Anwer S, Li H, Antwi-Afari MF, Umer W, Wong AYL. Evaluation of physiological metrics as a real-time measurement of physical fatigue in construction workers: Stateof-the-Art Reviews. Journal of Construction Engineering and Management (Accepted) Evaluation of physiological metrics as a real-time measurement of physical 1 2 fatigue in construction workers: State-of-the-Art Reviews 3 Shahnawaz Anwer, PhD Candidate*; Professor Heng Li, PhD; Dr. Maxwell Fordjour Antwi-Afari, PhD; Dr. Waleed Umer, PhD; Dr. Arnold Yu Lok Wong, PhD, 4 5 1. PhD Candidate, Department of Building and Real Estate, Faculty of Construction 6 and Environment, Hong Kong Polytechnic University, Hung Hom, Kowloon, 7 Hong Kong Special Administrative Region, Room No. ZN1002, Email: 8 anwerphysio@gmail.com, Shahnawaz.anwer@connect.polyu.hk 9 2. Chair Professor, Department of Building and Real Estate, Faculty of Construction 10 11 and Environment, Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong Special Administrative Region, Room No. ZS734, Email: 12 13 heng.li@polyu.edu.hk 3. Lecturer, Department of Civil Engineering, College of Engineering and Physical 14 15 Sciences, Aston University, Birmingham, B4 7ET, United Kingdom, Email: m.antwiafari@aston.ac.uk 16 4. Assistant Professor, Department of Construction Engineering & Management, 17 King Fahd University of Petroleum & Minerals, Saudi Arabia; Email: 18 19 Waleed.umer@kfupm.edu.sa 20 5. Assistant Professor, Department of Rehabilitation Sciences, The Hong Kong Polytechnic University, Hong Kong; Room No. ST512, Email: 21 22 arnold.wong@polyu.edu.hk 23 *Corresponding author 24 25 Shahnawaz Anwer, MPT 26 PhD Candidate ZN1002, Smart Construction Laboratory 27 Department of Building and Real Estate 28 Faculty of Construction and Environment 29 30 The Hong Kong Polytechnic University 31 Hung Hom, Kowloon, Hong Kong Email: anwerphysio@gmail.com; shahnawaz.anwer@connect.polyu.hk 32

34 Abstract

Physical fatigue is a major health and safety related problem among construction 35 workers. Many previous studies relied on interviews and/or questionnaire to assess 36 physical fatigue in construction workers. However, these traditional methods are not 37 38 only time consuming but also limited by recall bias. To overcome these limitations, many researchers have used physiological metrics (e.g., heart rate, heart rate variability, 39 40 skin temperature, electromyographic activity, and jerk metrics) to measure real-time 41 physical fatigue. While physiological metrics have shown promising results for realtime assessments of physical fatigue, no state-of-the-art review has been conducted to 42 43 summarize various physiological metrics in measuring physical fatigue among construction workers. Therefore, the current state-of-the art review aimed to summarize 44 45 existing evidence regarding the use of physiological metrics to measure physical fatigue 46 of construction workers in real-time. This review used systematic searches to identify relevant studies and critically appraised the application of physiological metrics in 47 measuring physical fatigue of construction workers. First, it summarized the application 48 of various physiological metrics for real-time measurement of physical fatigue in 49 construction workers. Second, various wearable sensing technologies for measuring 50 physiological metrics were identified. Third, this review discussed the potential 51 52 challenges for applying physiological metrics to measure physical fatigue. Finally, future research directions to advance the development and adoption of various 53 physiological metrics to monitor and mitigate physical fatigue in construction workers 54 55 were discussed.

56

57 Introduction

58	Fatigue can be defined as "a reduction in physical and/or mental capability as the result
59	of physical, mental, or emotional exertion which may impair nearly all physical abilities
60	including: strength; speed; reaction time; coordination; decision making; or balance"
61	(International Maritime Organization, 2001). While some authors suggested that fatigue
62	is unidimensional in nature (Michielsen et al., 2004), others described it as a
63	combination of physical and mental fatigue (Grandjean, 1979). Physical fatigue
64	occurred after prolonged physical workloads can reduce an individual's capacity to
65	perform physical work efficiently (Gawron et al., 2001). Similarly, mental fatigue
66	occurs after prolonged mental workloads and may lead to reduced behavioral and
67	cognitive performance (Boksem et al., 2005; Boksem and Tops, 2008). While mental
68	fatigue is known to be associated with impaired physical performance (Marcora et al.,
69	2009), the intensity of physical activity has differential effects on mental fatigue.
70	Specifically, light physical activities may improve cognitive function, whereas heavy
71	physical activities may impair cognitive performance (Davey, 1973); this indicates a
72	complex relationship between physical and mental fatigue. Additionally, mental fatigue
73	is more relevant to industries that require workers to be mentally active and alert, such
74	as long-distance driving (Tan et al., 2013), airport luggage screening (Basner and
75	Rubinstein, 2011), or nurses working long shifts (Geiger-Brown et al., 2012). However,

76	since most construction workers (such as manual laborers) may not require a high level
77	of mental alertness (Aryal et al., 2017), the current review focused on the discussion of
78	various potential real-time monitoring of physical fatigue in construction workers.
79	Physical fatigue is widely prevalent among construction workers given their job
80	nature, which often involves outdoor work in a harsh environment, manual labor, and
81	physical intensive repetitive tasks. Adverse effects of physical fatigue on health and
82	safety of construction workers have been well documented in the literature (Swaen et
83	al., 2003; Wu et al., 2017; Umer et al., 2018a). For example, prolonged physical fatigue
84	may lower immunity and causes chronic fatigue syndrome (Afari and Buchwald, 2003;
85	Evengard et al., 2008). Similarly, statistics indicated that 33% of all work-related
86	musculoskeletal injuries and disorders in the US construction industry were attributed
87	to fatigue and overexertion (BLS, 2016). Studies in the oil and gas construction industry
88	(Chan, 2011), as well as the building construction industry (Wong et al., 2004; Adane
89	et al., 2013) have also found physical fatigue as a major cause of work-related accidents.
90	As such, it is of paramount importance to detect the presence of physical fatigue in
91	construction workers in the field so that timely interventions (e.g., breaks) can be
92	introduced (Umer et al., 2017a).

93

Early detection and real-time monitoring of physical fatigue play vital roles in the

94	construction industry, especially when the industry is facing severe labor challenges in
95	many parts of the world such as high labor wages, manpower shortages, and an ageing
96	workforce (Yu et al., 2019). A previous review has reported that approximately 44%
97	and 12% of the workforce in the Hong Kong construction industry were older than 50
98	and 60 years, respectively (Ng and Chan, 2015). Older construction workers are more
99	prone to develop physical fatigue than their younger counterparts due to the ageing-
100	related reduction in muscle strength and physical work capacity (Faulkner et al., 2007;
101	Kenny et al., 2008; Umer et al., 2018b). Additionally, many developed countries/cities
102	such as the United Kingdom, Singapore, Hong Kong, and Australia are facing
103	manpower shortages in the construction industry because of ageing workers and the
104	reluctance of younger people in joining the construction workforce (Ducanes and
105	Abella, 2008; Sing et al., 2012). For example, the Construction Industry Council of
106	Hong Kong has predicted a significant shortfall of skilled construction workers during
107	2017 to 2021 (Construction industry council, 2016). To overcome these distressing
108	challenges in the construction industry, it is essential to effectively monitor and manage
109	physical fatigue in construction workers to ensure a more sustainable and productive
110	workforce for the industry in the future.

111

There are many ways to measure physical fatigue in construction workers. They

- 112 can be classified into subjective measurements and objective measurements. These
- 113 methods have pros and cons.

114 Traditional Subjective Physical Fatigue Assessments

In early 90s, various subjective questionnaires were developed to quantify physical 115 fatigue in the general population (Lee et al., 1991; Chalder et al., 1993). Later, many 116 constructions-related studies have developed various subjective questionnaires to 117 measure workload or physical fatigue in construction workers (Chan et al., 2012; Fang 118 119 et al., 2015; Mitropoulos and Memarian, 2013; Yi et al., 2016; Zhang et al., 2015). 120 However, since no standardized physical fatigue assessment scale has been developed, different studies used different scales to assess physical fatigue (Zhang et al., 2015), 121 preventing comparisons of findings across studies. Although the cost of using 122 subjective questionnaires is low, it is inconvenient/infeasible to administer 123 questionnaires on construction sites. This method is also subject to recall bias. 124 125 Importantly, these questionnaires cannot assess real-time physical fatigue with minimal interference to ongoing construction activities. 126

127 Real-Time Approaches to Assess Physical Fatigue

128 To overcome these limitations, some researchers have attempted to use various129 physiological metrics such as heart rate (HR), heart rate variability (HRV), skin

130	temperature, electromyography (EMG), and jerk metrics to monitor real-time fatigue
131	during construction-related activities (Abdelhamid and Everett, 2002; Cifrek et al.,
132	2009; Chan et al., 2012; Gatti et al., 2014; Wong et al., 2014; Yi et al., 2016; Aryal et
133	al., 2017; Umer et al., 2017b; Ueno et al., 2018; Zhang et al., 2018, 2019; Anwer et al.,
134	2020). For example, Yi et al. (2016) developed an automatic assessment and early
135	fatigue warning system for construction workers based on: (a) Wet Bulb Globe
136	Temperature measurements on construction sites; (b) work duration and activities; (c)
137	personal and demographic characteristics of workers (i.e., age, weight, height, smoking,
138	and alcohol drinking habit); and (d) real-time HR monitoring. They used an artificial
139	neural network (ANN) approach to identify heat strain/fatigue in construction workers.
140	Similarly, Aryal et al. (2017) developed a fatigue model using a machine learning
141	approach to detect and monitor physical fatigue in construction workers based on skin
142	temperature and HR. Since HR and skin temperature are considered as important
143	physiological metrics to assess physical strain during physical exercise (Cuddy et al.,
144	2013), multiple studies have used these metrics to monitor physical fatigue during
145	physically demanding construction activities (Abdelhamid and Everett, 2002; Chan et
146	al., 2012; Gatti et al., 2014; Ueno et al., 2018; Wong et al., 2014; Anwer et al., 2020).

