Sleep, cardiometabolic health, and neurocognitive performance in esports players

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Author Declaration

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The present thesis, entitled: *"Sleep, cardiometabolic health and neurocognitive performance in esports players,"* was jointly conceptualized by the author and the author's primary supervisor, Dr. Dale Rae, together with co-supervisors Assoc. Prof. Laura Roden and Dr. Gosia Lipinska. Ethical clearance for research studies that involved human participants was granted by the University of Cape Town's Human Research and Ethics Committee. Accordingly, the author and Dr. Dale Rae jointly completed the applications for ethical approval.

The screening process for Chapter 2 of the thesis (*Sleep in habitual adult video gamers: a systematic review*) was jointly conducted by the author and collaborator, Ms. Dominique Rosslee. The author performed the formal analysis and preparation of the original draft before being reviewed and edited by the author's supervisors and co-authors, Dr. Dale Rae, Assoc. Prof. Laura Roden, Dr. Gosia Lipinska, Ms. Paula Pienaar and Ms. Dominique Rosslee. This chapter was published in *Frontiers in Neuroscience* (Kemp et al., 2021), and all co-authors agreed that the author may include the publication in this thesis.

Chapter 3 of the thesis (*Assessing the validity and reliability and determining cut-points of the Actiwatch 2 in measuring physical activity*) was conceptualized by the author's supervisors, Dr. Dale Rae, Assoc. Prof. Laura Roden and collaborator Prof. Tracy Kolbe-Alexander. In consultation with the author's supervisors, the author developed the methodology for this chapter. The author also acknowledges Assoc. Prof. Jacolene Kroff for her consultation regarding the operation and calibration of the cardiopulmonary gas analyzers. Beyond this, the author facilitated the recruitment of all participants and performed all procedural experimentation (including cardiopulmonary testing and actigraphy). Finally, the author performed the formal analysis and preparation of the original draft before being reviewed and edited by the author's supervisors and collaborators, Dr. Dale Rae, Prof. Tracy Kolbe-Alexander, Assoc. Prof. Laura Roden, Ms. Paula Pienaar, and Dr. Rob Henst. This chapter was published in *Physiological Measurement* (Kemp et al., 2020), and all co-authors agreed that the author may include the publication in this thesis.

The author facilitated the recruitment of participants for Chapter 4 (*Sleep, cardiometabolic health, and neurocognitive performance in esports players*) and Chapter 5 (*Diurnal patterns of light exposure and physical activity in esports players*) of the thesis. In consultation with the author's supervisor, the author developed the methodology for these chapters. The author also acknowledges Dr. Karine Scheuermaier for her consultation regarding white light exposure data analysis. The author performed all procedural experimentation and analyses, except for phlebotomy, which was jointly conducted by Dr. Dale Rae and the author, and blood marker analysis, which was outsourced to a third-party pathology service (Lancet, Cape Town, South Africa). The original drafts of each chapter were written solely by the author before being reviewed and edited by the author's supervisors and co-authors, Dr. Dale Rae, Assoc. Prof. Laura Roden, Dr. Gosia Lipinska, and Ms. Paula Pienaar. At the time of thesis submission, the manuscripts for these chapters were being prepared for submission for publication.

The ideas and perspectives formulated in Chapter 6 of this thesis were of the author's view. This chapter was reviewed and edited by the author's supervisors, Dr. Dale Rae, Assoc. Prof. Laura Roden, Dr. Gosia Lipinska.

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X Signed by candidate

Chadley Kemp
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Signed by: trust_

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To God be all the glory.

About the Author

Chadley Kemp was born on 3rd October 1994, in Cape Town, South Africa. He graduated with a Bachelor of Science, double majoring in Human Physiology & Anatomy and Biochemistry from the University of Cape Town in 2016. Chadley completed a Bachelor of Medical Science (Honors) degree specializing in Exercise Science at the same institution in 2017. He developed an interest in sleep and circadian rhythms research and became a strong proponent of sleep and health during his tenure with his primary supervisor, Dr. Dale Rae. This interest would later prompt him to pursue further postgraduate research in this field. Recognizing the paucity of research in esports at the time and the apparent gap in the literature regarding the role of sleep as a factor of interest in cardiometabolic health and esports performance, he subsequently registered for a Master of Medical Science specializing in Physiology at the University of Cape Town in 2018. In early 2020, Chadley applied to upgrade his Master of Medical Science degree to a Doctor of Philosophy (Ph.D.). His application was subsequently approved by the Doctoral Degrees Board, at which time Chadley began synthesizing this thesis toward fulfilling his Ph.D. degree. Since 2016 and until the completion of this thesis in late 2023, Chadley Kemp has been actively involved in the commercial side of the international esports and gaming industry, which he described as one of his many passions; he was always an avid gamer at heart and still is to this day. His passion for video gaming and esports, coupled with his interest in sleep and circadian rhythms, would ultimately become significant factors compelling him to pursue his Ph.D. After completing his thesis, Chadley plans to move abroad to continue pursuing gaming and esports commercially.

"My unmatched perspicacity, coupled with my sheer indefatigability, makes me a feared opponent in any realm of human endeavor" – E.A.T III.

Table of Contents

Abbreviations

AUDIT-C	Alcohol Use Disorders Identification Test-Concise
BCST	Berg Card Sort Test
BIS	Bergen Insomnia Scale
BMI	Body Mass Index
COVID-19	Coronavirus Disease 2019
CPET	Cardiopulmonary Exercise Testing
CPM	Counts Per Minute
DAST	Drug Abuse Screening Test
DBP	Diastolic Blood Pressure
DSM	Diagnostic and Statistical Manual of Mental Disorders
DSPS	Delayed Phase Sleep Syndrome
EEG	Electroencephalography
ESL	Electronic Sports League
ESS	Epworth Sleepiness Scale
ET	Evening-type
FPS	First Person Shooter
GD	Gaming Disorder
HDL-C	High-Density Lipoprotein Cholesterol
HÖMEQ	Horne- Östberg Morningness-Eveningness Questionnaire
HREC	Human Research Ethics Committee
ICD	International Classification of Diseases
IGD	Internet Gaming Disorder
IOC	International Olympic Committee
ipRGC	Intrinsically Photosensitive Retinal Ganglion Cells
ISI	Insomnia Severity Index
MET(s)	Metabolic Equivalent(s)

MMORPG	Massively Multiplayer Online Role Play Game
MOBA	Multiplayer Online Battle Arena
MT	Morning-type
MVPA	Moderate-To-Vigorous Intensity Physical Activity
NCD	Non-Communicable Disease
NSF	National Sleep Foundation
NT	Neither-type
PANAS	Positive and Negative Affect Schedule
PHQ	Patient Health Questionnaire
PSG	Polysomnography
PSQI	Pittsburgh Sleep Quality Index
PVT	Psychomotor Vigilance Test
REM	Rapid Eye Movement
RMR	Resting Metabolic Rate
ROC	Receiver Operating Characteristic
SBP	Systolic Blood Pressure
SCN	Suprachiasmatic Nucleus
SE	Sleep Efficiency
SHI	Sleep Health Index
SOL	Sleep Onset Latency
TIB	Time-In-Bed
TST	Total Sleep Time
VGAQ	Video Game Addiction Questionnaire
WASO	Wake After Sleep Onset
WC	Waist Circumference
WESA	World Esports Association
WHO	World Health Organization

Abstract

Introduction

Esports players represent a growing and maturing population within the primary demographic of general video gamers, with a proclivity to engage with a high volume (i.e., dose, duration, and frequency) of video gaming activities. Accordingly, esports players are typically characterized by unique behaviors, including prolonged exposure to blue light from electronic screens, extended periods of sedentary behavior, irregular sleep patterns due to late-night matches or competitions, and high levels of stress, all of which may be undertaken to improve or maintain their competitive status. However, the concern is that these behaviors may, in turn, impact esports players' sleep, circadian rhythms, and physical and mental health over time.

Despite the growing popularity of esports among adults, few studies have investigated the relationships between sleep, cardiometabolic health, and neurocognitive performance in this population. Specifically, the vast majority of existing research on gaming and health has focused on children and adolescents, leaving a significant gap in our understanding regarding the potential health risks associated with regular high-volume gaming behaviors in adults. Relatedly, adult esports players might also be more vulnerable to the downstream effects of pathological (i.e., prolonged and excessive) gaming behaviors, given their implicit cardiometabolic disease risk susceptibility, which is attributable to aging but also unhealthy lifestyle behaviors and substance addictions like smoking and alcohol.

To address the gap in the literature, this thesis aims to investigate the associations between device-derived sleep patterns, white light exposure, cardiometabolic health status, and neurocognitive performance in adult esports players. In addition, the thesis will describe device-derived quantitative doses and 24-hour profile patterns of physical activity and white light exposure in these individuals. The work underlying this thesis is intended to be a stepping stone toward health regulation in gaming and esports, for which motives are to support individual decisions, governments, and policy makers through awareness and by providing evidence-based recommendations to adopt and maintain healthy gaming behaviors to ameliorate chronic health problems.

The purpose of this thesis was achieved through the following aims:

- To systematically review the evidence describing sleep in habitual adult gamers.

- To validate the Actiwatch 2 (AW2) as a tool for assessing sedentary behavior and physical activity by comparing its physical activity counts to both a reference physical activity monitor (Actigraph GT3X) and energy expenditure using indirect calorimetry; to determine the AW2-derived count cut-points, maximizing sensitivity and specificity, for sedentary, light-, moderate-, and vigorous-intensity physical activity using metabolic equivalent (MET) and count data, and Receiver Operating Characteristic (ROC) Curve analyses; and to assess the reliability of the AW2 to measure physical activity by comparing the physical activity counts across two independent assessment periods.
- To characterize and explore the associations between habitual sleep patterns, cardiometabolic disease risk factors, and neurocognitive performance in adult esports players.
- To examine the level and circadian rhythmicity of movement behavior and white light exposure in young adult esports players and non-gaming controls.

Methods

Chapter 2:

Systematic literature searches were conducted in three electronic databases (PubMed, Scopus, ISI Web of Science). Original peer-reviewed research studies examining or reporting on sleep in habitual adult gamers were considered for inclusion in the review.

Chapter 3:

In this validity and reliability study, twenty-eight males and twenty-two females completed a task battery comprising three sedentary tasks and six randomized physical activity tasks at varying intensities while wearing the AW2, a reference accelerometry device (Actigraph GT3X; GT3X), and a cardiopulmonary gas analyzer on two separate occasions. Validity was assessed using correlations (AW2 counts versus GT3X counts and metabolic equivalent (MET) values), reliability using Bland-Altman analyses, and cut-points were determined using receiver operating characteristic (ROC) area under the curve (AUC) analyses.

Chapter 4:

This cross-sectional experimental study collected clinical measures (anthropometry, blood pressure, and blood marker variables) and self-reported sleep (chronotype, sleep quality, daytime sleepiness) and video game addiction, and assessed cognitive performance (sustained attention, reaction time and accuracy, and executive function) using validated neurocognitive tests (Psychomotor Vigilance Test (PVT), Berg Card Sort Test (BCST), and N-Back Test) in 59 adult male participants (n=31 esports players; n=28 non-gaming controls). Continuous 24-hour sleep, physical activity patterns, and white light exposure were measured using a wrist-worn accelerometer for seven consecutive days. Descriptive data concerning participants' sleep patterns, video game habits, cardiometabolic health status, and cognitive performance were compared between the groups. Associations between independent behavioral variables (sleep parameters) and dependent variables (cardiometabolic disease risk factors and cognitive performance) were also assessed.

Chapter 5:

This cross-sectional experimental study was an extension of the previous study. Thirty-one esports players were compared to twenty-nine non-gaming controls from the general population to examine the dose and circadian pattern rhythmicity characteristics of movement behavior (sedentary behavior and physical activity at light, moderate, and vigorous physical activity intensities) and white light exposure. Continuous 24-hour sleep, physical activity patterns, and white light exposure were measured objectively in a free-living setting using a wrist-worn accelerometer for seven consecutive days. The proportion of waking time spent by participants in each group was compared at varying light levels (<10 lux to 1000 lux+) and physical activity intensity thresholds. The hourly-averaged free-living movement behavior and white light exposure according to clock time and with respect to each participant's daily sleep-wake times were also compared.

Results & Discussion

Chapter 2:

Twelve studies reporting on sleep in habitual adult gamers were included. The systematic review found that gamers with higher gaming addiction scores were more likely to have shorter, poorer quality sleep and greater daytime sleepiness and insomnia scores than gamers with lower gaming addiction scores and non-gamers. In particular, high-volume gamers were more likely to have shorter sleep duration and poorer sleep quality, with delayed sleep timing and an increased prevalence of insomnia compared to non-gamers. Despite limitations in the design of the studies in the qualitative synthesis, excessive gaming was found to be broadly associated with worsened sleep parameters.

Chapter 3:

The validation component of this study found that AW2 counts were positively correlated with GT3X counts (rho = 0.902, $p<0.001$) and METs (rho = 0.900, $p<0.001$). The reliability component of this study found that AW2-derived counts were comparable across independent assessment periods. The calibration component of this study found that sedentary (AUC = 0.99, cut-point: 256 counts per minute (CPM)) and vigorous activity (AUC = 0.95, cut-point: 720 CPM) were strongly characterized, and moderate activity (AUC = 0.66, cut-point: 418 CPM) was weakly characterized. The use of the AW2 in physical activity monitoring looks promising for sedentary behavior and moderate- and vigorous-intensity physical activity; however, further validation is needed.

Chapter 4:

A key finding in this study was that esports players had later sleep timing (sleep midpoint: 04:08 vs. 03:01, $p<0.001$) and a higher occurrence of evening chronotypes than controls (45.2% vs. 7.1%, $p=0.001$). In addition, esports players had shorter sleep onset latency (8.5 min vs. 15.9 min, $p<0.05$), better sleep efficiency (88.8% vs. 86.5%, $p<0.05$), and longer duration of daytime napping (1.4 h vs. 0.7 h, $p<0.01$) but comparable nocturnal sleep duration (6.3 h vs. 6.3 h, NS) to controls. No differences in cardiometabolic disease risk factors were observed between the groups; however, esports players had a higher smoking prevalence (42.9% vs. 14.3%, $p<0.05$). Furthermore, the esports players had better neurocognitive performance, as evidenced by them having more correct responses and lower attentional lapses in the PVT (both $p<0.001$), better accuracy in the 3-back task ($p<0.01$), and lower total and perseverative error rates in the BCST (both $p<0.05$), compared to the controls.

