sweat glucose response from the subjects. In another study, Emaminejad et al. (2017) tested a wearable device for noninvasive glucose monitoring and real-time sweat stimulation on a group of participants who participated in both fasting and post-glucose intake trials. In fasting subjects, oral glucose ingestion results in an increase in glucose levels in both sweat and blood, as measured by the wearable. In addition, Huang et al. (2022) used a newly designed epidermal, stretchable self-powered biosensor to measure glucose concentration in human sweat in situ. In combination with stretchable electronics and a microfluidic system, biosensors enable the self-powered sweat sensing equipment to gather sweat with astonishing precision regardless of how far it is stretched. The proposed biosensor can be used in wearable sweat sensing and healthcare monitoring scenarios, based on the results of glucose levels measured by individuals.

Biosensors for electrolytes

Furthermore, epidermal sensors have been used to detect several electrolytes in the literature. Bandodkar et al. (2014) successfully developed and tested an epidermal tattoo potentiometric sodium sensor for uninterrupted noninvasive monitoring of sodium excreted in sweat. There was no interference in analyte detection and wireless transmission using screen-printed devices, indicating their potential for use during the physical activity (Bandodkar et al., 2014). The Na^+ electrochemical amperometric sensor was developed by researchers in another study, according to which it is flexible and wearable (Wujcik et al., 2013). The sensor was built using a nylon-6 mat made from multiwall carbon nanotubes (MWCNTs). In order to produce supramolecular complexes with sodium ions, the MWCNTs were functionalized with cyclo-oligomeric calixarene. After the complex was formed, the charge carriers moved out of the layer to stop the flow of electricity. In this way, sodium ions might be detected at the correct level in the body. Additionally, a solid-contact ion-selective electrode and a liquid-junction-free reference electrode were used to detect sodium in sweat (Matzeu et al., 2016). To collect sweat samples, the potentiometric strips were coupled to a passive pump via a microfluidic chip (PotMicroChip). The system was attached to a 3D printed enclosure that contained a miniature wireless communication system. During stationary cycling sessions, the sodium concentrations of healthy volunteers were continuously monitored using the gadget. It is possible to compare these results to those of current analytical procedures using techniques like Ion Chromatography, atomic absorption, and commercial sodium meters (e.g., AquaTwinTM) (Matzeu et al., 2016). Similarly, it has also been designed and tested a completely integrated and wearable platform for the collection and analysis of sweat sodium concentration in real time during exercise. The platform was fabricated in significant part utilizing 3D printing, which greatly simplifies the process of construction and operation. Because of the 3D printed platform, the sample storage reservoir has been increased from 0.6 to 1.3 mL, assembly time has been reduced, and alignment and contact of the integrated solid-state ion-selective and reference electrodes with the sorbent material has been made simple. The platform was tested in the lab and during exercise trials, which lasted around 60 minutes with continuous monitoring and recording. According to the findings, the sodium content in sweat increased first to roughly 17 mM and then decreased progressively over the course of the trial to approximately 11–12 mM. Also recently created by Alam et al. (2018), a wireless sweat monitoring device provides a unique combination of user comfort, good accuracy, and continuous, non-obtrusive sweat electrolyte monitoring over an extended period of time. This system is composed of two modules: a disposable sensor/microfluidics module that is extremely flexible and a reusable electronics module that is durable. This makes it extremely adaptable and suitable for continuous Na^+ and K^+ measurement in sports or other physiological applications. Researchers have also used a fluorometric technique to detect Na^+ and Cl^- from eccrine sweat collected in a wearable microfluidic system with an imaging module for smartphones (Sekine et al., 2018). A smartphone equipped with an optics module observed variations in fluorescence excitation intensity as a result of the interaction of the micro reservoir probes with the specific ions. For human participants engaged in physical activity, the ion concentrations measured with this platform were identical to those obtained using more standard laboratory procedures, like ion chromatography for Cl^- and atomic absorption for Na^+. It is possible that microfluidics, rather than the current sweat patches, could provide significant advantages in measuring sweat rate and hydration levels. Additionally, a wearable sweat analysis platform was developed by Emaminejad et al. (2017), which included an electrochemically improved iontophoresis interface that was integrated with the platform. A variety of secretion profiles, including Na^+ and Cl^-, can be programmed into this interface to generate sweat for real-time study. Human subject studies were conducted in the context of cystic fibrosis diagnosis in order to establish the clinical utility of this platform. Using this technology, they were able to detect the increased electrolyte content in the sweat of cystic fibrosis patients as compared to healthy control individuals.

Biosensors for other sweat biomarkers

Guinovart et al. (2013) had made and tested a new potentiometric cell that could be used to monitor ammonium levels in sweat. Using a screen-printed design and all-solid state potentiometric sensors for both the working and reference electrodes, this skin-worn sensor can be made. It also has a polymer membrane that is ammonium-selective because it is made of the nonactic ionophore. The tattooed potentiometric sensor has a working range of between 104 M and 0.1 M, which is close to the amount of ammonium in sweat that is normal. Using screen-printed technology, epidermal integration, and potentiometric sensing is a good way to keep track of a wide range of electrolytes in human sweat without having to be invasive. Also, Renner et al. (2020) conducted ammonium measurements in blood and sweat during a stepwise incremental cycle ergometer test in 40 participants under controlled conditions in order to evaluate the relationship between ammonium concentrations in blood and sweat. Aside from that, blood lactate and heart rate were monitored to guarantee that the recorded quantities could be categorized appropriately. It was shown that while the blood ammonium concentration corresponded to the commonly acknowledged levels of physical fatigue, the sweat ammonium concentration appeared to decrease with physical exertion. This may be due to the dilution effects, which occurs as the rate of sweat rises (Gao et al., 2016;

Sonner et al., 2015). As a result, they suggested that wearable technologies will benefit greatly from this research since it sheds light on the relationship between blood and sweat parameters.

2.4.3 Sweat sensing approach

Understanding the complex chemical composition and physical properties of sweat can provide valuable insights on human health issues in a variety of application situations, including stress and fatigue. Chemically related devices are commonly used in the majority of sweat biosensing. A number of research studies have looked into the relationship between the quantities of chemical components in the environment and human health states in depth. For example, during activity, the salt and chloride concentrations in sweat can represent the amount of water lost by the human body through the skin (J. Kim et al., 2018; Zhang et al., 2020). It has been created electrochemical, colorimetric, and hybrid chemical sensing approaches to measure the amounts of these chemical components in sweat. This subsection primarily discusses about new technologies and how they can be used in chemical sensing.

Electrochemical sweat sensors

It has been proven that biomarkers in sweat alter dynamically in response to factors such as health, stress, and fatigue (Kaya et al., 2019). The monitoring of sweat biomarkers in real time is critical. Electrochemical sensors connected to the skin that use conductometric, amperometric, potentiometric, and voltametric measurement techniques can be used to constantly monitor analytes in sweat (Francis et al., 2019; Zhao et al., 2021). It is possible to establish a proportionate link between analyte concentrations and electrical signals, with high specificity and rapid response times, while using only a small amount of power. Thus, tiny sensor designs that are suitable for wearable platforms can be developed, which can communicate data to an external personal device assistant (such as a smartphone or smartwatch) for real-time sweat analysis can be performed.

Colorimetric sweat sensors

Elastomeric substrates with microfluidic channels placed in them can be used to collect and store sweat, which can then be used for various purposes. Sweat constituents of interest can be analyzed quantitatively by combining colorimetric (Choi et al., 2019) and fluorescence (Sekine et al., 2018) tests. When sweat is routed to discrete chambers, sweat components interact with specific chemical reagents to produce a distinct optical signal matching to a target analyte concentration, it is feasible to quantify sweat rate utilizing the natural pressure generated by sweat glands. This sort of instrument is used to determine the concentration of a target analyte in a sample. A smartphone-based image capture and color-based processing technique have recently been demonstrated to be effective in the quantification of sweat chloride, pH, lactate, glucose, urea, and creatinine, among other substances (Choi et al., 2019; Kim et al., 2019; Sekine et al., 2018).

Hybrid sweat sensors

Biomarkers can now be measured wirelessly, without the use of batteries, in continuous or spot check modes (e.g., cortisol, ascorbic acid, glucose, and sweat rate) using wearable sensors that combine optical and electrochemical sensing technologies in a single analytical platform (Kim et al., 2019). Colorimetric lateral flow immunoassay for cortisol, fluorescence assays for ascorbic acid and glucose, and impedance-based sensors for sweat rate and galvanic skin reaction are used in this dual sensing technique. Field testing shows that these features may be used to track physiological parameters related to physical and mental stress over the course of many days in the real world. This type of hybrid technique has the potential to provide long-term continuous and intermittent monitoring of physiological indicators and situations.

2.5 Conclusion

As a biofluid that may be used to evaluate and monitor a person's overall health, sweat has great clinical value. It is becoming increasingly common to use biosensors that can measure a wide range of sweat biomarkers to detect and prevent fatigue during high-intensity labor, such as construction. This chapter sorted out the number of biomarkers because of their relevance to fatigue or stress. Among these biomarkers, sweat rate, lactate, glucose, and sodium were selected to be further studied in this project since lactate and glucose are major energy sources to bodies whereas sodium and sweat rate could indicate dehydration states of bodies. And further research and testing of evaluation of using such biomarkers would be explored in the following chapters.

CHAPTER 3 SWEAT ANALYSIS-BASED FATIGUE MONITORING DURING SIMULATED CONSTRUCTION REBAR BENDING TASKS

This chapter conducts experiments to explore the feasibility of applying sweat based biomarkers to evaluate fatigue levels during a simulated construction rebar task. Sweat rate, sodium, lactate and glucose are measured to construct a fatigue model using machine learning approaches.

3.1 Introduction

Fatigue, *a sense of exhaustion, lack of energy, or tiredness* (Krupp, 2006), is often recognized as the primary cause of accidents. Fatigue arising from construction rebar benders contributes to prolonged working time, intensive physical exertion, and repetitive tasks, leading to workers developing fatigue related ill-effects such as sore or aching muscles, decreased productivity, impaired decision-making and judgment, poor concentration, and low motivation (Abdelhamid & Everett, 2002; Anwer, Li, Antwi-Afari, Umer, Mehmood, et al., 2021; J. K. Sluiter, 2006). To minimize or alleviate fatigue-related ill-effects, detecting fatigue could be the most effective approach.

Measurement of fatigue is difficult because it is a multifactorial symptom (Cincotta et al., 2016). Traditionally, survey-questionnaire methodology has been used to evaluate fatigue for its low cost and easy-to-use. Various subjective self-rating methods have been applied within the construction industry. For example, NASA-TASK Load Index (NASA-TLX) estimates workload (Hart, 2006a) and has been used to evaluate fatigue during construction masonry work (Mitropoulos & Memarian, 2013). Mingzong Zhang et al. (2015) developed a fatigue assessment scale specifically targeting construction workers' fatigue and confirmed the merits of targeting and simple features. Despite the advantages, the further application of survey-questionnaire assessment is hindered by its interruption of the work, time-consuming, intrusive nature, and unsuitable for real-time monitoring (Umer et al., 2022).

Recent studies have drawn attentions to wearable sensors for monitoring fatigue by measuring physiological parameters such as heart rate, heart rate variability (HRV), breathing rate, jerk metrics, and skin temperature (Anwer, Li, Antwi-Afari, Umer, Mehmood, et al., 2021; Anwer et al., 2020; Aryal et al., 2017; Umer et al., 2022; Yi et al., 2016; L. Zhang et al., 2019). Specifically, Anwer et al. (2020) employed a wearable EQ02 LifeMonitor system for fatigue monitoring. This system was designed to measure electrocardiography (ECG) and local skin temperature. Similarly, Umer et al. (2022) used EQ02 LifeMonitor system to obtain HRV data for physical exertion monitoring. Despite the promising results, there are several limitations. Firstly, such evaluations do not allow us to quantify a worker's metabolic profile in real-time with the goal of alleviating fatigue-related adverse effects like dehydration or cramping. Secondly, cardiovascular and thermoregulatory metrics can be easily affected by other external factors such as lifestyle and non-modifiable impact, which in turn will affect the accuracy of fatigue evaluations (Fatisson et al., 2016). Lastly, a hot and humid outdoor environment might induce perspiration heavily; thus, wearing an on-body vest EQ02 system might cause irritation and uncomfortable. To mitigate the shortcomings of these parameters, this study proposed measuring chemical biomarkers to assess fatigue levels of construction rebar benders by using sweat sensors.

3.2 Literature Review

Chemical biomarkers have been widely used in the medical and athletic fields to examine health issues (Baker, 2019). Also, because of their accuracy and lack of subjectivity in interpretation, current study has highlighted the use of chemical biomarkers as the ideal way for monitoring fatigue (Seshadri et al., 2019). Measurements of chemical biomarkers such as electrolytes, analytes, and neuropeptides allow quantifying fatigue profiles regarding the severity of physiological exhaustion (i.e. dehydration and lack of energy). Specifically, some of the biomarkers could directly indicate body states such as hydration/dehydration. A study discovered that modest changes in hydration had a negative impact on several symptoms, including vigor, fatigue, perception of task difficulty, focus, and headache (Armstrong et al., 2012). As such, physiological exhaustion could lead to or trigger fatigue. However, no previous study has applied chemical biomarkers in construction domain to address fatigue issues. Accordingly, the authors hypothesized that measuring chemical biomarkers could possibly be an innovative fatigue monitoring approach.

These chemical biomarkers can be found in bodily fluids such as saliva, sweat, tears, and blood. However, obtaining samples from saliva, tears, and blood is too invasive to adopt in construction industry. In contrast, measuring such chemical biomarkers through sweat can offer a non-invasive and accessible alternative. Sweat contains numerous rich biomarkers such as electrolyte ions and metabolites like lactate, glucose, ammonia, etc. (Seshadri et al., 2019). These biomarkers could reflect instant body conditions like dehydration or energy insufficiency, thus, potentially enabling instant fluid or nutrient supply recommendations during construction manual tasks. As a result, this could efficiently alleviate fatigue related ill-effects. Though sweat biomarkers have not been used in construction industry, they have nevertheless been employed to quantify physiological ‘cost’ of construction activities. Moreover, a harsh outdoor environment like high temperature and humidity makes construction manual workers perspire heavily; this enhances the utility of sweat-based biosensors in the construction field.

Among the detectable biomarkers from sweat, sodium, lactate, and glucose were selected. Besides, sweat rate was also measured in this study. These four parameters were chosen because: (1) the combined sweat rate and sodium levels could reflect hydration states of human bodies (Baker, 2017; Baker et al., 2020); (2) lactate and glucose are the main energy sources of human bodies (Bartlett et al., 1984), thereby, their concentrations might be varied significantly during high energy consumption activities (Buono et al., 2010; Karpova et al., 2020). Apparently, it is crucial to maintain appropriate hydration, nutrition, and electrolyte balance, particularly in physically demanding tasks such as construction manual work. For example, the current studies (Baker et al., 2020; Cheuvront & Kenefick, 2014; Hamouti et al., 2014; Nuccio et al., 2017; Wittbrodt & Millard-Stafford, 2018) found that body fluid and electrolyte deficiencies brought on by sweat loss from exertion and heat stress increase cardiovascular strain and may impair physical and cognitive functions. The low level of blood sugar (hypoglycemia), indicated by glucose concentration, can be dangerous during construction tasks as it can cause symptoms such as confusion, dizziness, and weakness (Cryer, 1993; Ivy, 1999).

Sodium (Na+) ions are the most abundant electrolytes within sweat and play a crucial role in stimulating the hydration of the human body (Baker, 2017; Baker et al., 2016). The analysis of sweat rate and sweat electrolytes (mainly sodium) could contribute essential facts about human bodies' dehydration/euhydration/hyperhydration states. Studies have shown that dehydration appears to have a detrimental effect on physical and cognitive performances (Cian et al., 2000; Montain & Tharion, 2010), leading to transitory subjective state, such as fatigue (Fadda et al., 2012). Specifically, even minor water losses of 2% of body weight can have a negative impact on body thermoregulation and physical activity capacity (Maughan, 2003), fatigue levels, mental concentration and alertness (Shirreffs et al., 2004), and cognitive function (N. Zhang et al., 2019).

Dehydration is induced by heat exposure, intensive physical activities or a combination of these conditions like construction works (Fadda et al., 2012). As such, it could occur more often in the summer, especially for individuals who perform highly demanding physical activities in a hot and humid environment. As it did in the case of construction rebar benders whose work entails intensely lengthy manual labor in a harsh outdoor environment. Accordingly, this study proposed using advanced sweat-based biosensors to measure sweat rate and sweat sodium level for fatigue monitoring of construction rebar benders.

To manage fatigue levels during physical activities, it is also crucial to measure lactate and glucose (Seshadri et al., 2019), which are the major energy sources to support bodies. Both originate from glycogen, one of the energy stored forms, made from carbohydrates in the diet and stored in the muscles/livers. When the body requires energy, glycogen is broken down into glucose and lactate, and the circulatory system distributes them as general fuels throughout the body. Though lactate and glucose are both general fuels, Brook's studies concluded that lactate is the primary fuel source of human bodies (Brooks, 2002, 2018; Brooks, 2020). Similarly, a study found that sport drinks combining lactate, glucose, and fructose were superior to that only containing glucose and fructose, for adding lactate allows athletes to benefit from the various ways their bodies burn fuel (Emhoff et al., 2013). And lactate enters the bloodstream twice as quickly as glucose and peaks in just 15 minutes instead of 30 minutes after consumption (Emhoff et al., 2013). However, some studies argued that glucose is our body's primary source of energy (Maher et al., 1994; Navale & Paranjape, 2016). For now, the answer to this scientific debate is still open. This study aimed to detect fatigue; therefore, a combination measurement of lactate and glucose concentrations would be enough to satisfy the primary goal. Owing to their energy supply roles, intensive physical activities could lead to variations in their concentrations; this might provide some support for using lactate and glucose to evaluate fatigue. Furthermore, significant statistical correlations between sweat glucose and blood glucose were found (Moyer et al., 2012; Olarte et al., 2013; Wang, 2008), as well as sweat lactate and blood lactate (Karpova et al., 2020). Taken together, a solid theoretical foundation is constructed to support the exploration of the usefulness of sweat-based lactate and glucose in the study.

Fig. 3.1 summarizes the methodologies adopted in this study. Sweat-based biosensors were employed to measure sweat rate, sodium, lactate, and glucose concentrations for fatigue level modelling. Two subjective assessments were used to evaluate fatigue, Borg Rating of Perceived Exertion 6-20 Scale (Borg 6-20) and Fatigue Assessment Scale (FAS). Among different populations, the Borg 6-20 is widely used in various exercise regimens to evaluate physical demands and has been proven to be a reliable tool (Carvalho et al., 2009; Day et al., 2004). Besides, as the goal of this study was to evaluate fatigue by monitoring physiological exhaustion (i.e., shortages of water and food within the body), the subjective fatigue tool, Fatigue Assessment Scale (Michielsen et al., 2003), was utilized to determine the exhausting level for the manual tasks. Machine Learning techniques, more precisely, supervised machine learning techniques, including Decision Tree, Random Forest, Support Vector Machine, K-Nearest Neighbor, and Multilayer Perceptron, were employed to conduct data analysis, thus, modelling fatigue.

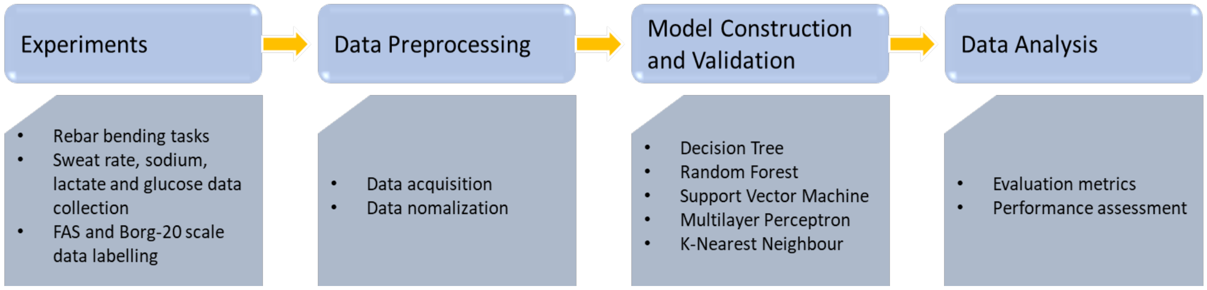


Fig. 3.1. The overall flowchart

3.3 Methodology

The overall research process consists of four steps (Fig. 3.1). The first step is to conduct the manual rebar bending experiments designed by the authors to collect raw data from the sensors and the survey questionnaires. The second step is pre-processing the collected data to generate the dataset. The third step is constructing classification models adopted to distinguish four fatigue states (low fatigue, medium fatigue, high fatigue, and very high fatigue). The last step is to select the optimal fatigue classification model based on the computational results of the evaluation metrics on the test set.

3.3.1 Participants

Twenty-eight health participants who are university students and staff were recruited to conduct a simulated rebar bending task. Their demographic information is displayed in Table 3.1. Individuals were asked to abstain from tea/coffee and alcohol before testing within 48 hours. They were also asked to get eight hours sleep before the test. The absence of musculoskeletal disorders in the previous 12 months and no history of cardio- or pulmonary ailments were requirements for participation in the experiments. The research protocol received approval from the university's ethical committee (Reference number: HSEARS20200922003) in accordance with the Declaration of Helsinki. Prior to data collection, participants were given written informed consent.

Table 3.1. Demographic Information of participants

	Age (years)	Height (cm)	Weight (kg)	BMI (kg/m²)
Mean	32.6 ± 3.46	177 ± 2.84	78 ± 3.67	24.9 ± 0.736
Range	13 (28-41)	8 (173-181)	13 (71-84)	2.79 (23.7-26.5)
Note: ± indicates standard deviation; BMI = body mass index				

3.3.2 Wearable Sweat-based biosensors

The prevalent methodologies that are used to detect chemical biomarkers from sweat are colorimetric and electrochemical technologies, owing to their noninvasive and low-cost features (Kaya et al., 2019). Colorimetric methods apply the change of colour to indicate the concentration of specific biomarkers, whereas electrochemical methods enable converting the biological information to electronic signals for measuring the biomarkers' concentrations. This study employed Gx sweat patch (Baker et al., 2020; BIOSYSTEMS, 2022), a colorimetric technology-based biosensor, to measure sweat rate and sodium level (Fig. 3.2 (a)). Meanwhile, an electrochemical technology based sweat biosensor (Huang et al., 2021) was used to measure lactate and glucose concentrations (Fig. 3.2 (b)).