147	Other physiological metrics, such as EMG activity of muscle and jerk (the time
148	derivative of acceleration) during tasks, have also been used to assess workers' fatigue.
149	Continuous monitoring of muscle EMG activity (a proxy to measure muscle activity)
150	can reveal local muscle fatigue during work (Cifrek et al., 2009; Umer et al., 2017b).
151	Surface EMG has been used in prior laboratory studies to detect real-time muscle
152	fatigue (Karlsson et al., 2000; Felici et al., 2001; Clancy et al., 2002; Antwi-Afari et al.,
153	2017, 2018). Likewise, Zhang et al. (2018) used inertial measurement unit (IMU)
154	sensors to measure jerk to indirectly detect physical fatigue during a repetitive
155	bricklaying task. Since physical fatigue adversely affects movement control and
156	movement quality, workers with fatigue demonstrate increased jerk values (Zhang et
157	al., 2019).
158	Although the assessment of these physiological metrics may help detect real-time
159	physical fatigue in construction workers (Wang et al., 2015; Awolusi et al., 2018; Ahn

160 et al., 2019), no state-of-the-art review has summarized various physiological metrics

161 in measuring physical fatigue in these workers. Therefore, the current state-of-the-art

162 review aimed to: (1) summarize various physiological metrics that have the potential to 163 measure real-time physical fatigue in construction workers; (2) summarize 164 commercially available wearable sensing technologies for measuring relevant

- 165 physiological metrics; (3) discuss potential challenges for using physiological metrics
- to measure physical fatigue in real-time; and (4) provide future research directions to
- 167 advance the development and use of various physiological metrics to better monitor
- and mitigate physical fatigue among construction workers.

169 Research Methods

- 170 The research method section is divided into three subsections namely: literature
- 171 search, selection criteria, and data extraction.

172 Literature Search

173 This review used a systematic approach to search relevant articles, and critically

appraised the applications and features of different wearable sensing technologies, as

175 well as summarized challenges of using physiological metrics to measure physical

176 fatigue in construction workers. Five electronic databases (i.e., PubMed, Medline,

- 177 CINAHL, EMBASE, and Web of Science) were searched from their inception to July
- 178 25, 2020. The first four databases contain many fatigue or ergonomic-related
- 179 publications, while the Web of Science is a multidisciplinary database that contains
- 180 construction-related journals (Gusenbauer and Haddaway, 2020). For instance, the web
- 181 of science covers more than 34,000 journals and over 155 million of records. Only
- 182 English language publications were retrieved. The major keywords (including fatigue,

183	physiological measures, heart rate, heart rate variability, skin temperature,
184	electromyographic activity, jerk metric, and construction workers) as well as their
185	related derivatives were used for the search. Table 1 details the search strategies used
186	in this review.

187 Selection Criteria

188 Relevant articles were included for review based on the criteria: (1) population:

189 construction workers; (2) outcome variables: physiological measures (e.g., heart rate,

190 heart rate variability, skin temperature, EMG activity, and jerk metrics) and physical

191 fatigue; and (3) types of study: observational and experimental studies. Studies were

192 excluded if outcomes related to physical fatigue or physiological measures were not

- 193 reported. Additionally, case reports, newsletters, theses, commentaries, conference
- 194 proceedings, and grey literature were excluded.

195 Data Extraction

196 Two reviewers (SA and MA) completed the screening of titles and abstracts according

- 197 to the selection criteria. Relevant full-text articles were then retrieved and reviewed
- 198 by the two independent reviewers. Any disputes between the two reviewers were then
- 199 resolved by a third reviewer (AW). Relevant data were extracted from the included
- 200 studies: authors/year, country, population, study design, sample size, type of

- 201 physiological measures, physical fatigue protocol, instrumentation used, results, and
- 202 conclusions.

203 **Results**

The results section is divided into two subsections namely: (1) characteristics of the

205 included studies; and (2) analysis of physiological metrics to measure real-time physical

- 206 fatigue in construction workers. The first subsection delineates the characteristics of the
- 207 included studies. The second subsection details the analysis of physiological metrics

208 under four sub-subsections (e.g., cardio-vascular metrics, thermoregulatory metrics,

EMG metrics, and jerk metrics).

210 Characteristics of the included studies

211 Of the 324 identified studies, 160 duplicates were removed (Fig 1). Twenty-three

studies involving 1,015 participants were included in this review. The characteristics of

the included studies (including the location where each study was conducted, types of

214 studies (e.g., laboratories or field studies), participants' demographics, types of

215 physiological metrics (e.g., HR, HRV, skin temperature, EMG, Jerk metric), and types

- of subjective and objectives tools used for validation) are shown in Table 2. Specifically,
- the included studies were conducted in nine regions, including Canada, China, Czech
- 218 Republic, Hong Kong, India, Latvia, Taiwan, United Arab Emirates, and the USA.

219	Thirteen field studies and ten laboratory studies (task simulation) were included. The
220	mean age of participants ranged from 26.4 to 45 years. Two included studies only
221	reported the age ranges of their participants (between 20 and 24 years old) (McDonald
222	et al., 2016; Calvin et al., 2016). Most of the included studies used HR metric (19
223	studies), five study used skin temperature, four studies used EMG metric, and only one
224	study used jerk metric to measure physical fatigue (Figure 2). Physical fatigue was
225	verified by the subjective feedback of the participants. In particular, seven and three
226	included studies used the rating of perceived exertion (RPE) scale (Borg 6-20 scale)
227	(Roja et al., 2006; Li et al., 2009; McDonald et al., 2016; Aryal et al., 2017; Yin et al.,
228	2019; Umer et al., 2020; Anwer et al., 2020) and Borg CR-10 scale (Chan et al., 2012;
229	Wong et al., 2014; Calvin et al., 2016) to report self-perceived physical fatigue,
230	respectively. Seven included studies used researcher-designed, self-reported
231	questionnaires to quantify physical fatigue (Abdelhamid and Everett, 1999, 2002; Hsu
232	et al., 2008; Chang et al., 2009; Mehta et al., 2017; Lee et al., 2017; Tsai, 2017), while
233	six included studies simply asked the participants for the presence of fatigue (Anton et
234	al., 2005; Bates and Schneider, 2008; Maiti, 2008; Das, 2014; Jankovský et al., 2018;
235	Zhang et al., 2019).

236	Heart rate, HRV, skin temperature, surface EMG, and jerk metrics were used as a
237	proxy to objectively measure physical fatigue (Fig 2). Ten included studies used various
238	chest band model devices to monitor HR (Abdelhamid and Everett, 1999, 2002; Anton
239	et al., 2005; Roja et al., 2006; Bates and Schneider, 2008; Maiti, 2008; Chang et al.,
240	2009; Li et al., 2009; Chan et al., 2012; Wong et al., 2014). One study manually
241	calculated HR using radial or carotid pulses (Das, 2014), while seven studies used
242	different wearable devices to measure HR (Hsu et al., 2008; Aryal et al., 2017; Mehta
243	et al., 2017; Lee et al., 2017; Jankovský et al., 2018; Yin et al., 2019; Umer et al., 2020;
244	Anwer et al., 2020). Two studies used photo plethysmography-based wearable sensors
245	to measure heart rate variability (Lee et al., 2017; Tsai, 2017). To measure the skin
246	temperature, infrared temperature sensors (Chan et al., 2012; Aryal et al., 2017),
247	wearable sensors (Mehta et al., 2017; Umer et al., 2020), and tympanic thermometers
248	were commonly used (Bates and Schneider, 2008). Similarly, different models of
249	surface EMG devices were used to measure the root mean square amplitude and median
250	frequency of EMG signals in the included studies to assess muscle fatigue during
251	construction tasks (Anton et al., 2005; McDonald et al., 2016; Calvin et al., 2016; Yin
252	et al., 2019). Additionally, wearable IMU-based motion capture systems were used to
253	measure the jerk metric in one study (Zhang et al., 2019).