Linear regression analyses with pooled data identified a medium-strength association between poor self-reported sleep quality with a worse cardiometabolic disease risk score ($\boldsymbol{\beta}=0.268$; 95% CI: 0.054, 2.309, $p<0.05$), elevated systolic blood pressure ($\boldsymbol{\beta}=0.293$; 95% CI: 0.655, 9.061, $p<0.05$) and higher HOMA-IR ($\boldsymbol{\beta}=0.296$; 95% CI: 0.016, 0.209, $p<0.05$). Greater irregularity around wake-up time was also associated with higher HOMA-IR ($\boldsymbol{\beta}=0.274$; 95% CI: 0.019, 0.548, $p<0.05$). In addition, shorter sleep duration was associated with worse reaction time performance in the 1-back task ($\boldsymbol{\beta}=-0.290$; 95% CI: -<0.001, -<0.001, $p<0.05$). However, in contrast to these results, poor self-reported sleep quality was linked to improved reaction time performance in the 3-back task ($\boldsymbol{\beta}=-0.259$; 95% CI: -0.127, -0.001, $p<0.05$). These findings provide important insights regarding young adult esports players' sleep patterns and health status but raise concerns about the potential long-term health implications of poor sleep habits affecting both groups.

Chapter 5:

These findings suggest that esports players spend more time in sedentary behavior (11.2 vs. 9.1 hours per day, $p<0.001$), less time in moderate-intensity (1.4 vs. 2.2 hours per day, $p<0.001$), and less time in vigorous-intensity physical activity (0.6 vs. 1.6 hours per day, $p<0.001$) than controls. This study also identified interesting temporal differences in movement behaviors between the groups, illustrated by esports players being less active between 05:00 and 08:00 ($p<0.001$) and at 09:00 ($p<0.05$), 18:00 ($p<0.05$) and 20:00 ($p<0.05$) but more active at midnight ($p<0.001$), compared to controls. As hypothesized, esports players spent a proportionally greater amount of the waking day exposed to very dim light levels (62.8% vs. 51.0%, $p<0.05$) and a correspondingly lower proportion of time exposed to moderate light (8.4% vs. 16.8%, $p<0.01$).

In addition, esports players demonstrated a robust delayed phase-shifted white light exposure profile, as evidenced by lower light exposure found between 06:00 to 08:00 ($p<0.001$) and at 09:00 ($p<0.05$) and greater light exposure between 23:00 to 01:00 ($p<0.001$) and at 02:00 ($p<0.05$) compared to controls. Finally, there were no differences in the morning- or evening-time light exposure relative to wake-up time and bedtime between the groups. These findings suggest that esports players' delayed sleep-wake patterns and propensity for nighttime gaming behaviors may largely be attributed to their evening chronotype rather than the acute melatonin-suppressing effect of nighttime light exposure. Furthermore, the lack of adequate natural light exposure and appetite for sedentarism in these young individuals may increase cardiometabolic disease risk over time.

Conclusion

The findings in this thesis indicate that esports players exhibit a strong evening-oriented phenotype, as evidenced by a later chronotype, delayed sleep patterns, and white light exposure profiles. While it may be argued that esports players' propensity for eveningness strongly contributes to nighttime gaming behaviors, more research is necessitated to explore the contribution of gaming exposure and light at night in reinforcing their evening chronotypes. Relatedly, device-derived light data demonstrated that esports players were exposed to very low levels of bright natural light, which may not only promote adverse health consequences but also support the later sleep-wake schedules of these players.

Furthermore, esports players demonstrated consistently higher levels of sedentary behavior than the controls, which is likely driven by the unique condition of prolonged seated gaming activities. Finally, regarding the negligible differences in current cardiometabolic disease risk factors between the groups, this observation could be attributed to the young age of the studied population. It is concerning that many risk factors were tentatively worse among gamers, in which case their trajectory could suggest worse cardiometabolic health in the future. This rationale is supported by pooled associations linking poor sleep habits with greater cardiometabolic disease, highlighting the need for further investigation and interventions targeting behaviors that disrupt sleep in young adults. These include non-gaming lifestyle behaviors like engaging with social media and electronic screen devices near bedtime. The findings of this thesis provide valuable and novel insights regarding an understudied population of young adult esports players. As such, the information may contribute to developing a framework designed to improve healthier gameplay standards and gaming performance, the latter of which may be attractive for other esports players to adopt and assist them in becoming more conscious of the factors influencing their sleep and health. Future research employing qualitative and longitudinal study designs may provide more insights into the complex interplay between sleep, lifestyle, and gaming behaviors in esports players and inform the development of more effective interventions.

Preamble

Introduction to esports

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A portion of this preamble has been published and is presented with some modifications from the publication with permission granted by the University of Cape Town's Doctoral Degrees Board. All co-authors have agreed that it may be included in the thesis.

Background of esports

Esports is an emerging global phenomenon, defined as a type of organized, professional video game competition in which there is a specific outcome (i.e., winning a championship title or prize money) and a clear distinction between the players and teams pitted against each other (McCutcheon et al., 2017). Esports also represent many game titles and are thus described as a conglomeration of competitive video games with an audience of about 474 million fans and estimated global market revenue of $1.1 billion (Newzoo, 2021). On its current trajectory, with year-on-year growth of 10.0% since 2020, esports is expected to have a total global audience of 577 million fans and global revenue of $1.6 billion by 2024 (Newzoo, 2021).

These statistics also reflect the meteoric growth of the video gaming industry, which has experienced tremendous expansion in the past decade. According to a Newzoo market report, forecasts suggest the global video game player base will exceed three billion users by 2024 (Newzoo, 2021). While the extent of esports currently appears to be overshadowed by mainstream sports, such as soccer, cricket, and rugby, the appetite for esports and gaming content is profound and encompasses several regions. The Asia-Pacific region (Central Asia, Southern Asia, and Southeast Asia) currently comprises the majority of the world's gamers (55%, ± 1.6 billion players), followed by the Middle East and Africa (15%, ± 434 million players), Europe (14%, ± 408 million players), Latin America (10%, ± 289 million players) and finally, North America (7%, ± 212 million players) (Newzoo, 2021). The interest in esports and gaming content also apparently transcends age. In the U.S., over 80% of the video gaming population is aged 18 years or older, with the majority (38%) of gamers aged between 18 and 34 years (Entertainment Software Association, 2021).

Reports indicate that viewers consumed approximately 1158 billion minutes of content on the streaming platform Twitch (Amazon, U.S.) alone between January and September 2021 (Twitch Tracker, 2021), while the cumulative livestreaming audience is reportedly 729 million viewers (Newzoo, 2021). These figures highlight the considerable volume of global esports and gaming content consumed each year. Although most standalone esports events are not yet comparable to Nielsen ratings of traditional U.S. sporting events like the Super Bowl, there are notable contenders. For example, the Garena Free Fire World Series (Sea Ltd., Singapore) became the most-watched esports event in history in 2021 after peaking at 5.4 million concurrent viewers (Frascarelli, 2021). In addition, the event smashed the previous world record held by the League of Legends 2019 World Championships (Worlds 2019; Riot Games Inc., United States), with a peak concurrent viewership of 3.9 million viewers (Frascarelli, 2021).

These data highlight the rapid globalization of video gaming and the steady maturation of esports as a competitive professional entity, especially compared to earlier forms of video gaming. The regular and frequent occurrence of large-scale tournaments with multimillion-dollar prize pools across several gameplay titles exemplifies this, with many events being viewed by hundreds of millions of spectators worldwide each year. Endemic sponsorships (i.e., computer and gaming brands) and non-endemic sponsorships (e.g., beverage brands) for teams and players often accompany such lucrative events and comprise a large share (i.e., 59%) of the global esports revenue stream (Newzoo, 2021). However, other revenue streams may include those derived from media rights, publisher fees, merchandise and ticket sales, digital licensing, and streaming (Newzoo, 2021). For example, The International 10, an annual tournament in Dota 2 (Valve Corporation, United States), crowdfunded a record-breaking $40 million prize pool by selling in-game digital real estate (Cooney, 2020). Remarkably, only 25% of revenue from these sales funded The International 10 prize pool, meaning that the tournament organizers raised approximately $160 million.

Training

Unlike traditional sports, esports is host to a dynamic competitive landscape. In particular, esports comprises an evolving "meta" (a colloquial term describing the current optimal playstyle) since the games' pace, style, and features change following regular or seasonal gameplay updates. With a relatively short-lived career, marked by an early age of peak performance (Kokkinakis et al., 2017), esports players must also continually adapt their playstyles or risk losing their competitive status. Reports indicate that esports athletes may dedicate as much as 14 hours daily to practices or matches (Jenny et al., 2017), risking potential burnout or fatigue. This has inspired some professional teams to incorporate wellness programs into their schedules to improve player performance and career longevity. In addition, elite esports organizations are established to invest large sums of money into residential gaming houses for players and coaches, where they follow strict training schedules over the competitive season. An article published on the Inven Global website (Kim & Hong, 2018) details the typical training day schedule of esports players as follows: wake up at 10:00, followed by training from 11:00 to 19:00, after which players may stream games to their followers until bedtime, at 02:00; this may change over the non-competitive season. Nevertheless, these cumbersome late routines demonstrate the discipline required to be proficient as an esports athlete and, understandably, place immense pressure on esports athletes to perform. Michael Phelps honored esports athletes at The Game Awards 2016 ceremony (Garfat, 2016), saying: "There is absolutely no question to me the level of skill, training, and devotion it requires to become a professional gamer."

Challenges

Despite the professionalism of esports and the dedicated training required to succeed, it has still been challenged as a reputable form of competition. This follows persistent efforts by the esports industry to prove its legitimacy, which included it being used as an exemplar at the PyeongChang Olympic Winter Games in 2018 (International Olympic Committee, 2017). Esports partners have also since engaged in discussions with the International Olympic Committee (IOC) regarding its inclusion as a demonstration title at the 2024 Summer Olympic Games in Paris (BBC Sport, 2018). Beyond this, the inclusivity of esports as a sporting activity continues to be deliberated, particularly regarding its sedentary nature (Hallmann & Giel, 2018). A statement by the IOC at the 7th Olympic Summit around the physicality of competitive gaming suggests that whether esports can be considered a sport in the traditional sense requires further discussion (International Olympic Committee, 2018).

Researchers have discussed the formal definition of a sport, noting that it must comprise elements of play, rules, competition, be comprised of skill (as opposed to chance), have a broad following, include physical skills (i.e., "skillful and strategic use of one's body") and demonstrate governance (Jenny et al., 2017, p. 5). Esports tick the first five elements, and few people would argue against the cognitive effort and skill required in gaming. Gamers utilize an array of cognitive processes (e.g., attention, reaction time, working memory) and fine motor skills (e.g., using the mouse or keyboard) (Bonnar et al., 2019a; Kokkinakis et al., 2017), all of which are central to their proficiency and require significant cognitive effort. The sticking point seems to be around the physicality of gaming. Indeed, sports should be viewed holistically without necessarily prioritizing athleticism. However, gaming is, at least for the most part, considered to be a sedentary activity. While there are sports like archery and shooting, which involve a limited degree of physical activity during competition, the physical training undertaken by these athletes to shoot successfully is comparable to that of more traditional athletes. In this regard, current forms of video gaming do not compare. Still, given the increasing popularity of motion-based video games (or exergames) and virtual reality, which may involve more gross motor activity, it is possible that esports could be viewed as a more credible sport in the future.

Governance

Although esports mimics traditional sports in many ways (debate around physicality notwithstanding), the most significant barrier regarding its inclusivity as a credible sport is arguably its lack of organizational structure (Hallmann & Giel, 2018). The IOC raised this issue in 2017, responding to failed attempts of governance by various stakeholders to ensure the implementation of policies (Zaccardi, 2017). The World Esports Association (WESA) is the purported representative body for esports players, teams, and organizations (ESL, 2015). It is also an official signatory of the World Anti-Doping Agency; however, WESA inspires little confidence to ensure or enforce compliance with regulatory practices. These should include random drug testing, player transfers, drafting of player contracts, and arbitration. Since esports titles remain the intellectual property of their respective game publishers, there is at least some level of authority regarding the enforcement of standardized rules and penalties for misconduct (Koot, 2019). This authority may extend to tournament organizers, such as ESL, formerly known as Electronic Sports League, who uphold and maintain their own rules, including matters involving fraud and deception. However, broad policy reform under the jurisdiction of a global esports authority is necessary to allow unbiased control and enforcement of policies regarding the matters of players, organizations, and tournament organizers.

The future of esports and its players

With the widespread availability of advanced technological devices like smartphones and high-speed internet, it is no surprise that video gaming has become increasingly popular. In addition, the professionalization of esports and lucrative monetary incentives available for competitors provide an implicit motive to engage with video games frequently and for prolonged periods to improve their competitive prowess. However, while esports continues to show record growth as a front-runner in the digital ecosystem, it is not a full-time commitment for many individuals, necessitating that their commitments to gaming practices and matches be balanced with other lifestyle commitments, including work, studies, or even both (Eickhoff et al., 2015).

Furthermore, despite esports being a highly competitive and commercially invested form of competition, it remains segregated from the sporting community. A call to refine the current definition of sport to be more inclusive without favoring physicality (McCutcheon et al., 2017) has initiated progress regarding the inclusivity of esports. In celebrating a new era in digital entertainment and sporting activity, researchers are encouraged to be objective and use the esports platform as an opportunity to extend health and performance research. Indeed, it is such research that may drive policy reform in esports. Beyond this, research should bridge the gap in the current understanding of esports and guide its development to become credible and broadly recognized. That being said, perhaps its acceptance as a credible sport is not a matter of fact or opinion but rather a matter of time.