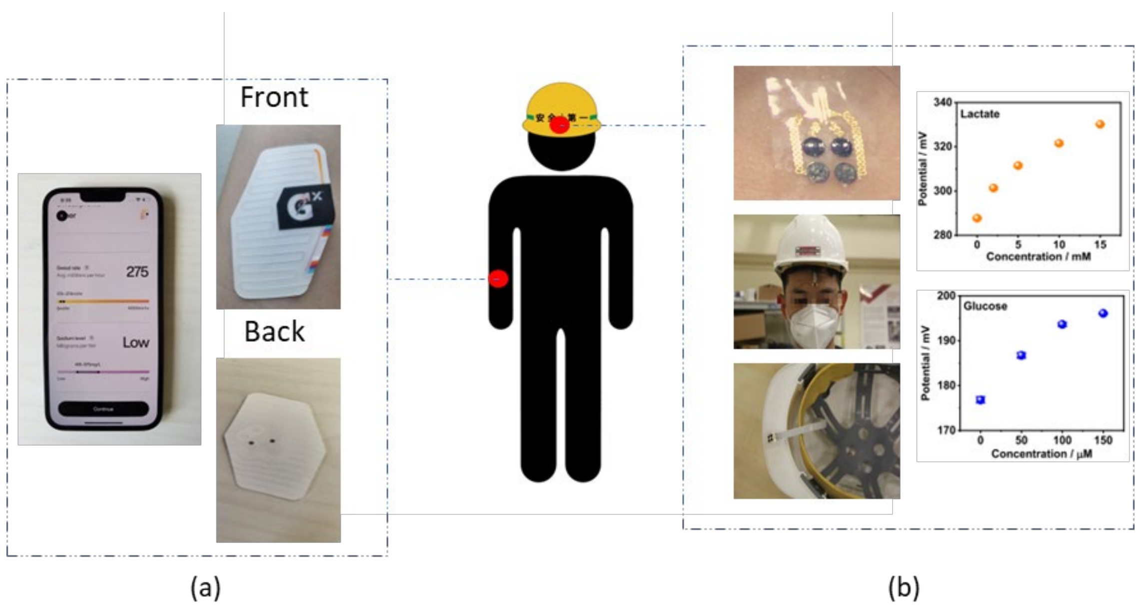


Fig. 3.2. Sweat sensors: (a) Gx sweat patch; (b) the sweat-based lactate and glucose biosensors

Gx sweat patch for measuring sweat rate and sodium

Gx Sweat Patch is a skin-like, wearable patch pairs with an easy-to-use software app to provide real time monitoring on sweat rate and sodium level (Fig. 3.2 (a)). This device could optimize hydrate and refuel personalized recommendations for users. Two microchannels were embedded capturing sweat during activities, and colorimetric feedbacks were used to provide real-time information. This sweat patch used microfluidic channels to collect sweat (Baker et al., 2020). A developed algorithms as part of a software application Gx IOS app empowering users to track their real time sweat profiles (Fig. 3.2 (a)). The output of sweat sodium concentration is a range region rather than an exact number. Therefore, in this study the median value of the sodium concentration was calculated for the data analysis.

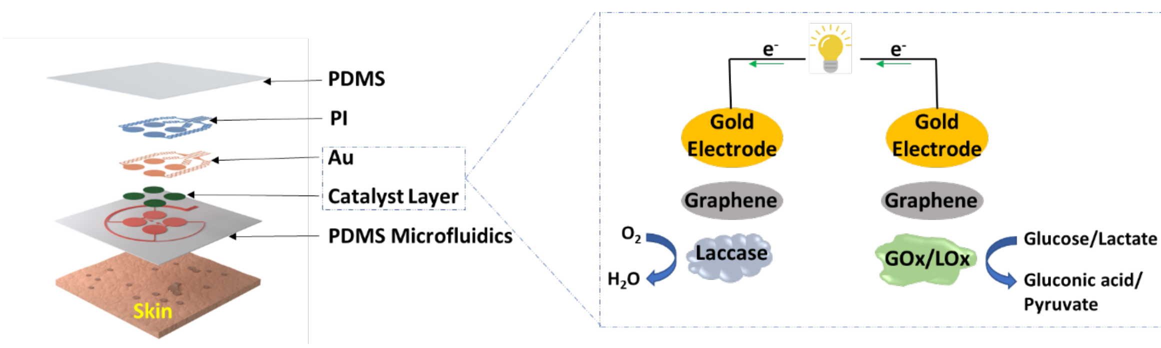
The sweat-based biosensors for measuring lactate and glucose

In Fig. 3.2 (b), a developed sweat-based biosensor was employed to measure lactate and glucose concentrations (Huang et al., 2021). This device owns two novel features: 1) epidermal flexible self-powered biosensor; 2) microfluidic channels for sweat collection. The sweat biosensor enabled enzymatic reactions occurring that converts biochemical signals (lactate and glucose concentrations) to electrical signals (voltages). Meanwhile, microfluidic design realized situ measurement in real-time.

Fig. 3.3 (a) shows a schematic of a stretchy epidermal sweat sensor that is self-powered and made up of four self-power biosensors and a microfluidics system. The design of biosensors uses a multilayer stacking layout. The microfluidic sweat collection layer that is used to collect sweat, which is defined by a thin-soft polydimethylsiloxane (PDMS) layer (170 μm) that acts as the substrate. Stretchable electrodes and connecting cables are defined by Au electrodes. Specifically, the catalyst layer in the biosensors contains enzymes and graphene. It catalyzes the reactions between lactate, glucose, and oxygen to produce electricity, shown in Fig. 3.3 (b). On top of the

Au circuits, a further layer of a 2 μm thick polyimide (PI) acts as an encapsulation to avoid short circuits. Another PDMS layer is added on top for waterproofing.

The design of the enzymatic biofuel cell is crucial for establishing self-powering behaviors (Huang et al., 2021). Fig. 3.3 (b) displays the fundamental ideas and conceptual representations of the biosensors based on biofuel cells. In the bioanode, glucose oxidase (gOx) oxidizes glucose into gluconic acid whereas lactate oxidase (LOx) converts lactate from sweat into pyruvate. The oxidation reaction releases electrons concurrently. Oxygen is reduced by laccase (Lac) into water (H_2O) in the biocathode, where electrons are obtained. As a result, there is a significant link between the open-circuit potential values of enzymatic biofuel cells and the levels of lactate or glucose in sweat (Fig. 3.2 (b)).



(a) (b)

Fig. 3.3. Schematic illustrations of (a) a sweat sensor for measuring lactate and glucose, (b) the mechanism of self-powered biofuel cell

3.3.3 Subjective Assessments

Two subjective fatigue assessments were employed, Borg 6-20 and Fatigue Assessment Scale (FAS). Borg 6-20 was used as the output feature whereas FAS was for the qualitative input feature. The use of subjective fatigue perception instruments is central to qualitative approaches.

Table 3.2 shows the classification of fatigue level based on Borg 6-20. It is a self-reported rating scale that measures perceived exertion and fatigue during exercise or physical activity (De Souza et al., 2023). The Borg 6-20 scale is a modified version of the original Borg Rating of Perceived Exertion scale (Borg, 1982), which ranges from 0 to 10. The Borg 6-20 was developed to capture better the perceived exertion of individuals performing more intense exercise (Aryal et al., 2017; De Souza et al., 2023). It is a scale ranging from 6 to 20, with higher numbers indicating greater perceived work or effort. And it consists of a series of words and numbers that describe different levels of exertion or fatigue, such as in description from “sitting and resting” to “maximal exhaustion” (Table 3.2). It has acquired general acceptance as a trustworthy instrument for monitoring the combination of physiological, psychological, and environmental elements that enable a person to judge how simple or difficult a task is and how exhausted they feel while accomplishing the tasks (Eston, 2012). Verbal anchors were now included in Borg 6-20 to guide participants, as indicated in Table 3.2. As such, participants could judge their level of effort in accordance with the descriptions suggested by the Centers for Disease Control and Prevention (CDC) (*Perceived Exertion (Borg Rating of Perceived Exertion Scale)*, 2022).

To use the Borg 6-20, individuals rated their perceived exertion during the experiment on a scale of 6 to 20, with 6 representing no exertion/fatigue at all and 20 representing maximal exertion/fatigue. The scale is subjective and based on the individual's perception of their own effort, rather than objective measures such as heart rate. The authors used four classifications for fatigue in order to simplify the analysis and interpretation of their results (Aryal et al., 2017). These classifications were based on the participants' Borg 6-20 scores, as follows: (1) low fatigue: Borg 6-20 score of 6-11; (2) medium fatigue: Borg 6-20 score of 12-14; (3) high fatigue: Borg 6-20 score of 15-16; (4) very high fatigue: Borg 6-20 score of 17-20.

Fatigue Assessment Scale, proposed by Michielsen et al. (2003), was employed to assess comprehensive fatigue (i.e. combined fatigue of physical and mental). FAS is a method for systematically assessing fatigue that consists of 10 items, each with a score ranging from 1 (no fatigue) to 5 (severe fatigue). The items ask about different aspects of fatigue, such as physical and mental fatigue, motivation, and activity level. Questions related to the evaluation of physical and mental exhaustion were included in the FAS questionnaire. In order to achieve the goal of detecting fatigue during a continuous repetitive task, FAS was modified by altering the 5 selection scales to the degree of with the 10 items rather than the frequency. In this case, FAS was employed as the qualitative input feature to model fatigue.

Table 3.2. Borg 6-20 description along with verbal anchors and classification (Aryal et al., 2017)

Borg 6-20	Level of Fatigue	Verbal anchors	Classification
6	sitting and resting	I am not tired; this is similar to resting	Low
7	Very, very light		
8		I am not tired; this is similar to walking	
9	Very light		
10			
11	Fairly light	I feel fine to continue	
12			Medium
13	Somewhat hard	I am getting tired, but I can continue	
14			
15	Hard		High
16			
17	Very hard	I am exhaustive; I have to push myself to continue	Very High
18			
19	Exhaustive hard	I am extremely exhaustive; This is one of the hardest things I have done	
20	Maximal Exhaustion		

3.3.4 Procedure

The experiment consisted of a rebar bending task (Fig. 3.4) for a duration of the 1-h bar bending and fixing activities which was preceded by 10-min baseline physiological parameters measurements while sitting. The baseline physiological data, including sweat rate, sodium concentration, lactate concentration, and glucose concentration, were measured along with the subjective fatigue levels determined by Borg 6-20 and FAS. Each participant was instructed to carry out rebar bending tasks for one hour following the baseline examinations (Fig. 3.4). Throughout the one-hour work, participants were advised to wear the Gx sweat patches at forearms and the sweat-based biosensors attaching to foreheads. Measurements of sweat biomarkers and subjective evaluations were taken every 15 minutes (i.e., at 15, 30, 45, and 60 min). At these measurement points, sodium and sweat rate were recorded using a mobile phone App that displayed the corresponding numerical values (Fig. 3.2a). Also, lactate and glucose sweat concentration were recorded by connecting the sweat sensor (Huang et al., 2021) to a personal computer to read out potentials, and then based on the linear relationship between potentials and lactate/glucose concentration (Fig. 3.2b), outputting the results. A total of 28 subjects participated in the experiment, and the physiological data and the FAS score were recorded when these subjects used the Borg 6-20 to report their fatigue. FAS score and four physiological data, such as sweat rate, sodium concentration, lactate concentration, and glucose concentration, were normalized and then utilized as input features. Fatigue levels of the subjects, including low, medium, high, and very high, obtained using the Borg 6-20, were manually labeled as 0, 1, 2, and 3 and used as the output. Each subject was assessed five times for fatigue levels using Borg 6-20, resulting in 140 sets of data generated.

Fig. 3.4. Experiment pictures

3.3.5 Data pre-processing

Before the captured data is fed into the fatigue classification model for training and prediction, the input features need to be pre-processed. Regarding the source of the input features, the Gx sweat patch was placed on the subject’s forearm (Fig. 3.2 (a)) whereas the invented instrument was attached to the subject's forehead (Fig. 3.2 (b)). These devices were adopted to measure some key indicators associated with human sweat. A description of the selected input features is provided in Table 3.3. Note that these features were collected from each subject during a simulated rebar bending task.

Table 3.3. Input features

No.	Feature	Description	Units of data
1	Sweat rate	Indicator of dehydration (Baker et al., 2020)	ml/h
2	Sodium Concentration	Indicator of dehydration (Baker, 2017)	mM
3	Glucose Concentration	Energy source (Wang, 2008)	µM
4	Lactate Concentration	Energy source (Brooks et al., 2022)	mM
5	FAS score	Fatigue Level (Michielsen et al., 2003)	-

Another significant point to be considered is that input features have different dimensions and orders of magnitude due to their different nature. For example, sweat rate is usually around several hundred ml/h, while sweat glucose does not exceed a maximum of 100 μM. If the original input features are directly used for analysis without considering the fact of existent different dynamic characteristics of these input features, the role of features with higher values in fatigue classification will be highlighted while the role of features with relatively lower values will be weakened. Therefore, to ensure the reliability of the results, the original values of input features need to be normalized. According to the Equation (1) (Fardhosseini et al., 2020), the values of all input features are mapped to [0, 1].

$$x^* = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (1)$$

where x and x^* represent the original and normalized values of the input features, respectively. $x_{\max}$ is the maximum value of an input feature sequence, while $x_{\min}$ is the minimum value of this input feature sequence. After the normalized preprocessing operation of the input features, the convergence speed of the fatigue classification algorithm can be accelerated, and the prediction performance of the algorithm is also expected to be improved.

Model selection and validation

For processing physiological data capturing from experiments, one of the most prevalent and effective methods is to use machine learning algorithms for analysis in order to accurately identify the physiological and psychological fatigue state of a worker. Various machine learning algorithms, such as decision tree (DT), random forest (RF), support vector machine (SVM), etc., have been applied in workers' fatigue classification (Elshafei et al., 2022; Fardhosseini et al., 2020; K et al., 2022; Marotta et al., 2021; Pinto-Bernal et al., 2021; Rahman et al., 2021; Varandas et al., 2022). In the machine learning domain, open-source packages have boosted, researchers can easily choose from a wide range of off-the-shelf implementations of machine learning algorithms to establish predictive models for complex data that meet the needs. This study compared five popular supervised machine learning classifiers that have shown promising results in detecting fatigue, including Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Multilayer Perceptron (MLP). The open-source python library "scikit-learn" (Pedregosa et al., 2011) is adopted to train, validate, and test these classifiers, thereby, extracting the model with the best prediction performance of workers' fatigue. The hyperparameters of each algorithm are summarized in Table 3.4. Readers are referred to (Han et al., 2011; James et al., 2013) for a detailed introduction to the mentioned classifiers.

Table 3.4. Hyperparameters of supervised machine learning algorithms

Classifiers	**Hyperparameters**	**Hyperparameters Description**
Decision Tree (DT)	max_depth	This argument represents the maximum depth of a tree.
	criterion	Function used to measure the quality of a split.
	max_features	The number of features to consider when computing the best split.
	min_samples_leaf	The minimum number of samples required to be at a leaf node.
Random Forest (RF)	n_estimators	This argument limits the number of decision trees in random forests.
	min_samples_split	The minimum number of data points placed in a node before the node is split.
	min_samples_leaf	The minimum number of data points allowed in a leaf node.
	max_features	The maximum number of features

		considered for splitting a node.
	max_depth	The maximum number of levels in each decision tree.
	bootstrap	Method for sampling data points.
Support Vector Machine (SVM)	C	Penalty parameter for regularization.
	kernel	‘linear’, ‘poly’, ‘sigmoid’, or ‘rbf’.
K-Nearest Neighbor (KNN)	metric	'euclidean', 'manhattan', 'minkowski', or 'chebyshev'.
	n_neighbors	Number of neighbors to use.
	weights	Function to weight the neighbors' votes.
Multilayer Perceptron (MLP)	activation	Activation function for the hidden layer.
	alpha	Strength of the L2 regularization term.
	hidden_layer_sizes	Number of hidden layers and number of units for each hidden layer.
	learning_rate	Learning rate schedule for weight updates.
	solver	The solver for weight optimization.

It should be noted that in this study, the input and output are constant. More specifically, there are five input features, including sweat rate, sweat sodium, sweat lactate, sweat glucose, and FAS. And the number of output features is set to 1, which represents the worker's fatigue level. For each algorithm, as illustrated in Table 3.4, the grid search method with K-fold cross-validation was employed to search and validate the optimal set of hyperparameters as shown in Fig. 3.5. The data training steps are described in Table 3.5.

Table 3.5. A detailed description of each step

Step 1	Shuffle the entire data set and then split it into the training set and the test set according to the ratio of 8:2.
Step 2	Determine the hyperparameters of each algorithm and define the grid search space.

Step 3	Divide the training set into k subsets, one of which is kept as validation data to evaluate the prediction performance of each algorithm under different combinations of hyperparameters, and the remaining k-1 subsets are utilized as training data for the training of the algorithm.
Step 4	Repeat Step 3 to train and validate each algorithm for k times until all subsets have been used as the validation data.
Step 5	Repeat the above steps until all hyperparameter combinations of the algorithms are traversed.
Step 6	Extract the hyperparameter combination with the highest score of each algorithm in k-time training and validation, which will also be adopted to evaluate the fatigue classification performance under this optimal hyperparameter combination based on the test set.

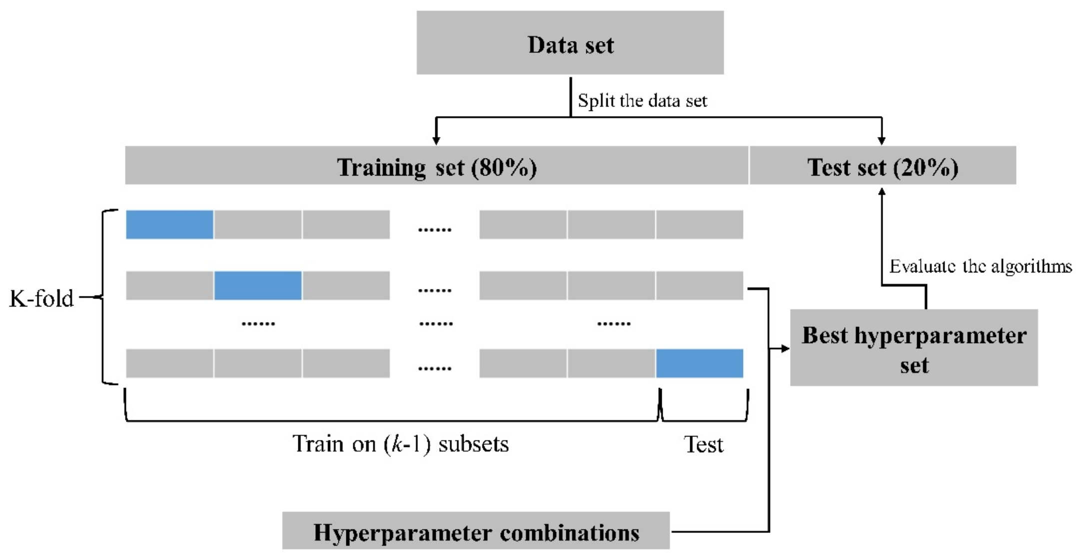


Fig. 3.5. Steps of the grid search method with K-fold cross-validation

Data Analysis

To evaluate the performance of machine learning algorithms with optimal hyperparameter combinations for workers' fatigue detection and classification, several evaluation metrics should be adopted to quantitatively assess the algorithms. Obviously, the prediction of workers' fatigue is a typical multi-classification problem. Therefore, Accuracy, which presents the percentage of correct classifications made by a given algorithm, was used to evaluate the performance of fatigue classification. For multiple fatigue level classes C_i, Accuracy can be defined as follows.

$$Accuracy = \frac{1}{n}\sum_{i=1}^{n} \frac{TP_i + TN_i}{TP_i + FN_i + FP_i + TN_i} \quad \text{(Varandas et al., 2022)}$$

where n is the number of the fatigue level categories C_i. TP_i represents the number of samples correctly classified as C_i, and FP_i is the number of samples that are incorrectly classified as C_i. FN_i denotes the number of samples of C_i that are mistaken for other classes. TN_i refers to the number of samples that are correctly classified as categories that are not C_i. In addition, the confusion matrix is employed to visualize the difference between the classification results of the algorithms and the ground-truth. The confusion matrix is a $n \times n$ matrix, each column of which denotes the class of the fatigue level predicted by the algorithm, while each row represents the ground-truth of the fatigue level. Notably, the elements on the diagonal from the upper left to the lower right of the confusion matrix are the results of correct classification.

3.4 Results

3.4.1 Experiment Data Analysis

A detailed statistical description of each variable is shown in Table 3.6. From the starting point through the completion of the task, the mean values of sweat rate, sodium concentration, and lactate concentration all rose. The mean glucose concentration levels, on the other hand, fell from the starting point through the task's completion. And the means of the two subjective evaluations show growing trends from the starting point to the task's completion.

Table 3.6. Descriptive statistics

Variables (N=28)	Timeline	Mean	SD	Range (Min – Max)
Sweat rate (ml/h)	Baseline	0	0	0
	At 30 min	569	110	334 (378 – 712)
	End of task	801	114	391 (594 – 985)

Sodium (mM)	Baseline	0	0	0
	At 30 min	32.5	12.0	45.0 (11.6 – 72.3)
	End of task	80.4	10.7	37.8 (59.7 – 97.5)
Glucose (µM)	Baseline	70.6	9.4	36.4 (52.2 – 88.6)
	At 30 min	46.7	9.49	41.9 (30.4 – 72.3)
	End of task	24.8	3.73	11.1 (19.4 – 30.5)
Lactate (mM)	Baseline	1.97	0.39	1.73 (1.05 – 2.78)
	At 30 min	20.9	5.08	18.9 (11.6 – 30.5)
	End of task	31.5	6.91	26.2 (20.5 – 46.7)
FAS	Baseline	10.5	0.51	1 (10 – 11)
	At 30 min	28.3	3.32	14 (21 – 35)
	End of task	41.0	3.39	16 (31 – 47)
Borg 6-20	Baseline	6	0	0 (6 – 6)
	At 30 min	13.7	1.68	8 (10 – 18)
	End of task	18.1	1.20	5 (15 – 20)

During the simulated rebar work, the values of sweat rate, sodium concentration, glucose concentration, and lactate concentration are shown in Fig. 3.6 along with timelines. With task completion, there were noticeable rising trends in sweat rate, sodium, and lactate concentrations. Contrarily, as the task progressed, the level of glucose fell.

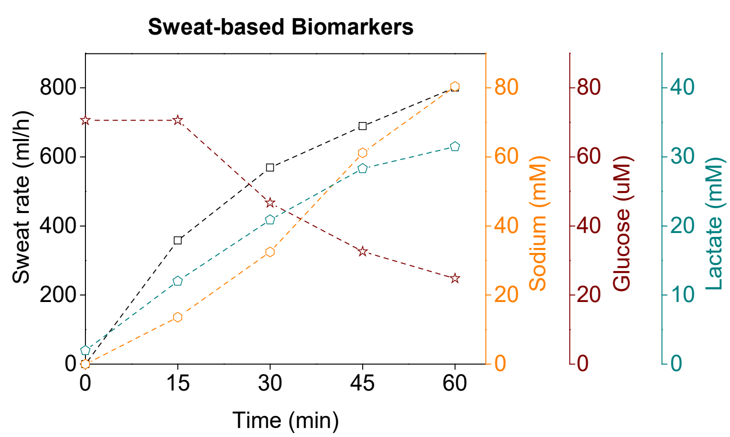


Fig. 3.6. Figures of Sweat rate, Sodium concentration, Glucose concentration and Lactate concentration

3.4.2 Fatigue Model Analysis

Classification assessment used five variants of feature-sets to model fatigue level including (1) sweat rate, (2) sodium concentration, (3) lactate concentration, (4) glucose concentration, and (5) FAS. A total of 140 sets of data were collected through the experiments described in Section 2, which were then split into the training set and the test set in the ratio of 8:2. Table 3.7 summarizes the sample distribution of the four fatigue states in the training and the test set. It can be seen from Table 3.7 that the low-fatigue state has the largest number of samples in both the training and the test set, accounting for 33.04% and 57.14%, respectively. However, the difference in the number of samples representing the remaining three fatigue states is not significant. Firstly, the optimal sets of hyperparameters for the above-mentioned five classifiers were obtained using the training set based on the grid search method with 5-fold cross-validation (k = 5). Second, on the basis of the gained optimal hyperparameter set of each algorithm, the test set was employed to calculate the *Accuracy* by comparing the predicted results with the ground-truth, and thus the best algorithm for predicting the workers' fatigue level with the highest *Accuracy* can be finally obtained.