254 Analysis of physiological metrics to measure real-time physical fatigue in

255 construction workers

256 Cardio-vascular metrics

Heart rate is the most commonly used physiological measure to monitor physical 257 exertion in construction workers (Abdelhamid and Everett 2002; Chan et al. 2012; Gatti 258 et al. 2014; Wong et al. 2014; Ueno et al. 2018; Anwer et al., 2020). Cardiovascular 259 responses to physical exertion depend on multiple factors, including the intensity, 260 261 duration, and frequency of physical exertion, as well as the working environment (Burton et al., 2004). During physical exertion, the cardiovascular load increases as 262 muscle contraction increases. The heart needs to pump more blood around the body 263 (Burton et al., 2004). The increased demand of blood flow to muscles requires an 264 increased cardiac output. Since the heart cannot increase its stroke volume 265 266 instantaneously, only heartbeat can be increased to improve blood transportation. 267 Therefore, average HR is a good indicator of physical stress and workload (Wickens et al., 2004; Zhu et al., 2017). In fact, 19 out of 23 included studies in the current review 268 269 used HR as a proxy to measure physiological demands during construction tasks. 270 Lifting and lowering from floor-to-floor resulted in a higher HR as compared to other 271 heights of lifting and lowering (Li et al., 2009). Likewise, Li et al. (2009) reported a

272	higher HR for a lifting task performed twice a minute as compared to once a minute.
273	Alferdaws and Ramadan (2020) also found that the HR during high frequency lifting
274	was significantly higher than that during low frequency lifts. In fact, previous studies
275	have shown a positive relationship between HR and lifting frequency (Hafez and Ayoub,
276	1991; Chen et al., 1992; Al-Ashaik et al., 2015; Ghaleb et al., 2019). The work-related
277	increases in HR would decrease as the workload decreases (Jankovský et al., 2018).
278	More recently, Anwer et al. (2020) reported a significantly higher HR after a simulated
279	fatigue task as compared to baseline HR scores. Additionally, they reported a strong
280	correlation between HR and the corresponding subjective fatigue scores as measured
281	by the Borg scale (Anwer et al., 2020). Since HR has been found to be positively related
282	to subjective fatigue score among high-elevation construction workers (Chang et al.,
283	2009), HR can be used as a surrogate to measure physical fatigue.
284	While aforementioned studies attempted to directly correlate HR with physical
285	fatigue, some studies tried to categorize HR values at different fatigue levels. Astrand
286	and Rodahl (1986) classified the severity of physical workload based on HR responses
287	(e.g., light work, HR – up to 90 beats/min; moderate work, HR – 90 to 110 beats/min;
288	heavy work, HR – 110 to 130 beats/min; very heavy work, HR – 130 to 150 beats/min;

289 extremely heavy work, HR – 150 to 170 beats/min). Similarly, Adi and Ratnawinanda

290	(2017) classified fatigue levels according to the percentage cardiovascular load (defined
291	as CVL (%) = $(HR_{work}-HR_{rest}) / (HR_{max}-HR_{rest}) \times 100$ and gave recommendation to
292	workers based on their CVL values. Notably, they classified workers with CVL values
293	less than 30% as no fatigue, while workers with CVL values between 30 and 60%, were
294	recommended to have rest-breaks. For workers with CVL values between 60 and 80%
295	and between 80 and 100%, they are supposed to have a short period of work, and special
296	treatment, respectively. For those with CVL values greater than 100%, they should
297	completely stop working.
298	Recently, research showed that combining HR with other physiological measures
299	could improve the prediction of fatigue. For example, Umer et al. (2020) predicted 95%
300	of physical fatigue levels using a combination of HR, thermoregulatory, and respiratory
301	metrics in university students during a simulated construction task. However, the
302	accuracy dropped to 57% if only HR data was used to predict fatigue. Similarly, Aryal
303	et al. (2017) reported a 72% prediction accuracy in estimating physical fatigue using
304	combined findings of HR and skin temperature; however, the accuracy dropped to 59%
305	if only HR data was used. These results highlight the benefit of using combined metrics
306	to predict physical fatigue in individuals.

307	Despite the usefulness of HR for fatigue monitoring, multiple factors (e.g.,
308	physical demands, stress and anxiety) can increase HR (Abdelhamid and Everett, 2002;
309	Chan et al., 2012; Gatti et al., 2014). HR can also be influenced by changes in body
310	posture (e.g., sitting to standing) and muscle contraction forces (Astrand and Rodahl,
311	1986). Therefore, these factors should be considered when HR is intended to be used
312	for fatigue monitoring.
313	In addition to HR, HRV is a metric of beat-to-beat variation of HR and is found to
314	be a strong marker of cardiac health (Acharya et al. 2004). The measurement of HRV
315	may be an important metric to measure physical fatigue (Achten and Jeukendrup, 2003;
316	Makivic et al., 2013) because a diminished high frequency component of HRV value
317	may indicate heavy physical loads or fatigue in construction workers (Tsai, 2017). A
318	study reported a significant association between workplace stress (physical and mental)
319	and reduced HRV in sedentary and public sector workers (Tonello et al., 2014).
320	Previous construction research has also suggested to monitor both HR and HRV to
321	estimate physical strain in roofers (Lee, 2018; Lee et al., 2017). Nevertheless, previous
322	studies have not directly analyzed the impacts of physical fatigue on HRV parameters.
323	Therefore, future studies should clarify this relationship to determine whether HRV can
324	be used to improve the monitoring of fatigue development during construction activities.

325 Thermoregulatory metrics

Thermoregulatory measures have also been found to be strongly related to fatigue 326 development during cycling (González-Alonso et al., 1999) and construction tasks 327 (Aryal et al., 2017). Infrared temperature sensors are commonly used to monitor skin 328 temperature and related thermoregulatory changes during fatigue development. Skin 329 temperature is affected by underlying muscular activity, cutaneous blood flow, and 330 sweating patterns at a certain body parts (i.e., cheek, ear, forehead, and temple) 331 332 (Formenti et al., 2017). During physical exercise, the core body temperature increases, and the body attempts to maintain the core body temperature within a normal 333 physiological limit through thermoregulation. In particular, the skin plays its role by 334 assisting heat transfer from the core body to the atmosphere (Kenney and Johnson, 335 1992). Five included studies in the current review used skin temperature as a proxy to 336 assess physical fatigue at workplaces among construction workers in different trades 337 338 including rebar workers, oil and gas industry workers, and manual material handling workers (Chan et al., 2012; Mehta et al., 2017; Aryal et al., 2017; Umer et al., 2020; 339 Anwer et al., 2020). Anwer et al. (2020) reported a significantly increased local skin 340 temperature after 30 minutes of simulated construction task. Similarly, Aryal et al. 341 342 (2012) reported an increased skin temperature during construction activities. Chan et al.

343 (2012) reported a rapid increase in the participants' aural temperature in the first 35 minutes of rebar work followed by subsequent slight drop in the core temperature 344 before rising again. These studies show that analyzing the pattern of thermoregulatory 345 changes in perspiration and/or temperature of specific body parts (i.e., cheek, ear, 346 forehead, and temple) have the potential to detect fatigue development. 347 348 **EMG** metrics Physical fatigue of a local muscle can be detected by analyzing changes in the median 349 350 frequency or root mean square amplitude of surface EMG signals (Enoka and Duchateau, 2008; Powell and Copping, 2016). Surface EMG has been extensively used 351 to detect muscle fatigue given its noninvasiveness and easy application (Cifrek et al., 352 2009). By putting two bipolar surface electrodes on a target muscle, the corresponding 353 EMG signals can be measured to estimate the muscle activity. A review highlights that 354 355 many surface EMG indices (e.g., root mean square of EMG signals, median, and mean 356 power frequencies) can be used to assess muscle fatigue (Cifrek et al., 2009). Specifically, the root mean square amplitude of surface EMG signals in fatigued 357 muscles is significantly higher than that of non-fatigued muscles because fatigue 358 359 muscles need to activate more muscle fibers to sustain the required force (Dimitrov et 360 al. 2008). Conversely, during muscle contraction, the median frequency and mean

361	power frequency of EMG signals in fatigued muscles are significantly lower than that
362	of non-fatigued muscles (Dingwell et al., 2011; Tenan et al., 2011; Wang et al., 2015).
363	Previous research has suggested that continuous monitoring of muscle fatigue is
364	feasible by measuring surface EMG activities of the target muscle during various tasks
365	(Cifrek et al., 2009). Four included studies in the current review assessed muscle fatigue
366	using surface EMG metrics (e.g., median frequency and root mean square amplitude)
367	during repetitive tasks among construction workers (e.g., mason) and asymptomatic
368	university students (Anton et al., 2005; McDonald et al., 2016; Calvin et al., 2016; Yin
369	et al., 2019). McDonald et al. (2016) examined the surface EMG activity of shoulder
370	muscles during a simulated upper limb repetitive task. They found statistically
371	significant decreases in median frequency and increased root mean square amplitude of
372	EMG activity immediately following task-related muscle fatigue. Another study
373	revealed significant increase in the average EMG amplitude of fatigued back muscles
374	after a repetitive lifting task (Yin et al., 2019). Similarly, Calvin et al. (2016) detected
375	signs of muscle fatigue (i.e., increased EMG amplitude and decreased median
376	frequency of EMG signals) in the affected shoulder muscles following simulated
377	repetitive work performed at a workstation. The role of EMG in measuring muscle
378	fatigue was further substantiated by Anton et al. (2005). They reported surface EMG

amplitudes of various muscles (i.e., lumbar erector spinae, upper trapezius, and forearm
flexors and extensors) in bricklayers during the task of laying lightweight concrete
blocks (less fatiguing task) was significantly smaller than that during laying standard
weight blocks.