Chapter 1

General introduction

1.1 Introduction and scope of the thesis

Cardiometabolic diseases are a leading cause of global mortality and encompass a range of health conditions, including obesity, insulin resistance, type 2 diabetes, dyslipidemia, and cardiovascular diseases (World Health Organization, 2021). While over 4.8 million adults reportedly died from cardiometabolic diseases between 1990 and 2017 in the U.S. (Centers for Disease Control and Prevention, 2020), the risk for premature mortality could be reduced by modifying unhealthy lifestyle behaviors, such as physical inactivity, cigarette smoking, excessive alcohol use, and consumption of unhealthy foods (Deaton et al., 2011; James, 2008; Shaw et al., 2010; Yusuf et al., 2001). However, despite the widely accepted role of physical activity in preventing and managing non-communicable diseases like cardiometabolic diseases and certain cancers, global estimates show that up to 70% of people's waking hours are spent being sedentary (Owen et al., 2010; Reiner et al., 2013). In addition, there is mounting evidence that short-duration, mistimed, and poor-quality sleep have a significant impact on cardiometabolic disease risk (Chattu et al., 2019; Lloyd-Jones et al., 2022). Globally, sleep insufficiency is regarded as a largely unrecognized public health epidemic spanning various ages, with severe implications on cardiometabolic health and premature mortality (Chattu et al., 2019; Lemoine et al., 2007). In addition to these negative health impacts, it is understood that cardiometabolic diseases pose a significant economic burden, necessitating broad reform in public health policies to address this growing problem (Centers for Disease Control and Prevention, 2023).

For vulnerable populations such as esports players, the adverse health risk can be even more detrimental to their general well-being and quality of life, underscoring the urgent need for further research and governance. In particular, this follows reports of esports players engaging in over 3.5 hours of seated gaming per day or as much as 10 hours of daily gaming time during elite-level competitions (Rudolf et al., 2020; Thomas et al., 2019). This is compounded by findings that excessive video gaming can increase cardiometabolic disease risk, as demonstrated by a positive association between gaming time and several risk factors in adolescent console gamers, including higher diastolic blood pressure, mean arterial pressure, blood lipids, and composited cardiometabolic risk score (Martinez-Gómez et al., 2012).

Furthermore, current data on esports players' physical activity habits are largely inconclusive and heavily reliant on self-report methods with no control groups, highlighting the need for additional research to better understand their waking movement behaviors and the proportion of their day spent being sedentary while playing. This research will help inform policies and strategies to promote physical activity and reduce sedentary behavior among esports players in the future. On the one hand, it is suggested that there is a high prevalence of physical inactivity among esports players (Trotter et al., 2020). However, other studies report conflicting data arguing to the contrary. For example, one study found that at least 60% of players participated in some form of exercise (Rudolf et al., 2020), while another reported that 66.9% of esports players engaged in moderate-to-vigorous physical activity (MVPA) for at least 2.5 hours per week, congruent with physical activity recommendations for healthy adults (DiFrancisco-Donoghue et al., 2019). Despite there being preliminary evidence to support a dose-dependent relationship between gaming time and physical activity (i.e., longer gaming time is associated with lower total vigorous-intensity physical activity) (Mario et al., 2014), it is difficult to draw definitive conclusions about esports players' associated cardiometabolic disease risk status[1].

Furthermore, the addictive, immersive, and evening nature of video games may also lead to reduced sleep quality and quantity, compounding the negative health effects described previously. More specifically, prolonged exposure to video games at nighttime is understood to lead to short sleep duration, poor sleep quality, and (to a limited extent) adverse changes to sleep structure, which may be associated with increased downstream cardiometabolic disease risk (Peracchia & Curcio, 2018). These deficits were evident in a study on adolescent gamers, which showed that gaming addiction was negatively associated with sleep duration, which in turn was linked with a higher risk of obesity (Turel et al., 2016). The same study also showed that curtailed sleep was associated negatively with several other cardiometabolic biomarkers and thus thought to mediate the association between excessive and problematic gaming, obesity, and cardiometabolic consequences (Turel et al., 2016).

Beyond the associated health consequences, video gaming demands a high level of cognitive effort, as evidenced by the many mental skills required for optimal performance among elite-level esports players (Himmelstein et al., 2017). These skills include reacting to dynamic in-game circumstances, adapting to competitors, communicating with team members, and coping with stress and negative emotions in real-time (Himmelstein et al., 2017; Poulus et al., 2020). Furthermore, it is widely recognized that prolonged exposure to video games enhances cognitive processes that underpin esports performance, such as attention, vigilance, information processing speed, and executive functions like cognitive flexibility and

[1] Cardiometabolic disease risk status refers to a person's likelihood of developing cardiac or vascular disorders and metabolic diseases like diabetes and insulin resistance.

problem-solving (Buelow et al., 2015; Gross & Grossman, 2010; Pallavicini et al., 2018), which may serve as markers of gaming ability. However, sleep is considered a crucial determinant of esports performance (Bonnar et al., 2019a) since inadequate sleep duration and poor sleep quality selectively impair cognitive functions, resulting in slower reaction times, impaired decision-making, and reduced endurance in matches (Killgore, 2010; Lo et al., 2016). Despite this, there is limited evidence on the relationship between sleep and gaming performance in esports players. In this regard, exploring markers of neurocognitive performance might shed light on how short sleep duration and poor quality sleep could erode the benefits attributed by video gaming and how sleep characteristics could be viewed as potential determinants of success for esports players. Furthermore, optimal sleep for maintaining performance could also motivate gamers to reassess their sleep-wake behavior and mitigate potential chronic health consequences caused by prolonged video gaming exposure.

While previous research has examined various aspects of video gaming, including its effects on aggression, psychological state, and gaming addiction, such studies have primarily focused on children, adolescents, and non-habitual gamers. Another issue is that these studies typically did not account for the different gaming platforms (i.e., console versus computer), prior years of gaming history, or regular frequency of gaming exposure. In contrast, esports players are a growing and maturing population within the general video gaming demographic, characterized by unique behaviors such as engaging in high levels of gaming activity for extended durations, frequent sessions, and intense competition to improve their competitive status. Therefore, this thesis aims to bridge the gap by investigating the sleep-wake patterns, cardiometabolic health status, and neurocognitive performance of adult esports players who may be particularly vulnerable to the downstream effects of detrimental gaming behaviors. This vulnerability is attributable to their implicit cardiometabolic disease risk, which can be influenced by aging, unhealthy lifestyle behaviors, and substance addictions such as smoking and alcohol consumption. Specifically, this thesis will focus on the “missing middle” esports population, comprising competitive but non-professional adult esports players, who represent a large proportion of the gaming population that has mostly been overlooked in prior studies. By focusing on this population, the thesis aims to shed light on the potential health risks associated with regular esports players' behaviors to inform future interventions to improve their overall sleep, health, and general well-being.

1.2 Sleep health

Sleep is an integral and evolutionarily conserved physiological function underpinning optimal health and quality of life. While many theories have been proposed to describe why humans sleep, none have been conclusive. Overall, researchers concede that sleep is pivotal in rejuvenating and maintaining many aspects of physical and mental health. This includes energy conservation and emotional regulation, along with supporting cognitive functions like memory consolidation, learning, and other elements of cognitive performance (Mignot, 2008). Notwithstanding sleep's obvious importance for life, recent statistics from industrialized societies indicate that, on average, humans sleep less every year. In a study examining the sleep duration trends in the U.S., the number of adults achieving inadequate quantities of sleep (i.e., ≤6 hours daily) nearly doubled, increasing from 38.6 million to 70.1 million between 1985 and 2012 (Ford et al., 2015).

However, this trend is not limited to the U.S., as the evidence demonstrates that a substantial proportion of individuals on other continents may not be getting enough sleep. For example, in Japan, the prevalence of sleep insufficiency was reported to be as high as 23%, while in Sweden and Finland, 12% and 9% of individuals, respectively, reported insufficient sleep (Chattu et al., 2018). These figures highlight that sleep insufficiency is not limited to a particular region or population but is observed worldwide. Moreover, while sleep insufficiency may have striking adverse public health implications, if left unchanged, the economic cost in the U.S. alone has been estimated to reach $456 billion by 2030 (Hafner et al., 2017).

More recently, researchers have proposed "sleep health" as a novel concept encompassing a broad range of dimensions beyond sleep restriction and the mere absence of sleep disorders. A definition has been proposed by one expert as "a multidimensional pattern of sleep-wakefulness, adapted to individual, social, and environmental demands, that promotes physical and mental well-being" (Buysse, 2014, p. 12). In his paper, Buysse speculated that sleep health might provide a more holistic framework to characterize the multidimensional nature of sleep and its corresponding myriad health outcomes. Sleep health was originally proposed to comprise five dimensions: "subjective satisfaction, appropriate timing, adequate duration, high efficiency, and sustained alertness during waking hours," all of which are independent dimensions attributed to sleep-wakefulness (Buysse, 2014, p. 12), and has now been extended to also include a sixth dimension, sleep regularity (Dong et al., 2019).

1.2.1 Sleep duration

According to the National Sleep Foundation (NSF) based in the U.S., there is an acceptable range in the quantity of sleep required for optimal overall health and well-being, as well as cognitive, emotional, and physical health (Hirshkowitz et al., 2015). As such, the recommended sleep duration for adults (aged 16 to 64 years) is between 7 to 9 hours daily (Hirshkowitz et al., 2015). There is also interindividual variability in sleep need, whereby individuals may regularly achieve sleep durations at the extremes of the guideline ranges without any significant adverse effects (Hirshkowitz et al., 2015). However, it is broadly accepted that sleeping ≤ 6 hours per day is not appropriate to support optimal health in adults, particularly after considering the wide-ranging adverse outcomes linked to short sleep, including a greater risk for type 2 diabetes, hypertension, obesity, cardiovascular diseases, obesity, metabolic syndrome, as well as an increased risk of premature death (Dejenie et al., 2022; Grandner et al., 2010; Itani et al., 2017).

Likewise, sleeping for more than 10 hours daily (or "long sleep") carries a substantial risk for cardiovascular disease and mortality. While there is less agreement among sleep experts regarding the certainty of risk associated with long sleep than with short sleep, it is understood that both short and long sleep are risk factors for cardiovascular disease mortality and all-cause mortality (Cappuccio et al., 2011; Chien et al., 2010; Li et al., 2014; Magee et al., 2013; Yeo et al., 2013). Sleep medicine and research experts have yet to agree on the upper bounds of the recommendations for sleep duration. However, they concur that occasional bouts of long sleep in healthy individuals may be appropriate in certain circumstances, such as post-exercise recovery or following substantial sleep loss (Consensus Conference Panel: et al., 2015). While physiological and genetic factors primarily drive this variability in sleep need, the sleep duration achieved by individuals is affected by behavioral, sociocultural, and environmental factors (Deboer, 2018; Grandner et al., 2010). Indeed, achieving an adequate quantity of sleep is an essential component of health; however, as an isolated and arguably overemphasized concept, sleep duration may not fully describe the distal outcomes of poor sleep on health, disease, and physiological functioning.

1.2.2 Sleep timing and regularity

Beyond sleep duration and sleep quality, there are other essential dimensions of sleep health with critical roles in the etiology of sleep and circadian rhythm disorders, including insomnia and advanced or delayed sleep phase syndromes, that can impact physiological and mental health. These dimensions include sleep timing and sleep regularity, which describe bedtime and wake-up time in 24 hours, and the day-to-day variability of sleep timing or duration, respectively. A review exploring sleep regularity found consistent evidence linking greater sleep irregularity with poorer cardiometabolic outcomes (Zuraikat et al., 2020). In particular, the review noted that increased irregularity around sleep duration and sleep timing was associated with increased adiposity, glucose dysregulation, and higher odds of metabolic syndrome prevalence (Zuraikat et al., 2020). A separate longitudinal study echoed these findings and declared actigraphy-measured irregular sleep duration and sleep timing as novel risk factors for cardiovascular disease, even after adjusting for other lifestyle and sleep-related risk factors (Huang & Redline, 2019). Moreover, over a median follow-up period of five years, the researchers also reported an increased hazard ratio for incident cardiovascular disease in individuals with more irregular sleep timing and duration (Huang & Redline, 2019).

A study assessing the device-derived Sleep Regularity Index (SRI) scores of 60,977 participants from a UK Biobank (ages: 62.8 ± 7.8 years, 55.0% female, SRI: median: 81.0, interquartile range: 73.8 – 86.3) over a 7.8-year follow-up period, found that greater sleep regularity was associated with a 20-48% lower risk of all-cause, cancer, and cardiometabolic mortality across scores in the top four quintiles (SRI 71.6-98.5) than the bottom quintile (SRI<71.6) (Windred et al., 2024). This relationship was robust even after controlling for various confounding factors, including age, sex, ethnicity, sociodemographic, lifestyle, and health. The researchers concluded that sleep regularity was a stronger predictor of all-cause mortality than sleep duration (Windred et al., 2024). These findings align with a recent consensus statement that emphasizes the significance of daily regularity in sleep timing for health and performance (Sletten et al., 2023). The panel of researchers agreed that regular sleep schedules were linked with improved outcomes in numerous health and performance markers, including alertness, cardiovascular and metabolic health, mental health, academic and cognitive performance, as well as sleep duration and quality (Sletten et al., 2023).

In addition to the sleep dimensions previously discussed, the parameters: sleep satisfaction, sleep efficiency, and alertness during waking hours, are considered comparably important measurable components of sleep health associated with various physical, mental, and neurobehavioral outcomes (Buysse, 2014). Each of these dimensions of sleep health reflects high ecological validity, in which case the interpretability of their values can be readily understood by experts and the general public (Buysse, 2014).

1.2.3 Sleep satisfaction

Sleep satisfaction refers to the subjective assessment of the quality of one's sleep and is primarily characterized by self-report tools like retrospective sleep questionnaires, sleep diaries, or validated tools like the PSQI (Buysse et al., 1989; Buysse, 2014). However, emerging evidence suggests that sleep satisfaction may also have a physiological correlate. For instance, studies have shown that deeper sleep, characterized by more time being spent in slow wave sleep (SWS), otherwise characterized by delta-wave EEG (electroencephalography) activity, is a strong predictor of sleep satisfaction (sleep stages are discussed more in **Section 1.6.1**) (Krystal & Edinger, 2008; Riedel & Lichstein, 1998). Moreover, there is a substantial body of evidence supporting the association between poor sleep satisfaction and worse overall health outcomes, including an increased risk of depression (Baglioni et al., 2011), coronary heart disease (Hoevenaar-Blom et al., 2011; Laugsand et al., 2011), hypertension and type 2 diabetes (Knutson et al., 2011; Rod et al., 2011; Vgontzas et al., 2009), and mortality (Rod et al., 2011).