Table 3.7. The sample distribution of the 4 fatigue states according to the training and the test set

Fatigue level	**Training set**		**Test set**	
	Number	Percentage	Number	Percentage
Low fatigue	37	33.04%	16	57.14%
Medium fatigue	22	19.64%	7	25%
High fatigue	23	20.54%	2	7.14%
Very high fatigue	30	26.78%	3	10.72%
Total	112	100%	28	100%

Table 3.8 reports the optimal hyperparameter sets and their *Accuracy* for the implemented 5 classifiers, with the best result highlighted in bold. As can be seen from Table 8, the classification *Accuracy* obtained using the features such as sodium, and lactate, ranged from 71.43% (SVM) to 96.43% (KNN). Each algorithm has good performance in the classification of workers' fatigue level, especially KNN with the *Accuracy* reaching 96.43%, which can effectively and accurately classify the fatigue states of workers. Therefore, the KNN algorithm was selected to detect and classify the workers' fatigue level.

Table 3.8. Performance of the implemented 5 classifiers with their optimal hyperparameter sets and *Accuracy* (the bold value shows the best *Accuracy*)

Algorithms	**Hyperparameters**	***Accuracy***
Decision Tree (DT)	max_depth: 3 max_features: 6 min_samples_leaf: 2	82.14%
Random Forest (RF)	n_estimators: 20 min_samples_split: 25 min_samples_leaf: 20 max_features: 'auto' max_depth: 10 bootstrap: False	92.86%
Support Vector Machine (SVM)	C: 10 kernel: 'rbf'	82.14%
K-Nearest Neighbor (KNN)	metric: 'euclidean' n_neighbors: 15 weights: 'uniform'	**96.43%**
Multilayer Perceptron (MLP)	activation: 'tanh' alpha: 0.0001 hidden_layer_sizes: (10, 30, 10) learning_rate: 'constant' solver: 'adam'	71.43%

Fig. 3.7 shows the confusion matrix obtained from the test set based on the best classifier (KNN) through the grid search method with 5-fold cross-validation. In the confusion matrix, the ground-truths are listed along the x-axis and the predictions of workers' fatigue levels are listed along the y-axis. Additionally, the numbers on the diagonal of the confusion matrix represent the number of correct classifications for each class. It can be intuitively seen from the confusion matrix that KNN algorithm is effective and accurate in the classification of workers' fatigue states.

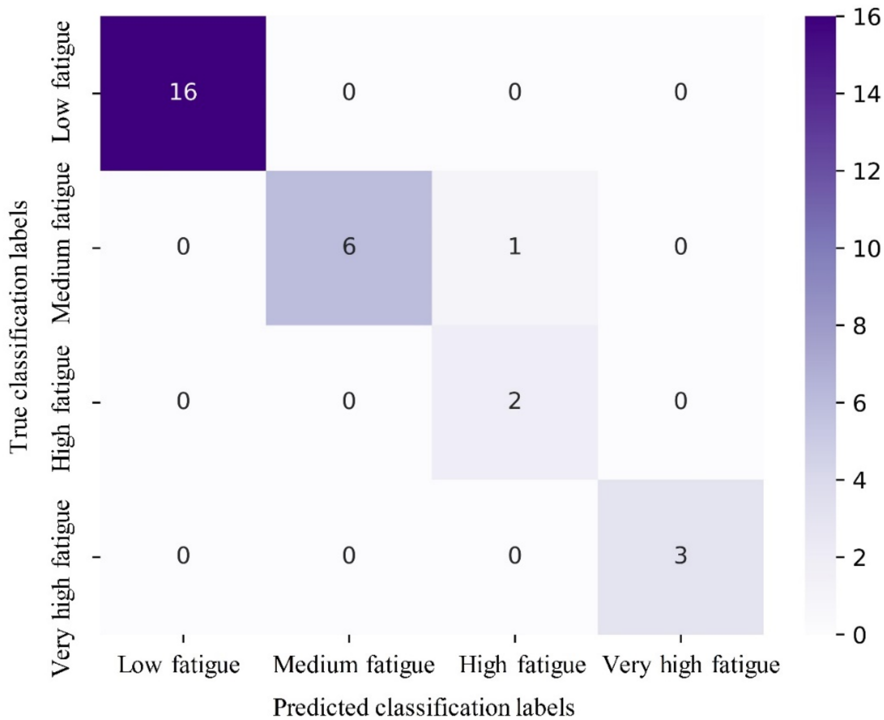


Fig. 3.7. Confusion matrix for KNN algorithm with five input features

3.5 Discussion

Despite the previous study linking the sweat factor to fatigue of construction workers (Aryal et al., 2017), further exploration is limited by the lack of devices. The is the first in the construction industry to quantify sweat profiles to evaluate fatigue using sweat-based biosensors. Two types of features were used to determine and classify the four levels of fatigue: (1) quantitative sweat methodological approaches using the sweat rate, sodium concentration, lactate concentration, and glucose concentration; and (2) qualitative methodologies using the Fatigue Assessment Scale and Borg 6-20. The results of this study highlight that the analysis of sweat-based biomarkers using machine learning algorithms can be a feasible methodology to model physiological exhaustion for evaluating fatigue levels of construction rebar workers.

One of the most apparent findings to emerge from Table 3.6 and Fig. 3.6 is that sweat rate and sodium concentration increased as the task processing and correlated positively with subjective assessments of FAS and Borg 6-20. According to a variety of studies in various domains (Baker, 2017; Baker et al., 2020), the combined result of sweat rate and sodium could reflect dehydration level, which has a major impact on human physical and cognitive function and is therefore very important to the onset of fatigue (Aphamis et al., 2019; Armstrong et al., 2012; Cian et al., 2000). Similarly, Table 3.6 and Fig. 3.6 also show that sweat lactate stepped up; this confirms that lactate was created productively during physical demanding work such as rebar tasks. Glucose, on the contrary, appeared to decrease. One explanation for this could be that there was a shortage of plasma glucose in the body, which would reflect a reduction in sweat glucose, and this might either cause or exacerbate fatigue (Coyle & Montain, 1992). The findings of rising lactate and falling glucose levels during demanding physical tasks not only advance knowledge about the development of fatigue but they may also back up the hypothesis that, given its continuous rising pattern, lactate is primarily for the energy support of human bodies (Brooks, 2002, 2018; Brooks, 2020).

In Table 3.7, the dataset distribution indicates that the significant class difference in the training set was 13.4%, which is considered a modest imbalance for data analysis and computational modelling (Krawczyk, 2016; Skiena, 2017). According to Fernández et al. (2018), minor imbalances are considered typical problems of standard categorization predictive models. Apparently, in Table 3.8, all the five selected algorithms achieved good performances in the classification of workers' fatigue levels. KNN algorithm is the most desirable one, for it had the highest classification accuracy 96.43%. Similarly, the confusion matrix (Fig. 3.7) indicates that the prediction fatigue model through KNN algorithm was effective and accurate.

Sweat biomarkers have a number of advantages in comparison to heart rate, which is a prevalent physiological indicator of fatigue (Anwer et al., 2020; Umer et al., 2022; Yi et al., 2016). First, monitoring these physiological chemical biomarkers is more desirable and feasible for improving workers' comfort. Apparently, throughout the experiment, it was seen that the participants were heavily perspiring (Aryal et al., 2017). In this circumstance, on-body heart rate monitoring devices like the vest EQ02 Lifemonitor may induce a significant strain for users. On the other hand, the flexible sensor on the forehead and the small sweat patch on the forearm are more comfortable to wear and provide superior performance. Therefore, adopting sweat-based biosensors is more valuable and appropriate for challenging outdoor working scenarios such as construction. Second, heart rate parameter is more relevant to managing the intensity of the activities rather than controlling the individual's fatigue. Notably, it does not inversely correlate with a person's level of fatigue (Cunha et al., 2010; Pinto-Bernal et al., 2021). For example, if the person is exercising at a steady speed, the heart rate might stay consistent. Still, the person might be feeling a level of exhaustion or fatigue that is not reflected in the measurement. Third, the justification for not addressing heart rate was the knowledge that it depends on various factors, including gender, age, and the physical health and comorbidities of the individual (Pinto-Bernal et al., 2021). In contrast, chemical biomarkers from sweat may have a universal standard for each individual, similar to those from blood. For example, diagnosing at a hospital by measuring biomarkers from blood is the same standard criterion for everyone. The same may be true for biomarkers from sweat, for they originate from plasma-derived biomarkers (Seshadri et al., 2019). Last, the result of these selected sweat biomarkers not only could be used to assess fatigue but also provide a possibility to enable a real-time fluid/nutriment recommendation which could reduce fatigue's adverse effects. As such, this might be the first potential method that simultaneously evaluates and lowers fatigue.

Despite the promising results, several limitations need to be noted. First, due to the limited funding, participants are students and university staff, whose physical abilities may not be as well-honed as those of construction workers. For example, someone with more work experience in a physically demanding job may have a higher sweat rate than someone who is less/no experienced. Besides, this study was conducted in a simulated scenario which might not replicate construction rebar tasks. A future study should confirm these findings on real construction sites with a large number of workers performing various tasks over an extended time. This kind of extensive, long-term research may offer reliable training data for physiological depletion of construction workers to be monitored and modelled on-site. Second, more variables, such as temperature and respiration rate, might also contribute to the development of physiological fatigue states, which could increase the validity and accuracy of the assessment model. Last, although the commercial product could provide sodium levels, its primary mechanism of colorimetric sensing device limits its usefulness since there is no exact number output but only a range of sodium concentration and the degree of levels (low, medium, high). As such, the authors are applying electrochemical biosensors to detect or measure the amounts of electrolytes like sodium and chloride in the upcoming investigation; this could provide more precise results.

3.6 Conclusion

For the first time, sweat-based biosensors were used to assess fatigue based on physiological exhaustion. Sweat rate, sodium concentration, glucose concentration, and lactate concentration were used as sweat-based features to classify the fatigue level model employing supervised machine learning techniques. The results highlight that KNN algorithm achieved the best accuracy. Also, the study substantiates the use of sweat biomarkers to predict fatigue level. These findings have significant implications for the construction industry. They suggested sweat-based biomarkers could predict fatigue levels and potentially identify when workers need additional fluid or nutrient intake to maintain optimal physical performance. Additionally, this study highlights the importance of staying hydrated, eating well, and maintaining electrolyte balance during construction manual labor tasks. Future research could focus on developing sweat-based wireless sensors that can measure metabolites like glucose or lactate. Given that the amount of lactate in sweat is higher than that of glucose, we have decided to develop a sweat-based lactate sensor system, which comprises a wireless transmission device and an app display on a mobile phone. And the fabrication process of the sweat-based lactate sensor would be demonstrated in the next chapter.

CHAPTER 4 FABRIC OECT-BASED SWEAT LACTATE SENSOR

This chapter demonstrates the methodology for developing organic electrochemical transistor (OECT) based sweat lactate sensors. Thanks to the introduction of a graphene oxidase polyetherimide (GO-PEI) membrane on the gate electrode of an OECT biosensor, the device achieves high selectivity. Moreover, the device enables in-situ monitoring of lactate levels via a wireless device and embedded mobile phone application.

4.1 Introduction

One of the richest and most readily available source of biochemical information to detect fatigue is human sweat (Jadoon et al., 2015). A comprehensive analysis of physiological health condition may be attained by harvesting sweat from a body. Sweat from humans is highly promising biofluid for non-invasive biosensing. It is distributed widely throughout the body with over 100 glands per square centimeter (Sonner et al., 2015). And it contains abundant biochemical compounds such as sodium, chlorine, potassium, lactate, calcium, glucose, and various neuropeptides and cytokines (Heikenfeld, 2016). The presence of these biochemical compounds in sweat has the potential to provide valuable insights into individuals' health and level of fatigue (Koh et al., 2016). Out of all the detectable biomarkers present in sweat, lactate is considered the most suitable for assessing fatigue among construction workers. This is due to its high concentration levels in sweat and its essential roles in supporting body functions (Brooks, 2018; Brooks et al., 2022; Derbyshire et al., 2012). Specifically, it is a major energy resource in supporting the functional operations of muscles and brain during high energy-consuming activities, both physically and mentally (Brooks, 2020; Brooks et al., 2022; Gallagher et al., 2009; van Hall et al., 2009a). As it did in the case of construction workers who are often required to perform tasks that are physically and mentally demanding, such as operating heavy machinery and working at heights, they may likely to experience an increase in their sweat lactate levels as becoming fatigued. Therefore, by monitoring sweat lactate levels in real-time, wearable biosensors can provide a non-invasive assessment of fatigue among construction workers, allowing for timely interventions and potential prevention of accidents or injuries caused by fatigue-related errors.

Research studies have demonstrated the potential of utilizing various types of sensors for detecting biomarkers in sweat (Buono et al., 2010; Onur Parlak et al., 2018; Pierre et al., 2019). Baker et al. (2020) developed a sweat sensor that uses a colorimetric technique to measure sweat rate and electrolyte losses, which allows for real-time personalized fluid-electrolyte intake recommendations. However, this technique is limited in terms of sensitivity, selectivity, and accuracy, which hampers its usefulness in the wearable sensor industry. Therefore, some researchers have explored electrochemical techniques to fabricate wearable sweat sensor, realizing real-time repetitive and more accurate measurements of ion concentration in human sweat (Chen et al., 2020; Keene et al., 2019; Y. Kim et al., 2018). Electrochemical devise directly converts biological/chemical signals into electrical signals without labelling process, thereby, plays a dominant position in manufacturing sweat-based sensor (Windmiller & Wang, 2013). Specifically, regarding transducing chemical signals, the electrochemical techniques can be classified as transistors, amperometric and voltametric sensors (Kaya et al., 2019).

Among the above transducers, organic electrochemical transistors (OECTs) can realize in situ amplification of detected signals. This contributes its merits including high transconductance at low-voltage, high selectivity to the specific analyte, and a low limit of detection (Chen et al., 2020; Khodagholy et al., 2013). In addition, OECT is well applicable for sensing of charged species in an electrolyte solution such as sweat, because it works by translating ionic currents between two electrodes to modulation in the conductivity of a conductive polymer film. And its sensitivity to the ionic strength of the analyte is dependent on a wide range of chemicals rather than one species (Keene et al., 2019). Moreover, OECTs enable a simple process to fabricate the devices on a broad choice of flexible and stretchable substrates as to they are made from biocompatible polymer (Khodagholy et al., 2013; Yang et al., 2018). As such, the characteristics of various high conductivity conjugated polymers, inherent flexibility, and facile processability enable organic electrochemical transistors (OECTs) to grow primarily in sweat-based biosensors. (Chen et al., 2020). Although OECTs show a very promising potential for detecting chemical biomarkers in human perspiration, rich contents in sweat still challenge the sensitivity and selectivity of the sensors. As such, this project proposed to utilize enzyme-based OECT to achieve high sensitivity, while also implementing gate modification of the transistors to attain exceptional selectivity.

4.2 Literature Review

Recent interest has been expressed in the use of sweat as a non-invasive alternative to blood testing to provide information on human physiology, health and performance (Baker, 2019). The development of wearable equipment and detection techniques for the diagnosis of sweat is a rapid growing arena. Various techniques have been studied to detect sweat using electrochemistry, conductometry, and optics (Kaya et al., 2019). Electrochemical measurements involve detecting electrochemical processes in sweat through a set of electrodes (known as ion-selective electrodes), which results in an impedance change. This change can be used to determine the quantities of targeted biomarkers in sweat (Wang et al., 2021). Conductometric sensors measure the ionic conductivity of sweat by applying an electrical potential through electrodes immersed in the sweat solution, creating an electrochemical cell (Kaya et al., 2019). And by measuring the ion concentration in the solution, the amount of sweat can be determined. Optical equipment, on the other hand, uses dye-sensitive solutions to identify colour changes brought on by perspiration concentration (Min et al., 2023).

Among these techniques, electrochemical sensor is a popular detection methodology for measuring biomarkers in bodily fluids (Gao et al., 2016). The success in detecting of biochemicals including blood-alcohol level in the breadth (Bihar et al., 2016), glucose levels in saliva (Soni & Jha, 2015), and blood (Gifford, 2013) has made it drawn more and more attentions. Due to its high sensitivity, low cost, and simplicity, an enzyme-based electrochemical sensor for detecting lactate, whether in blood or perspiration, has shown tremendous potential (Wang et al., 2021). Although some commercial devices for measuring lactate concentration from blood has been approved, the urgent need for non-invasive wearable sensors encouraged more and more research on exploring the possibility of detecting lactate from sweat. Therefore, this project proposed using organic electrochemical transistor-based sensor to measure sweat lactate concentrations.

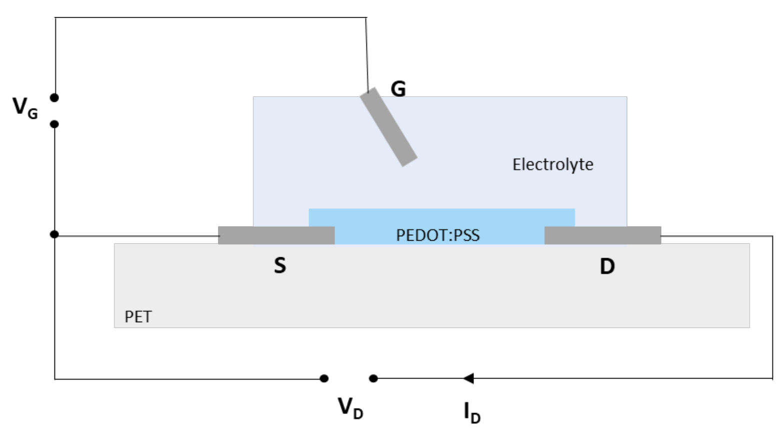


Fig. 4.1. Schematic structure of a typical OECT-based biosensor (Note: G is for Gate; S is for Source; and D is for Drain; IN is for inlet; OUT is for outlet.)

Organic electrochemical transistors are a type of organic thin-film transistor that have gained popularity in biosensing applications because of their excellent biocompatibility and high sensitivity (Malliaras et al., 2018). The operation mechanism of an OECT is based on the modulation of the electrical conductivity of an organic semiconductor by electrochemical reactions. Fig. 4.1 shows a universal OECT which is composed of three electrodes (gate, source and drain), a channel (organic semiconductor), and electrolyte. A gate electrode is separated from the organic semiconductor material by an electrolyte layer. As the gate voltage is varied, the electrical conductivity of the organic semiconductor material changes, leading to a corresponding change in the current flowing between the source and drain electrodes. This change in current can be used to amplify electrical signals and perform signal processing. Overall, the operation mechanism of an OECT involves the modulation of the electrical conductivity of an organic semiconductor, which enables the device to function as an amplifier and signal processor.

OECTs offer several advantages over conventional transistors (H. Liu et al., 2021a). First, low voltage operation: OECTs can operate at low voltages, thus, they consume less power and generate less heat. This makes them suitable for low-power applications and wearable devices. Second, high sensitivity: OECTs have high sensitivity to the changes in the electrochemical potential of the surrounding environment, which makes them suitable for sensing applications such as biosensors. Third, biocompatibility: Organic materials used in OECTs are biocompatible, which means that they can be used for implantable medical devices and bioelectronics. Fourth, low-cost fabrication: OECTs can be fabricated using low-cost, solution-based printing techniques, which reduces the cost of production. In summary, OECTs offer a unique combination of low voltage operation, high sensitivity, biocompatibility, and low-cost fabrication, making them promise for various applications in electronics, biosensors, and medical devices.

OECT-based techniques have been utilized to develop wearable biosensors to revolutionize healthcare technology by many research studies (Malliaras et al., 2018). Specifically, O. Parlak et al. (2018) presented a solution in the form of an electrochemical transistor and a tailor-made synthetic and biomimetic polymeric membrane that can facilitate stable and selective molecular recognition of cortisol. The sensor is integrated into a wearable sweat diagnostics platform that provides accurate sweat acquisition and precise sample delivery to the sensor interface. The integrated devices have been successfully used in both ex-situ and on-body real-sample analysis, demonstrating their potential in wearable biosensor technology. Besides, OECTs also can be used to detect electrolytes from sweat. Keene et al. (2019) reported on the integration of ammonium and calcium ion-selective membranes with a poly(3,4-ethylenedioxythiophene): poly(styrenesulfonate)-based OECT for multiplexed sensing of NH^{4+} and Ca^{2+} in sweat with high sensitivity and selectivity. The integrated devices have been successfully tested with both ex-situ measurements and on human subjects, demonstrating their potential for real-time analysis using a wearable sensor assembly. Also, Y. Kim et al. (2018) developed single-strand fiber-type skin-mountable OECTs by introducing a source-gate hybrid electrode, and the microfiber sensors can perform real-time repetitive measurements of the ion concentration in human sweat. Chen et al. (2020) summarized the latest research advances in OECT fabrication techniques and applications and demonstrated that OECTs are capable of amplification and efficient ion-to-electron transduction at low operating voltages.

To optimize the characteristics of OECT-based biosensors, researchers have applied various methodologies aimed at improving their selectivity and sensitivity. Liao et al. (2015b) used flexible OECTs as enzyme biosensors for detecting uric acid and glucose. The researchers found that the sensitivity and selectivity of the sensors were improved by modifying the gate electrodes with bilayer polymer films and enzymes that had positive or negative charges. And they realize the detection of uric acid in human saliva non-invasively. Qing et al. (2019) presented a new wearable biosensor for dopamine monitoring based on fiber-based organic electrochemical transistors. The device exhibited superior sensitivity, selectivity, and reproducibility, rapid response time, and continuous cycling stability. It also showed mechanical compatibility with the human body and potential for integration into fabric products. Accordingly, this project proposed to use GO-PEI membranes to modify the gate electrode of OECT for improving the selectivity of the sweat lactate sensor.

4.3 Experimental Section

4.3.1 Materials

Poly(3,4-ethylenedioxythiophene)-polystyrene sulfonate (PEDOT:PSS) (Clevios PH 500) was purchased from Heraeus Ltd. Zinc acetate. Dimethyl sulfoxide (DMSO), glycerin, nafion aqueous solution (5%), polydimethylsiloxane (PDMS), and bovine serum albumin (BSA), lactate oxidase (LOx), lactic acid (LA), glucose (GLU), dopamine (DA), cholesterol (CHO) were purchased from Sigma-Aldrich, Inc. Urea, urea acid (UA), urate oxidase (UOx), ascorbic acid (AA) were purchased from J&K Scientific (Hong Kong) Ltd. Phosphate-buffered saline (PBS) was purchased from Thermo Fisher Scientific Inc. AZ5214 and SU-8 2002 photoresists were purchased from MicroChem Corp. Graphnene oxidase (GO) was purchased from Hangzhou Gaoxi Technology Co., Ltd. And polyetherimide (PEI) was purchased from International Laboratory USA.