383 Jerk metric

384 Recent advancement in the wearable sensing technology has provided an opportunity

for assessing field-based real-time fatigue (Zhang et al., 2019). Specifically, a typical

386 wearable IMU-based motion capture system, which integrates magnetometers,

- 387 accelerometers, and gyroscopes to detect velocity, acceleration, and body orientation,
- is a noninvasive, wireless, and cost-effective technology for measuring body motion
- during construction tasks (Miller et al., 2004; Yan et al., 2017; Antwi-Afari et al., 2018;

390 Umer et al., 2018b; Yu et al. 2019). Such technology samples kinematic data at a high

- 391 frequency, enabling the assessments of jerk metrics (the time derivative of acceleration)
- 392 of the target body parts. Since fatigue may lead to poor motion control and movement
- 393 quality, increased jerk values during work may hypothetically indicate physical fatigue

394 (Zhang et al., 2019). Jerk metric has been used in clinical research to measure motor

- 395 control (Zhang et al., 2019). In particular, jerk has been used to: (a) differentiate
- 396 pathological and non-pathological movements (Hogan and Sternad, 2009;

397	Balasubramanian et al., 2015); (b) assess motor learning and recovery
398	(Balasubramanian et al., 2011); (c) identify impaired motions (Lapinski, 2013); and (d)
399	assess performance output (Nelson, 1983; Seifert et al., 2014).
400	Multiple studies have evaluated the feasibility of using the jerk metric to detect and
401	monitor fatigue among healthy adults. Van Dieen et al. (1996) used an optoelectronic
402	system to evaluate the effect of repetitive lifting on joint coordination, loading, and jerk.
403	They revealed that only jerk metric in the lower back and lower extremity joints
404	significantly increased following repetitive lifting. This indicates that jerk metric is
405	sensitive to detect changes in post-fatigue movement patterns, which alters the
406	acceleration, torque and position of body parts. Zhang et al. (2013) used IMUs and
407	machine learning approach to classify normal and post-fatigue walking after a squat
408	exercise. They found that increased acceleration and jerk metric values of lower limbs
409	were associated with the characteristics of post-fatigue gait. Additionally, Maman et al.
410	(2017) used low-noise analogue accelerometers and generalized regression models to
411	detect physical fatigue during simulated manufacturing tasks. They found that features
412	associated with jerk and acceleration at the wrists and hips were better predictors of
413	physical fatigue than features associated with HR. However, only one experimental
414	study has evaluated the feasibility of using jerk metric to monitor physical fatigue

415	among masonry workers (Zhang et al., 2019). The jerk metrics of 11 body parts (i.e.,
416	upper arms, forearms, hands, pelvis, thighs, and legs) were measured by wearable IMU
417	sensors. The results showed that the values of jerk metric at the beginning of the task
418	were significantly smaller than the corresponding metrics during a repetitive
419	bricklaying task, indicating physical fatigue (Zhang et al., 2019). Although these results
420	support the idea that the jerk metric can be a potential physiological parameter to
421	measure physical fatigue, further studies that quantify the relationship between jerk
422	metric and physical fatigue are warranted.

423 Discussion

The discussion section is divided into two subsections namely: wearable sensing 424 technologies for monitoring physiological metrics, and challenges for the application 425 of physiological metrics to assess real-time physical fatigue in construction workers. 426 427 The first subsection discusses features of different wearable sensing technologies for monitoring physiological metrics. The second subsection includes four sub-subsections: 428 (1) limited validity of physiological metrics for physical fatigue assessments; (2) noise 429 and signal artifacts affecting wearable sensing technology in field measurements; (3) 430 unclear information regarding the cutoff value of each physiological metric for severe 431

432 physical fatigue; and (4) user acceptance, social and privacy issues in deploying

433 wearable sensing technology.

434 Wearable sensing technologies for monitoring physiological metrics

A wide range of wearable sensing technologies are available to monitor real-time 435 physiological metrics. However, to obtain a widespread user acceptance in the 436 construction industry, these wearable technologies should be minimally intrusive and 437 fulfil several specific criteria (Dinges and Mallis, 1998). First, the technology should 438 439 be valid to measure what it is supposed to measure. Second, the technology should provide reliable measurements over time. Third, the technology should have high 440 sensitivity and adequate specificity to detect a true positive case (e.g., physical fatigue) 441 and a true negative case (e.g., no fatigue). Finally, the technology should have the 442 generalization properties so that it can reliably measure the same outcome (e.g., 443 physical fatigue) in the target population. 444

While some included studies in the current review did not specify a particular construction trade (Abdelhamid and Everett, 2002; Aryal et al., 2017; Hsu et al., 2008; Maiti, 2008; Li et al., 2009), other included studies examined HR in different types of construction workers such as craft workers (Abdelhamid and Everett, 1999), masonry workers (Anton et al., 2005; Das, 2014), road maintenance workers (Roja et al., 2006),

467 straps include a long elastic band containing a small electrode pad that presses against

carpenters (Bates and Schneider, 2008), manual laborers, high elevation construction 450 workers (Chang et al., 2009), rebar workers (Chan et al., 2012; Wong et al., 2014), 451 roofers (Lee et al., 2017), and cabin field machine operators (Jankovsky et al., 2018). 452 Some studies also examined HR in healthy individuals during simulated construction 453 tasks such as repetitive works and manual material handling task (Anwer et al., 2020; 454 455 Umer et al., 2020; Yin et al., 2019). Mobile heart rate monitors are commonly used to monitor HR and HRV during 456 457 rest or physical activity. These monitors demonstrate very high validity in measuring HR (r = 0.95 to 0.98) (Goodie et al. 2000; Terbizan et al. 2002) and HRV (r = 0.75 to 458 0.99) (Nunan et al. 2008; Giles et al. 2016; Tsitoglou et al. 2018; Hernando et al. 2018) 459 in healthy individuals. These monitors can assess the functioning of cardiovascular and 460 autonomic systems during and after physical activity. They can be used to monitor real-461 time physical fatigue and the recovery from fatigue in workers who are involved in 462 463 physically demanding jobs in the construction industry. There are two types of HR monitors, namely chest straps and optical HR monitors (measuring 464 photoplethysmography (PPG)). Both types of HR monitors are low-cost, commercially 465 available devices to measure real-time HR and HRV during free-living activities. Chest 466

468	the skin and a transmitter. The strap is worn around the chest with the electrodes picking
469	up the electrical signals from the heart, which are then transmitted to a transmitter
470	attached in the strap that contains a microprocessor to record and analyze the heart rate.
471	The processed data is then transmitted to a smartphone, a fitness watch, or a computer
472	for real time display or offline analysis. However, this type of device may impede
473	physical activity and is prone to slipping off. Therefore, PPG devices have been
474	developed as an alternative to monitor HR by using light to measure blood flow. A
475	typical PPG device contains a photo detector and several light-emitting diodes of
476	different wavelengths (e.g., red, infrared, and green). The photodetector captures the
477	light refracted off blood flowing through a body part (e.g., wrist, forehead, or ears) to
478	estimate the HR (Allen, 2007). PPG devices are designed to non-invasively collect the
479	volumetric changes of blood flow using low sampling rates (e.g., 64 – 125 Hz) (Ahn et
480	al., 2019). A previous study compared the HRs measured by a PPG device and an
481	electrocardiography (ECG) system in different construction workers including
482	electrician, as well as masonry and dry wall workers (Hwang et al., 2016). They found
483	high validity of using a PPG device to measure HR ($r = 0.85$ to 0.98). Another study
484	also reported high validity of a PPG device (as compared to ECG-based device) in
485	measuring HRV in healthy individuals ($r = 0.83$ to 0.95) (Arberet et al., 2013). Since

486	PPG devices only use a single sensor and the location of sensor placement is very
487	convenient (e.g., wrist), they are suitable for HR monitoring. Various physiological
488	metrics (e.g., HR, HRV, skin temperature) can also be extracted from PPG signals to
489	assess physical fatigue in construction workers. However, since PPG sensors do not
490	measure cardiac activity directly, there is a delay in measuring cardiac activity using
491	PPG (Lu et al., 2009). Furthermore, PPG signals can be significantly affected by
492	multiple factors such as biological factors (blood content), sensing factors (sensor
493	geometry) and cardiovascular factors (e.g., arterial blood volume) (Lemay et al., 2014),
494	as well as motion artifacts (Mashhadi et al., 2015). Therefore, headband- or ear-type
495	PPG devices may be used to replace wristband-type PPG devices to monitor HR during
496	tasks that involve a lot of wrist movement. Researchers have also used noise-
497	cancellation algorithms based on HR data obtained from daily activities (e.g., running)
498	in a well-controlled laboratory to improve the accuracy of PPG-based HR monitoring
499	(Parak et al., 2014; Tamura et al., 2014; Zhang et al., 2015). Additionally, many PPG
500	devices have built-in data pre-processing algorithms to improve the accuracy of HR
501	monitoring during various intensive physical activities (Tamura et al., 2014). However,
502	further studies are warranted to examine the validity of using these methods to

503 continuously monitor cardiovascular functioning in construction workers whose tasks

⁵⁰⁴ may involve excessive motion artifacts and high physical demands.