1.2.4 Sleep efficiency

On the other hand, sleep efficiency reflects the proportion of time spent asleep in relation to the total time spent in bed, with good sleep health characterized by having high sleep efficiency (Buysse, 2014). It is calculated by dividing the total time spent asleep (total sleep time; TST) by the total time spent in bed (time-in-bed; TiB), expressed typically as a percentage. The most practical method to measure sleep efficiency involves using sleep monitoring devices, such as PSG or actigraphy, which are discussed in more detail in **Section 1.6.1** and **Section 1.6.2**, respectively (Spielmanns et al., 2019). In addition, self-report tools, such as sleep diaries and questionnaires (discussed in **Section 1.5.3**), can also estimate sleep efficiency, although they may be less accurate than objective measures (Reed & Sacco, 2016). In line with many other sleep health dimensions, research has demonstrated that low sleep efficiency is associated with an increased risk of adverse health outcomes, such as diabetes (Cappuccio et al., 2010; Knutson et al., 2011), hypertension (Vgontzas et al., 2009), heart disease (Grandner et al., 2012; Laugsand et al., 2011), and development of the metabolic syndrome (Troxel et al., 2010).

1.2.5 Alertness

Alertness reflects the ability to maintain wakefulness during waking hours (Buysse, 2014). However, daytime alertness is reduced by poor sleep quality, insufficient sleep, or mistimed and irregular sleep-wake patterns. In addition, inadequate alertness is associated with impaired cognitive and neurobehavioral performance, negatively impacting daily functioning and emotional well-being (Dinges et al., 1997; Taillard et al., 2006; Thomas et al., 2000). Aspects of alertness can be measured subjectively with the Satisfaction, Alertness, Timing, Efficiency, and Duration (SATED) questionnaire, a reliable and validated tool that can be used to measure sleep health dimensions at a general population level (Benítez et al., 2020; Buysse, 2014). Specifically, the SATED questionnaire demonstrated robust internal consistency (Cronbach's $\alpha = 0.77$), and all five individual items correlated significantly with the SATED score total (rho=0.55-0.69). Both exploratory and confirmatory factor analyses confirmed a single-factor model and supported an acceptable model fit (Benítez et al., 2020). Furthermore, the questionnaire's criterion validity was found to have satisfactory correlations with validated sleep questionnaires like the PSQI (Buysse et al., 1989) and ESS (Johns, 1991), and construct validity was corroborated through its relationship with relevant psychological measures (Benítez et al., 2020). Additionally, objective tools exist to examine other markers of alertness, such as the Psychomotor Vigilance Test, which measures sustained attention (Dinges & Powell, 1985). It is important to note that while alertness involves general wakefulness and readiness to respond, sustained attention is specifically the ability to maintain focus on a task over prolonged periods.

1.3 Associations between poor sleep health and cardiometabolic disease outcomes

Emerging evidence has found that poor sleep health is associated with a greater risk for cardiometabolic disease morbidity and mortality (Hale et al., 2020; Sletten et al., 2023; Windred et al., 2024). For example, a longitudinal study assessing multidimensional sleep health in 4555 adults (49 ± 18 years) from the 2017–2018 National Health and Nutrition Examination Survey showed that having a better sleep health score (including factors: sleep duration, regularity, and symptoms of sleep disorders) was associated with lower odds of hypertension, obesity, and central obesity (Makarem et al., 2022). Specifically, individuals with “ideal and moderate” sleep health scores had 62% and 41% lower odds of hypertension, respectively, versus those with “poor” scores. Similar trends were seen for obesity and central adiposity. Moreover, individuals with “ideal” sleep health scores had 32% and 40% lower odds of prevalent cardiovascular disease and type 2 diabetes, respectively, than those with "moderate" or "poor" scores. Better sleep health scores were also associated with lower blood pressure, BMI, waist circumference, and fasting glucose concentrations (Makarem et al., 2022). Another study conducted on 1,275 extended care workers (38.6 ± 12.4 years, 7.5 % male) reported that SATED-measured sleep health (factors: self-reported sleep sufficiency, actigraphy-derived WASO, and daytime napping) was associated with lower cardiometabolic disease risk, independent of (and interacting with) sleep apnea symptoms (Buxton et al., 2018). The group also explored sleep health in 577 information technology workers (46.0 ± 12.4 years, 60.1% male); however, no significant main effects of sleep health indicators on cardiometabolic disease risk were discovered. The researchers postulated that this null effect may be due to information technology workers having more positive overall sleep health than extended care workers (Buxton et al., 2018). While strong and consistent evidence supports the association between poor sleep health and greater cardiometabolic disease risk, it is important not to overlook the impact of lifestyle factors like sedentary behavior and physical activity levels.

1.4 Sedentary behavior as a health risk factor

Sedentary behavior is a putative independent determinant of health and a contributor to chronic disease (Biswas et al., 2015; Matthews et al., 2016). It is characterized by waking behavior where the energy expenditure is less than or equal to 1.5 metabolic equivalents (METs) and comprises sitting, passive standing, reclining, or lying down (Bames et al., 2012). There is no widely accepted classification for excessive sedentary behavior; however, several studies have defined "high levels of sedentary behavior" as ≥ 8 hours of sedentary behavior per day (Motuma et al., 2021; Peltzer et al., 2019; Stubbs et al., 2018; Vancampfort et al., 2018). The evidence linking sedentary behavior with all-cause mortality is profound, with a study in U.S. adults demonstrating an association between higher levels of sedentary behavior (10 hours per day versus 6 hours per day) with a 29% greater risk of premature death (hazard ratio (HR): 1.29, confidence interval (CI): 1.1-1.5) (Matthews et al., 2016). The same study also revealed that substituting one hour of sedentary behavior for light-intensity physical activity or MVPA was associated with an 18 and 42% lower mortality risk among inactive individuals, respectively, independent of physical activity and other confounders (Matthews et al., 2016). These findings have been echoed by other studies and meta-analyses, demonstrating that greater levels of sedentarism are linked with greater odds of developing metabolic syndrome, cardiovascular disease, and even certain cancers (Biswas et al., 2015; Edwardson et al., 2012; Whitaker et al., 2018).

One study showed that reallocation of 30 minutes of sedentary behavior per day to either sleep, light-intensity physical activity, or MVPA significantly reduced cardiovascular disease risk biomarkers, providing evidence to support the health-enhancing effects of displacing some sedentary behavior time in favor of MVPA (Buman et al., 2014). A large, consistent body of evidence links sedentary behavior to adverse cardiometabolic disease outcomes. For example, a systematic review of 29 cross-sectional studies demonstrated that total sedentary time was associated with poorer insulin sensitivity, greater fasting insulin, and triglyceride levels (Brocklebank et al., 2015). In addition, a population-based cohort study reported similar findings, linking increased television viewing time (a sedentary behavior) of 10 hours per week over five years to greater waist circumference, diastolic blood pressure, and cardiometabolic disease risk scores, even after adjusting for confounders (Wijndaele et al., 2010). Interestingly, a large body of research supports the notion that regular, intermittent bouts of sedentary behavior (in the form of standing or light-intensity exercise) may decrease cardiometabolic disease risk compared to prolonged, uninterrupted sedentary time (Buffey et al., 2022; Dempsey et al., 2018; Gillen et al., 2021; Healy et al., 2008). Likewise, a meta-analysis of thirteen experimental studies also highlighted favorable postprandial glycemic effects in adults after interrupted sitting with at least light-intensity physical activity; however, the authors cautioned that evidence regarding interruption of more prolonged bouts of sedentary behavior remains unclear (Chastin et al., 2015). Together, these findings support the associations between sedentary behavior and the development of overweight and obesity, type 2 diabetes, and cardiovascular disease, with higher levels of physical activity acting as an effective risk-mitigating intervention strategy. Furthermore, the intertwining nature of these factors calls for effective monitoring and assessment methodologies.

1.5 Sleep monitoring

To fully grasp the relationship between sleep and cardiometabolic disease risk, it is crucial to reliably, reproducibly, and accurately measure the different dimensions of sleep. There are various approaches to assessing and measuring sleep, including objective techniques like polysomnography (PSG) and actigraphy, as well as subjective methods such as self-administered sleep diaries and validated questionnaires. However, each method has its own inherent strengths and limitations that must be considered when choosing an appropriate measure for use in research or clinical settings, which will be discussed in the following sections.

1.5.1 Polysomnography

Although PSG was not formally used in this thesis, the following discussion has been included for comprehensiveness. PSG is the gold standard approach to assessing sleep, involving the continuous measurement of multiple sleep-related signals such as neurophysiological, cardiorespiratory, and musculoskeletal parameters over one or more nights. (Bloch, 1997). These parameters are integral for understanding the functional importance and interplay of multiple physiological systems on sleep architecture and wakefulness. However, PSG is invasive and requires numerous sensors to record variables such as brain waves (using electroencephalography), eye movements (using electrooculography), and muscle activity (using electromyography) (Wolpert, 1969). Other paradigms might also include the recording of blood oxygen saturation (using pulse oximetry), airflow (with nasal cannular), heart activity (with electrocardiography), respiration (using sensors placed around the ribcage and abdomen), and sound (to detect snoring) (Berry et al., 2017).

Although PSG is a highly accurate method of measuring sleep, it is not typically used to assess habitual sleep patterns. Instead, it is regarded as a fundamental diagnostic tool in evaluating sleep disorders or researching sleep architecture, which reflects the structural organization of different sleep stages within each sleep episode (Colten & Altevogt, 2006; Markun & Sampat, 2020). Specifically, the sleep stages are categorized into rapid eye movement (REM) sleep and three non-REM stages: N1 ("light sleep"), N2 ("deeper sleep"), and N3 ("slow wave sleep"), which exist on a "continuum of relative depth" (Colten & Altevogt, 2006, p. 34). Each stage is characterized by specific electroencephalographic amplitude and frequency ranges together with the presence or absence of neurological and physiological markers (e.g., k-complexes, sleep spindles, eye movements, and muscle atonia), as governed in a standardized scoring manual (Berry et al., 2017). Typical PSG outcome variables include sleep latency, total sleep time, sleep efficiency, wake after sleep onset (WASO), number of awakenings, REM latency, and the proportion of time spent in each sleep stage.

Although PSG is a highly accurate method of measuring sleep, it is expensive and time-consuming, requiring specialist technicians to interpret the data. For these reasons, it is also not practical to use PSG for more than one or two nights per individual. In this regard, it may not be sufficient to provide a comprehensive understanding of habitual sleep patterns. In addition, many patients and research participants might also find PSG uncomfortable, reporting that it perturbs their sleep, which may affect the generalizability and accuracy of the results. For these reasons, less invasive and more practical methods, such as wearable devices, are preferred to monitor sleep over extended periods (Morgenthaler et al., 2007) and might offer a more representative view of an individual's habitual sleep. Nevertheless, despite its high cost and invasive nature, PSG is still regarded as a gold standard for sleep monitoring and provides a high-resolution view of an individual's sleep architecture and sleep stage distribution, which can also be used to diagnose or research sleep disorders (Bloch, 1997).

1.5.2 Actigraphy

Actigraphy is a non-invasive objective method to monitor habitual sleep and movement behavior. This monitoring technique can be applied in a free-living or clinical setting and involves using small, often wrist-worn, wearable devices (explained in more detail in **later in this section**). There are many advantages to using actigraphy versus PSG. For instance, actigraphy can be employed over several days and is more cost-effective, particularly when studying large cohorts (Martin & Hakim, 2011). Actigraph units also integrate the occurrence and magnitude of movement autonomously (Martin & Hakim, 2011), in which case scoring is remarkably faster without necessitating specialist technicians. Importantly, actigraphic measures from many research-grade devices have been validated against PSG, demonstrating a strong association ($r>0.85$) with polysomnographic measures of sleep or wakefulness in apparently healthy individuals (Sadeh, 2011). Among the many parameters reported by actigraphy are sleep timing (wake-up time and bedtime), sleep duration (total sleep time and time-in-bed), sleep onset latency, wake after sleep onset, number of awakenings, and sleep efficiency (Fekedulegn et al., 2020; Sadeh, 2011). Moreover, these devices provide information on habitual sleep over time, including sleep pattern regularity and sleep timing, making them particularly useful for assessing sleep and circadian rhythm disorders (Morgenthaler et al., 2007). Better still, the devices require less effort from the wearer and do not impede natural behaviors; thus, they are preferred for organically tracking sleep and activity behaviors.

Actigraphy relies on the magnitude of placement-specific movement (e.g., on the wrist or at the hip) and uses a motion sensor (i.e., accelerometer) to infer sleep-wake outcomes (Fekedulegn et al., 2020). There are different types of sensors employed by actigraph units; however, generally, these sensors record and integrate movement data (stored as "counts") over defined epochs into quantifiable information representative of wakefulness or resting states (Fekedulegn et al., 2020). This process is facilitated by specialized sleep scoring functions (or sleep estimation algorithms), which calculate a moving average based on activity levels measured prior to and immediately after the epoch (Fekedulegn et al., 2020). The integrated value is then compared to a user-defined threshold, and a corresponding "sleep" or "wake" value is assigned to define that epoch. Notably, the sleep estimation algorithms used by actigraphic devices may differ remarkably according to the manufacturer, device, or models, and the accuracy of actigraphic-measured sleep parameters depends on epoch length, data type, and age of the population under study (Fekedulegn et al., 2020).

It is important to note that actigraphy does not measure sleep directly like PSG but instead infers sleep-wake cycles by movement activity. The threshold at which movement is categorized as waking activity or sleep might depend on preset sensitivity and intensity-dependent cut-points. Thus, in theory, a single actigraphic device could be used to measure sleep and waking movement behavior, including sedentary behavior, light-intensity physical activity, and MVPA, concomitantly (Hjorth et al., 2012; Rosenberger et al., 2019). In addition, certain actigraphs are also fitted with color-sensitive photodiode sensors capable of measuring light exposure over multiple spectra, thus conferring the ability to examine the modifying effects of light exposure on sleep-wake behaviors and circadian rhythms (relatedness explained in **Section 1.6**) (Fekedulegn et al., 2020). Although monitoring devices measure sleep, light exposure, and physical activity independently, the benefits of using a single "all-in-one" monitor are intuitive, reducing measurement bias and participant burden while offering a holistic perspective of interrelated daily activities connected through time (Rosenberger et al., 2019). Specifically, sleep and physical activity are integral parts of a finite 24-hour sleep-wake cycle, influencing not only one another but also their associated health benefits (Rosenberger et al., 2019). As a result, there is a compelling need for a unified objective measurement tool that can effectively capture this 24-hour sleep-wake paradigm.