4.3.2 OECT Device Fabrication

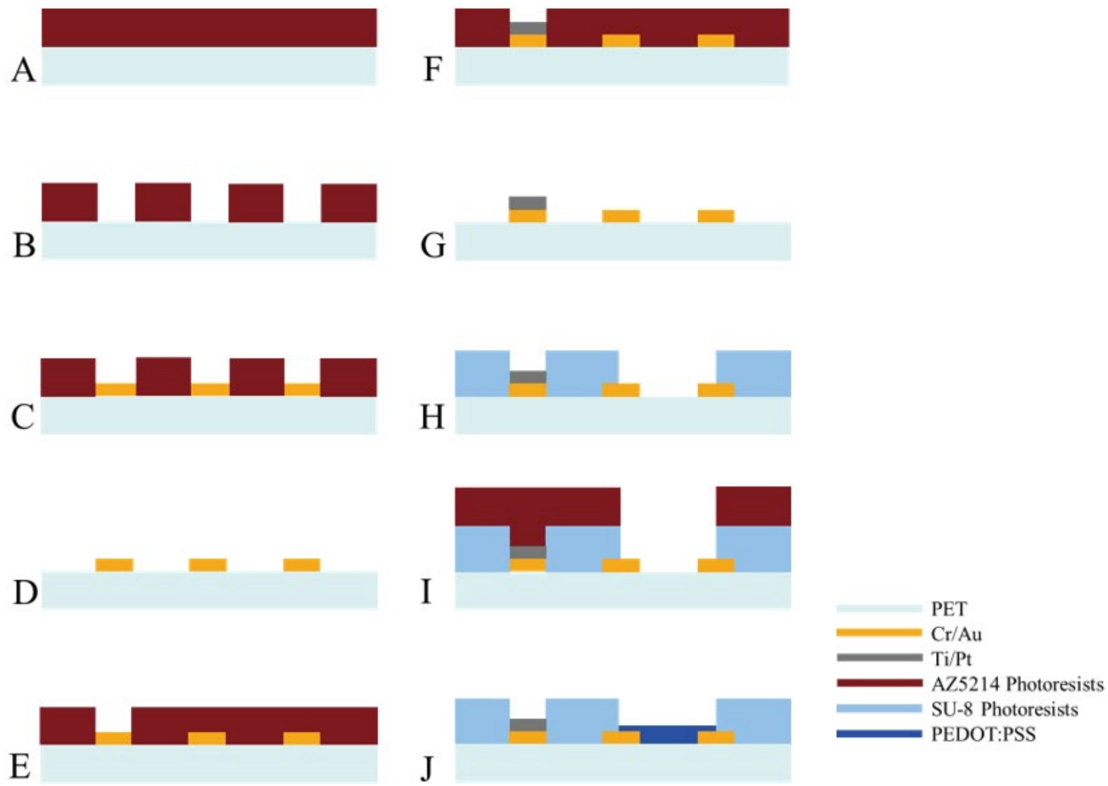


Fig. 4.2. Device fabrication process: (A-D) Cr/Au electrode deposition. (E-G) Ti/Pt electrode deposition. (H) SU-8 photoresists encapsulation. (I-J) Patterning of PEDOT:PSS channel semiconductor.

Fig. 4.2 illustrates the process of fabricating the OECT biosensors. The OECT device was created on PET substrates by first applying AZ5214 photoresist and using Karl Suss MA6 Mask aligner to transfer the desired pattern (Fig. 4.2 A-B). Then, Cr/Au (thickness: ~10 nm/~100nm) and Ti/Pt (thickness: ~10 nm/~90nm) layers were deposited using a radio frequency magnetron sputtering system to serve as source/drain electrodes and gate electrodes, respectively (Fig. 4.2 C-G). The device was then encapsulated with SU-8 photoresist, except for the channel and gate areas (Fig. 4.2 H). The channel window was opened with a photolithography process, and further spin-coated with PEDOT:PSS aqueous solution consisting of 90% Clevios PH-500, 5% DMSO and 5% glycerin, and then annealed at 110 ºC in nitrogen for 20 mins (Fig. 4.2 I). Finally, acetone was used to remove excess PEDOT:PSS, revealing a channel width and length of 120 μm × 30 μm (Fig. 4.2 J).

4.3.3 Gate modification strategies

To modify the OECTs, Nafion solution (5 mg/mL) was applied to the Pt gate electrodes followed by the placement of a GO membrane with a PDMS shield nearby. The LOx solution (200 U/gate electrode) was then coated on the surface of the GO membrane and immobilized using chitosan acetic solution (8 mg/ gate electrode). The equipment was subjected to drying in a moist environment at 4 °C after each step of solution modification. Before sensing measurements, the instrument was washed with PBS solution to eliminate any residues.

4.3.4 Sweat acquisition layer design and device assembly

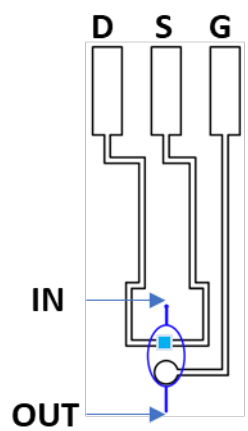


Fig. 4.3. OECT circuit with microfluidic channels

A microfluidic system was designed with two channels and one chamber for lactate detection to achieve on-skin sweat collection. A microchamber is connected to the inlet channel (100 μm width), which has a diameter of 0.5 mm to allow sweat to flow in (Fig. 4.3). According to one estimation (Yokochi & Rohen, 1978), this hole's diameter typically covers 2–3 sweat glands on the palm. Because of the osmolality discrepancies between sweat and plasma that are produced by glands, sweat could be drawn into the microchannel by hydraulic pressure (Sonner et al., 2015).

And the gathered sweat fluid could then flow to the chamber after being steered through a bifurcation nozzle. Finally, sweat flows out through the outlet channel (100 μm width).

4.3.5 Device characterizations

The transfer characteristics (I-V curve) of OECTs were assessed using a wireless detection platform that comprised a flexible OECT sensor, hardware (signal conditioning and signal processing system), and software (wireless transmission via smartphone). The I-V curves were measured by sweeping the gate voltage (V_G) from 0 to 1 V, while fixing the drain-source voltage (V_D) at 0.1 V, and calculating the relative change of the gate voltage ΔV_G after the redox reaction on the gate electrode's surface. The Keithley source meters (Keithley 2400) were used to measure the real-time channel current response (I-T curve) of OECTs to various analytes (e.g., lactic acid (LA), urea, urea acid (UA), cholesterol (CHO), glucose (GLU), dopamine (DA), ascorbic acid (AA), and bovine serum albumin (BSA)). During the measurement of the I-V characteristic, V_D was fixed at 0.1 V, and V_G was fixed at 0.5V.

4.3.6 Mobile meter design and wearable measurements

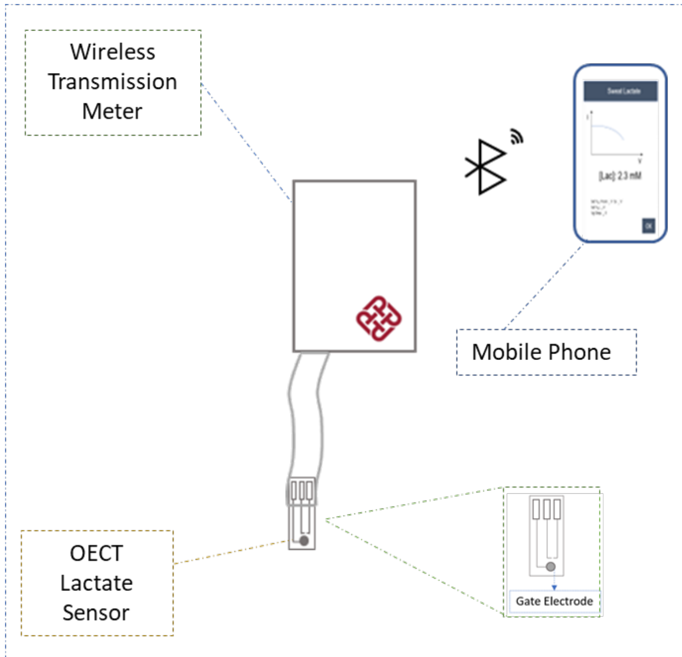


Fig. 4.4. Schematic drawing of wearable sweat lactate sensor

The wearable sweat-based lactate sensing system is shown schematically in Fig. 4.4. It consists of three main parts: an organic electrochemical transistor (OECT) lactate sensor with a sweat collection microfluidic system, a wireless transmission meter, and a mobile phone. Organic electrochemical transistors serve as sensing modules with highly sensitive and selective features that enable the conversion of biochemical signals (lactate concentration in our case) to electronic signals. The microfluidic channels, made of a thin and flexible polydimethylsiloxane (PDMS) layer, not only efficiently collect sweat but also provide excellent mechanical performance with stable output. The portable wireless transmission meter consists of four primary modules, namely the central CPU, analogue to digital circuits (ADC), digital to analogue circuits (DAC), and Bluetooth module. To enable wearable sweat lactate detection, the integrated device can be placed in a wearable arm batch or a hard safety hat. In addition, a custom mobile app was utilized to monitor the skin-mounted device's channel current response. As Fig. 4.4 shows, the working procedure of this sensing system is that OECT lactate sensors covert sweat metabolic signals (lactate concentration) to electrical signals. The electrical signals are then received by a wireless transmission meter through a flexible flat cable. Finally, the lactate concentration is displayed by an embedded app on a mobile phone through Bluetooth transmission.

4.4 Characteristics of OECT-based Sweat Lactate Sensor

4.4.1 Operation Mechanism

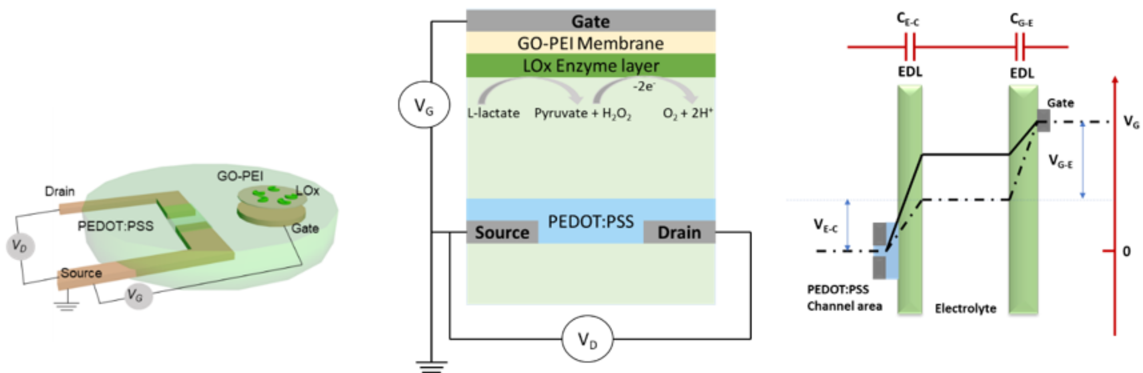


Fig. 4.5. OECT: (a) OECT-based Lactate biosensor Structure; (b) Schematic diagram of an OECT with LOx/GO-PEI membrane/Pt gate; (c) Voltage variations between the gate and channel of the OECT before (dash line) and after (solid line) the addition of Lactate in the electrolyte (Liao et al., 2015b).

Fig. 4.5 (a) shows the structure of OECT-based lactate sensor. It has a simple structure where a thin layer of organic semiconductor (PEDOT: PSS) is placed on the channel region between the source and drain electrodes and subjected to an electrolyte together with the gate electrode. Pt electrodes (gate, source, and drain) were selected in our study because Pt is a biocompatible material with high suitability for on-body devices(Liao et al., 2015b). Organic electrochemical transistors (OECTs) serve as sensing modules with highly sensitive and selective features that enable the conversion of biochemical signals (lactate concentration in our case) to electronic signals. Fig. 4.5 (b)&(c) illustrates the working principles of OECT operation and the details were given below (Liao et al., 2015b).

Reaction of lactate with lactate oxidase

The lactate oxidase (LOx) on the GO-PEI membranes can catalyze aerobic oxidation of lactate into pyruvate, further releasing hydrogen peroxide (H_2O_2) (Alam et al., 2018). The produced H_2O_2 was then oxidized into oxygen and lose two electrons on the Pt gate electrode (Erden & Kılıç, 2013), this electron transfer on the gate electrode changed the channel current.

$$\mathrm{L-lactate} \xrightarrow{\mathrm{LOx}} \mathrm{pyuvate} + \mathrm{LOx_{red}} \qquad (1)$$

$$\mathrm{LOx_{red}} \xrightarrow{\mathrm{O_2}} \mathrm{LOx_{ox}} + \mathrm{H_2O_2} \qquad (2)$$

$$\mathrm{H_2O_2} \xrightarrow{\mathrm{Pt}} 2\mathrm{H^+} + \mathrm{O_2} + 2\mathrm{e^-} \qquad (3)$$

where LOx_{red} is reduced LOx, LOx_{ox} is oxidized LOx.

Operation of OECTs

The channel current (I_D) of an OECT is shown as follows:(Inal et al., 2017; H. Liu et al., 2021b)

$$I_D = \frac{C_i \mu W}{L}\left(V_p - V_G^{eff} + \frac{V_{DS}}{2}\right) V_D \ \left(\text{when } |V_D| \ll |V_p - V_G^{eff}|\right) \qquad (4)$$

$$V_P = \frac{q p_0 t}{C_i} \qquad (5)$$

$$V_G^{eff} = V_G + V_{offset} \qquad (6)$$

where C_i is the effective capacitance per unit area of the OECT, μ is hole mobility, W is the channel width, L is the channel length, V_p is the pinch-off voltage, V_G^{eff} is the effective gate voltage, V_D is the source-drain voltage, q is electron charge, p_0 and t are the initial hole density and thickness of organic semiconductor layer, respectively, V_G is gate voltage, V_{offset} is an offset voltage at two electric double layer (EDL) interfaces.

C_i and V_G are both related to two interfaces including electrolyte/channel and electrolyte/gate connected in series, and given by:

$$\mathrm{Ci} = \frac{C_{E-C}C_{G-E}}{(C_{E-C} + C_{G-E})S} \quad (7)$$

$$V_G = V_{E-C} + V_{G-E} = \left(1 + \frac{C_{E-C}}{C_{G-E}}\right) V_{E-C} \quad (8)$$

Where $C_{E\text{-}C}$ and $C_{G\text{-}E}$ are the capacitances of the two EDL close to the channel and the gate, respectively, S is the area of active layer, $V_{E\text{-}C}$ and $V_{G\text{-}E}$ are voltages applied on two EDL close to the channel and the gate, respectively.

Mechanism of Lactate sensor

The channel current change is attributed to the change of the effective gate voltage of the OECT (Liao et al., 2015a), which is modulated by the reaction of lactate with lactate oxidase and equations are given by:

$$V_{G-E} = -2.30\frac{kT}{2q}\log([H_2O_2]) + C_1 \quad (9)$$

$$V_{E-C} = V_G + 2.30\frac{kT}{2q}\log([H_2O_2]) - C_1 \quad (10)$$

$$V_G^{eff} = 2.30\left(1 + \frac{C_{E-C}}{C_{G-E}}\right)\frac{kT}{2q}\log([H_2O_2]) + C_2 \quad (11)$$

$$V_G^{eff} = A\log([LA]) + C_3 \quad (12)$$

Where k is Boltzmann constant, T is temperature, $[H_2O_2]$ is the concentration of H_2O_2, [LA] is the concentration of LA, A, C_1, C_2 and C_3 are constants. Thus V_G^{eff} and log[LA] are linearly dependent, and V_G^{eff} corresponding to different lactate concentration from the transfer curve of OECT sensor can be read out, lactate concentration can also be calculated by V_G^{eff}.

Summary

The lactate oxidase enzyme (LOx) was coated at the top of the Pt gate electrode to trigger the enzymatic reaction between lactate and oxygen. It outputs hydrogen peroxide (H_2O_2) that releases electrons to stimulate the electronic circuit, as Equations (1), (2) & (3) show, consequently, leading to variations of the circuit potentials, the relationship is shown in Equation (12).

4.4.2 The principle of GO-PEI membrane in obtaining high selectivity

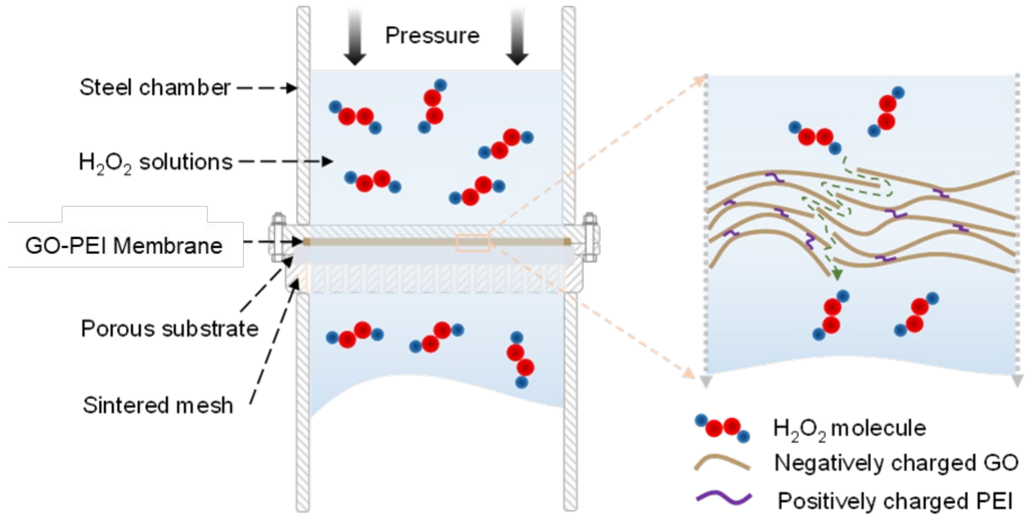


Fig. 4.6 Schematic drawing the transport of H_2O_2 through anti-swelling GO-PEI membranes

Working Mechanism: Although the Pt gate electrode is sensitive to H_2O_2, it is also sensitized to other molecules in sweat, such as urea, glucose, ammonia, etc. (Baker, 2019; Liao et al., 2015b). Therefore, Pt gate electrodes of OECTs were modified in our project with GO-PEI membrane to increase the devices' selectivity to H_2O_2; this can be achieved because it is highly challenging for biomolecules like glucose, urea, and others to pass through the membrane's nanochannels. Of all the analytes in sweat, the hydration volume of H_2O_2 is relatively small (around 9.88×10^{-13} m), thus being able to penetrate the multilayer membrane. As illustrated in Figure 4.6, an anti-swelling graphene oxide polyetherimide membrane was designed to facilitate the transport of hydrogen peroxide (H_2O_2) while preventing the pass of other biomolecules. This enables a precise detection of lactate in bodily fluids like sweat and saliva based on OECTs.

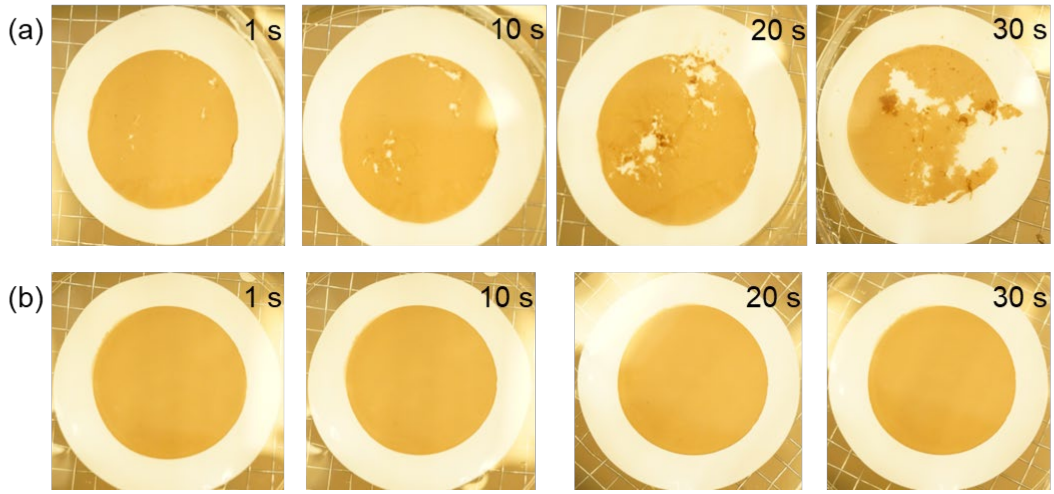


Fig. 4.7. Pictures recording the ultrasonic tests of (a) a GO membrane; and (b) a GO-PEI membrane for 30 seconds.

PEI Function: GO membranes were prepared using the traditional vacuum filtration method. However, these membranes, which consisted of hydrogen-bond crosslinked graphene oxide sheets, were prone to swell and loose instability in water. In fact, as depicted in Fig. 4.7, an ultrasonic test on a GO membrane in water caused it to disintegrate in just 30 seconds. To address this issue, we incorporated a positively charged polymer called polyetherimide (PEI) into the GO. Since GO is a two-dimensional nanosheet with a negative charge, the addition of positively charged PEI resulted in an electrostatic interaction network between the GO sheets. This, in turn, enhanced the stability of GO membranes in aqueous solutions. As shown in Fig. 4.7 (b), the GO-PEI membrane exhibited anti-swelling behavior in water and retained its structural stability during ultrasonic testing.

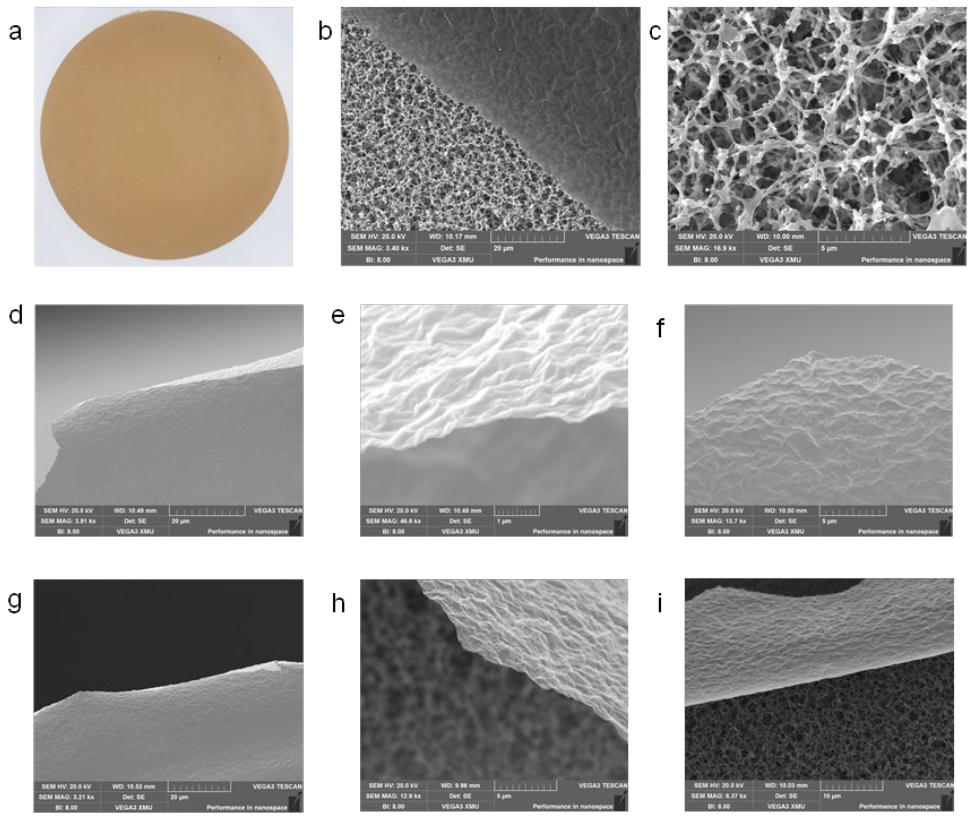


Fig. 4.8. (a-c) Structures of anti-swelling GO-PEI membrane on a porous substrate. (d-f) SEM images of a self-standing anti-swelling GO membrane. (g-i) SEM images of a self-standing anti-swelling GO membrane after soaking-drying in water.