505	Additionally, some assessment tools (e.g., Zephyr Bioharness TM and Equivital
506	EQ02 LifeMonitor) use several wearable sensors together to assess biomechanical (e.g.,
507	acceleration) and physiological (e.g., skin temperature, HR, HRV, and breathing rate)
508	data during work tasks. However, only a few studies have evaluated the reliability and
509	validity of using these technologies in construction workers. The Zephyr Bioharness TM
510	is the most popular wearable sensor originally designed to optimize the performance of
511	professional athletes by continuously monitoring several physiological data to track
512	functional movements and workload (Pantelopoulos and Bourbakis, 2009; Li et al.,
513	2016). Bioharness TM is moderately reliable in measuring skin temperature (ICC = 0.61)
514	(Johnstone et al. 2012b). Some studies reported excellent reliability of using this device
515	to measure HR (ICC = 0.92 to 0.98) (Kim et al. 2013; Dolezal et al. 2014; Rawstorn et
516	al. 2015; Nazari et al. 2017) and breathing rate (ICC = 0.90) (Hailstone and Kilding,
517	2011). Conversely, Johnstone et al. (2012a) found good to excellent validity of using
518	Bioharness TM to measure HR but the breathing rate data showed more variability during
519	a walk-jog-run test protocol in healthy individuals. Similarly, the test-retest reliability
520	of the device showed excellent reliability for HR monitoring (intraclass correlation

521	coefficient, ICC = 0.91), whereas the breathing rate data showed fair reliability (ICC =
522	0.46). The low reliability of Bioharness TM in measuring breathing rate may be attributed
523	to the higher variability in the breathing rate during high velocity activities (Johnstone
524	et al. 2012a). Lee et al. (2017) used Bioharness TM to measure HR and HRV in roofers
525	and found that HR and HRV data collected from roofers in a single day was not
526	sufficient to monitor the physical demands of these workers. They recommended using
527	the average HR in two days and average HRV in four days to better reflect the typical
528	workload of these workers at works. Collectively, Bioharness TM may have the potential
529	to monitor the real-time physiological status of construction workers but further
530	validation is needed before using it to modify workers' work intensity or to avoid
531	physical fatigue and fatigue related workplace accidents.
532	Likewise, the Equivital (EQ02) is marketed as a safe, wearable vest embedded
533	with textile-based electrodes to monitor real-time cardiorespiratory (e.g., HR, HRV,
534	breathing rate) and thermoregulatory (e.g., skin temperature) parameters. A previous
535	study compared the reliability and validity of using the EQ02 to measure HR, breathing
536	rate, and skin temperature during physical activities of different intensities (e.g., rest,

- 537 low- and moderate intensities) in healthy individuals with reference to respective
- 538 standard measurement devices (Liu et al. 2013). The EQ02 demonstrated excellent

539	reliability and validity in measuring HR (ICC = 0.99 ; r = 0.98), breathing rate (ICC =
540	0.96; $r = 0.97$), and skin temperature (ICC = 0.97; $r = 0.96$). Compared to the
541	measurements of standard devices, the EQ02 only showed small mean differences in
542	the HR (1.2 beats/minute), breathing rate (0.2 rate/minute), and skin temperature (0.59
543	$^\circ\!\mathrm{C}$) during all tasks. Similarly, the EQ02 found very small mean differences in two
544	repeatedly measured HRs (-0.8 beats/minute), breathing rates (-0.2 rate/minute), and
545	skin temperatures (0.25 $^\circ\!\mathrm{C}$), indicating good test-retest reliability of the device.
546	Additionally, Akintola et al. (2016) compared the EQ02 with a Holter device for
547	continuous monitoring of HR and HRV in healthy individuals at home. They
548	demonstrated that the HR and HRV data measured by the EQ02 were highly correlated
549	with those measured by the Holter device ($r = 0.99$ and 0.78, respectively) when the
550	component of motion artifacts was small (20% or lower artifacts). The relative mean
551	absolute difference in HR between the EQ02 and the Holter device was small (1.5%)
552	when the motion artifacts was $<20\%$. Interestingly, they found least active people
553	(based on the step counts taken during the study period) showed significantly lower
554	motion artifacts percentage (73.3% of the data had <20% artifacts) as compared to
555	moderately and highly active individuals (66.2% of the data had <20% artifacts). Since
556	the accuracy and precision of the EQ02 is highly affected by movement artifacts, the

⁵⁵⁷ EQ02 may be inappropriate for monitoring workers' physiological status during construction activities because they involve a lot of body movements. 558 Surface EMG is an easy, convenient, and reliable technology to assess local 559 muscle fatigue (Dedering et al., 2000; Koumantakis et al., 2001; Ali et al., 2001; Arnall 560 et al., 2002; Farina et al., 2003). The test-retest reliability of surface EMG in measuring 561 muscle fatigue ranged from 0.51 to 0.97 (intraclass correlation coefficients) (Dedering 562 et al. 2000; Koumantakis et al. 2001; Ali et al., 2001; Arnall et al. 2002). EMG sensors 563 564 comprise bipolar surface electrodes attached to specific muscle masses to capture the myoelectrical activity of target muscles. The EMG signals often produce two 565 standardized EMG metrics namely time-domain metrics (e.g., mean absolute value, 566 compression normalization, root-mean-square normalization) (Anton et al., 2001; Trask 567 et al., 2007, 2010) and frequency domain metrics (e.g., mean frequency, median 568 frequency, and power spectrum density) (Jebelli and Lee, 2019). Previous studies have 569 570 attached EMG sensors to workers' different body parts (neck, shoulders, forearm, back) during masonry tasks (Anton et al., 2005), lifting activities (Anton et al., 2005; 571 572 Nimbarte et al., 2010), or overhead activities (Anton et al., 2001; Jia et al., 2011) to measure muscle fatigue. Although surface EMG measurements appear to suit the non-573 574 invasive monitoring of muscle fatigue during construction tasks, surface electrodes

should be attached to the target muscle, which may interfere with construction workers'

575

576	work. Furthermore, EMG signals can be easily compromised by the quality of skin
577	preparation, sweating, ambient temperature, and movement artifacts. Therefore, its
578	application in the field is limited and needs further research/refinement.
579	An IMU-based motion capture system is a noninvasive, wireless, and effective
580	technology designed to measure body motion and jerk during movement. This system
581	comprises 17 IMU sensors, each includes a three-axis magnetometer, three-axis
582	accelerometer, and three-axis gyroscopes to detect velocity, acceleration, and body
583	orientation. They can provide a high-frequency sampling rate to assess a jerk metric.
584	Akin to surface EMG measurements, motion sensors need to be attached or put onto
585	the target body parts to measure body kinematics. However, commercially available
586	sensors are quite expensive, and the wearing of such sensors may interfere with
587	construction workers' performance. Therefore, lighter and more affordable sensors are
588	needed to assess jerk metrics and physical fatigue in the field. Additionally, the
589	reliability and validity of IMU for jerk measurement have not been reported. Future
590	studies should examine the reliability and validity of the jerk metrics in assessing
591	physical fatigue during certain construction tasks.

592 Challenges for the applications of physiological metrics for real-time physical

- 593 fatigue assessment during construction tasks
- 594 Although various physiological metrics (such as HR, HRV, skin temperature, EMG, and
- 595 jerk metrics) may be used to estimate physical fatigue during construction tasks, there
- are some challenges in using wearable sensing technologies to monitor physiological
- 597 metrics for the real-time physical fatigue assessments.

598 Limited validity of physiological metrics for physical fatigue assessments

599 While preliminary results of applying physiological metrics to assess physical fatigue

- are promising, only limited studies have directly examined the relationship between
- 601 changes in physiological metrics and physical fatigue in construction workers. To the
- 602 best of our knowledge, no study has evaluated the use of physiological sensors in
- 603 assessing fatigue in a large sample of construction workers over a prolonged period
- 604 (e.g., a few days or weeks). Furthermore, no study has validated the use of physiological
- 605 metrics against the gold standard physical fatigue assessment (i.e., blood lactate level).
- 606 That said, a few studies have suggested that the combined physiological metrics can
- 607 predict fatigue level with a higher accuracy as compared to a single metric. Additionally,
- 608 certain physiological metrics (e.g., HR, HRV, skin temperature) have the face validity
- to evaluate generalized physical fatigue, while others (e.g., EMG and jerk metrics) are

610 more suitable to assess localized muscle fatigue.