Having said that, sleep and waking behavior (in terms of physical activity) have traditionally been examined in isolation. Thus, many actigraphy devices have been developed with the specific intention of measuring either sleep or physical activity (depending on the location worn), incorporating distinct algorithms and hardware features to facilitate the intended purpose (Cheung et al., 2018; Hills et al., 2014; Sylvia et al., 2014). In instances where sleep and physical activity were intended to be measured concomitantly, multiple devices were often employed. However, as alluded to previously, the recent trend leans towards a more holistic approach, with a single device measuring both aspects in tandem. Wrist-worn devices are considered an ideal "all-in-one" option, given their compact and unobtrusive design, particularly during sleep, which engenders higher wear compliance (Troiano et al., 2014). It is crucial to note, though, that while algorithms for sleep estimation from wrist-worn devices exist, their ability to accurately measure physical activity remains under-researched (Neil-Sztramko et al., 2017;

Quante et al., 2015). Beyond this, hip-worn devices are broadly considered criterion approaches for physical activity monitoring (Plasqui & Westerterp, 2007; Welk et al., 2004), whereas wrist-worn devices are generally considered optimal for sleep estimation (Ancoli-Israel et al., 2003). As such, certain monitoring devices may have limited validity in accurately measuring disparate outcomes not only due to their algorithmic differences but also based on the purpose for which it is used (e.g., wrist-worn devices may not estimate physical activity as precisely as hip-worn devices, and vice versa) (Bassett Jr et al., 2012; Sasaki et al., 2016). Therefore, further investigation is required to validate the use of a single monitoring device to measure sedentary behavior, physical activity, light exposure, and sleep concurrently and to improve our understanding of their combined role in the etiology of cardiometabolic diseases.

1.5.3 Subjective sleep questionnaires

Subjective sleep tools such as self-report questionnaires and sleep scales can be a rapid, inexpensive, and straightforward method to assess self-reported sleep timing, duration, efficiency, and satisfaction (Natale et al., 2015). They can also measure important components of sleep health (Buysse et al., 1989), such as daytime sleepiness or dysfunction, and identify risks for sleep disorders like insomnia and sleep apnea. In contrast to objective measures such as PSG, subjective measures in general are more accessible, require little to no specialized equipment, and are easier and less time-consuming to implement in research and clinical settings, especially those involving large populations. Additionally, subjective measures rely on self-reported data, providing a personalized and qualitative assessment of individual sleep experiences that can be applied remotely (e.g., online) (Thorndike et al., 2011). Importantly, the only way to assess an individual's satisfaction with sleep or perception of the extent to which sleep interferes with daytime function is to make use of self-report questionnaires. Moreover, because they are non-invasive, subjective sleep measures can provide a comprehensive assessment of sleep characteristics over a longer period, offering a holistic view of an individual's sleep health that may otherwise go undetected by objective sleep monitoring on a single night. Examples of validated subjective sleep tools that are widely used in research include the PSQI (Buysse et al., 1989), Epworth Sleepiness Scale (ESS) (Johns, 1991), Insomnia Severity Index (ISI) (Bastien et al., 2001), the Berlin (Netzer et al., 1999) and STOP-Bang Questionnaires (Chung et al., 2016), and the Restorative Sleep Questionnaire (REST-Q) (Robbins et al., 2022). In addition, the Horne-Östberg Morningness-Eveningness Questionnaire (HÖ-MEQ) (Horne & Ostberg, 1976) and Munich Chronotype Questionnaires (Roenneberg et al., 2003), which reflects circadian rhythm behavior, an important component of sleep timing, are also widely used by researchers to determine chronotype (expanded in greater detail later).

While sleep scales effectively quantify the subjective perception of an individual's sleep, most scales assess sleep quality and habits retrospectively, making them susceptible to recall and response biases (Ibáñez et al., 2018; Martin & Hakim, 2011). Sleep diaries can combat this and provide a better resolution of habitual sleep; however, requesting participants to complete sleep diaries daily can be burdensome, and compliance regarding the use of sleep diaries may vary substantially. Given these strengths and limitations, researchers argue that subjective tools are best employed adaptively and concomitantly with objective tools like PSG or actigraphy. For example, sleep diaries can be helpful to inform actigraphic or PSG sleep stage scoring and improve the estimation of measured sleep parameters to represent true sleep better.

1.6 Circadian rhythms and light

Circadian rhythms refer to internal physiological processes and behaviors that naturally fluctuate over roughly 24 hours. Examples of circadian-regulated processes include metabolism, thermoregulation, and neurohormonal signaling (Bailey et al., 2014; Gnocchi & Bruscalupi, 2017; Mohawk et al., 2012). Most notable is the circadian-driven sleep-wake cycle, which contributes to the regulation of human sleep patterns by determining the preferred timing of sleep and wakefulness. Thus, circadian rhythms and sleep are inextricably linked. Endogenous circadian rhythms are synchronized to the natural light-dark cycle via a central circadian oscillator located in the suprachiasmatic nucleus (or "SCN") in the hypothalamus (Rietveld, 1992). Accordingly, the SCN maintains and regulates the circadian cycle by synchronizing endogenous timing to the environment through a complex signaling cascade involving the expression of clock genes and interconnected molecular feedback loops (Blume et al., 2019). The regulation of circadian rhythms primarily begins upstream at the retina, where the light signals are first received. Photic input is then relayed to the SCN via the optic nerve by melanopsin-expressing intrinsically photosensitive retinal ganglion cells (ipRGCs) with a peak spectral sensitivity similar to blue wavelength light (of 480 nm) (Bedrosian & Nelson, 2017). While several intrinsic and extrinsic cues (or "zeitgebers") might influence circadian rhythms, including non-photic cues like social factors, temperature, eating, and physical activity, the key zeitgeber entraining circadian rhythms is light (Mohawk et al., 2012).

Light is critical for human functioning and has many non-image-forming actions, most notably inducing neuroendocrine changes (e.g., acute melatonin suppression) and circadian phase-shifting (Blume et al., 2019). Melatonin is a hormone synthesized by the pineal gland and secreted in response to darkness, regulating the timing of circadian rhythms and sleep. Specifically, melatonin is regarded as the primary synchronizer of peripheral clocks, operating in coordination with the master clock (Blume et al., 2019; Doghramji, 2007). The SCN receives input about the intensity and spectral composition of light from the environment via the retinohypothalamic tract and, in turn, modulates the release of melatonin to regulate the sleep-wake cycle. At the same time, melatonin feeds back on the SCN to reduce neuronal firing, forming a feedback loop that regulates the diurnal variations between wakefulness and sleep (Blume et al., 2019; Doghramji, 2007). Ambient light levels and the spectral composition thereof have varying chronobiological effects on the circadian oscillator, typically marked by higher luminescence light exhibiting the most profound downstream effects. The spectral sensitivity of circadian phase-shifting and melatonin suppression with the photopigment melanopsin differs such that the systems regulating these actions are regarded as mutually exclusive (Rahman et al., 2018). The effect of light on the circadian system is also time-dependent. For example, bright light exposure in the morning has a phase-advancing effect, while the evening-timed light phase delays the circadian system. Interindividual factors, including age, sex, genetics, photic history, and long-term adaptation to light exposure, might influence light sensitivity and, thus, circadian rhythms and sleep timing (Chellappa, 2021).

There are also individual differences in the temporal organization of circadian rhythms and, as a consequence, sleep-wake schedules. These behavioral differences are observed as chronotypes, which describe the propensity of an individual to sleep, wake, work, be physically active, and even eat at specific times of the day (Roenneberg et al., 2003). Chronotypes exist on a spectrum, ranging from extreme morningness to extreme eveningness, with sleep-wake timing and diurnal peaks of alertness being earlier or later in a given 24-hour period, respectively (Lack et al., 2009; Roenneberg et al., 2003). Despite inter-individual variation in circadian rhythms and thus chronotype having a genetic basis, exposure to light has been shown to influence individual differences in the timing of melatonin secretion and sleep rhythms, which may manifest sleep and circadian problems. For example, evening-type chronotypes exhibit greater circadian advances after exposure to only natural light such that the timing of their internal clocks becomes more similar to earlier chronotypes (Wright Jr et al., 2013). Similarly, the circadian clocks of evening-type individuals become more delayed when exposed to less sunlight and more artificial lighting at night, potentially leading to the development of circadian rhythm and sleep disorders like insomnia or delayed sleep-wake phase syndrome (Wright Jr et al., 2013).

1.6.1 Circadian disruption

Circadian disruption describes the misalignment of the circadian clock (SCN) with environmental timing, as well as the misalignment of the central clock with peripheral clocks (e.g., liver, pancreas, kidney, gut, muscle), and is a modifiable risk factor for disease (Vetter, 2020). Notably, circadian disruption occurs at different organizational levels, ranging from molecular to organismal scales, and adversely affects hormones, metabolic activity, and the sleep-wake cycle (Chellappa, 2021; Vetter, 2020). Overall, the effects of circadian disruption vary in severity, ranging from transient deficits in performance to chronic disorders with severe implications for cardiometabolic health and disease risk (Reutrakul & Knutson, 2015). Circadian disruption is believed to arise from disease (e.g., cancer) or genetic mutations, which can lead to the uncoupling of interconnected molecular feedback loops that regulate clock gene expression. However, it can also be caused by behavioral factors such as rotating night shift work or jetlag resulting from transmeridian travel (Vetter, 2020). In addition, exposure to mistimed light or irregular light-dark patterns has also been shown to play a critical role in disrupting circadian rhythms, contributing to the etiology of various disorders (Figueiro, 2017). For instance, a study observed significant individual differences in circadian timing in response to reduced natural daylight exposure and exposure to artificial light at night, with electrical lighting in industrialized areas leading to a phase delay of the circadian clock compared to natural light-dark cycles while camping at night (Wright Jr et al., 2013). Specifically, it is believed that light at night can suppress or change the timing of melatonin synthesis and lead to circadian disruption by affecting the synchronization between the SCN and downstream peripheral clocks (Figueiro, 2017).

1.6.2 Social jetlag

Social jetlag is a term that has garnered significant traction recently and describes the desynchrony between biological and social timing, characterized by the absolute difference between the midpoint of sleep on workdays and free days (Wittmann et al., 2006). Most striking is that the prevalence of social jetlag is reportedly as high as 69% among adults living in industrialized societies (Koopman et al., 2017). In this regard, social jetlag understandably represents a widespread problem in contemporary society whereby individuals attempt to align their sleep-wake schedule to meet the demands of work, school, or social commitments (Wittmann et al., 2006). Interestingly, social jetlag is more prevalent among evening-type chronotypes because of a more remarkable implicit discrepancy between preferential and societal sleep-wake timing (Martínez-Lozano et al., 2020). For example, evening-types typically follow later bed and wake-up timing on free days; however, on non-free days, they are conflicted by having to wake up and go to bed earlier for school or work, and thus, through forced shifting of their sleep-wake cycle, may experience a greater degree of social jetlag.

The downstream effects of social jetlag on cardiometabolic health are profound and linked with a greater risk of overweight and obesity, hypertension, insulin resistance, and type 2 diabetes (Koopman et al., 2017; Roenneberg et al., 2012). One study on midlife adults echoed these effects, demonstrating associations between social jetlag with lower levels of high-density lipoprotein cholesterol and higher levels of triglycerides, fasting insulin, insulin resistance, and adiposity after controlling for sleep parameters, depression, and health behaviors (Wong et al., 2015). A separate study replicated the associations between social jetlag with overweight and obesity, highlighting links with obesity-related biomarkers for inflammation and type 2 diabetes among metabolically unhealthy obese individuals (Parsons et al., 2015). Together, these findings suggest a strong relationship between social jetlag and cardiometabolic disease risk. Beyond this, social jetlag has also been shown to have pervasive effects on sleep quality and duration; hence, it has also been associated with worsened academic performance (Haraszti et al., 2014; Roenneberg et al., 2012).

1.7 Health implications for gamers and esports players

It is not uncommon for some esports players to displace sleep or physical activity time in favor of their gaming activities, with some gamers dedicating up to 10 hours per day to gaming (DiFrancisco-Donoghue et al., 2018). Playing games before bedtime is also associated with shorter sleep duration and worsened sleep quality, illustrated by increased sleep onset latency, decreased sleep efficiency, adverse changes to sleep architecture (i.e., shorter REM), and reports of insomnia (Exelmans & Van den Bulck, 2015; Higuchi et al., 2005; Miskoff et al., 2019; Peracchia & Curcio, 2018). Researchers speculate that REM sleep suppression could be due to greater catecholamine secretion and reflective of a "high arousal state," marked by a higher sympathetic tone after playing an exciting video game (Higuchi et al., 2005). In addition, more recent studies suggest that exposure to radiofrequency electromagnetic fields emitted from wireless gaming devices could also deteriorate sleep parameters (Männikkö et al., 2020). Ultimately, research points to prolonged nighttime gaming activities as significant contributors to problematic sleep, leading to daytime dysfunction and cognitive impairment in the subsequent waking days (Peracchia & Curcio, 2018).

Another concern is gaming's potential phase-delaying effect on circadian rhythms from gamers gazing at brightly lit electronic displays in the nighttime. In particular, blue-enriched light from electronic media, such as computer screens, produces alerting effects that suppress melatonin secretion and alter circadian regulation of the sleep-wake cycle through phase-shifting (Chang et al., 2015; Vandewalle et al., 2009). Indeed, the melatonin secretion delay induced by nocturnal light exposure is understood to delay the onset of sleepiness, thereby delaying bedtime and sleep initiation. In turn, this leads to a shorter sleep opportunity and, subsequently, reduced sleep duration and poorer sleep quality. This could provoke a vicious cycle, with gaming being a type of sleep avoidance strategy, thus further impairing sleep (Männikkö et al., 2020). There is also the concern that screen-based gaming could lead to social jetlag (Hamre et al., 2022; Hena & Garmy, 2020), marked by discrepant sleep timing between working and free days. This disruption may occur when individuals accumulate higher sleep debt during the week and attempt to compensate by catching up on sleep during the weekend. While the proclivity for short duration or problematic sleep is perhaps inherent among gamers, perpetuated by a cultural narrative that "sleep is for the weak," the downstream long-term cardiometabolic disease risk associated with chronic gaming is highly concerning and understudied.