Soaking-Drying Test: Fig. 4.8 (a)-(b) depict images of a GO-PEI membrane attached to a hydrophilic porous substrate made of a mixture of polymer fibers (Fig. 4.8 (c)). The use of a porous substrate provided excellent support for the GO-PEI films and allowed for the rapid pass of hydrogen peroxide and water molecules. Additionally, the self-standing GO-PEI membrane (Fig. 4.8 (d)-(f)) was ultra-thin and highly flexible, and it could be easily detached from the substrate. To evaluate the stability of the GO-PEI membrane, we conducted a swelling-drying cycle test and analyzed its microstructures. As shown in Fig. 4.8 (g)-(i), the microstructures of the GO-PEI membrane remained nearly unaltered after the cycle, demonstrating its robustness and resilience to environmental stressors.

4.4.3 Laboratory Tests of the OECT biosensor

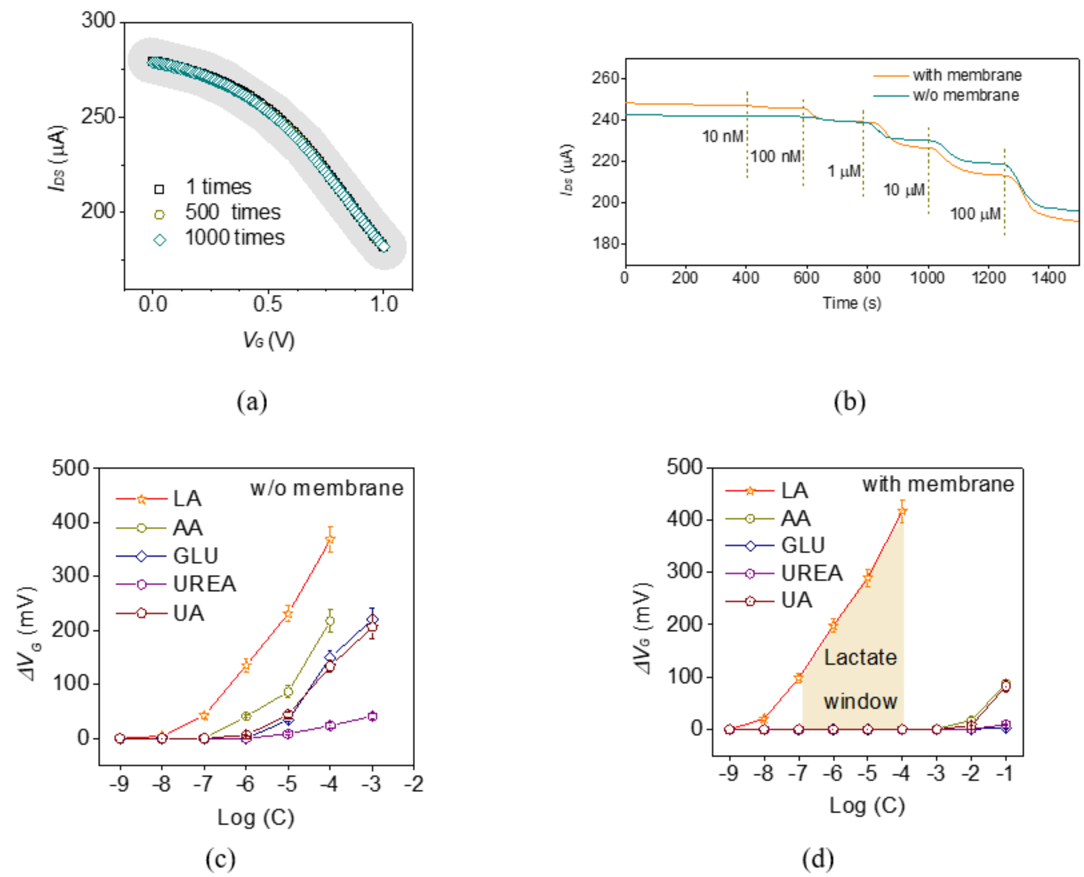


Fig. 4.9. (a) The transfer characteristics of an OECT measured in PBS solution after the repeated tests up to 1000 times. (b) The response of OECT to lactic acid and lactate oxidase with and without GO-PEI membrane. (c) The selectivity test without GO-PEI membrane; (d) The selectivity test with GO-PEI membrane

The modified OECT exhibit remarkable stability during cycle tests, withstanding up to 1000 cycles (see Fig. 4.9 (a)). When being immersed in a solution, lactate oxidase (LOx) catalyzes the conversion of lactate into H_2O_2, leading to a charge exchange on the gate electrode (Pt) in OECT. This, in turn, causes changes in drain-source current (I_{DS}). By combining OECT and LOx, we can accurately monitor the concentration of H_2O_2, and therefore the lactate concentration in sweat. As demonstrated in Fig. 4.9 (b), the I_{DS} significantly decreases with increasing amounts of lactic acid from 10 nM, 100 nM, 1 μM, 10 μM to 100 μM, with and without the coating of GO-PEI membranes on the gate electrode. This indicates that the GO-PEI membrane has negligible influence on the detection of lactate by OECT.

In addition, we conducted a selectivity test by using the sensors to detect various biomolecules in sweat. As illustrated in Fig. 4.9 (c), aside from lactate (LA), other biochemicals, such as Urea, ascorbic acid (AA), uric acid (UA), and glucose (GLU), present in body fluids can interfere with current signals in OECTs. After coating the gate with GO-PEI membranes, the selectivity of OECT was notably enhanced by the reduction of LogC for UREA, AA, UA, and GLU, while the sensitivity remained almost unaffected (Fig. 4.9 (d)). This indicates that GO-PEI membrane improves the selectivity of OECT sensor significantly.

4.4.4 Validation Experiment of OECT-based biosensor

Table 4.1. Comparison of electrochemical and colorimetric measurement of sweat lactate

Sample No.	Electrochemical	Colorimetric
Sample 1 (mM)	30.6 ± 2.7	30.8 ± 0.5
Sample 2 (mM)	31.4 ± 0.9	31.1 ± 0.5

We conducted a comparison and validation experiment as we developed this device. Lactate Assay Kit (Sigma-Aldrich, MAK064) was purchased to measure sweat lactate concentrations as a validation method for the device. The lactate detection kit's (lactate dehydrogenase colorimetry) detection principle is that lactate dehydrogenase (LDH) catalyzes the simultaneous synthesis of lactate pyruvate and nicotinamide adenine dinucleotide (NADH), and the lactate level can be evaluated by colorimetric analysis of these reaction products using the spectrophotometrically obtained absorbance at 570 nm. The endogenous lactate content of samples in body fluids such as sweat, blood, and salivary can be determined by this kit.

Sample collection and processing proceeded as follows: as the participant was running, a 1.5-mL plastic centrifuge tube was used to collect sweat from the forehead. This experiment aimed to validate the device by comparing the results with a commercial lactate assay kit. The sweat samples (sample 1 and sample 2) were collected from one participant who ran 2400 m. After that, the samples were measured by using the electrochemical sweat lactate device and the lactate assay kit for testing. Table 4.1 illustrates the results of colorimetric measurements, which have fewer variances. The two measurements correspond very closely to the same patch of sweat samples. Hence, the electrochemical sweat lactate sensor developed possesses good properties and can detect lactate in sweat.

4.5 Conclusion

To summarize, lactate biosensors based on organic electrochemical transistors (OECTs) have demonstrated highly selective capabilities with the introduction GO-PEI membranes, thus, enabling accurate measurements. With a wireless portable device and a mobile phone embedded App, these sensors can now facilitate real-time monitoring of sweat lactate. This technology paves the way for the development of efficient wearable systems that utilize OECT-based sensors in combination with microfluidic techniques to provide quick and on-site examination of metabolites in bodily fluids. It has the potential to significantly improve personalized and non-invasive healthcare management, as well as continuous physiological and clinical research. The applications of the proposed sensor in the construction field would be explored in the next two chapters.

CHAPTER 5 VALIDATE THE RELIABILITY OF THE SWEAT-BASED LACTATE BIOSENSOR FOR ASSESSING FATIGUE DURING A SIMULATED CONSTRUCTION TASK

This chapter presents the accuracy and usefulness of the sweat-based lactate biosensor in measuring the fatigue levels of construction equipment operators. The consistency of the sweat-based lactate sensor is evaluated by conducting a between-day test-retest experiment. Lactate measurements of the sweat sensor are compared to measurements from blood lactate to assess the reliability of the sweat sensor.

5.1 Introduction

Accidents involving equipment contribute to a substantial proportion of total accidents on construction sites (Gürcanlı et al., 2015; Jebelli et al., 2020). Many studies have identified operators' fatigue as a primary cause of these accidents (Gürcanlı et al., 2015). Owing to the nature of construction work, equipment operators have to attentively perform their tasks while sitting in their control cabins for prolonged periods. Mental fatigue caused by the sustained attention required and physical fatigue arising from prolonged sitting have been identified as principal risk factors.

Physical fatigue, also known as muscle fatigue, refers to a decrease in a muscle's ability to generate force (Mahdavi et al., 2020). Mental fatigue refers to a mental state associated with tiredness and loss of motivation experienced during sustained cognitively demanding tasks (Ahmed et al., 2016; Meijman, 1997). It is, therefore, also called "cognitive fatigue." Fatigue arises from prolonged sitting and sustained concentration required for construction equipment operation work. This could lead to aches in the muscles (Zhang et al., 2023), an overload of cognitive capabilities, and a loss of task engagement and alertness (Matthews et al., 2019). Consequently, operators may often experience a combination of physical and mental fatigue, or combined fatigue (Kar & Hedge, 2020). The physical and mental health of a worker will be impacted by chronic fatigue over time. (Goetz et al., 2022). To prevent fatigue-related ill effects, it is vital to develop feasible and non-invasive methods to detect combined fatigue.

5.2 Literature Review

Existing methodologies that might be used for monitoring fatigue among construction equipment operators include survey questionnaires, eye-tracking glasses, and Electroencephalogram (EEG). Survey questionnaires (Michielsen et al., 2003; Umer et al., 2020) rely on collecting the subjective opinions of subjects, which could cause inaccuracy and task interruption. Eye-tracking glasses (Li et al., 2020) can be significantly interfered with by background noise and light, limiting their adoption in various construction scenarios. Li et al. (2012) say that EEG requires a lot of small sensors to be placed on the scalp, which can be irritating and uncomfortable.

Recently, chemical biomarkers have been studied for fatigue monitoring because of their accuracy and objectivity (Seshadri et al., 2019). Notably, rich concentrations of biomarkers were found in sweat, including sodium, chloride, potassium, lactate, urea, glucose, and so on (Baker, 2019). Measuring sweat biomarkers to evaluate fatigue appears to be a non-invasive, easy, and practical approach.

Among detectable biomarkers in sweat, lactate, as a metabolite, presents a high concentration in sweat (Weiner & van Heyningen, 1952). The lactate shuttling theory, proposed by Brooks (2018), describes that lactate plays three main functions in the human body as: (1) a significant fuel source for the body (i.e., muscle and brain), (2) a significant element in maintaining blood sugar levels, and (3) a potent indicator of metabolic fatigue and stress adaptation. Lactate is continuously produced in the body, but the majority (70 – 80%) is formed during functional activities to fuel the muscle, heart, and brain (Brooks et al., 2022). Therefore, lactate, as a body energy supplier, is not only for physical exercise but also for cognitive activities. For instance, lactate levels rise when the human body is subjected to high energy demands, such as during continued exhaustive exercise or a stressful scenario. This could offer evidence of how lactate levels change in response to physical and mental exhaustion. The mechanism of the lactate shuttle is shown in Fig. 5.1. Lactate is the ultimate byproduct of glucose and glycogen metabolism, which involves a lengthy series of complex steps. Lactate and glucose are interchangeable in response to body alterations. As a result, lactate levels may rise to cope with sustained muscle and brain activity. As it did in the case of equipment operation scenarios involving high energy consumption in both muscles and brain, this may result in an increase in lactate levels. Since lactate is affected by both muscle and mental activity, it could be used as a biomarker to measure the combined level of fatigue in equipment operators.

On the other hand, although lactate is found in blood, sweat, tears, and saliva (Saha et al., 2021), devices measuring lactate from blood, tears, and saliva are not suitable for construction scenarios due to their invasiveness. Moreover, lactate within sweat has a higher concentration than in other body fluids (R Segura, 1996; Saha et al., 2021; Sakharov et al., 2010b). Therefore, this research adopts a sweat-based lactate sensor to evaluate if sweat lactate can be an effective indicator of the combined fatigue level of equipment operators.

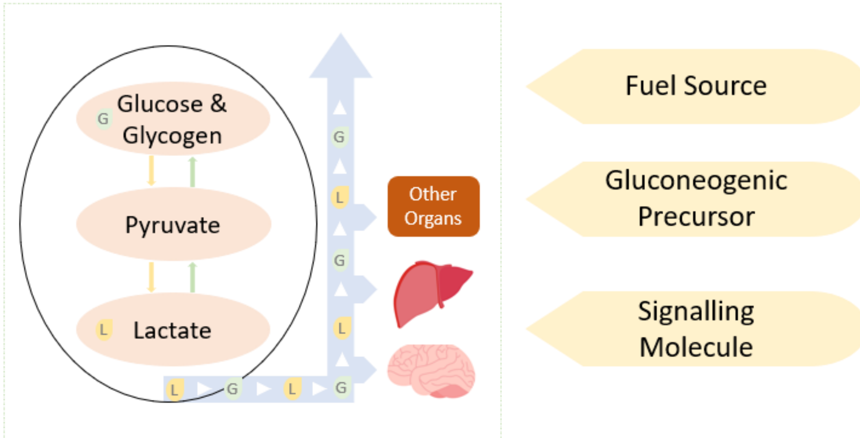


Fig. 5.1: "Lactate-shuttle" (Brooks, 2018) within a human body

In this study, we applied a sweat-based lactate device to evaluate the fatigue levels of equipment operators. Blood lactate was measured to validate the accuracy of lactate measurement from the sweat-based sensor. The validity of fatigue assessment based on sweat lactate was evaluated again using a subjective fatigue method, the Fatigue Assessment Scale (FAS) (Michielsen et al., 2003). Lastly, a test-retest experiment was conducted to evaluate the reliability of the sweat-based lactate sensor for monitoring fatigue.

5.3 Methods

5.3.1 Participants

Table 5.1 gives basic information about the five participants. All the participants slept for at least eight hours before the experiment. They are also advised not to consume alcoholic beverages for at least 48 hours. The mean age is 29.8 years, with a standard deviation of 1.9 years. The mean weight is 80.2 kg with a 3.6 SD. The mean height was 177.2 ± 2.6 cm. The average Body Mass Index is 25.5 ± 0.8 kg/m^2. The protocol was approved by the university ethical committee (Reference number: HSEARS20200922003), and the study adhered to the Declaration of

Helsinki's requirements. Prior to the collection of data, participants provided written informed consent.

Table 5.1: Basic information of participants

	Mean	SD	Range (Min-Max)
Age (Years)	29.8	1.9	5 (28 - 33)
Height (cm)	177.2	2.6	6 (174 - 180)
Weight (kg)	80.2	3.6	9 (75 – 84)
Body Mass Index (kg/m²)	25.5	0.8	2 (24.5 – 26.1)

5.3.2 Materials

This study used a sweat-based lactate biosensor, a Nova Biomedical blood lactate meter, and a fatigue questionnaire, the fatigue assessment scale (FAS), shown in Fig. 5.2, to obtain biomarkers from participants, including sweat lactate (SL) concentration, blood lactate (BL), and a subjective fatigue score.

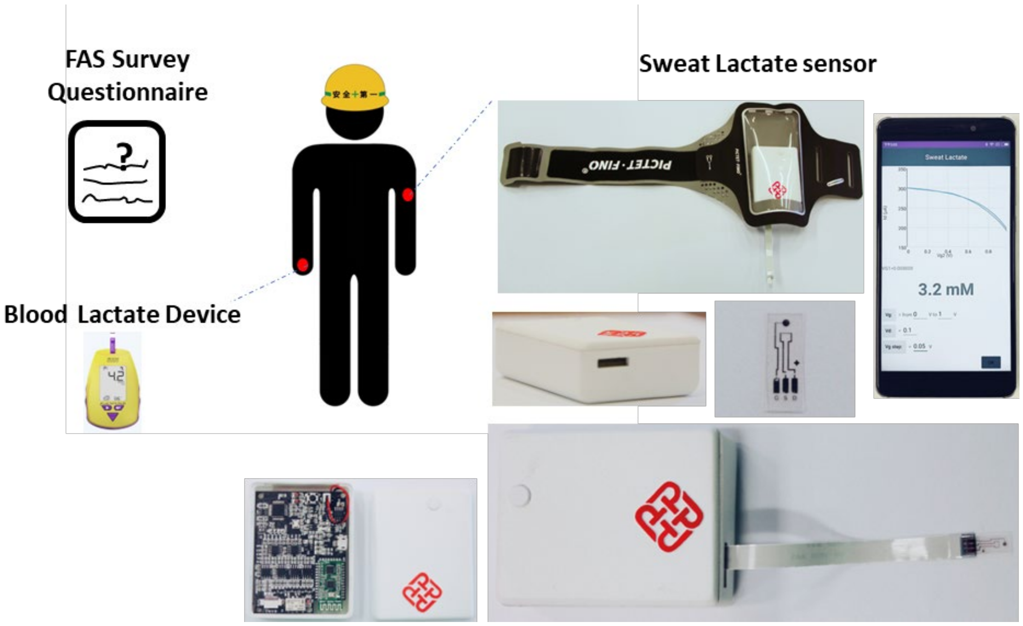
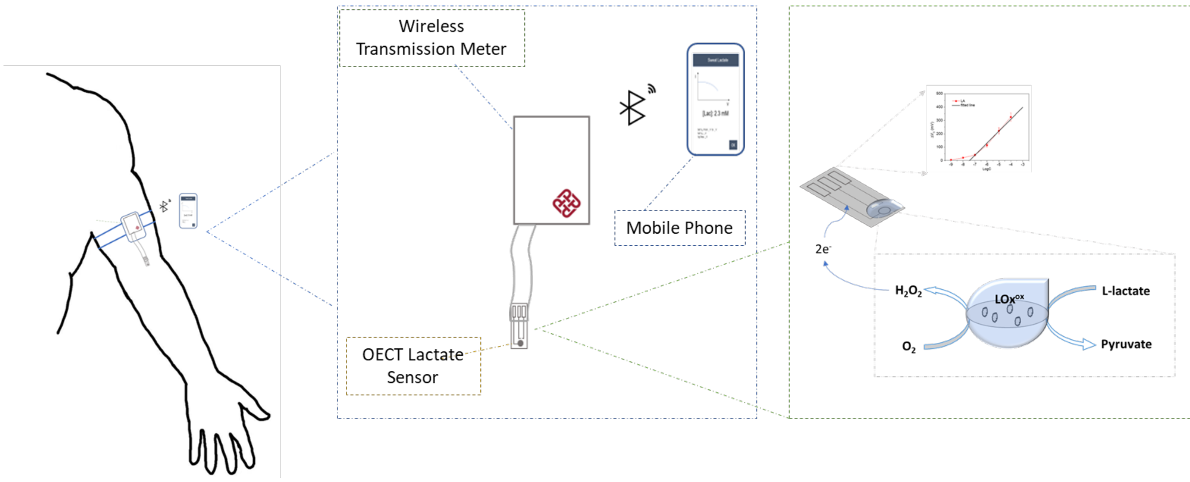


Fig. 5.2: Overview of Devices for measuring biomarkers

Description of developed sweat-based lactate sensor

Wearable sweat-based biosensors have received considerable attention in the health monitoring field. The rich content of molecules in sweat challenges the accuracy of the biosensors. Herein, we applied a developed sweat-based biosensor with flexibility and high sensitivity and selectivity in an epidermal electronic format to measure sweat lactate concentration in situ. Fig. 5.3 (a) presents a schematic representation of the wearable sweat-based lactate sensing system. It comprises by an organic electrochemical transistor (OECT) lactate sensor, a wireless transmission meter, and a mobile phone. As Fig. 5.3 (b) shows, the OECT lactate sensor converts lactate concentration to electronic signals, which are transmitted to a wireless transmission meter via a flexible flat cable. Finally, the lactate concentration is displayed on a mobile phone using Bluetooth transmission. Thanks to the microfluidic system and the wireless meter, our device realizes the goal of measuring sweat lactate concentration on skin in real-time. Also, the highly sensitive and selective features of OECT enable reliable measurements of lactate.



(a) (b)

Fig. 5.3: Schematic drawings of (a) wearable sweat-based lactate sensor on Arm; (b) OECT sensor for measuring Lactate concentration

Fatigue Assessment Scale

FAS is a systematic and comprehensive fatigue assessment methodology comprising 10 items and 5 selection scales for each item (Michielsen et al., 2003). The common subjective fatigue measurement techniques, such as the Borg-20 Scale and NASA-TLX, focus on a single type of fatigue, either physical or mental; therefore, they are not suitable for measuring fatigue arising from equipment operation tasks, which induce combined fatigue, both physically and mentally. FAS, as a new fatigue assessment methodology, was developed by selecting the most effective items from an original item pool of 40 items taken from four commonly used fatigue questionnaires: the Fatigue Scale (FS) (Chalder et al., 1993); the Checklist Individual Strength (CIS) (Panitz et al., 2015); the Maslach Burnout Inventory Emotional Exhaustion (MBIEE) (Schaufeli et al., 1994); and the Energy and Fatigue subscale of the World Health Organization Quality of Life (WHOQOL-EF) (Harper et al., 1998), which covers all types of fatigue. As such, FAS can be applied to evaluate combined fatigue. In our case, a modified FAS survey questionnaire was applied in which the five selection scales were altered to measure the degree of agreement with the 10 items rather than the frequency because the aim of this study was to monitor fatigue during a continuous operation task and not a day-to-day fatigue development assessment. The FAS score ranges from 10 to 50, with 10 being the least amount of fatigue and 50 being the most.