611 Noise and signal artifacts affecting wearable sensing technology in field

612 measurements

While physiological metrics are better than the traditional questionnaire approach to 613 monitor physical fatigue without impeding workers' ongoing activities, it is challenging 614 615 to apply wearable sensing technologies to monitor physiological metrics at construction sites. The accuracy and function of the wearable sensing technology in monitoring 616 617 physiological metrics can be influenced by multiple factors (Jebelli et al., 2018a; Ahn et al., 2019). Any undesirable signals or signals that obstruct the target signals are 618 known as signal artifacts (De Luca et al., 2010). There are two types of physiological 619 signal artifacts: intrinsic and extrinsic, and both may interfere with the target signals 620 (Ahn et al., 2019). While intrinsic signal artifacts are originated from the body, such as 621 respiration, pulse, skin, motion, muscles, and ocular artifacts, extrinsic signal artifacts 622 623 are usually generated from external sources such as environmental noise and workers' movements (Ahn et al., 2019), motion artifacts, device power-line interference, 624 625 electrode movement artifacts, and sensor deployment and placement (Jebelli et al., 2018a). Unlike collecting physiological metrics in a well-controlled laboratory setting 626 627 with minimal environmental noise, data collection of these metrics at construction sites

needs to face frequent workers' movements and the ever-changing construction 628 environment. Therefore, wearable sensing technology in construction sites should be 629 refined to improve the data collection of physiological metrics for physical fatigue 630 631 assessments. Since both extrinsic and intrinsic signal artifacts may conceal desirable signals, it 632 is recommended to remove or reduce those signal artifacts before signal processing 633 (Ahn et al., 2019). Many filtering methods have been developed to minimize these 634 635 signal artifacts (Iriarte et al., 2003; Manoilov, 2006; Ram et al., 2012; Daly et al., 2013). For instance, previous research used a wavelength shrinkage method to minimize the 636 mixed noise recorded from the wearable sensing device (Kang et al., 2017). Similarly, 637 Gibbs and Asada (2005) developed an active noise cancellation method to minimize 638 signal artifacts originated from body movement during data collection using a wearable 639 PPG sensing technology. However, these techniques may be inadequate to apply in 640 641 construction sites due to the significantly higher signal artifacts in the field. Accordingly, signal processing methods are suggested to eliminate both extrinsic 642 and intrinsic signal artifacts recorded from wearable sensors in construction sites 643 (Jebelli et al., 2018b). Jebelli et al. (2018b) used filtering methods (including band-pass 644 645 filter, low-pass filter, and notch filter) to reduce the signal artifacts obtained from

646	external sources (e.g., body movement, electrode movement artifacts, etc.). They also
647	used an independent component analysis method to identify and minimize internal
648	signal artifacts (e.g., vertical eye movement, eye blinking, and muscular movement)
649	during recording with PPG wristband-type sensing technology. Although the results of
650	these methods are promising, future studies should evaluate the quality and type of
651	signals obtained from wearable sensing technology under various conditions at the
652	construction sites so as to understand various forms or sources of artifacts, and to
653	remove and minimize these noises from the captured signals (Ahn et al., 2019).

654 Lack of information regarding the cutoff value of each physiological metric for

655 severe physical fatigue

Another major challenge of applying physiological metrics to assess physical fatigue 656 during construction tasks is the lack of information regarding the cutoff value of each 657 658 physiological metric for severe physical fatigue. While it is thought that people experience physical fatigue for a prolonged period may cause specific physical 659 symptoms and increases the risk of musculoskeletal disorders and work-related injuries, 660 little is known regarding the cutoff values for various physiological signals to indicate 661 extreme fatigue. This is one of the most important challenges when analyzing the 662 663 outcomes of physiological metrics obtained from the wearable sensing technology
664	because each individual has specific fatigue response when doing different tasks in
665	different environments. Therefore, it is important to determine the task-specific cutoff
666	value for each physiological metric value in individual, above which would indicate
667	severe unsafe fatigue.

- 668 User acceptance, social and privacy issues in deploying wearable sensing
- 669 technology

User acceptance in wearing these sensors in terms of comfort level, privacy issues, 670 671 expected effort for don and doff, usefulness, and willingness to use have become important considerations when applying and deploying wearable sensing technologies 672 at construction sites. A previous study indicated that only about 10% of construction 673 workers were using wearable sensing technology, although more than 90% of workers 674 used smartphones (Zack, 2016). Various models of technology acceptance, such as the 675 use of technology and unified theory of acceptance (Venkatesh et al., 2003), and the 676 677 technology acceptance model (Davis et al., 1989) have been proposed and examined in different fields. Based on these models, various practical models such as web-based 678 training (Park et al., 2012), project management information system (Lee and Yu, 2012), 679 building information modeling (Son et al., 2015; Zhang et al., 2013), and mobile 680 681 computing (Son et al., 2012) have been developed by construction researchers to assess

682 factors affecting the acceptance of technology by users. Future studies should adapt these models to evaluate the best approach to improve the acceptance of using wearable 683 sensors to measure physical fatigue in construction workers. 684 Another pragmatic issue that can affect the uptake of wearable technology for 685 fatigue monitoring in the construction field is data security. In order to protect the 686 health-related information collected from wearable sensors, all communication 687 between sensors and servers should be encrypted to prevent the loss of user's privacy 688 689 and data (Jovanov et al., 2005). Since wearable sensing technologies are susceptible to data breaching and security risk, robust security measures should be in place to protect 690 against cyberattacks that can destroy or steal personal data (Awolusi et al., 2018). In 691 short, the wearable sensing technology should be minimally invasive, and equipped 692 with the highest possible security and safety for construction industrial use (Cheng et 693 al., 2011). 694

695 Future research directions

696 While the included studies have shown that different physiological metrics (i.e., HR, 697 HRV, skin temperature, EMG activity, and jerk metrics) have the potential to objectively 698 detect physical fatigue during construction tasks, further research is warranted to 699 improve the application and development of wearable sensing technology to measure

700 physiological metrics for real-time physical fatigue monitoring in construction workers.

701 The following sections discuss various potential future research directions.

702 Reliability and validity of wearable sensing technologies for collecting physiological

703 *metrics in construction workers*

Previous studies only investigated the reliability and validity of using wearable sensing 704 technologies to monitor physiological metrics for physical fatigue assessments in a 705 706 small number of participants in laboratories. They failed to validate the fatigue findings 707 obtained from wearable sensing technologies with the gold standard method (blood lactate concentration). Future field research should compare physical fatigue results as 708 measured by wearable sensing technology with the corresponding blood lactate 709 concentration. Additionally, further research is warranted to quantify the associations 710 between changes in these physiological metrics and corresponding changes in fatigue 711 712 levels during various construction tasks. Since many of these physiological parameters 713 can be affected by multiple factors (e.g., surrounding temperature, weight, age), future research should derive relevant fatigue prediction models for each parameter after 714 considering different potential confounding variables. Specifically, different cutoff 715 716 values for each physiological metric should be determined to help distinguish different 717 physical fatigue levels. For example, the maximum acceptable value of each

718 physiological metric should be determined in order to ensure workers work safely without fatigue for each construction activity. Given inter-individual variations in 719 physiological responses to tasks, people may show different physiological metric values 720 for the same level of perceived exertion. For example, Umer et al. (2020) found that for 721 a perceived exertion level of 14 out of 20 (measured by Borg RPE 20-scale), 722 participants' heart rates ranged from 87 to 132 beats per minute. The authors 723 724 hypothesized that biochemical markers for fatigue (e.g., blood lactate levels) might be 725 very closely related to the threshold values of certain psychometric metrics although this hypothesis should be tested in future research. 726

727 Integration of two or more wearable sensing technologies

729

728 The applications of wearable sensing technologies in real construction environments

are often affected by noise and signal artifacts. While many filtering methods have been

730 proposed to minimize these signal artifacts, combining information from two or more

technologies would negate the impacts of signal noise, and improve the accuracy of

fatigue measurements. Fusion of sensors has already been practiced in medical research

to eliminate motion-related signal artifacts in physiological data recorded by wearable

- sensing technology (Ahn et al., 2019). Specifically, IMUs sensors were used to measure
- 735 physical movements to negate movement-related signal artifacts in physiological

736	sensor data. A previous study used IMU data to adjust for signal artifacts originated
737	from gait-related body movements in EEG analyses (Kline et al. 2015). The same
738	principle can be applied to wearable sensor technologies to eliminate movement
739	artifacts collected from physiological sensors. Future studies can determine the signal-
740	to-artifacts/noise ratio as well as artifacts/noise spectrums in different physiological
741	metrics during various construction tasks so as to refine the estimation of task-specific
742	physical fatigue.

743 Development of personalized wearable warning-based technologies for mitigating

744 workers' physical fatigue

Previous studies have suggested that the application of warning-based sensing 745 technologies can minimize the risk of fatal and nonfatal occupational accidents at 746 construction sites (Heng et al., 2016; Yi et al., 2016). Yi et al. (2016) designed a mobile 747 748 communication warning-based system using environmental sensors to warn workers at 749 risk of heat stress during hot and humid environments. Similar future studies should develop a personalized wearable warning-based technology to monitor real-time 750 fatigue levels using automatically collected physiological metrics. This technology may 751 also be used by construction site managers to monitor workers who are at risk of 752 753 excessive physical fatigue or recovering from physical fatigue at work.