A previous study in children and adolescents (mean age: 13.1 years) demonstrated that self-reported gaming activity during a 4-hour window before bedtime was associated with greater abdominal adiposity, which was thought to be mediated by reduced sleep quality (Turel et al., 2017). Additionally, the researchers found that a higher average gameplay duration was associated with higher sweet drink consumption while playing and reduced sleep quality. Similarly, a different study comprising 181 adolescents (range: 13-17 years) reported adverse associations between gameplay time with diastolic blood pressure, mean arterial pressure, triglycerides, and a clustered cardiometabolic disease risk score; the findings were independent of age, MVPA, and waist circumference (Martinez-Gómez et al., 2012). Together, these findings suggest a possibly adverse association between gaming activity and cardiometabolic disease risk, a topic that has largely been overlooked in prior studies. Beyond this, gaming is a primarily sedentary activity, and sedentary behavior is independently associated with poor health outcomes (Matthews et al., 2016). Therefore, the combined adverse health effects of short duration, poor quality sleep, and sedentary behavior resulting from gaming are thought to exacerbate cardiometabolic disease risk. Indeed, the cardiometabolic consequences of chronic sleep loss, poor sleep quality, and chronodisruption are unanimous and well characterized, yet the mechanisms through which they manifest are still unclear. Finally, while there is limited research on the effects of chronic gaming on cardiometabolic health in children and adolescents, there is a paucity of evidence regarding adult gamers.

1.8 Sleep and performance in gamers and esports players

As discussed in **Section 1.1**, video gaming is considered a highly immersive and cognitive-demanding activity requiring a range of mental skills for optimal performance (Himmelstein et al., 2017; Taylor, 2012). In particular, esports titles not only require rudimentary cognitive processes and complex executive functions but also demand that players readily cooperate with other team members in a highly competitive and fast-paced environment. This has led some researchers to believe that esports require similar mental skills to certain traditional sports (Bonnar et al., 2019a; Campbell et al., 2018; Murphy, 2009). Furthermore, in non-professional games, esports players are randomly assigned to teams for each match, which requires dynamic adjustments to the unique continuous changes of gameplay conditions and other players' playstyles and temperaments. As such, emotional regulation and stress-coping mechanisms are vital to ensuring esports players' success, especially during high-pressure competitive settings when in-game ranks, prestige, and prize monies are at stake (Poulus et al., 2020).

Accordingly, the cognitive processes involved in video games and esports comprise a combination of elementary and executive functions, such as attention and vigilance, reaction time, cognitive flexibility, working memory, problem-solving, and decision-making abilities (Kokkinakis et al., 2017; Poulus et al., 2020; Toth et al., 2020). For example, sustained attention and working memory are crucial in first-person shooter (FPS) games to concurrently track the positions and movement of allied and enemy players, health points, ammunition, and other relevant elements of gameplay for extended periods. Likewise, vigilance and reaction time are required to react quickly to continuous changes in the game environment, all while being aware of and reflecting on individual performance (or "metacognition"). Furthermore, players must anticipate and adapt to future scenarios based on the current trajectory of the game, which necessitates a high degree of cognitive flexibility. Relatedly, in multiplayer online battle arena (MOBA) games, the demands for strong decision-making and problem-solving abilities are paramount to adapt esports players' strategies to dynamic conditions and obstacles or to analyze new information, such as item builds, player behavior, map control, and vision. Furthermore, esports players require strong visuomotor functioning to manipulate mouse movements and keystrokes (in the case of computer gamers) or controllers (in the case of console gamers) in response to these changing in-game conditions.

Importantly, brief lapses in awareness and impaired tactical decision-making can drastically affect match outcomes, especially in high-ranking and elite-level esports where differences in skill between players are negligible. Therefore, given the heavy reliance on cognitive abilities in gaming, it is believed that sleep could be a key determining factor of esports performance, especially when sleep loss and poor sleep can selectively impair cognitive functions that might underpin esports success (Bonnar et al., 2019a). For example, a meta-analysis reported that sleep restriction was negatively associated with executive function, sustained attention, and long-term memory. Accordingly, these effects were found to be moderated by age, time of day, cumulative days of curtailed sleep, subjective sleepiness, sleep latency, and sex (Lowe et al., 2017). In addition, impaired psychomotor functioning has also been reported during episodes of acute sleep restriction comparable to alcohol intoxication, with cognitive impairment diminishing productivity and increasing the rate of errors in workplace settings (Philip & Åkerstedt, 2006; Williamson & Feyer, 2000). Similarly, sleep quality was negatively associated with cognitive performance at a population level, with poor sleepers having a 1.26-fold (95% CI: 1.16, 1.36, $p<0.001$) odds for low cognitive performance in adjusted models (Wang et al., 2022). Beyond this, preserving sleep and appropriating healthy lifestyle behaviors would be an appealing motive for gamers and esports players to bolster their in-game performance and offset potentially adverse outcomes associated with chronic gaming, especially since health is typically not a highly regarded priority for young people.

1.8.1 Approaches for neurocognitive performance testing in esports players

While it is broadly understood that sleep may impair cognitive functioning (Fullagar et al., 2015; Lowe et al., 2017; Van Dongen et al., 2003), it is not widely established whether and to what degree these decrements apply to esports players. Therefore, it is important to conduct research that directly investigates the relationship between sleep and esports performance to better understand the potential impact of sleep on this population. A first step towards filling this gap in the literature may be through exploring the extent to which sleep might impact cognitive processes in adult esports players by employing measures like computerized PVT, BCST, and n-back tests to assess markers of neurocognitive performance. These markers could, in turn, serve as proxies for gaming ability since they measure cognitive processes critical for successful esports performance.

It is important to note that while paper-based cognitive tests may remove the risk of method and familiarity biases, computerized cognitive test batteries offer greater precision in accurately measuring certain parameters, such as reaction times (Noyes & Garland, 2008). They also offer the ability to manipulate paradigm difficulty, which would otherwise be impractical in paper-based tests, and are presented in a standardized format. Additionally, computerized tests reduce the risk of human error since they are automated (Noyes & Garland, 2008) and are arguably more practical choices for measuring game-focused cognitive outcomes. Moreover, the previously mentioned tests have been applied in various research settings and assessed for their ecological validity in non-gaming samples. For example, the PVT is the *de facto* gold standard for assessing the neurological effects of sleep loss and is considered free of practice effects across various system configurations (Basner et al., 2018; Dinges & Powell, 1985; Reifman et al., 2018). Likewise, the BCST – a non-proprietary version of the Wisconsin Card Sort Test described by Berg – is commonly applied to assess cognitive flexibility in nonclinical populations with high internal validity and repeatability and in some clinical populations (Berg, 1948; Chiu et al., 2018; Fox et al., 2013; Kopp et al., 2021). This computerized adaptation of the original test is susceptible to practice effects; however, the effects can be mitigated by programming random rule changes (i.e., color, number, or form) into the computer software. Finally, the n-back test has high face validity to assess working memory in nonclinical populations with limited transfer effects and generalizability to other cognitive tests and real-world applications (Kirchner, 1958; Soveri et al., 2017).

However, using computer-based cognitive performance measures in video gaming research is not without methodological challenges, particularly considering that video gaming can improve cognitive functioning across a range of domains (Buelow et al., 2015; Pallavicini et al., 2018). For example, one study demonstrated that gamers who played games for two hours or more per day (versus non-gamers) demonstrated superior performance in an array of cognitive tasks, including analogy, processing speed, deductive reasoning, and mathematical intelligence (Hisam et al., 2018). As a result, method bias may result from testing mental skills specific to esports and video gaming using computer-based tests, where the testing modality is presumably more familiar to esports players. In this regard, it could be argued that computer-based cognitive performance measures may give gamers an advantage over non-gamers. However, this potential advantage could be limited by most young people in industrialized settings being familiar with using computers due to the increased availability of technology devices and the more recently accelerated digital transformation process due to the coronavirus pandemic (Evans, 2020; Hargreaves et al., 2004; Noyes & Garland, 2008). Nevertheless, to negate any potential benefit that might be attributed to gamers through years of extensive play, the difficulty level of these tasks could be calibrated to be challenging enough to assess the relevant cognitive abilities but not so difficult that gamers would have an unfair advantage. In addition, participants could be familiarized with the test battery before the test is administered. Overall, it is important to balance ecological validity and minimize methodological biases when selecting cognitive tests for gaming research.

1.9 Purpose of the thesis

The purpose of the thesis is to characterize and explore the associations between device-derived sleep patterns, cardiometabolic health risk factors, and neurocognitive performance in adult esports players. In addition, the thesis will quantify and profile the 24-hour patterns of physical activity and white light exposure in these individuals. The first aim of the thesis will be to systematically review evidence describing sleep in habitual adult gamers to understand the associated risk for cardiometabolic disease or the benefits to gaming performance, critically examine methodological limitations, and highlight the knowledge gaps in the extant literature. (**Chapter 2**). Next, the validity and reliability of a single actigraphy monitoring device (Actiwatch 2), typically used to measure sleep patterns and light exposure, will be assessed for its ability to quantify sedentary behavior and physical activity intensity levels against a reference monitoring device. In addition, a calibration study will be used to determine the device's threshold values (i.e., count cut-points) for discriminating sedentary, light-, moderate-, and vigorous-intensity physical activity. The premise of this aim will be to use the Actiwatch 2 to concomitantly measure sleep patterns, white light exposure, sedentary behavior, and physical activity in the subsequent chapters (**Chapter 3**). Subsequently, esports players' cardiometabolic health status, sleep characteristics, and neurocognitive performance (as a secondary outcome of interest) will be assessed and compared to a control group of non-gamers. Moreover, the relationship between sleep characteristics with cardiometabolic health risk factors and neurocognitive parameters will be assessed (**Chapter 4**). Finally, the thesis will describe the circadian rhythmicity of white light exposure and waking movement behavior patterns during a week of free-living monitoring with the Actiwatch device and quantify the level of sedentary behavior and physical activity of esports players at light-, moderate-, and vigorous-intensity levels (**Chapter 5**). The work underlying this thesis is intended to be a stepping stone toward health regulation in gaming and esports, for which motives are to support individual decisions, governments, and policy makers through awareness and by providing evidence-based recommendations to adopt and maintain healthy gaming behaviors aimed at ameliorating chronic health problems attributed to unhealthy gaming behaviors.

Chapter 2

Sleep in habitual adult video gamers: a systematic review

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2.1 Introduction

In recent years, video gaming has become an increasingly popular and globally recognized phenomenon. Contemporary forms of gaming not only span multiple genres of games but multiple modalities, including computer, console, and mobile platforms (Newzoo, 2021). While gaming takes place both recreationally and competitively, the most notable form is esports, which describes the conglomeration of competitive gaming titles and organized professional gaming events (McCutcheon et al., 2017). It is estimated that esports will have a total audience of 646 million people and global revenue of $1.6 billion by the end of 2023 (Newzoo, 2021). There are also schools of thought dedicated to extending health and performance research and optimizing the performance of esports athletes (Bonnar et al., 2019b; Kemp et al., 2020).

In the past, gaming research has explored several domains, including the effect that games have on the psychological state (e.g., aggression), their use in cognitive training (e.g., gamification), and gaming addiction (Palaus et al., 2017; Pallavicini et al., 2018). However, most of these studies have investigated children and adolescents, in addition to the large body of literature investigating video game-based interventions in older adults. Despite reports indicating that most general gamers are now in their early thirties (Entertainment Software Association, 2021) and that most esports athletes are aged between 21 and 25 years (ESPN, 2017), few studies have considered young adults (i.e., 18 to 35 years). While there is less disparity in the sex distribution of gamers today, 45% of the general gaming population identifies as female (Entertainment Software Association, 2021), and much of the contemporary research in gaming has been conducted among males. Thus, there is a need for research to consider young adults and females in the context of gaming.

It is stereotypical that gamers may spend many hours gaming at night, usually at the expense of sleep. This stereotype is corroborated by reports of some gamers spending up to 10 hours playing games and achieving as little as 5.5 hours of sleep in 24 hours (DiFrancisco-Donoghue et al., 2018; Turel et al., 2016). These reports have prompted growing awareness and concern regarding the adverse health risks associated with excessive gaming (Holden et al., 2018). In particular, gaming is associated with longer sleep onset latency, short sleep duration, and poor sleep quality (Kristensen et al., 2021). There is also evidence describing altered sleep architecture from gaming, including reduced slow-wave sleep and rapid eye movement sleep (Dworak et al., 2007; Higuchi et al., 2005; Weaver et al., 2010). These pervasive effects on sleep are thought to be due to excessive screen exposure and attributed to the sleep-suppressing effect of catecholamines, which operate as part of the physiological arousal response to gaming (Kim et al., 2016; Lam, 2014; Weaver et al., 2010). However, there is little evidence of the mechanism that causes or underly these effects. Sleep disturbances may also manifest as sleep disorders, such as insomnia, and challenge the initiation and maintenance of healthy sleep. This could provoke problematic gaming behaviors, whereby gamers displace sleep with gaming activities to cope with sleeplessness (Kristensen et al., 2021). A vicious cycle may thus ensue, in which unhealthy sleep practices and problematic sleep perpetuate problematic gaming behaviors (Kristensen et al., 2021), translating to profound acute and chronic implications on cardiometabolic health. A recent study involving adolescent gamers found that curtailed sleep mediated the negative association between gaming addiction and abdominal obesity, which in turn was linked to higher blood pressure, altered lipid profiles, and insulin (Turel et al., 2016). Chronic short and long sleep durations have been independently linked with greater all-cause mortality rates and risk for cardiometabolic disease (Yin et al., 2017). However, the implications of chronic gaming exposure as a contributor to adverse cardiometabolic health through poor sleep are not yet fully understood and are arguably multifaceted.