5.3.3 Experiment Process

Five individuals in good health were recruited for the study. All the participants in both the experimental and control trials were required to complete them. A prolonged two-hour task was designed to induce cognitive and muscle fatigue. The procedure followed by the experimental trial group is depicted in Fig 5.4. To account for the possibility that some operators may work in an air-conditioned environment, where they may not produce enough sweat for accurate measurement of biomarker levels using a sweat sensor, this study utilized pilocarpine as a cholinergic parasympathomimetic agent to induce sweating (Buono & Sjoholm, 1988). Pilocarpine stimulates muscarinic receptors, leading to increased secretion by exocrine glands and contraction of the ciliary and iris sphincter muscles (Davis et al., 2005). Biagi et al. (2012) previously applied pilocarpine stimulation to collect eccrine sweat at rest for investigating sweat lactate and pyruvate. As such, this study applied the pilocarpine sweating technique on the forearm region to stimulate perspiration. While participants were briefed about the experiment, their demographic data was being collected. Participants had 10 minutes to familiarize themselves with the simulation system before the start of the trial. After waiting five minutes, the experiment began with the first BioMarker-1 reading. Sweat lactate, blood lactate, and the FAS survey were all measured at each stage. Participants repeated the work at 30-minute intervals until the BioMarker-6 measurement was completed. There was a total of 120 minutes of working time, followed by a 10-minute break. The exact same experimental method was performed with the same individuals two days later to establish test-retest reliability of the sweat sensor device. The same approach was used, but the control group was instead exposed to non-work-related television programs. For each of the six time points (baseline, 30 min, 60 min, 70 min, 100 min, and 130 min), there are corresponding biomarkers (1, 2, 3, 4, 5, and 6). Fig. 5.5 presents the simulated equipment operation system with an on-body sweat-based lactate device.

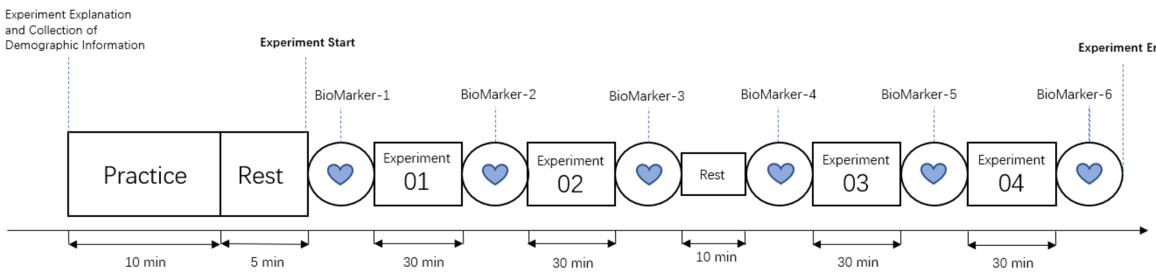


Fig. 5.4. Experiment procedure

Fig. 5.5. Pictures of construction equipment operation simulation system with on-body Sweat-based Lactate Device

5.3.4 Data processing and analysis

In this study, the SPSS Version 27 software, OriginPro 9.0, and Microsoft Excel were employed to carry out statistical analysis and visualization of the data. Pearson's correlation coefficients were applied to examine the relations between sweat lactate and other measurements, including blood lactate and FAS score. The comparisons between the experimental and control groups were constructed in terms of sweat lactate, blood lactate, and FAS score. A two-way random-effects model with intra-class correlation [$ICC_{2,1}$] (Antwi-Afari et al., 2021; Anwer, Li, Antwi-Afari, Umer, Mehmood, et al., 2021) was used to assess the test-retest reliability of the sweat-based lactate sensor. The ICCs were interpreted using the following scale: excellent (> 0.90), good (0.76-0.90), moderate (0.50-0.75), and poor reliability (0.5) (Moffroid, 1993). The distribution of the reliability error scores was displayed using Bland-Altman plots (Gant et al., 2006; Kelechi et al., 2006). More reliable equipment is that with individual error scores that are close to zero.

5.4 Results

Table 5.3 displays the demographic information of the subjects. At baseline, the mean SL concentration was 1.46 mM; after completing the simulated operation task, it was 18.7 mM. As the simulated operating task progressed, the mean BL concentration rose from 1.92 mM at baseline to 4.82 mM at the end of the task. At baseline, the mean FAS scale score was 11.7; at task completion, it was 38.3. What stands out in the table is that the values of the three measured parameters appeared to increase at task completion.

Table 5.3: Descriptive statistics of experiment data

Variables (N = 5 x 2)	Mean	SD	Range (Min – Max)
SL at baseline (mM)	1.46	0.39	**1.18 (0.98 - 2.16)**
SL at the end of the task (mM)	18.7	2.52	**12.4 (13.05 – 25.45)**
BL at baseline (mM)	1.92	0.14	**0.8 (1.5 - 2.3)**
BL at the end of the task (mM)	4.82	0.87	**3.7 (2.3 – 6)**
FAS scale at baseline	11.7	1.15	**4 (10 – 14)**
FAS scale at the end of the task	38.3	7.71	**37 (13-50)**

Note: SL-sweat lactate; BL-blood lactate; FAS-fatigue assessment scale.

Fig. 5.6 shows the values of sweat lactate, blood lactate, and FAS scores of the five subjects along with timelines. The Pearson's correlation coefficient was used to determine the relationship between sweat lactate concentration and the other two parameters. The statistical analysis revealed strong associations between SL and FAS scores; they were 0.856, 0,973, 0.767, 0.948, and 0.957. The Pearson's correlation coefficient of average SL and FAS was 0.941. Similarly, the correlation coefficients of blood lactate and sweat lactate were fairly strong: 0.616, 0.965, 0.955, 0.963, and 0.989, while the average was 0.978. Figure 5.6 also shows the average values of the five people in the experimental group along the timeline.

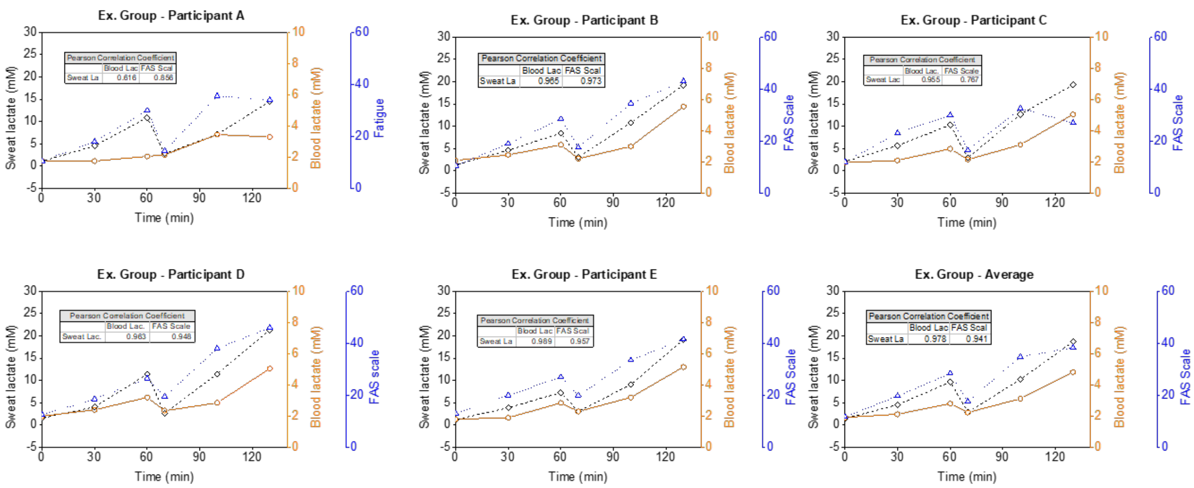


Fig. 5.6. Figures showing SL concentration, BL concentration, and FAS scale of five participants and their average values

In Fig. 5.7, sweat lactate concentration, blood lactate concentration, and FAS score are compared between the experimental and control groups. In comparison to the experimental group, the control group had lower and more stable values of SL, BL, and FAS. As shown in Fig. 5.7 (c), those who completed the simulated operation task had a higher FAS score, which increased as the task progressed.

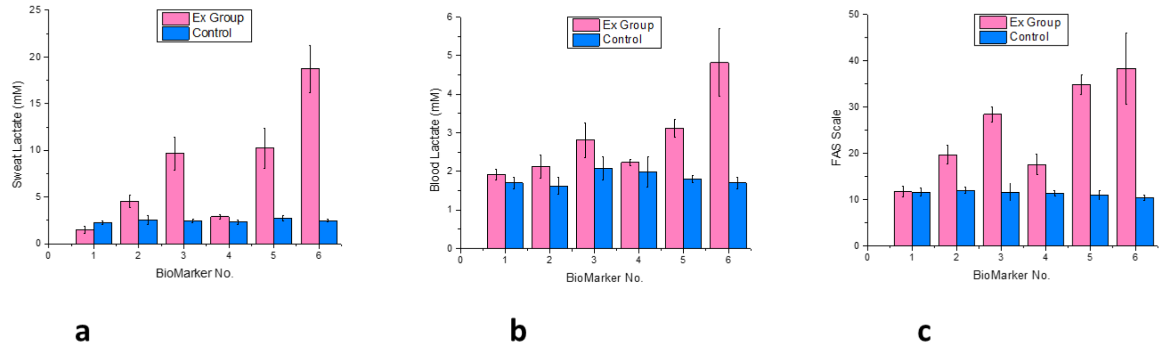


Fig. 5.7: Comparisons of (a) sweat lactate, (b) blood lactate, and (c) FAS scale between experimental and control group

Table 5.4 displays the data analysis of the between-day test-retest experiment for validating the reliability of the sweat-based lactate sensor. The last row represents the average values of the five participants, along with the timeline. The degree of reliability of the sweat lactate sensor ranged from good to excellent, and the values of the ICC were from 0.842 to 0.983. And most of the values of bias were close to zero, also indicating that the device was reliable.

Table 5.4. Mean difference, Bland-Altman's LOA between test-retest assessments of sweat lactate using sweat-based lactate biosensor

Comparison Groups	Bias	LOA	ICC (95% CI)
Participant A	-0.933	-3.03 to 2.85	0.978
Participant B	-3.96	-12.3 to 4.40	0.894
Participant C	1.91	-5.65 to 9.47	0.915
Participant D	1.74	-10.0 to 13.5	0.842
Participant E	-0.487	-3.85 to 2.88	0.983
AVG	-0.954	-5.56 to 3.65	0.992

Fig. 5.8 presents scatter diagrams of the mean difference and Bland-Altman's limits of agreement (LOA) between test-retest assessments of the sweat lactate biosensor. It indicates reasonable agreements between the test-retest scores of sweat lactate concentrations for almost all the points within the scope of the LOA.

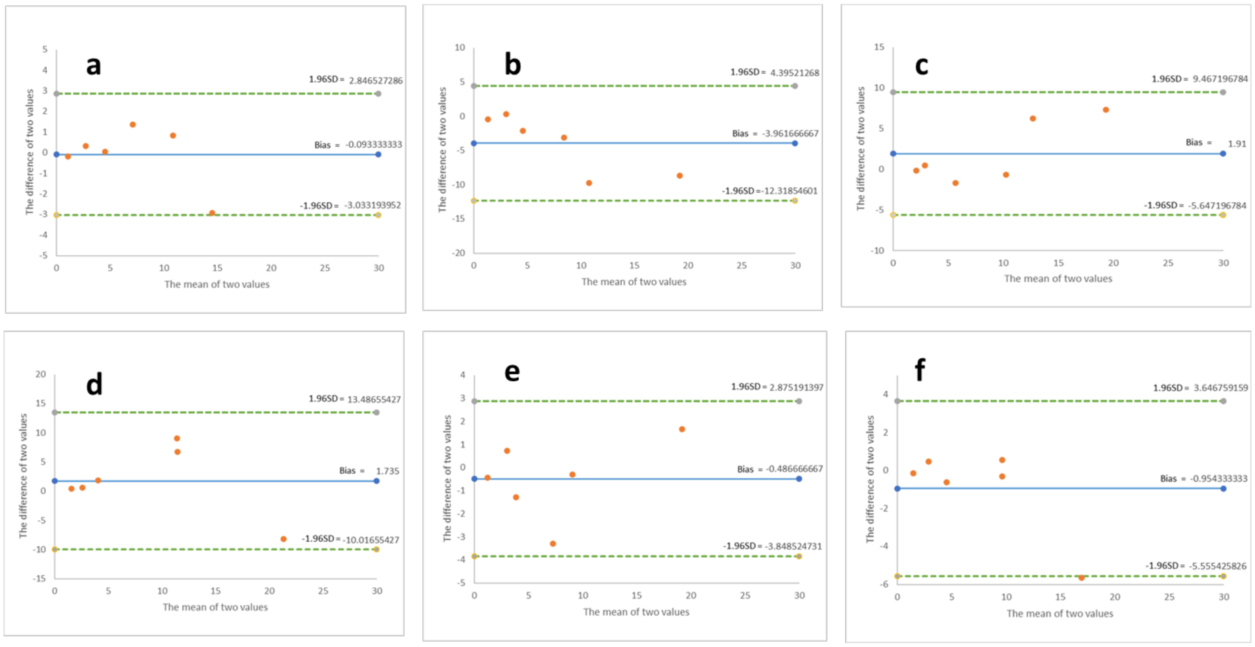


Fig. 5.8: Bland Altman plots of Test-retest for (a) Participant A; (b) Participant B; (c) Participant C; (d) Participant D; (e) Participant E; (f) AVG of test-retest at different timelines (0, 30, 60, 70, 100, 130)

Table 5.5 presents the correlations between the FAS scale and the other two physiological parameters. There was a strong association between sweat lactate and the FAS scale, ranging from 0.896 to 0.975. The correlation between blood lactate and the FAS scale appeared to be good as well, ranging from 0.758 to 0.968.

Table 5.5: Pearson's correlation coefficient between physiological parameters and subjective fatigue scores

Parameters	Fatigue Scores	FAS scale					
	Participants	A	B	C	D	E	AVG
Sweat Lactate		0.856	0.973	0.767	0.948	0.957	0.941
Blood Lactate		0.827	0.884	0.552	0875	0.945	0.887

5.5 Discussion

Given the need to monitor the combined fatigue of construction equipment operators, many recent studies have entailed questionnaires and wearable devices such as eyeglasses and EEG to tackle the challenge. However, these methodologies are either too interruptive or too intrusive, limiting their adoption in construction scenarios. Besides, their accuracy might be a concern because they were measuring the underlying mechanism of fatigue rather than the mechanism itself. This study employed a novel, non-invasive approach to monitor combined fatigue using a sweat-based lactate sensor. Experimental results highlight that sweat lactate can be used to measure the combined fatigue of operators due to the significant correlations between sweat lactate concentration and FAS score. When comparing to existent studies on lactate (Brooks, 2018; Hermann et al., 2019), the variation of sweat lactate in this study is consistent with the working mechanism of lactate theory proposed by Brooks (2018), in which, lactate plays as fuel and signal of fatigue/stress, generating productively when a human body is subjective to high energy demanding activities. This finding can also be supported by studies that demonstrate lactate provides more than half of overall energy in the brain and muscles (Boumezbeur et al., 2010; Brooks et al., 2022; van Hall et al., 2009b). Furthermore, the current findings demonstrated a strong relationship between sweat lactate concentration and blood lactate concentration, enhancing the applicability of sweat lactate in health issues. This result broadly supports the work of other studies linking sweat lactate and blood lactate (Karpova et al., 2020; Sakharov et al., 2010b). Higher lactate concentrations presented in sweat than in blood reflect those of Sakharov et al. (2010b), who also found that sweat lactate concentration was many times higher than blood lactate concentration, for lactate concentration in sweat is not only from blood lactate but also generated by the eccrine glands (Gordon et al., 1971; Weiner & van Heyningen, 1952). This indicates that sweat lactate might be a better option to assess fatigue, not only for its non-invasive characteristic but also for its physiological nature. The comparison results showed that the experimental group and control group differed regarding sweat lactate, blood lactate, and FAS scale, suggesting that operation tasks might induce a rise in lactate levels. Taken together, these results provide important insights into sweat lactate, which could be a reliable biomarker for assessing the fatigue of equipment operators.

The reliability of the sweat-based lactate sensor was examined by conducting a between-day test-retest experiment. The results indicate that this developed device presented excellent reliability for ICC values ranging from 0.842 to 0.992. What is more, Fig. 5.8 displays the Bland-Altman plot, a way of visualizing the agreement between test-retest values. According to Bland and Altman (1999), the agreement requirements were satisfied if 95% of the score discrepancies were contained within the 95% bounds of agreement. It can be seen from Fig. 5.8 that more than 95% of the points were within the scope of the LOA boundaries. There was clear evidence that the sweat-based lactate sensor was accurate in its measurements.

Though our primary goal is basically achieved in this study, there remain options to be explored for improving the accuracy of combined fatigue monitoring. First, since the results of this study indicated that equipment operation tasks could induce variations in lactate in sweat and blood, other biomarkers such as glucose, cortisol, and ammonia might have relevance as well. As per research done by Gao et al. (2016), who proposed the feasibility of measuring six sweat biomarkers in a single wearable device, we could try to develop a sweat-based sensor that enables measuring multiple biomarkers in sweat. This will provide a more comprehensive evaluation of combined fatigue. Second, traditional fatigue data analysis using the summary statistics of all the participants may have limitations due to the heterogeneity in how people perceive fatigue and how their physiologically based chemical biomarker reactions vary. Therefore, person-specific data characteristics could be eliminated using methods like first-order differentiation.

While the study has successfully demonstrated that the sweat-based lactate sensor is reliable to realize fatigue monitoring by measuring sweat lactate, a number of limitations need to be noted. First, due to the limited funding amount and the involvement of blood sampling, the experimental study was conducted on only five subjects, which is relatively small in terms of sample size. Therefore, the results of this experiment may not have a sufficient statistical basis. Another limitation was that all the participants were not professional operators in the construction industry. Therefore, their overall physical and mental conditions may differ from those of equipment operators, which may incur bias. In addition, the scope of this study was limited in terms of operation scenarios, for it was a simulated operation task that could not replicate construction equipment operations. However, notwithstanding the limitations, as our research focus is on examining the usefulness and validity of the sweat-based sensor in measuring lactate concentration, we believe the overall objective has been achieved.

5.6 Conclusion

This study evaluated the reliability of using the state-of-the-art sweat-based lactate sensor to assess fatigue. Specifically, sweat lactate, blood lactate, and FAS score were collected from five subjects while they performed a simulated equipment operation task. The statistical relationships among them were analyzed using the Person's correlation coefficient method. Experimental results enable us to state that sweat lactate is a reliable biomarker for evaluating the combined fatigue of construction equipment operators. The sweat-based sensor appears to be non-invasive, accurate, quantifiable, and portable. The experimental results clearly indicated a strong association between sweat lactate concentration and fatigue level. These experiments also confirmed that sweat lactate and blood lactate had a positive correlation and that sweat lactate concentration was slightly higher than blood lactate concentration, especially given the exhaustive status of the body. However, future research is needed to engage a sufficient number of actual construction equipment operators in the experimental study to generate statistically reliable results.

CHAPTER 6 VALIDATION OF SWEAT LACTATE FOR ASSESSING PHYSICAL AND MENTAL FATIGUE AT CONSTRUCTION SITES

The chapter discusses a hypothesis that lactate can be used to measure both physical and mental fatigue. Experiments were conducted using sweat lactate to assess physical and mental fatigue, respectively. And the results were compared to other established methods such as heart rate, breathing rate, skin temperature, Borg 6-20 for physical fatigue, and EEG signals and NASA Task Load Index for mental fatigue.

6.1 Introduction

Construction workers are highly susceptible to physical and mental fatigue due to their unpredictable schedules, physically demanding workloads, and challenging working conditions (Suraji et al., 2001). Specifically, construction work requires significant physical exertion due to long working hours and high work intensity, which can result in physical fatigue and impair physical functioning (Xiuwen Dong, 2005). Meanwhile, the unpredictable and harsh working environment of construction work can cause mental fatigue, which can impair cognitive function (M. Zhang et al., 2015). It is important to note that impaired physical and cognitive functioning can decrease productivity and increase the risk of injury in the workplace. For example, Öztürkoğlu and Bulfin (2012) discovered that as workers experience fatigue, the time required for task completion increases. This not only escalates physical exertion but also induces greater cognitive stress, ultimately contributing to a potential hazardous cycle of safety risks. Consequently, there is a pressing need to establish an approach capable of addressing the onset of physical and mental fatigue.

Existing studies have proposed using the EQ02 system for physical fatigue assessment (Anwer, Li, Antwi-Afari, Umer, Mehmood, et al., 2021) and EEG and eye-tracking glasses for mental fatigue assessment (H. Li et al., 2019; J. Li et al., 2019; Mehmood et al., 2023), but these devices can be bothersome when worn for extended periods and primarily exhibit significant responses to specific type of fatigue. Moreover, their measurements represent the consequences of fatigue rather than the immediate physiological responses during the development of fatigue. As a result, these assessment methodologies may introduce a time delay and may not provide a precise reflection of fatigue levels in real-time. Chemical biomarkers might offer a more suitable means of assessing fatigue for two key reasons: 1) they provide instantaneous physiological responses that track the progression of fatigue development, and 2) both physical and mental fatigue can lead to variations in chemical biomarkers within the body (Seshadri et al., 2019). Among the detectable chemical biomarkers, we have identified lactate as a potential candidate that is produced effectively during both physical and mental exertions. Therefore, it could serve as a valuable indicator of fatigue in both physical and mental contexts. This is primarily due to its significant functions within the body: 1) *a major energy source* ; 2) *a main material to keep blood sugar level*; and 3) *an important signal for metabolic adaptation to fatigue* (Brooks, 2018; Brooks et al., 2022). This is demonstrated in Brooks's "Lactate Shuttle Theory" (Brooks et al., 2022). Therefore, we propose the utilization of sweat lactate as a non-invasive indicator for assessing both physical and mental fatigue. To validate this hypothesis, we conducted two experiments in the construction setting. In the assessment of physical fatigue, sweat lactate was validated by comparing it with established subjective measures like Borg Rating of Perceived Exertion 6-20 (Borg 6-20) and objective measures such as skin temperature, breathing rate, and heart rate during construction material handling tasks. Similarly, for evaluating mental fatigue, sweat lactate was compared with established subjective measures like NASA Task Load Index (NASA-TLX) and objective measures such as electroencephalogram (EEG) during construction equipment operation tasks. And the credibility of sweat lactate measurements was substantiated through a comparison with the visualized brain activity patterns derived from EEG.

6.2 Literature Review

Fatigue is often associated with high energy consumption (Berger et al., 1991; Jie Ma et al., 2023) and occurs frequently in the construction domain (M. Zhang et al., 2015). It is a disagreeable and subjective symptom that can cause a range of bodily sensations from tiredness to extreme exhaustion, leading to a persistent state that hinders a person's ability to function normally (Ream & Richardson, 1997). The biological mechanism, psychosocial issues, and behavioral expressions are all intricately intertwined in this process (Lauren S. Aaronson et al., 1999). And the challenge has been a long-standing one for scientists.