754 Evaluation of user acceptance and privacy issues of using wearable sensing

755 technologies for collecting physiological metrics

756 User acceptance and privacy issues affect the adoption of wearable sensing technology for monitoring physical fatigue-related physiological metrics. Recently, Choi et al. 757 (2017) reported that privacy issues, usefulness, and social impact are the commonest 758 factors affecting construction workers' acceptance of smart vest and wristband based 759 760 wearable sensing technologies. Although this study provided some theoretical 761 frameworks regarding the acceptance of wearable sensing technology in the construction industry, the relationship between various features of wearable sensing 762 technology (e.g., design and function), context of use (e.g., monitoring) and impacts on 763 user acceptance remains unknown. Future studies should evaluate the best method to 764 promote usage of wearable sensing technology for fatigue monitoring in construction 765 766 workers. Specific scales (e.g., a visual analogue scale) can be developed to assess user 767 acceptance of using the wearble sensing technologies based on their comfort level, social and privacy issues, perceived efforts for don and doff, and perceived usefullness. 768 Conclusions 769

The current review summarized the state-of-the-art of physiological metrics for the realtime measurement of construction workers' physical fatigue. This review used
systematic search methods to solicit relevant data, and to critically appraise the

application of physiological metrics in measuring physical fatigue in construction 773 774 workers. Several physiological metrics have the potential for real-time measurement of physical fatigue in construction workers. While the HR metric is the most commonly 775 776 used physiological metric to measure fatigue during construction works, other physiological metrics (skin temperature, EMG, HRV, and jerk metrics) can also 777 evaluate fatigue. The current review highlights that using multiple physiological 778 779 metrics are more accurate than using a single metric in monitoring physical fatigue 780 during construction tasks. Various wearable sensing technologies have been developed to measure these physiological metrics, but many technical challenges (e.g., limited 781 782 validity, noise and signal artifacts, lack of cutoff value for fatigue, user acceptance, and 783 social and privacy issues) remain to be overcome before these physiological metrics 784 can be adopted to assess real-time physical fatigue. As such, it is important to compare 785 the fatigue findings measured by wearable sensing technologies with that by the gold 786 standard blood test to refine the fatigue prediction. Since multiple intrinsic and extrinsic artifacts may lower the accuracy of wearable sensing technologies in assessing real-787 time fatigue, it is paramount to improve the data processing approach in order to 788 minimize errors. Future studies should also quantify the signal-to-artifacts/noise ratio, 789 790 as well as artifacts/noise spectrums in different physiological metrics during various construction tasks so as to refine the estimation of task-specific physical fatigue. 791 792 Collectively, a better real-time detection of construction workers' physical fatigue can help design appropriate personalized work-rest schedules, or proper work task 793 794 adaptations to mitigate their health hazards and optimize their productivity and work 795 quality.

796

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803	
804	Declaration of interest: None
805	

- 806 Data Availability: All data, models, and codes generated or used during the study
- 807 appear in the submitted article.

808 Figure Legend

- Fig 1. Study selection process and results of the literature search
- 810 Fig 2. Number of citations for each physiological measure (HR, Heart rate; HRV,
- 811 Heart rate variability; ST, Skin temperature; EMG, Electromyography)

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Table 1:	Search	strategy
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Keywords (25-07-2020)	Web of	PubMed	Medline	CINAHL	EMBASE
	Science			Complete	
Fatigue OR Exertion OR	275,734	173800	167,660	49,576	586,726
Tiredness OR physical effort OR					
muscle fatigue OR Physical					
fatigue					
Heart rate OR heart rate variability	399,341	707351	449,290	75,300	1,293,271
OR thermoregulation OR skin					
temperature OR electrocardiogram					
OR respiration frequency OR					
breathing frequency OR core body					
temperature OR electromyography					
OR muscle activity OR Jerk OR					
physiological measures					
Construction workers OR	647,715	133672	136,655	39,324	143,199
Construction industry OR					
Construction trade OR					
Construction sector OR Industrial					
Construction OR Construction					
Combined	72	60	56	22	114
Total after duplication removed			164		

Table 2:	Characteristics	and fir	idings of	f included	l studies
			0		

Authors	Country	Study design	Sampl e size	Participants	Physical tasks	Physiologi cal metrics (Objective fatigue measures)	Subjective fatigue assessment	Instrumentation used	Results	Conclusions
Abdelhamid and Everett, 1999	USA	Cross- sectional study Laborator y study (task simulation)	N = 8 Age: Mean 30.7 ±5.39 years	Constructio n craft workers	Concrete slab placing and finishing work	HR (bpm)	Questionnair e	POLAR Vantage XL heart rate monitor (Polar Electro Oy, Kempele, Finland)	An increase in HR was followed by an increase in VO ₂ during works. Similarly, a decrease in HR was followed by decrease in VO ₂ during rest period.	Most of the workers experienced physical fatigue during tasks as reflected by increased HR.
Abdelhamid and Everett, 2002	USA	Cross- sectional study Field study	N = 100 Age: Avera ge	Constructio n workers (12 trades)	Multiple construct ion tasks	HR (bpm)	Questionnair e	POLAR Vantage XL heart rate monitor (Polar Electro Oy, Kempele,	Mean HR values indicated that about 45% of construction workers were	20 to 40% of craft workers routinely worked at a level exceed the thresholds of

		36.7					Finland)	performing	physiological
		years						heavy to	loads for manual
								extremely heavy	work as measured
								work. Peak HR	by HR. These
								values indicated	workers were
								that about 63%	vulnerable for
								of construction	physical fatigue.
								workers were	
								performing	
								heavy to	
								extremely heavy	
								work.	
Anton et al., USA	Cross-	N =	Apprentice-	Construc	HR (bpm)	None	Polar S720i heart	The mean	Laying of light-
2005	sectional	21	level,	tion of	Surface		rate monitors	maximum HR	weight concrete
	study		Masonry	concrete	EMG		Surface EMG	was 117 (SD	blocks caused
		Age:	workers	block	(Root		(EMG-67,	11.5) bpm for	lower EMG
	Laborator	Mean	Mean age =	walls	mean		Therapeutics	light-weight	amplitudes
	y study	33.5	33.5 Years		square		Unlimited, Iowa	concrete blocks	compared to
	(task	±10.4			amplitude)		City, IA, USA)	and 119 (SD	standard-weight
	simulation	years						12.3) bpm for	blocks. However,
)							standard-weight	there were no
								blocks (p =	significant

									0.58). A significant difference in the changes of EMG activity was noted while laying of light- weight concrete blocks and standard-weight blocks (p = 0.01).	differences in HR noted between laying the two types of blocks.
Roja et al., 2006	Latvia	Cross- sectional study Field study	N = 20 Age: Mean 35 ± 4 years	Road maintenanc e workers	sand layer construct ion cycle chipping layer construct ion cycle asphalt layer	HR (bpm)	Borg scale (6 – 20)	Polar S810 Heart Rate Monitor (Polar Electro Inc., Woodbury, NY, USA)	Fatigue in workers as indicated by increased HR during road construction and repairing works.	This study concluded that a complex ergonomic analysis comprising of HR monitoring is adequate to evaluate work fatigue during

					construct					these construction
Bates and Schneider, 2008	UAE	Longitudi nal observatio nal study Field study	N = 22 Age: not report ed	Carpenters steel fixers general laborers	construct ion of a large concrete water feature	HR (bpm) Aural temperatur e (degree centigrade)	None	Polar S720i heart rate monitors Tympanic thermometers	Changes in HR was statistically non-significant during 3 days of construction works. Aural temperature of the workers was remained unchanged during 3 days of construction works.	Since construction tasks did not cause any adverse physiological effects, workers did not have fatigue to show significant changes in HR or body temperature.
Hsu et al., 2008	Taiwan	Longitudi nal observatio nal study Field	N = 80 Age: Mean 39.3 ±	Constructio n workers	Construc tion of high-rise building	HR (bpm)	Research Committee on Industrial Fatigue scale	Wrist blood pressure meter (Terumo, Model ES-P2000, Japan)	Worker's HR increased by 9 to 14% after construction work.	High-rise building construction work is physically demanding. Workers are prone to develop fatigue

		study	12.02 years							as indicated by increased HR during construction tasks.
Maiti, 2008	India	Observatio nal study	N = 20	Constructio n workers	Multiple manual	HR (bpm)	None	Pacer heart rate monitor (Polar	Average working HR of	Higher workload as measured by
				•	tasks			Sport Tester TM,	workers were	HR in building
		Field	Age:					Polar Electro Oy,	124.1 bpm. The	construction
		study	28 –					Finland)	working HR	industry may
			32						was	cause unsafe
			years						significantly	working condition
									correlated with	for construction
									the resting time.	workers.
Chang et	Taiwan	Cross-	N =	High-	Construc	HR (bpm)	Questionnair	Polar Vantage NV	The baseline HR	The extent of
al., 2009		sectional	302	elevation	tion of		e	Heart rate	of the workers	fatigue varies
		study		construction	high-rise			monitor (Sark	were not	among different
		Field	Age:	workers	building			Production, MA)	associated with	occupations of
		study	Mean						the occupations	construction
			38.2						and the average	workers as
			± 8.9						HR in each	indicated by HR.
			years						occupation	

ranged between 73 and 77 bpm. The average changes in HR was 112.4 bpm for all workers. Li et al., Experimen Taiwan N = 8 Constructio Box HR (bpm) Borg scale (6 POLAR Vantage The average HR Both frequency 2009 handling XL heart rate was higher and height tal study n workers -20)Age: task monitor (Polar during tasks variables of Laborator Mean Electro Oy, performed at the construction tasks 25.3 Kempele, frequency of significantly y study ± 4.3 Finland) impact worker's twice per minute than that of once physiological years per minute response on (111.3 vs 97.0 whole body fatigue as bpm). indicated by HR (r=0.49) was associated with increased HR physical fatigue during box as measured by handling task. RPE. POLAR Vantage Chan et al., Hong Experimen N =Rebar fixing HR (bpm) Borg CR10 The resting HR Fatigue was