Another concern is the effect of gaming on circadian rhythms, including the sleep-wake cycle (Ceranoglu, 2014). Gamers may inadvertently phase delay their circadian rhythms in two ways: exposure to excessive light at night or gaming-induced behavior of late or delayed bedtimes. Short wavelength (i.e., blue) and bright light emitted from device screens may delay the onset of nocturnal melatonin secretion by the pineal gland and increase neurophysiologic arousal; this, in turn, delays sleepiness and, thus, the onset of sleep, as well as the phase of other circadian-regulated processes (Gooley et al., 2011; Shechter et al., 2018). Through gaming at night, natural bedtimes might be delayed, which in turn may contribute to circadian disruption through a phenomenon known as social jetlag, a discrepancy between biological and social clocks, usually observed as the difference between sleep timing across weekdays and weekend days (Chakradeo et al., 2018; Wittmann et al., 2006). Circadian disruption, regardless of the mechanism (i.e., shift work, jet lag, social jetlag), has been associated with increased risk for obesity, inflammation, insulin resistance, hypertension, type 2 diabetes, and cardiovascular disease (Lucassen et al., 2012; Parkar et al., 2019; Wong et al., 2015). Thus, gamers are likely at risk for short sleep duration, disrupted sleep, and disrupted circadian rhythms, which justifies the importance of studying cardiometabolic health in this population. Although chronic diseases may be more prevalent in older populations, the implicit risk associated with gaming behavior is profound, such that health risk factors presenting as an acute disease phenotype in young adults may translate to worsened chronic health implications later in life.

In addition to these cardiometabolic diseases, psychiatric disorders have historically been linked to light, circadian disruption, and impaired sleep (Baron & Reid, 2014; Walker et al., 2020; Wulff et al., 2010). In fact, disrupted sleep is a diagnostic criterion for most psychiatric disorders, including depression, bipolar disorder, anxiety, and post-traumatic stress disorder (American Psychiatric Association, 2013). More recently, however, circadian disruption and problematic sleep have also been linked to behavioral addictions, such as Internet Gaming Disorder (IGD), in which sleep problems are also thought to be mediators (Lam, 2014; Starcevic & Khazaal, 2017). A longitudinal study on a large sample of Singaporean children revealed that high gaming volume was one of several risk factors linked to gaming addiction (Gentile et al., 2011). The study also demonstrated that most (84%) pathological gamers remained addicted to gaming after two years and presented with several comorbid mood disorders, including depression, anxiety, and social phobias (Gentile et al., 2011). Gaming addictions have also been associated with poor sleep quality and insomnia, suggesting a bidirectional relationship between problematic gaming with mood disorders, circadian rhythms, and sleep problems (Lam, 2014). Therefore, problematic gaming can exacerbate affective symptoms in vulnerable individuals. Since parents may exercise their parental discretion regarding their child's gaming activities, adults unable to self-regulate their gaming behaviors are arguably at greater risk for these more immediate pervasive effects.

There is an abundant body of work describing the positive aspects of gaming, including studies demonstrating cognitive benefits attributed to gaming (Buelow et al., 2015; Pallavicini et al., 2018). Cognitive processes critical to gaming may include elementary processes such as alertness, psychomotor and cognitive speed, and vigilance, in addition to executive processes such as planning, problem-solving, working memory, and decision-making (Gross & Grossman, 2010). While these processes may be susceptible to the effects of sleep restriction (Killgore, 2010; Lo et al., 2016), it is unclear to what extent poor quantity and quality of sleep may impair the cognitive skills required for optimal gaming performance. For example, there is evidence that sleep potentiates problem-solving in individuals challenged with a game involving logical reasoning (Beijamini et al., 2014). However, the decrement in executive processes following sleep restriction has been widely challenged, with the basis for the argument being that sleep loss affects the frontal lobes (the location of executive processing) more than most other regions of the brain (Tucker et al., 2010). Ultimately, managing sleep to preserve and optimize performance would presumably be an appealing motivation for gamers to reconsider their sleep-wake behavior and consequently act to negate deleterious long-term metabolic consequences resulting from excessive gaming.

Despite the plethora of studies involving gaming, there is a paucity of evidence involving habitual adult gamers. This cohort of predominantly young adults consists of individuals who self-identify as gamers or engage with gaming regularly and consistently for recreational (e.g., social gamers) or competitive (e.g., esports players) purposes. There is also a lack of research describing these individuals' gaming behaviors, health status, and sleep patterns. The present systematic review aimed to examine the evidence describing sleep in habitual adult gamers, with a view to understand what is known regarding the associated risk for cardiometabolic disease or the benefits concerning gaming performance or markers thereof in the future.

2.2 Methods

2.2.1 Search strategy

The search strategy used in the review process followed standardized procedures outlined in the Preferred Reporting Item for Systematic Review and Meta-Analysis (PRISMA) Statement (Liberati et al., 2009). Systematic literature searches were conducted across three electronic databases: PubMed, Scopus, and ISI Web of Science. These databases were used to retrieve studies published between 1 January 2000 and 22 April 2020. In addition, all citation libraries in the Web of Science Core Collection were considered, including Science Citation Index Expanded (SCI-EXPANDED), Social Sciences Citation Index (SSCI), Arts and Humanities Citation Index (A&HCI), and Emerging Sources Citation Index (ESCI) library indexes.

The electronic search strategy used the following terms: "esport*" or "e-sport*" or "electronic sport*" or "computer gam*" or "video gam*" or "internet gam*" or "gamer*" or "gaming" or "cybergam*" or "cyber gam*" and "sleep*" or "insomnia" in the title and abstract, or MeSH fields ("sleep" and "insomnia" only) for PubMed. Title, abstract, and keyword fields were used for Scopus, and topic fields were used for ISI Web of Science. The following search filters were applied to their respective database searches: Language: English; Publication Dates: 2000 - 2020; Species: Human; Document Type: Article; Source Type: Journal. The complete search strategy for each database is presented in Table 2.1.

Table 2.1. Systematic search strategy used in electronic databases.

Database	Search query
PubMed	esport*[tiab] OR e-sport*[tiab] OR “electronic sport*” [tiab] OR “computer gam*” [tiab] OR “video gam*” [tiab] OR “internet gam*” [tiab] OR gamer* [tiab] OR gaming [tiab] OR cybergam* [tiab] OR “cyber gam*” [tiab] AND sleep* [tiab] OR insomnia [tiab] OR sleep* [MeSH] OR insomnia [MeSH] Filters: Language: English; Species: Humans Publication Dates: From 2000 to 2020
Scopus	TITLE-ABS-KEY (esport* OR e-sport* OR "electronic sport*" OR "computer gam*" OR "video gam*" OR "internet gam*" OR gamer* OR gaming OR cybergam* OR "cyber gam*") AND TITLE-ABS-KEY (sleep* OR insomnia) AND PUBYEAR > 1999 AND PUBYEAR < 2021 AND (LIMIT-TO (SRCTYPE, "j")) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English"))
ISI Web of Science	TS = (esport* OR e-sport* OR "electronic sport*" OR "computer gam*" OR "video gam*" OR "internet gam*" OR gamer* OR gaming OR cybergam* OR "cyber gam*") AND TS = (sleep* OR insomnia) Limits: Language: English; Timespan 2000 – 2020 Document types: Article

2.2.2 Eligibility criteria

Original peer-reviewed research studies examining or reporting on sleep in habitual adult gamers were considered for inclusion in the present review. Habitual gamers were defined as individuals who self-identified as gamers or individuals who played games regularly or consistently in either a recreational (i.e., social gamers), competitive, or professional capacity (i.e., esports players). Studies that did not specifically recruit gamers were considered only if the data reported were stratified by game playing dose, exposure, duration, or frequency. The reasoning behind this decision was to discriminate regular or habitual gamers (as defined above) from a general population of non-gamers who would otherwise not self-identify as gamers or would not regularly engage with gaming. Gaming was defined as playing an electronic game on a personal computer, game console (e.g., PlayStation, Xbox, Nintendo), or mobile phone. Studies involving arcade video game systems were therefore excluded. The search strategy was restricted to include studies published after January 2000 to examine only contemporary game-playing modalities.

Studies were included if they: (1) used an experimental trial design (e.g., randomized controlled trial, observational or prospective cohort study design), (2) reported data on habitual gamers, (3) used electronic gaming platforms, (4) had a sample of adult participants (i.e., aged 18 years or older); or in the case of studies with large samples with broad age ranges, had stratified the data by age (i.e., 18-30 years, 31-40 years, etc.), (5) reported at least one subjectively or device-derived parameter of sleep, (6) were published in English and (7) were published from 2000 onwards.

Studies were excluded if they used games as a stressor (i.e., to induce a physiological or psychosocial response), intervention tool (e.g., for educational or training purposes), or involved the use of gamified or simulated training or educational tools. The reasoning was to exclude studies that primarily examined the effects of game technologies on a general population group rather than habitually engaged gamers. Conference abstracts, other published abstracts, and gray literature (e.g., reports, white papers, academic theses, or dissertations) were also excluded.

2.2.3 Study selection

Figure 2.1 provides an outline of the study selection process. Studies were initially screened by assessing the title and abstract only. The appraisal of studies was performed by conducting full-text screening of the filtered studies using standardized methods by two independent reviewers (C.K. and D.T.R.). In the event of uncertainty or disagreement, disputes were resolved by consensus and arbitration (D.E.R.) or by contacting the corresponding authors.

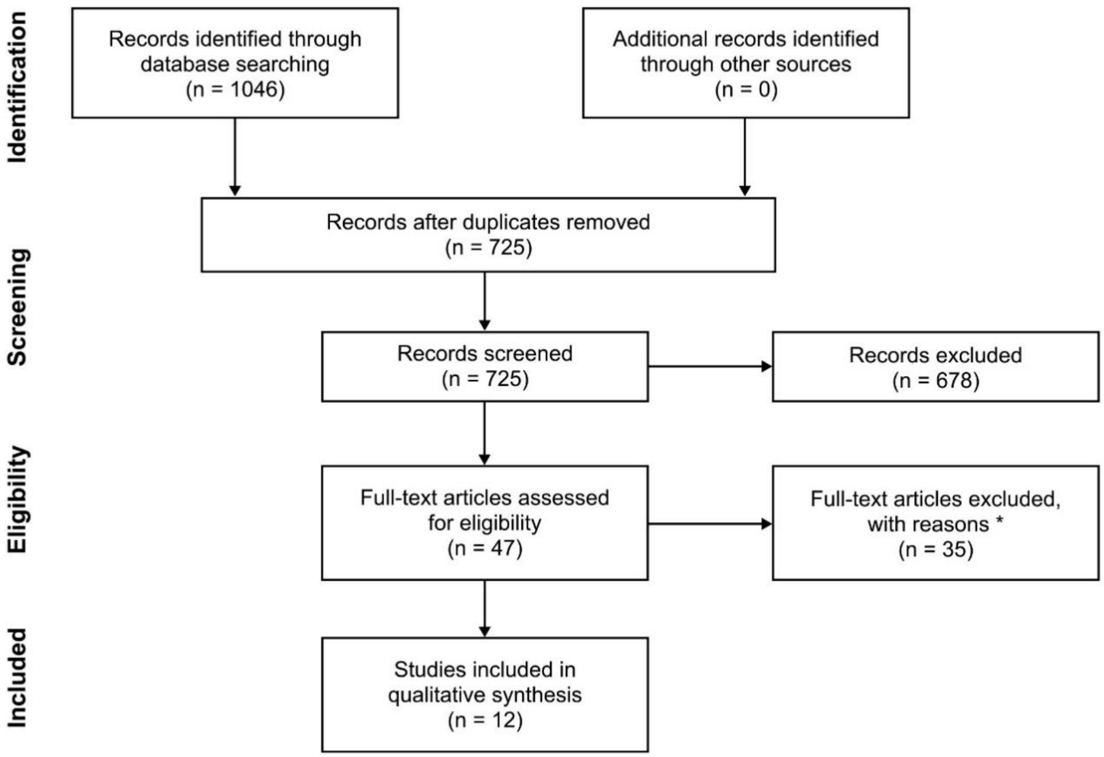

Figure 2.1. PRISMA diagram of the study selection process. * No experimental group of habitual gamers (n = 19); no valid parameters of sleep or insomnia (n = 10); non-adult cohort (n = 4); unable to retrieve full text for appraisal (n = 1); article was retracted by the publishing journal (n=1).

2.3 Results

2.3.1 Synthesis of evidence

The study selection process (Figure 2.1) yielded a total of 1046 records, of which 151 (14.4%) were extracted from PubMed, 317 (30.3%) from Scopus, and 578 (55.3%) from ISI Web of Science. The 321 duplicate records were removed, leaving 725 unique records eligible for screening. Of these, 47 records were identified for full-text appraisal, with the remaining 678 excluded. A further 35 records were excluded during the appraisal process for the following reasons: (i) no experimental group of habitual gamers (n=19); (ii) no valid parameters of sleep or insomnia were reported (n=10); (iii) non-adult cohort was used (n=4); (iv) unable to obtain the full-text and attempts to contact the authors had failed (n=1); and (v) article was retracted by the publishing journal (n=1). Therefore, 12 records were eligible for inclusion in the qualitative synthesis.