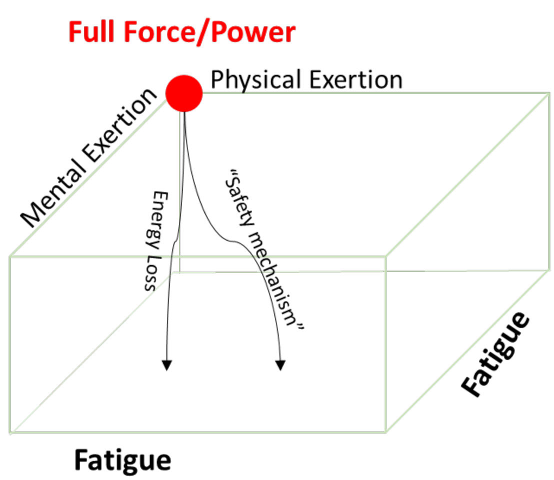


Fig. 6.1. Fatigue development

Fatigue occurs when there is an imbalance in the utilization and restoration of resources, leading to a decreased capacity for performing physical and/or mental tasks, which can be caused by factors like excessive demand or malfunctioning mechanisms. Fig. 6.1. illustrates the process of fatigue and demonstrates that both physical and mental exertions result in a physiological reduction of energy in bodily organs. In response to this energy loss, the body activates a "safety mechanism" that include generating lactate in organs to provide energy and support to the body (Brooks et al., 2022; MacLaren et al., 1989). Lactate accumulation or efficient production is therefore not the cause of fatigue but is the major energy substrate to response exhaustion states (i.e., muscle and cognitive fatigue). Indeed lactate accumulation not just happens in physical exertion activities, but also in mental exertion activities (Schurr, 2008; van Hall et al., 2009a). A release of lactate from muscles, skin, and other driving cells provides energy for working muscles (Bergman et al., 1999; Stanley et al., 1986) and brain (Glenn et al., 2015b).

Lactate production in the body is intricately tied to a metabolic process known as glycolysis. This process involves the conversion of glucose into pyruvate which can subsequently be metabolized to generate lactate, fulfilling the body's energy requirements (Chaudhry R, 2022 ; Granchi et al., 2010; MacLaren et al., 1989). At exhaustion state the lactate: pyruvate ratio increases more than 10-fold (MacLaren et al., 1989). This metabolic progression is illustrated in Equations (1) and (2):

$$Glucose \rightarrow 2Pyruvate + 2H^{+} \tag{1}$$

$$Pyruvate + NADH + H^{+} \underset{LDH}{\longleftrightarrow} LACTATE + \ NAD^{+} \tag{2}$$

According to “safety mechanism” and “lactate shuttle theory”, the process of fatigue development entails “safety mechanism” to cope with physical and/or mental energy consumption; for instance, the efficient lactate production at exhaustion to meet energy needs in muscle and/or brain (Brooks, 2018; MacLaren et al., 1989). This supports the feasibility that using lactate as an indicator to evaluate complex fatigue state.

While lactate is present in various bodily fluids such as blood, sweat, tears, and saliva (Saha et al., 2021), devices that measure lactate levels in blood, tears, and saliva are not appropriate for construction environments due to their invasive nature. Additionally, the concentration of lactate in sweat is higher than in other bodily fluids (Jie Ma et al., 2023; R Segura, 1996; Saha et al., 2021; Sakharov et al., 2010b). Accordingly, this study introduced the utilization of sweat lactate as a biomarker of assessing fatigue. To facilitate this, a wireless sweat lactate biosensor was integrated to quantify lactate concentrations.

To confirm the suggested hypothesis, this study compared the results of sweat lactate with other established methods to validate the capability of sweat lactate in evaluating physical and mental fatigue. In order to obtain accurate measurements, two experiments were conducted. The first one is for physical fatigue assessment: thirteen construction operators performed construction manual material handling task for one hour, and the established methods included subjective (Borg 6-20) and objective metrics (EQ02 device). Borg 6-20 was used to measure subjective workloads while EQ02 device was used to measure heart rate, breathing rate, and skin temperature. The EQO2 LifeMonitor is a device for assessing physical fatigue during construction tasks (Anwer et al., 2020). Studies have found that it accurately measures heart rate, skin temperature, and breathing rate to assess physical fatigue (Anwer, Li, Antwi-Afari, Umer, Mehmood, et al., 2021). Additionally, machine learning techniques applied to EQ02 data have yielded high accuracy in estimating physical exertion levels (Umer et al., 2020).

The second one is for mental fatigue assessment: the same group of participants performed construction equipment operation tasks for one hour, and EEG headband (*Muse S*, 2023) was applied as a standard objective measurement, whereas NASA-TLX was used as the subjective assessment. EEG sensors are a popular method for measuring mental fatigue in various fields, including knowledge workers (Okogbaa et al., 1994), long-distance drivers (Jap et al., 2009; Lal et al., 2003), and construction workers (Chen et al., 2016). Specifically, EEG has been used to monitor workers' mental workload during construction activities that require climbing, nut selection, and tightening. Low frequency brain signals were found to be valid indicators of mental workload in these workers (Chen et al., 2016; Mehmood et al., 2022).

A one-hour experimental period was designated to ensure the induction of a singular type of fatigue across these tasks. By corroborating the utility of sweat lactate as an indicator for evaluating both physical and mental fatigue, this study offers the prospect of a valuable tool in monitoring and assessing fatigue levels among construction workers. Such an advancement has the potential to enhance safety and productivity on construction sites.

6.3 Methodology

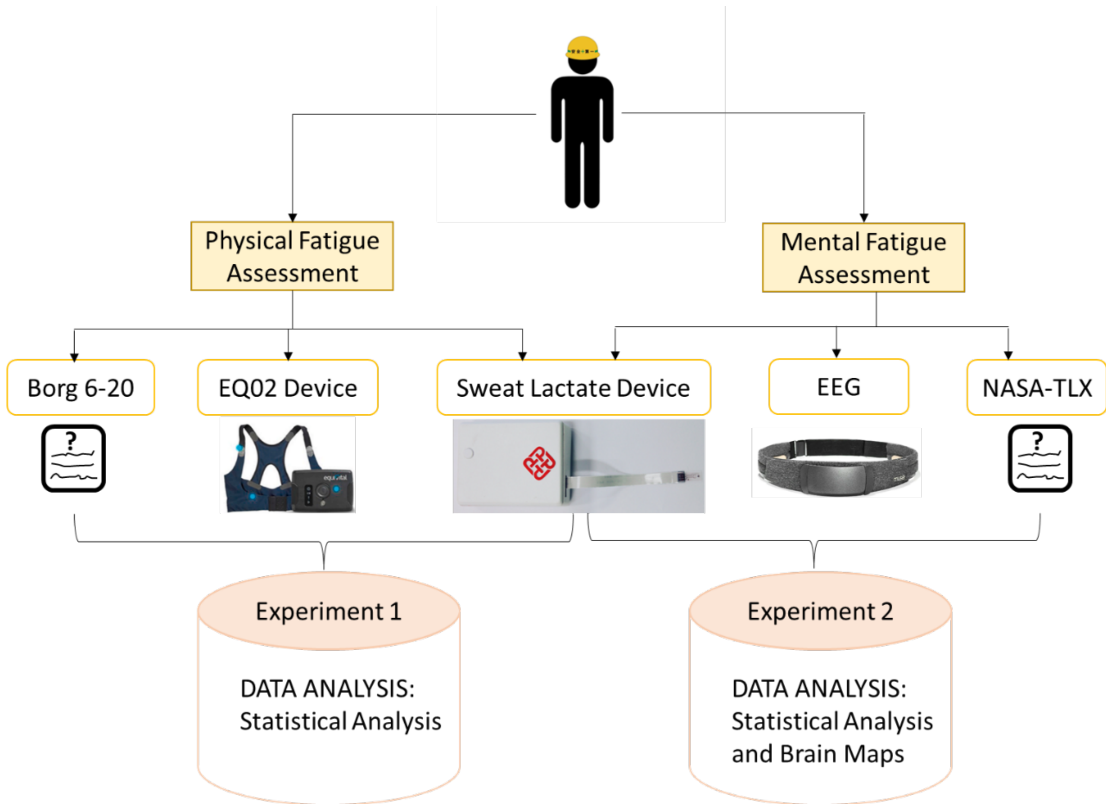


Fig. 6.2. Overview of the research

Fig. 6.2 provides a summary of the research investigation. Two experiments were conducted in this study. Experiment 1 was carried out to confirm the feasibility of using sweat lactate biomarker in physical fatigue assessment. Meanwhile, the purpose of Experiment 2 was to determine whether sweat lactate biomarker can be used to evaluate mental fatigue.

6.3.1 Participants

Table 6.1 Participants' demographics

	Age	**Height**	**Weight**	**BMI**
Mean	30.2 ± 3.51	176 ± 3.79	78.4 ± 4.56	25.1 ± 0.692
Range	11 (25-36)	14 (170-184)	16 (70-86)	2.76 (23.7-26.4)

The demographic information of thirteen construction equipment operators was summarized in Table 6.1. They were recruited to conduct Experiment 1 and Experiment 2. The sample size was selected based on the previous research studies which had similar purposes with this paper. Ten (Umer et al., 2022), five (P. Liu et al., 2021), and six (Arsalan et al., 2019; Li et al., 2020) were recruited in these studies. According to the prior literature research, more than ten subjects would be enough for the investigation and to support the findings.

Prior to the experiments, each participant was required to abstain from alcohol and caffeinated beverages for at least 24 hours. Subjects had to be free of musculoskeletal issues in the past 12 months and have no history of cardiovascular or pulmonary diseases in order to take part in the study. All participants provided informed consent before participating in the study. The study protocol was approved by the university's ethical committee, and all procedures were conducted in accordance with the Declaration of Helsinki (Reference number: HSEARS20200922003). Confidentiality of participant data was ensured throughout the study.

6.3.2 Material and Equipment

The list of tools utilized in this investigation can be found in Fig. 6.2.

Laboratory Sweat Lactate Sensor

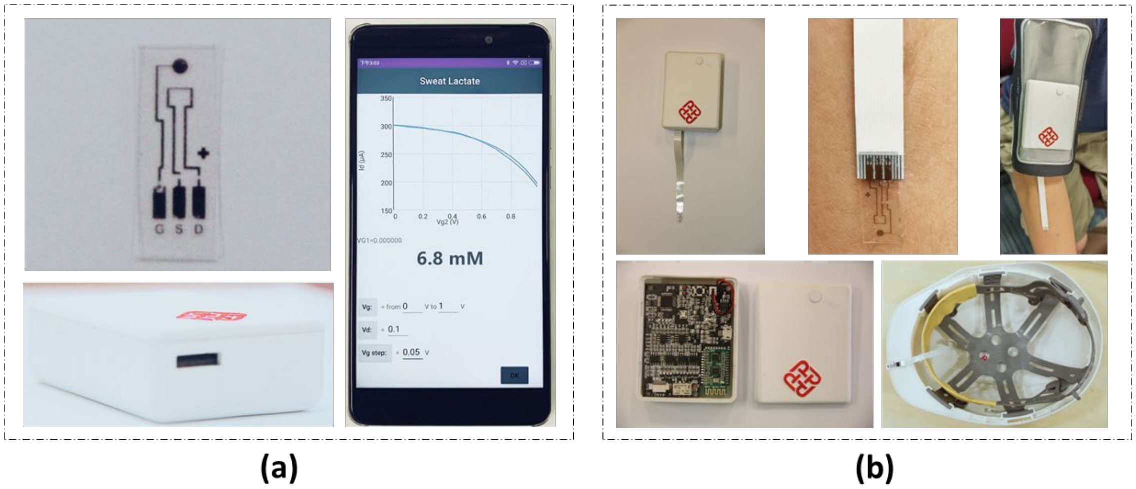


Fig. 6.3. Sweat Lactate Sensor: (a) the three main components; (b) the structure and on-body application

The laboratory sweat lactate sensor is shown in Fig. 6.3. It consists of three major components: (1) the organic electrochemical transistor (OECT) lactate biosensor; (2) the wireless transmission device; and (3) the App imbedded mobile phone. The OECT lactate biosensor, which was applied to the skin, converts the biological signal (sweat lactate concentration) into an electrical signal by an enzymatic lactate oxidase (LOx) reaction, shown in Equation (3) & (4). And after that, the electrical signal was transmitted into the wireless transmission device using a flexible flat cable, which later used Bluetooth to send the signal to the mobile phone for analysis and displaying the results. As shown in Fig. 6.3 (b), the sweat lactate sensor can be attached to different areas of bodies; this extends its application scenarios.

$$\text{L-lactate} + O_2 \xrightarrow{L-lactate\ Oxidase} \text{Pyruvate} + H_2O_2\,, \qquad (3)$$

$$H_2O_2 \longrightarrow O_2 + 2H^+ + 2e^-\,, \qquad (4)$$

Commercial Devices (EQ02 and EEG)

The EQ02 device (*EQ02 LifeMonitor*, 2023), is a highly suitable device for monitoring human physiology across various applications, such as sports and exercise research, clinical trials, biofeedback, military training, and deployment, as it can measure clinical-grade data including cardiorespiratory function, temperature, breathing rate, and activity levels from people who are on-the-go. The device stores the data on the sensor and can be wirelessly transmitted for viewing on a mobile phone.

Muse headband (*Muse S*, 2023) was used to capture EEG signals. It is a versatile and user-friendly EEG recording device. Dry electrodes are located at AF7, AF8, TP9, and TP10 on this headband, which also has four channels. The reference electrode, designated as FPz, is positioned on the forehead. EEG data is captured by the Muse headband at a sampling rate of 256 Hz. Data could be transmitted by connecting the Muse headband through Bluetooth to a smartphone. EEG data was captured on a smartphone using the "Mind Monitor" software and then transferred to a Laptop for further processing (Arsalan et al., 2019).

Subjective assessments

Borg 6-20 was employed to assess physical fatigue while NASA-TLX was used to evaluate mental fatigue.

Borg 6-20 is a useful tool for assessing an individual's fatigue level during physical activity. As such, it is highly relevant in the context of occupational safety and health, as it can help identify potential risks and inform appropriate measures to promote worker well-being (Williams, 2017). The scale ranges from ‘6’ to ‘20’, and this value serves as an indicator to the intensity of activity. Borg 6-20 has been widely utilized for a variety of workout regimens for various populations and has been discovered to be a trustworthy instrument to assess physical demands for the corresponding jobs (Carvalho et al., 2009; De Souza et al., 2023; Scherr et al., 2013).

NASA-TLX is used to evaluate how mentally taxing a task is (Hart, 2006b). Six subscales are used to determine the score: mental demand, physical demand, temporal demand, performance, effort, and frustration. Higher scores indicate higher levels of workload. Each subscale is scored on a scale from 0 to 100. The NASA-TLX score is determined by adding the subscale scores together and ranking them according to their relative importance to the task being evaluated. Higher scores indicate higher degrees of task workload, and the resulting score ranges from 0 to 100. The mental workload of pilots, air traffic controllers, and other professionals is frequently assessed using the NASA-TLX score in aviation, the military, and other high-performance contexts. It can also be applied in academic research to assess participants' mental effort while they complete various tasks (Li et al., 2020; Liu et al., 2016; Puspawardhani et al., 2016).

6.3.3 Procedure and Data Analysis

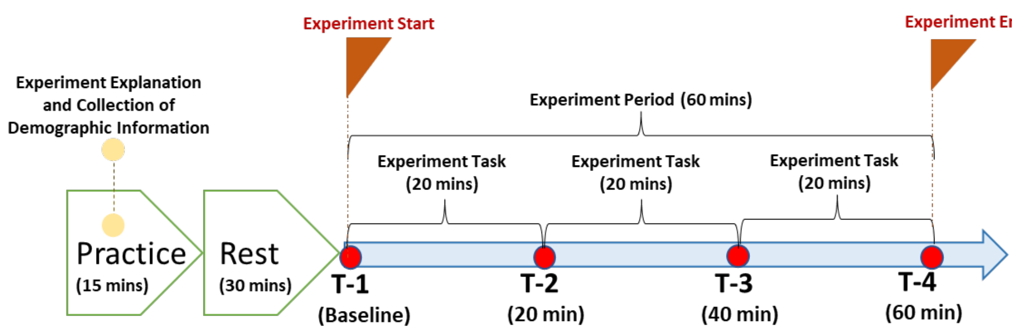


Fig. 6.4 Experiment Process

The two experiments followed the same chronological order as depicted in Figure 6.4. By designing the tasks to induce specific type of fatigue, the participants were asked to undergo relaxed sitting for 30 minutes before starting the experiment task. Also, the task that lasted for one hour was deliberately designed to ensure that the construction manual material task would primarily cause physical fatigue, while the construction equipment operation task would primarily cause mental fatigue.

Experiment 1

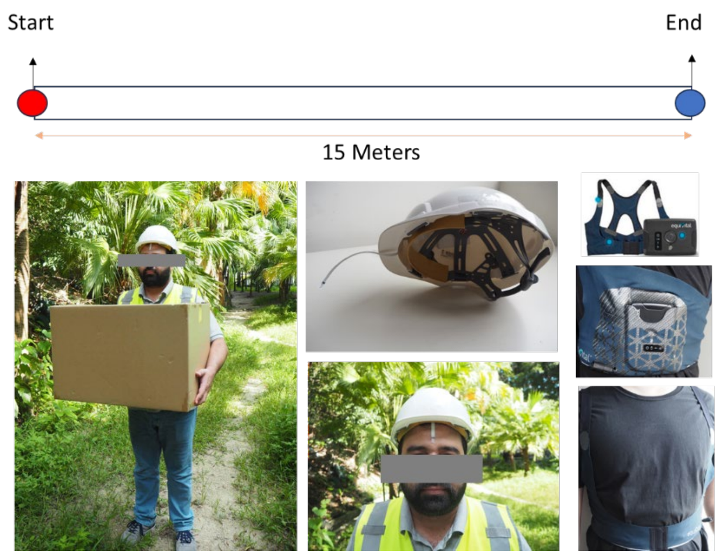


Fig. 6.5 The pictures of the Experiment 1

The thirteen construction equipment operators were recruited to participate in the study. A range of 88% to 95% humidity accompanied the temperature, which was between 29 and 31 °C. Therefore, perspiration was induced naturally by the environment in Experiment 1. Each participant was given a standardized training session on proper lifting and material handling techniques. To stabilize their physiological characteristics, the subjects were then instructed to sit for 30 minutes (Fig. 6.4). During the experimental process, participants were asked to carry a 15 kg box during a period of one hour, performing a set of standardized tasks; this involved picking up the box from the start point and carrying it 15 meters to the finish point, after that, taking a two-minute break and picking up the box to return to the start point again (Fig. 6.5). As shown in Fig. 6.4, The experimental process was divided into three segments, with data collection occurring every 20 minutes (i.e., T-1 baseline, T-2 20 min, T-3 40 min, and T-4 60 min). The Borg 6-20 scale was used to assess participants perceived physical exertion at the baseline and the end of each 20-minute segment. The scale is from 6 to 20, with higher scores indicating higher levels of perceived physical exertion. Objective measurements of sweat lactate concentration, heart rate, breathing rate, and skin temperature were collected at the baseline and the end of each 20-minute segment. Sweat lactate concentration was measured using the laboratory developed lactate sensor on sweat samples taken from the participants' foreheads (Fig. 6.5). Heart rate, breathing rate, and skin temperature were measured using EQ02 LifeMonitor wearable device (*EQ02 LifeMonitor*, 2023) (Fig. 6.5), which must be worn next to individual's skin.

Data from the Borg scale, sweat lactate concentration, heart rate, breathing rate, and skin temperature were collected and analyzed for each segment. Descriptive statistics were used to summarize the data. The correlations between sweat lactate and other parameters were analyzed by Pearson correlational coefficients. The responsiveness of the sweat lactate sensor and the EQ02 systems in measuring changes from baseline to post-task was calculated using the standardized response mean (SRM) which is a unit-free yardstick. The SRM is calculated by dividing the mean change in the variable by the standard deviation of the change (Liang et al., 1990). The resulting value represents the number of standard deviations that the change in the variable exceeds. It provides a standardized measure of the effect size, which can help determine the significance of the change (Rosenthal et al., 1994).

Experiment 2

Fig. 6.6 The pictures of the Experiment 2

The thirteen construction equipment operators participated in this study. The experiment was conducted on different days at the same timeslot (i.e., from 9.00 am to 11.00 am). Considering the possibility that some operators may work in an air-conditioned environment and will therefore not have enough sweat for the accurate measurement of biomarker levels using the sweat sensor. Pilocarpine was used to induce sweat in Experiment 2 (Biagi et al., 2012; Buono & Sjoholm, 1988; Davis et al., 2005). Before starting the experiment, each participant was given a standardized tutorial session (i.e., Practice 15 mins) on collecting their demographic information and learning the progress of the experiment (Fig. 6.4). All of the excavator operators were given an hour to accomplish an excavation operation that involved digging up the ground and moving the debris from pits to transport vehicles (Fig. 6.6). The time-on-task approach was used to intentionally produce mental fatigue and avoid from physical fatigue. Data collection took place every 20 minutes across the three sections of the trial (Fig. 6.4). The participants were given the NASA-TLX questionnaire to determine their perceived mental effort at the baseline and end of each 20-minute phase. To measure the physiological reactions to the task, objective measurements of sweat lactate concentration and EEG were made at the baseline and end of each 20-minute phase. The lactate concentration in sweat was assessed using the lactate sensor developed in the laboratory by collecting sweat samples from the participants' forearms. In addition, EEG was measured using a wireless, dry electrode device (*Muse S*, 2023) to capture brain wave activity from the subjects' scalps.

During each segment, data was collected and analyzed from the NASA-TLX questionnaire, sweat lactate concentration, and EEG. Descriptive statistics, including correlation and p-value analyses, were used to summarize the data. The physiological signals obtained from EEG were analyzed by performing a paired t-test on the absolute power for each frequency band of the EEG signal obtained from all the channels of the MUSE headband during the four experimental phases: baseline, 20 min, 40 min, and 60 min. A null hypothesis and p-value were used to determine the t-test decision. A significant difference between the groups was considered if the p-value was less than 0.05, and the null hypothesis was 1. To confirm the effectiveness of the suggested approach, the researchers utilized Pearson correlation coefficients to analyze the relationship between changes in sweat lactate levels and NASA-TLX scores. Additionally, this study computed correlation coefficients between the average sweat lactate measurements and an EEG metric $[(\theta + \alpha) / (\alpha + \beta)]$ to enhance the ecological validity of the method for construction equipment operators. This specific EEG metric was chosen based on the previous study conducted by Jap et al. (2009) which reported it as the most commonly used metric for computing mental fatigue.

6.4 Results

6.4.1 Experiment 1-Physical Fatigue Assessment

The demographic information for each parameter is displayed in Table 6.2.

Table 6.2 Description of experiment data for physical fatigue assessment

Variables (N=13)	**Mean**	**SD**	**Range (Min – Max)**
SL at baseline (mM)	1.15	±0.171	1 (6 – 7)
SL at the end of the task (mM)	44.9	±5.18	5 (15 – 20)

HR at the baseline (Beats/minute)	71.1	±7.89	24 (60 – 84)
HR at the end of the task (Beats/minute)	114	± 14.1	52 (91 – 143)
BR at the baseline (breaths/minute)	15.2	±1.2	5.1 (13.2 – 18.3)
BR at the end of the task (breaths/minute)	26.6	±1.49	4.9 (24.6 – 29.5)
ST at the baseline (°C)	28.5	±0.763	2.8 (26.8 – 29.6)
ST at the end of the task (°C)	37.2	±1.20	4.6 (34.3 – 38.9)
Borge-20 at the baseline	6.31	±0.48	1 (6 – 7)
Borge-20 at the end of the task	17.1	±1.63	5 (15 – 20)

Note: SL is for sweat lactate; HR is for heart rate; BR is for breathing rate; ST is for skin temperature; SD is for standard deviation.