2012	Kong	tal study	19	workers	and	Temperatu	Scale	XL heart rate	was decreased	accompanied by
		Field			bending	re (degree		monitor (Polar	slightly at the	increased HR
		study	Age:		steel	centigrade		Electro Oy,	beginning and	during rebar
			Mean		reinforce)		Kempele,	remained stable.	work.
			45 ±		ment			Finland)	The HR	Additionally,
			8.3		bars			Infrared tympanic	increased	rapid increase of
			years					electronic	gradually at the	core temperature
								thermometer	time of rebar	was seen at the
								(Genius TM2,	work. The	beginning of
								COVIDIEN,	average HR of	fatigue and then
								USA)	the participants	temperature was
									increased by 40	reduced and
									bpm.	maintained at a
									Core	stable condition.
									temperature was	
									rapidly	
									increased at the	
									beginning of 35	
									minutes of rebar	
									works. After 35	
									minutes of rebar,	
									core temperature	
									of most	

									participants was	
									decreased and	
									remained stable.	
Das, 2014	India	Cross-	N =	Constructio	brick	HR (bpm)	None	Manual	The participants	Brick field
		sectional	220	n workers	field				HR rose to >	workers had
		study			works				100 bpm. The	severe
		Field	Age:						average HR of	physiological
		study	Mean						brick field	stress as indicated
			33.5						workers was	by increased HR.
			±6.2						148.6 bpm after	
			years						the construction	
									tasks.	
Wong et al.,	Hong	Experimen	N =	Rebar	Bar	HR (bpm)	Borg CR10	POLAR heart rate	Bar fixing task	HR metric can be
2014	Kong	tal study	39	workers	bending		Scale	monitor (Polar	induced	used to assess
			Age:		and bar			Electro Oy,	significantly	physical fatigue
		Field	Mean		fixing			Kempele,	higher HR	during rebar
		study	42.2		task			Finland)	(113.6 vs. 102.3	working.
			±10.9						bpm), than bar	
			years						bending task.	
McDonald	Canada	Cross-	N =	University	Simulate	Surface	Borg scale (6	Surface EMG	Surface EMG	Participants
et al., 2016		sectional	12	students	d	EMG	- 20)	(Trigno, Delsys	signals revealed	showed sign of
		study	Age:		repetitive	(Root		Inc., Natick, MA,	decrease median	muscle fatigue as

			20–24		work	mean		USA)	frequency and	indicated by
		Laborator	years			square			increase root	decrease median
		y study				amplitude			mean square	frequency and
		(task				and			amplitude	increase root
		simulation				median			following	mean square
)				frequency)			repetitive work.	amplitude signal
										of surface EMG
										during work.
Calvin et	Canada	Cross-	N =	University	Simulate	Surface	Borg CR-10	Surface EMG	Signs of muscle	Although the
al., 2016		sectional	12	students	d	EMG	scale	(Trigno, Delsys	fatigue (i.e.	results of this
		study			repetitive	(Root		Inc., Natick, MA,	increased EMG	study identified
			Age:		work	mean		USA)	amplitude,	muscle fatigue
		Laborator	20–24			square			decreased EMG	due to repetitive
		y study	years			amplitude			frequency) in	works,
		(task				and			anterior deltoid	participants were
		simulation				median			muscle	able to complete
)				frequency)			following	post-fatigue tasks
									simulated	by adaptation of
									repetitive work	muscle
									(pulling,	recruitment.
									pushing, and	
									drilling works)	

									were noted in	
									the affected	
									muscles.	
Aryal et al.,	USA	Experimen	N =	Constructio	Simulate	HR (bpm)	Borg's RPE	Wrist band	An increase in	Physical fatigue
2017		tal study	12	n workers	d	Skin	scale (6 – 20)	(Garmin vivofit)	the HR during	can be identified
			Age:		material	temperatur		Non-contact	simulated	by assessing
		Laborator	Mean		handling	e (degree		infrared	material	physiological
		y study	43.8		task	centigrade		temperature	handling task,	measures
			±15.2)		sensors	and reduced HR	including HR and
			years					(MLX90614)	during rest time.	skin temperature.
									Skin	
									temperature	
									increased during	
									physical activity.	
Lee et al.,	USA	Reliability	N = 6	Constructio	Roofing	HR (bpm)	Questionnair	Zephyr	Significant	Participants
2017		study		n workers	activities	HRV	e	BioharnessTM	differences in	showed
			Age:			(milliseco		sensors	HR, HRV, and	significantly
		Field	Mean			nds)		(Medtrionic,	energy	increased HR,
		study	33.5			Energy		Dublin, Ireland)	expenditure	HRV, and energy
			±7.12			expenditur		ActiGraph GT9X	were noted	expenditure
			years			e		unit (ActiGraph,	during	during 5 days of
						(kcal/min)		LLC., Pensacola,	construction	roofing works.

								Florida)	activities.	
Mehta et	USA	Observatio	N =	Oil and gas	offshore	HR (bpm)	The Swedish	EQ02	Average HR	Physiological
al., 2017		nal study	10	extraction	shiftwor	Skin	Occupation	LifeMonitor,	increased for all	measures
				(OGE)	k	temperatur	Fatigue	Equivital™,	workers and	highlighted the
		Field	Age:	industry		e (degree	Inventory	Cambridge, UK	remained high at	negative effects of
		study	Mean	workers		centigrade	(SOFI)		the end of	shiftwork on HR
			31.3)			works.	responses.
			± 6.1							However, lack of
			years							correlation was
										noted between
										subjective fatigue
										perceptions and
										physiological
										responses.
Tsai, 2017	Taiwan	Experimen	N =	Constructio	Multiple	HRV	Perceived	Photo	Physiological	Assessment of
		tal study	20	n workers	construct	(milliseco	fatigue	Plethysmography-	status	HRV is a useful
		Field	Age:		ion tasks	nds)		based wearable	monitoring of	approach to
		study	25 - 32					device (Garmin,	workers using	evaluate real-time
			years					2016)	HRV identified	fatigue during
									more fatigue	construction
									risk than manual	tasks.
									inspection.	

Jankovský et al., 2018	Czech Republi c	Observatio nal study Field study	N = 5 Age: Mean 42.8 ±8.8 years	Cabin field machines operators	Operatin g field machine	HR (bpm)	None	Biofeedback 2000 x-pert device	The average working HR of the machine operators was 91 bpm, and their resting HR was 66 bpm. The average HR of the operators was 90 bpm at the beginning of the shift, while it was 86 bpm in the middle of the shift, and it was 100 bpm at the end of the shift	The elevated HR during operating filed machine depends on various factors including type of machine, part of shift (middle), and height and weight of operators.
									shift.	
Yin et al.,	China	Experimen	N =	Healthy	repetitive	HR (bpm)	Borg's RPE	Digital heart rate	The average	Increased HR and
2019		tal study	12	individuals	lifting	Surface	6–20 scale	monitor (PC-80D,	post-testing HR	EMG amplitude
		Laborator			task	EMG		China)	was higher than	of erector spinae
		y study	Age:			(Root		Surface EMG	that of pre-	muscle suggests

	Canada	Eunorimon	Mean 26.4 ± 5.1 years	Magangu	Driaklavi	mean square amplitude and median frequency)	None	(ME6000-8, Bittium Inc., Kuopio, Finland)	testing HR. Post-testing EMG amplitude of erector spinae muscle was higher than the pre-testing value.	physical fatigue during repetitive lifting task.
Zhang et al 2019	Canada	tal pilot	N = 32	workers	ng task	Jerk metric	None	A wearable IMU-	ierk metric	Jerk is an indicator of
, _ • • • •		study	Age:			(g/sec -		capture suit,	could be used to	physical fatigue
		2	Mean			time-		Noitom	differentiate	during a
		Laborator	26.7			derivative		Perception	fatigue and non-	bricklaying task.
		y study	± 3.1			of the		Neuron	fatigue states.	
			years			acceleratio				
						n				
						magnitude				
)				
Anwer et	Hong	Experimen	N =	Healthy	Simulate	HR (bpm)	Borg's RPE	EQ02	Mean HR was	The results of this
al., 2020	Kong	tal study	25	individuals	d manual	Skin	6–20 scale	LifeMonitor,	increased from	study suggest the
		Laborator	Age:		material	temperatur		Equivital™,	70.2 BPM at	use of HR and
		y study	31.8		handling	e (degree		Cambridge, UK	baseline to	skin temperature

 ± 1.8	task	centigrade	120.2 BPM after	to assess physical
years)	30 minutes of	fatigue during a
			simulated	simulated
			fatigue task.	construction task.
			Local skin	
			temperature was	
			increased from	
			31.5°C at	
			baseline to 34.9	
			°C after 30	
			minutes of	
			simulated	
			fatigue task.	
			There were	
			significant	
			correlations	
			found between	
			HR or skin	
			temperature and	
			the	
			corresponding	
			Borg scores at	
 			the end of	

									simulated	
Umer et al., 2020	Hong Kong	Experimen tal study Laborator y study	N = 10 Age: Mean 27.5 ±2.76 years	Healthy individuals	Simulate d manual material handling task	HR (bpm) Skin temperatur e (degree centigrade)	Borg's RPE scale (6 – 20)	EQ02 LifeMonitor, Equivital™, Cambridge, UK	Combined HR and skin temperature metrics can predict fatigue levels with a higher accuracy (95%). However, the accuracy dropped to 57% for individual metric for fatigue prediction	This study concluded the advantage of using multiple physiological metrics to measure physical fatigue in construction workers.

HR: Heart rate; bpm: beat-per-minute; HRV: Heart rate variability; SD; Standard deviation; EMG: Electromyography; RPE: Rating of perceived exertion; N: Number



Fig. 1. Study selection process and results of the literature search.



Fig. 2. Number of citations for each physiological measure (HR = heart rate, HRV =

heart-rate variability, ST= skin temperature, and EMG = electromyography)