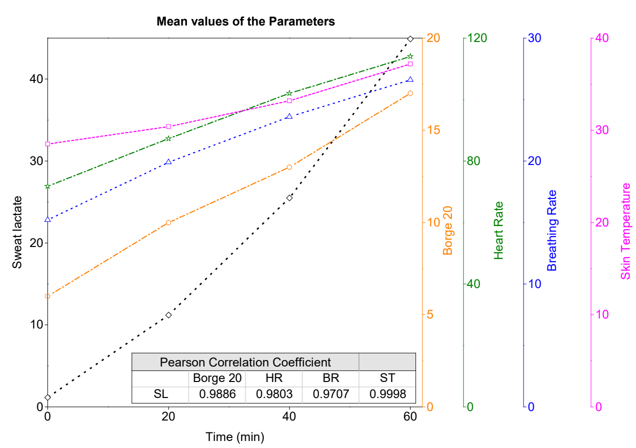


Fig. 6.7. The mean values of the five parameters in Experiment 1 along with timespan

As seen in Fig. 6.7, there were strong positive relationships between sweat lactate concentration and Borg 6-20 (r = 0.9886) as well as other physiological parameters including heart rate (r = 0.9803), breathing rate (r = 0.9707), and skin temperature (r = 0.9998). All of the characteristics tend to rise as the task progresses.

Table 6.3 Responsiveness of biomarkers for the assessment of physical fatigue during material handling task

Indices of responsiveness	Sweat Lactate	Heart Rate	Breathing Rate	Skin Temperature (°C)

	(mM)	(beats/minute)	(beats/minute)	
Baseline	1.15 (0.171)	71.8 (7.89)	15.2 (1.2)	28.5 (0.763)
Post work	44.7 (5.18)	114 (14.1)	26.6 (1.49)	37.2 (1.20)
Mean Difference	43.55	42.2	11.4	8.7
Pooled standard deviation	2.31	4.69	1.64	1.40
Standard deviation of paired differences	5.15	13.6	1.92	1.21
(SRM) Standardized response mean	8.48	3.12	5.97	7.20

Table 6.3 illustrates the responsiveness of physiological measures for assessing physical fatigue during construction material handling tasks. All the physiological parameters including sweat lactate (SRM = 8.48), heart rate (SRM = 3.12), breathing rate (SRM = 5.97), and skin temperature (SRM= 7.20) received positive values of SRM, thereby, there were significant shifts in the physiological parameters' reactivity from the baseline to its post-work.

Table 6.4 Correlations between physiological parameters and Borg 6-20 scale score

Parameters		Borg 6-20 scale score			
	Time	Baseline	20 min	40 min	60 min
Sweat Lactate	Baseline	0.522			
(mM)	20 min		0.833**		
	40 min			0.687**	
	60 min				0.817**
Heart rate	Baseline	0.679*			
(beats/minute)	20 min		0.662*		
	40 min			0.744**	
	60 min				0.844**
Breathing rate	Baseline	-0.459			
(breaths/minute)	20 min		-0.080		

	40 min			0.333	
	60 min				0.165
Skin Temperature (°C)	Baseline	0.401			
	20 min		0.124		
	40 min			0.410	
	60 min				0.326

Note: *Correlation is significant at the 0.05 level; **Correlation is significant at the 0.01 level.

Table 6.4 displays the relationships between the four physiological parameters and subjective fatigue ratings during the whole experiment phases. There was a significant correlation between sweat lactate and Borg 6-20 scale at 20 min (r = 0.833), 40 min (r = 0.687) and 60 min (r = 0.817) of work. Significant correlations were also found between the heart rate and the corresponding subjective fatigue levels at baseline (r = 0.679), 20 min (r = 0.662), 40 min (r = 0.744) and 60 min (r = 0.844) of work. There was no significant correlation between skin temperature measurements and subjective fatigue scores. Also, little correlation exists between subjective fatigue scores and breathing rate.

Table 6.5 Correlations between sweat lactate and cardiorespiratory/thermoregulatory measures

Parameters		Sweat lactate			
	Time	Baseline	20 min	40 min	60 min
Heart rate (beats/minute)	Baseline	0.681*			
	20 min		0.241		
	40 min			0.592*	
	60 min				0.780**
Breathing rate (breaths/minute)	Baseline	-0.596*			
	20 min		-0.268		
	40 min			0.177	
	60 min				0.001

Skin Temperature (°C)	Baseline	-0.205			
	20 min		-0.137		
	40 min			0.016	
	60 min				0.333
Note: *Correlation is significant at the 0.05 level; **Correlation is significant at the 0.01 level.					

Table 6.5 displays the associations between sweat lactate concentration and various physiological metrics. There were significant positive correlations between sweat lactate and heart rate at baseline (r = 0.681), 20 min (r = 0.592), and 60 min (r = 0.780) of work. However, there was no substantial relationships found between breathing rate and sweat lactate. Similarly, no significant correlation between skin temperature and sweat lactate was found.

6.3.2 Experiment 2-Mental Fatigue Assessment

Table 6.6 Statistical description for mental fatigue assessment

Parameter (N=13)	Mean	SD	Range
SL at baseline (mM)	1.44	±0.361	1.13 (0.98 – 2.11)
SL at 20 min (mM)	4.01	±1.32	3.76 (2 – 5.76)
SL at 40 min (mM)	8.29	±1.13	3.31 (6.89 – 10.2)
SL at the end of the task (mM)	13.2	±2.35	8.07 (10.43 – 18.5)
NASA-TLX at baseline	10.1	±3.48	13 (4 – 17)
NASA-TLX at 20 min	31.4	±4.35	14 (23 – 37)
NASA-TLX at 40 min	45.8	±4.31	15 (40 – 55)
NASA-TLX at the end of the task	68.2	±6.66	20 (59 – 79)

Table 6.6 lists the demographic details of the study participants. As the task progresses, the ground truth NASA-TLX shows an obvious increase of the mental workload while the sweat lactate concentration also went up.

Table 6.7. Correlation between sweat lactate concentration and other parameters (EEG metric and NASA-TLX)

Parameters		Sweat Lactate			
	Time	Baseline	20 min	40 min	60 min
EEG $[(\theta+\alpha)/(\alpha+\beta)]$	Baseline	0.406			
	20 min		0.172		
	40 min			0.340	
	60 min				0.539*
NASA-TLX	Baseline	0.354			
	20 min		0.867**		
	40 min			0.923**	
	60 min				0.561*
Note: *Correlation is significant at the 0.05 level; **Correlation is significant at the 0.01 level.					

The correlations between sweat lactate and other established parameters (EEG metric and NASA-TLX) for mental fatigue are shown in Table 6.7. There were significant positive correlations between NASA-TLX and sweat lactate at 20 ($r = 0.867$), 40 ($r = 0.923$) and 60 ($r = 0.561$) min of the task. And positive relationships between EEG metric $[(\theta+\alpha)/(\alpha+\beta)]$ and sweat lactate were discovered through the experiment phases. Specifically, there was a significant correlation at 60 ($r = 0.539$) min of the work.

Table 6.8. p-values for EEG power spectral densities in different brain regions

Time	Channels	EEG Frequency Bands (p values by t-test)				
		Delta	Theta	Alpha	Beta	Gamma
T1-T2 (0&20 min)	AF7	0.444	0.568*	0.552	0.658*	0.649*
	AF8	0.473	0.275	0.752**	0.847**	0.918**
	TP9	-0.016	0.304	0.688**	0.750**	0.896**
	TP10	-0.029	0.140	0.339	0.565*	0.914**
T2-T3 (20&40 min)	AF7	0.659*	0.638*	0.369	0.749**	0.666*

	AF8	0.683*	0.871*	0.600*	0.744**	0.652*
	TP9	0.616*	0.620*	0.617*	0.658*	0.768**
	TP10	0.620*	0.626*	0.451	0.765**	0.816**
T3-T4 (40&60 min)	AF7	0.779**	0.852**	0.788**	0.817**	0.820**
	AF8	0.901**	0.798**	0.642*	0.686**	0.651*
	TP9	0.731**	0.747**	0.767**	0.857**	0.818**
	TP10	0.820**	0.821**	0.821**	0.704**	0.758**

Note: *Correlation is significant at the 0.05 level; **Correlation is significant at the 0.01 level.

Table 6.8 illustrates a statistically significant difference between the EEG power spatial density in several brain areas. According to the t-test applied to EEG signals, the Alpha band was found to have significant statistical differences at the right frontal channel AF8 and the left temporal channel TP9 during all experiment phases. At the left frontal channel AF7 and right temporal channel TP10, it was found to have significant statistical differences only between experiment phases at 40 minutes and 60 minutes. The Beta and Gamma Bands have significant statistical differences at all the channels (AF7, AF8, TP9 and TP10) across all the experiment phases. The Delta band was found to have significant statistical differences at T2-T3 and T3-T4 experiment phases. Moreover, the theta band showed statistically significant differences at the frontal and left regions of the brain across the whole experiment phases.

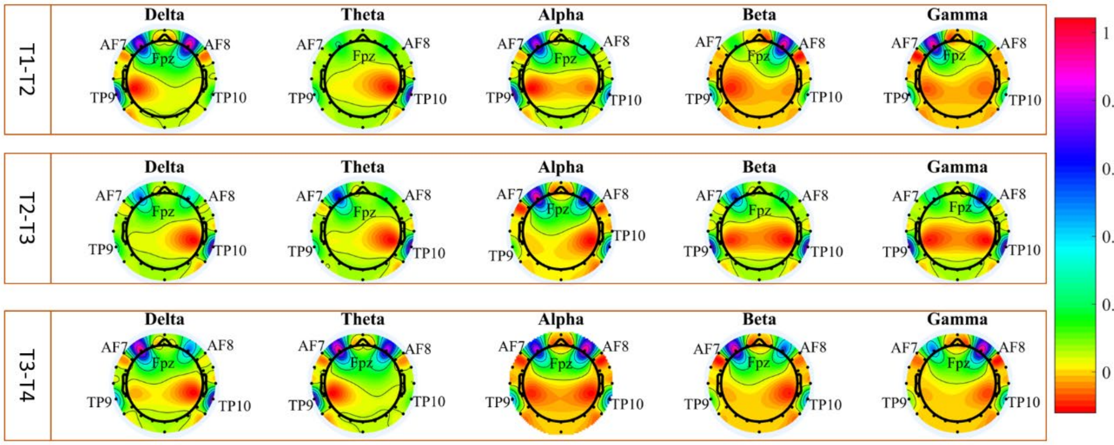


Fig. 6.8 Brain Map

The brain activity of the construction equipment operators during the four phases of the experiment was visualized using the power spectral density of the EEG data, and this is presented in Fig. 6.8. The brain maps indicate strong cortical activity by the color red and little brain activity by the color orange. It is evident from the brain maps that the alpha and beta bands of the AF7 and AF8 frontal channels have visually distinguishable brain activity across all the phases of the experiment.

6.4 Discussion

The present study posited a hypothesis that sweat lactate levels could potentially serve as an indicator of both physical and mental fatigue. To investigate this hypothesis, two separate experiments were carried out to assess the feasibility of using sweat lactate as a chemical biomarker to evaluate physical and mental fatigue. The physical fatigue assessment revealed that strong Pearson correlation coefficients existed between sweat lactate levels and other established measures, including heart rate, breathing rate, skin temperature, and Borg 6-20 scale. This finding corroborated the hypothesis that sweat lactate could be an effective biomarker for evaluating physical fatigue. As for the mental fatigue assessment, positive correlations were observed between sweat lactate levels and subjective ratings on the NASA-TLX scale throughout the entire experiment. The results support the hypothesis that sweat lactate could be utilized as a metric to assess mental fatigue. Moreover, a significant correlation was found between the EEG metric and sweat lactate levels at the conclusion of the task. Overall, the study's findings validate that sweat lactate could serve as a valuable biomarker for evaluating combined fatigue.

The study revealed increasing trends in sweat lactate concentrations during both physical and mental activities, which confirms the lactate shuttle theory that suggests lactate as the primary energy source to support the body (Brooks, 2018; Brooks et al., 2022). Additionally, research by Seifert et al. (2010) indicates that lactate serves as an energy source for the brain and triggers the release of cerebral brain-derived neurotrophic factor (BDNF), which promotes neuronal growth, survival, and memory formation. As observed in the construction operation task, an increase in lactate levels may play a “safety mechanism” role in protecting the body from energy loss. It also could be used to indicate the intensity of energy consumption. Furthermore, lactate levels potentially could serve as a recommended nutrient intake indicator to relieve fatigue related ill-effects. Studies by Hashimoto et al. (2018) and Wang et al. (2017) suggest that lactate uptake is directly related to executive function and can improve cerebral functioning, respectively. These findings suggest that lactate could be utilized as a fatigue indicator and provide recommendations on lactate nutrition intake to alleviate fatigue, enhance endurance during activities, and increase productivity in the construction industry. Therefore, lactate as a fatigue indicator could be a valuable tool for promoting productivity and preventing work-related accidents.

While various methodologies such as the EQ02 device and EEG have been used to monitor fatigue in studies, sweat lactate sensors offer competitive advantages in fatigue assessment. Firstly, by examining the internal physiological reaction to fatigue development, sweat lactate sensors can provide more accurate results. Additionally, the variations of sweat lactate concentrations can indicate both physical and mental fatigue, making this method effective in most fatigue scenarios. Secondly, the small size of the sweat lactate sensor allows for placement in various positions on the body, making it versatile in different scenarios. Thirdly, lactate can serve as a means of compensating for energy loss, and by keeping track of lactate levels, one can suggest the immediate consumption of lactate nutrients as a way to reduce fatigue and boost endurance, thereby, increasing productivity.

While this study confirms the potential of sweat lactate to evaluate physical and mental fatigue, there are some limitations to consider. Firstly, the small sample size may limit the generalizability of the findings. Secondly, due to funding constraints, the same group of participants performed both tasks to ensure consistency between experiments. However, construction operators may have varying levels of familiarity with manual handling tasks or different health conditions from construction manual workers, thereby, could affect their results. Thirdly, the mean value of sweat lactate from mental fatigue assessment was lower than that from physical fatigue assessment, which could be due to different perspiration stimulations and activity types. Future studies could conduct cross-experiments to investigate the influence of sweat stimulation on lactate concentrations.

6.5 Conclusion

Construction workers often suffer from physical and mental fatigue simultaneously, but until now, there has been no established physiological metric or methodology to monitor this comprehensive fatigue situation. This study, therefore, aimed to evaluate the effectiveness of sweat lactate as a physiological metric in measuring both physical and mental fatigue for the first time. The results of the study demonstrated that the proposed hypothesis is practical for assessing both physical and mental fatigue throughout various construction tasks. The findings highlight the lactate's energy resource role in physical and mental consumption and confirm the suitability of sweat lactate as a tool for monitoring fatigue in the construction industry. The study proposed a monitoring system that can assess both physical and mental fatigue using a single device, eliminating the need for separate systems for each type of fatigue. By offering a non-invasive tool for simultaneous monitoring and proactive control of physical and mental fatigue, this technology might contribute to better productivity of construction workers. Also, it could provide prompt advice on nutrient intake to mitigate the negative effects of fatigue and aid in lowering the number of accidents related to physical and mental exhaustion at construction sites.

CHAPTER 7 CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

Considering fatigue management, which still has remained interesting issues to tackle. Studies have shown that the metabolic changes could be the responses of fatigue development (Brooks et al., 2022; Seshadri et al., 2019), this provides a cutting-edge methodology to detect and manage fatigue. Our project explored the usefulness of non-invasive sweat biosensors to measure sweat biomarkers for fatigue assessment. Overall this study highlights that sweat biomarkers have huge potential for evaluating fatigue. Comparing the existent physiological fatigue indicators, it has a broader application in construction industry for it can be used to detect fatigue arising from manual workers and equipment operators. Sweat biosensor offers an innovative tool to achieve non-invasive, real-time, and accurate fatigue assessment. The instant results might also be used to mitigate fatigue levels by recommending fluid or nutrient intake.

The conclusions and suggestions are outlined below based on the individual studies conducted for this research project:

6.1 Systematic Review

A systematic review was conducted to report the results of an evaluation of wearable biosensors for the real-time assessment of stress and fatigue utilizing sweat biomarkers. Sweat has been offered as an alternative to traditional Biofluid tests because it is both readily available and reliable when it comes to evaluating a wide range of biomarkers. Biosensors have been developed for the analysis of sweat-based biomarkers for stress and fatigue assessment. There were 13 publications included in this review that looked at the biomarkers of sweat. Results revealed that metabolites (i.e., Lactate, Glucose), electrolytes and amino acids were found as sweat biomarkers. Sweat-based biomarkers are frequently monitored in real-time using potentiometric and amperometric biosensors. Wearable biosensors such as an epidermal patch or a sweatband have been widely validated in the scientific literature. The bio-signals recorded by these wearable sensors took anywhere from 1 to 20 minutes to begin. For the evaluation and monitoring of general health, including stress and fatigue, sweat is an important biofluid. It is becoming increasingly common to use biosensors that can measure a wide range of sweat biomarkers to detect and prevent fatigue during high-intensity work, such as construction. Even though wearable biosensors have been validated for monitoring various sweat biomarkers, such biomarkers can only be used to assess stress and fatigue indirectly. As a result, further investigation and testing studies are warranted to identify the relationship between sweat biomarkers and fatigue development before any clear conclusions can be formed.

6.2 Sweat Biomarkers and Fatigue Development

This study proposed a novel approach to monitor the fatigue levels of construction rebar benders by measuring chemical biomarkers using sweat sensors. Fatigue resulting from dehydration and energy depletion can severely endanger the safety and health of construction workers. Sodium, lactate, glucose, and sweat rate were chosen as detectable biomarkers in this study, as their concentrations could indicate hydration status, energy consumption, and electrolyte balance, making them suitable for fatigue monitoring. The results were used to construct a fatigue model using supervised machine learning approaches. Construction rebar experiments were conducted while the sweat-based biosensors were applied to rebar workers to evaluate their fatigue with five different classifiers, demonstrating accuracy rates ranging from 71.43% to 96.43%. The results suggested that sweat-based biomarkers offer a non-invasive and accessible fatigue monitoring alternative. This could potentially help alleviate fatigue-related adverse ill-effects like dehydration or cramping by enabling instant fluid or nutrient supply recommendations during construction manual tasks. It also provided valuable insights into the physiological effects of rebar work. Besides, this study presented a valuable model for predicting workers' fatigue levels, which could be applied in the construction industry to improve workers' safety and productivity. Furthermore, the study highlighted the importance of maintaining appropriate hydration, nutrition, and electrolyte balance during physically demanding tasks like construction manual work.

6.3 Wearable OECT-based Sweat Lactate Device Fabrication

Because traditional electrochemical sensors have a limited range of detection and low sensitivity, they are not frequently employed in wearable technology. In contrast, organic electrochemical transistors (OECTs) have become a popular choice for wearable applications due to their ability to amplify signals and convert ions to electrons. This study developed a highly sensitive and selective sweat lactate sensor using an OECT-based platform. The sensor was designed with a wireless transmission device and a mobile app for data analysis. The sensor's strong selectivity was shown by the fact that its response to lactate was more than two orders of magnitude greater than its sensitivity to other interferences. In summary, a wearable sweat lactate sensor has the potential to enable real-time monitoring of lactate concentrations in sweat.

6.4 Validation of the Sweat Lactate Device

A study was conducted to investigate the accuracy and usefulness of a sweat-based biosensor in measuring the fatigue levels of construction equipment operators. Specifically, the paper firstly elaborated on the suitability of selecting sweat lactate as a biomarker for measuring combined fatigue (i.e., a combination of physical and mental fatigue) that construction equipment operators often experience. The results revealed that sweat lactate could be an effective indicator of assessing fatigue during operation tasks. Further, a between-day test-retest experiment validated the reliability of the sweat-based lactate sensor. Importantly, a positive correlation was found between blood lactate and sweat lactate. And this also validated the accuracy of the sweat sensor. The Fatigue Assessment Scale, a subjective fatigue method, validated sweat lactate as a fatigue assessment biomarker. Analytical results indicate that the lactate measurements from the sweat-based sensor do reflect the fatigue level of equipment operators, and the device had good reliability for measuring sweat lactate concentration.

6.5 Validation of sweat lactate for assessing physical and mental fatigue

Owing to the nature of construction work, construction workers may experience both physical and mental fatigue, making it challenging to assess their fatigue levels accurately. One way to evaluate combined fatigue (i.e., combination of physical and mental fatigue) is to use lactate, a major source of energy. This study aimed to validate the usefulness of sweat lactate as an indicator of physical and mental fatigue by conducting two experiments. In the first experiment, sweat lactate for physical fatigue assessment was validated through comparing with subjective (the Borg Rating of Perceived Exertion 6-20 (Borg 6-20)) and objective measures (skin temperature, breathing rate, and heart rate) during construction material handling tasks. In the second experiment, sweat lactate for mental fatigue assessment was evaluated through comparing with subjective (NASA Task Load Index (NASA-TLX)) and objective measures (electroencephalogram (EEG)) during construction equipment operation tasks. The results showed that sweat lactate concentrations varied over time in both experiments. Specifically, sweat lactate was strongly correlated with validated parameters (Borg 6-20 and heart rate), confirming the feasibility of using it to assess physical fatigue. Similarly, sweat lactate was found to be ecologically valid for assessing mental fatigue, as it correlated with ground truth (NASA-TLX) and EEG results. Besides, the brain visualization pattern obtained from EEG was also associated with sweat lactate concentrations. Overall, this study suggests that sweat lactate can be used to monitor combined fatigue state among construction workers.

6.6 Recommendations for future studies

The potential of sweat biomarker analysis is vast and future research can explore multiple avenues to further expand its application. One of the key areas of research could be measuring a greater number of biomarkers from sweat biofluid using a single wireless platform while simultaneously improving detection techniques for increased sensitivity and specificity. This will make it possible to analyze numerous physiological and biochemical processes, such as stress and fatigue, more thoroughly and accurately.

Additionally, researchers may explore the utility of sweat biomarker outputs such as electrolytes, glucose, and lactate to recommend instant nutrition intake and their impact on alleviating the negative effects of fatigue. The information gathered from sweat biomarkers can provide crucial insights into the physiological and metabolic state of an individual and can help to personalize nutrition intake. This could optimize the management of worker fatigue and enhance worker safety and productivity in the construction industry.

Further, longitudinal studies may be conducted to track changes in biomarker levels over time in response to different stressors or interventions. These studies can provide valuable information on the dynamic nature of biomarker changes and help to develop more targeted stress and fatigue management strategies. By providing reliable diagnostic and screening tools for stress and fatigue assessment, employers can better monitor the health and safety of their workers and make more informed decisions regarding work schedules and safety protocols.

Overall, this study represents an essential step towards improving the health and well-being of construction workers and underscores the potential for incorporating sweat-based biomarkers into fatigue monitoring protocols. And continued research into sweat biomarker analysis can lead to significant advancements in the fields of personalized health, stress and fatigue management, and occupational health and safety.

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