2.3.2 Study characteristics

The study characteristics are summarized in Table 2.2. Ten of the included twelve studies employed an observational design (Achab et al., 2011; Akcay & Akcay, 2020; Altintas et al., 2019; Evren et al., 2019; Exelmans & Van den Bulck, 2015; King & Delfabbro, 2009; Ko et al., 2020; Mario et al., 2014; Rudolf et al., 2020; Wong et al., 2020), one study was a randomized crossover trial (Thomas et al., 2019) and another was a prospective cohort study (Thomée et al., 2015). All observational studies employed an online or survey approach, apart from two studies that also included interviews (Exelmans & Van den Bulck, 2015; Ko et al., 2020) and one study that also performed clinical measures in a controlled setting (Mario et al., 2014). Sample sizes of the included studies ranged from 9 to 1066 participants, with cohorts spanning ten countries. Overall, the sex distribution of the studies was biased toward males and included: two studies with all-male populations (Mario et al., 2014; Thomas, C. J. et al., 2019), six studies with populations that were majority male (range: 77% to 98%) (Achab et al., 2011; Altintas et al., 2019; King & Delfabbro, 2009; Ko et al., 2020; Rudolf et al., 2020; Thomée et al., 2015) and four studies with populations that were majority female (range: 56% to 71%) (Akcay & Akcay, 2020; Evren et al., 2019; Exelmans & Van den Bulck, 2015; Wong et al., 2020). The cohorts in six of the studies comprised gamers from the general population (Achab et al., 2011; Altintas et al., 2019; Exelmans & Van den Bulck, 2015; King & Delfabbro, 2009; Rudolf et al., 2020; Thomée et al., 2015) and one study cohort comprised an elite team of League of Legends esports players (Thomas et al., 2019). The rest of the included studies enrolled university students in their cohorts. The gaming platforms that participants reported using varied between mobile, console, and computer. Four studies did not define the gaming platforms at all (Altintas et al., 2019; Evren et al., 2019; Ko et al., 2020; Wong et al., 2020), and three studies included participants who played games on the computer (Achab et al., 2011; Thomas et al., 2019; Thomée et al., 2015). The remaining studies did not discriminate between gamers by gaming platform and comprised cohorts using various gaming platforms. The studies poorly defined prior exposure to gaming. Four studies reported prior gaming exposure (range: <1.0 to 8.5 ± 6.7 years) (Achab et al., 2011; Akcay & Akcay, 2020; Ko et al., 2020; Mario et al., 2014). Three of these studies used gaming exposure as an inclusion criterion and did not report prior gaming exposure as an outcome measure (Akcay & Akcay, 2020; Ko et al., 2020; Mario et al., 2014). Gaming frequency was reported as hours of gaming per day (range: 0.8 ± 1.0 to 10.3 ± 2.1 h) (Akcay & Akcay, 2020; Exelmans & Van den Bulck, 2015; Thomas et al., 2019; Thomée et al., 2015; Wong et al., 2020) or per week (range: <7.0 to 36.8 ± 22.0 h) (Achab et al., 2011; Altintas et al., 2019; King & Delfabbro, 2009; Ko et al., 2020; Mario et al., 2014; Rudolf et al., 2020). Only one study did not report gaming frequency (Evren et al., 2019).

Table 2.2. Demographic characteristics of the included studies.

Citation	Country	Study design	Population or subgroup	Age (years)	Sample size	% Male	Gaming platform	Gaming exposure	Gaming frequency
Achab et al. (2011)	France	DOS [a]	Addicted (DAS+) and non-addicted (DAS-) MMORPG gamers	All: 26.6 ± 7.1 DAS+: 25.7 ± 6.5 DAS-: 27.0 ± 7.3	All: 448 DAS+: 123 DAS-: 325	All: 82.7 DAS+: 87.0 [b] DAS-: 81.2 [b]	PC	All: nr DAS+: 8.41 ± 5.93 y DAS-: 8.54 ± 6.66 y	All: 30.3 ± 18.7 $h \cdot wk^{-1}$ DAS+: 36.8 ± 22.0 $h \cdot wk^{-1}$ DAS-: 27.7 ± 16.7 $h \cdot wk^{-1}$
Akçay & Akçay (2020)	Turkey	DOS [a]	University students	22.76 ± 2.21	892	29.5	PC, console, mobile, tablet	Not playing to ≥5 y	Daily mean: 0.8 ± 1.0 $h \cdot day^{-1}$ Weekday: 0.4 ± 0.9 $h \cdot day^{-1}$ Weekend: 1.8 ± 1.6 $h \cdot day^{-1}$
Altintas et al. (2019)	France	DOS [a]	Online game players with high (HSQ) and low (LSQ) sleep quality profiles	All: 24.40 ± 6.98 HSQ: 24.02 ± 6.77 LSQ: 24.64 ± 7.31	All: 217 HSQ: 132 LSQ: 85	All: 80.6 HSQ: nr LSQ: nr	nr	nr	All: 18.14 ± 17.90 $h \cdot wk^{-1}$ HSQ: 17.52 ± 14.87 $h \cdot wk^{-1}$ LSQ: 19.12 ± 21.85 $h \cdot wk^{-1}$
Evren et al. (2019)	Turkey	DOS [a]	University students with (present) and without (absent) probable insomnia	All: nr Absent: 21.93 ± 3.50 Present: 21.51 ± 2.88	All: 1010 Absent: 810 Present: 200	All: nr Absent: 41.1 Present: 35.5	nr	nr	nr
Exelmans & Van den Bulck (2015)	Belgium	DOS	Adults in Flanders, Belgium	46.0 ± 17.76	844 [c]	43.8	PC, console, internet, or social media games	nr	All: 22.8 $min \cdot day^{-1}$ Gamers [c]: 67.0 $min \cdot day^{-1}$
King & Delfabbro (2009)	Australia	DOS [a]	Subgroup of heavy adult game players	20.1 ± 3.9	45	98.0	PC, console	nr	(i) >30.0 $h \cdot wk^{-1}$ (ii) >4 days per week (iii) 3h mean session duration

Ko et al. (2019)	Taiwan	DOS	Subgroups of university students who are regular gamers (RG) and IGD gamers (IGD)	RG: 24.59 ± 3.41 IGD: 25.32 ± 4.20	All: 138 RG: 69 IGD: 69	All: 78.3 RG: 78.3 IGD: 78.3	nr	>2 y	RG: 44.9% play >25 $h \cdot wk^{-1}$ IGD: 97.1% play >25 $h \cdot wk^{-1}$
Mario et al. (2014)	UK	DOS	University student gamers playing frequently (>7 $h \cdot wk^{-1}$) and infrequently (≤7 $h \cdot wk^{-1}$)	All: 21.0 (20.0 - 22.0) Frequent: 21.0 (20.0 - 22.0) Infrequent: 21.0 (21.0 - 22.0)	All: 45 Frequent: 21 Infrequent: 24	100	PC, console, exergames	>1 y	Frequent: >7 $h \cdot wk^{-1}$ Infrequent: ≤7 $h \cdot wk^{-1}$
Rudolf et al. (2020)	Germany	DOS [a]	Online gamers and esports players (including professional, former-professional, amateur, regular, and occasional players)	22.9 ± 5.9	1066	91.9	PC, console	nr	24.4 ± 15.9 $h \cdot wk^{-1}$ [d]
Thomas et al. (2019)	USA	RCT	Team of elite LoL esports players	20.8 ± 2.0	9	100	PC	nr	10.3 ± 2.1 $h \cdot day^{-1}$ (LoL only) 1.8 ± 2.8 $h \cdot day^{-1}$ (other games)
Thomée et al. (2015)	Sweden	PCS [a]	Subgroup of male and female "high gamers" from the Swedish adult population registry playing games >2 $h \cdot day^{-1}$	Males: 21.9 ± 1.4 Females: 21.8 ± 1.3	Males: 319-325 Females: 96-99	~76.8	PC, mobile, tablet [e]	nr	Males: >2 $h \cdot day^{-1}$ Females: >2 $h \cdot day^{-1}$
Wong et al. (2020)	China	DOS [a]	University students	20.89 ± 1.48	300	40.67	nr	nr	1.12 ± 1.53 $h \cdot day^{-1}$

Data are presented as mean ± standard deviation or median (interquartile range) unless otherwise indicated. DOS - Descriptive Observational Study; RCT - Randomized Crossover Trial; PCS - Prospective Cohort Study; MMORPG - Massive Multiplayer Online Role-Playing Game; PC - Personal Computer; IGD - Internet Gaming Disorder; GD - Gaming Disorder; LoL - League of Legends; nr - data not reported. [a] - exclusively survey-based; [b] - a calculated value representing the distribution of males per group, based on sample sizes reported in the study; [c] subset (34.4%) of the total population self-identified as gamers; [d] - a subset of the total population (n=978); [e] - mobile and tablet platforms were included in year five only.

Five studies reported interactions between sleep and gaming addiction (Achab et al., 2011; Akcay & Akcay, 2020; Evren et al., 2019; Ko et al., 2020; Wong et al., 2020). A further four studies reported on interactions between sleep and gaming behavior (i.e., volume, duration, or intensity) (Altintas et al., 2019; Exelmans & Van den Bulck, 2015; Mario et al., 2014; Rudolf et al., 2020) and one study reported on interactions between sleep and physical health (Altintas et al., 2019). All of the studies employed self-report tools to measure parameters of sleep, which included the use of validated questionnaires such as the Pittsburgh Sleep Quality Index (PSQI) (Buysse et al., 1989), Insomnia Severity Index (ISI) (Bastien et al., 2001), Bergen Insomnia Scale (BIS) (Pallesen et al., 2008), and Epworth Sleepiness Scale (ESS) (Johns, 1991). Otherwise, studies also presented self-report data derived from non-validated means. Sleep characteristics reported across the included studies are presented in Table 2.3.

Table 2.3. Sleep characteristics reported by the included studies.

Citation	Self-reported sleep duration (h)	PSQI (total score)	Other sleep parameters		
			Restful sleep (% No)	Sleep deprivation due to gaming (% Yes)	Daytime sleepiness (% Yes)
Achab et al. (2011)	All: 7.1 ± 1.3 DAS+: 6.8 ± 1.4 DAS-: 7.2 ± 1.3 p=0.043 OR: 0.78, 95% CI: 0.66-0.93, p=0.004 [b]	nr	All: 19.1% DAS+: 53.5% DAS-: 46.5% p<0.001 OR: 0.23, 95% CI:0.14-0.38, p<0.001 [b]	All: 36.8% DAS+: 40.9% DAS-: 59.1% p<0.001 OR: 2.83, 95% CI: 1.83-4.38, p<0.001 [b]	All: 22.7% DAS+: 48.0% DAS-: 52.0% p<0.001 OR: 3.10, 95% CI: 1.92-5.00, p<0.001 [b]
			ESS	Bedtime	Wake-up time
Akçay & Akçay (2020)	All: 7.5 ± 0.9 Stratified by gaming frequency: Not playing [c]: 7.2 ± 0.9 <2 h • day^{-1} [d]: 7.6 ± 1.3 ≥2 h • day^{-1} [e]: 7.5 ± 0.9 p<0.001	All: 8.5 ± 2.7 Stratified by gaming frequency: Not playing [c]: 8.2 ± 2.3 <2 h • day^{-1} [d]: 8.3 ± 2.7 ≥2 h • day^{-1} [e]: 10.5 ± 3.0 p<0.001	All: 3.0 ± 3.9 Stratified by gaming frequency: Not playing [c]: 4.0 ± 3.9 <2 h • day^{-1} [d]: 2.6 ± 3.7 ≥2 h • day^{-1} [e]: 4.9 ± 4.7 p<0.001	All: 23:42 ± 01:48 Stratified by gaming frequency: Not playing [c]: 00:00 ± 00:54 <2 h • day^{-1} [d]: 23:30 ± 01:54 ≥2 h • day^{-1} [e]: 00:54 ± 01:48 p<0.001	All: 07:24 ± 01:00 Stratified by gaming frequency: Not playing [c]: 07:18 ± 00:48 <2 h • day^{-1} [d]: 07:18 ± 0:54 ≥2 h • day^{-1} [e]: 08:30 ± 02:00 p<0.001
			Good sleepers	Poor sleep	
Altintas et al. (2019)	nr	All: 6.24 ± 3.12 HSQ: 6.36 ± 2.99 LSQ: 6.07 + 3.32 p=0.51	All: 44.70% HSQ: nr LSQ: nr	All: 55.30% HSQ: nr LSQ: nr	
Evren et al. (2019)	nr	nr	Probable insomnia (ISI total score)		

			Absent: n=810, 80.2% Present: n=200, 19.8%		
Exelmans & Van den Bulck (2015)	nr	4.56 ± 2.66 [a]	Bedtime (hh:mm) 23:25 ± 1:05 [a]	Wake-up time (hh:mm) 07:30 ± 1:25 [a]	
King & Delfabbro (2009)	nr	nr	SHI total score 30.2 ± 7.1		
Ko et al. (2019)	nr	nr	Bedtime (< 1:00, 1:00-3:00, >3:00) RG: 60.9%, 36.2%, 2.9% IGD: 17.4%, 52.2%, 30.4% $p<0.001$	Wake-up time (<9:00, 9:00-12:00, >12:00) RG: 62.3%, 33.3%, 4.3% IGD: 30.4%, 37.7%, 31.9% $p<0.001$	Sleep duration (<4h for ≥ 2 days • wk^{-1}) RG: 4.3% IGD: 58.0% $p<0.001$
Mario et al. (2014)	nr	All: 6.0 (4.0 - 8.0) Frequent: 6.0 (5.0 - 9.0) Infrequent: 5.5 (4.0 - 7.0) $p=0.08$			
Rudolf et al. (2020)	7.1 ± 1.3	nr		Sleep quality [mode] "Quite good" (n=642, 60.2%)	
Thomas et al. (2019)	8.1 ± 1.2	nr			
Thomée et al. (2015)	Males: 7.7 ± 1.1 Females: 7.9 ± 1.5	nr			
Wong et al. (2020)	nr	6.63 ± 2.14			

Data are presented as mean ± standard deviation or median (interquartile range) unless otherwise indicated. BMI - body mass index; DAS(+) – addicted gamer; DAS(-) – non-addicted gamer; HSQ: high sleep quality profile; LSQ: low sleep quality profile; PSQI - Pittsburgh Sleep Quality Index; ESS - Epworth Sleepiness Scale; SHI - Sleep Hygiene Index; ISI - Insomnia Severity Index, OR: odds ratio; CI: confidence interval; nr - data not reported. [a] - subset (34.4%) of the total population self-identified as gamers; [b] - adjusted for age, sex, and educational level; [c] - n=195; [d] - n=640; [e] - n=57.

Studies involving gaming addiction had calculated total scores using varying scales. However, they were all adapted or based on the Diagnostic and Statistical Manual of Mental Disorders (DSM) (American Psychiatric Association, 2013) or the International Classification of Diseases (ICD) criteria for substance dependence or internet game addiction. The scales that were used included: DSM-IV Substance Dependence Adapted Scale (DAS) (Achab et al., 2011), Game Addiction Scale for Adolescents - Short Form (GAS-SF) (ANLI, 2018), Internet Gaming Disorder Scale - Short Form (IGDS9-SF) (Pontes & Griffiths, 2015), Young's Internet Addiction Test - Short Form (YIAT-SF) (Pawlikowski et al., 2013); and Addictive Intensity Evaluation Questionnaire (AIE-Q) (Décamps et al., 2010).

2.3.3 Sleep

Self-reported sleep duration was reported in five of the included studies, with gamers sleeping on average between 6.8 ± 1.4 to 8.1 ± 1.2 hours per day (Achab et al., 2011; Akcay & Akcay, 2020; Rudolf et al., 2020; Thomas et al., 2019; Thomée et al., 2015). One study indicated that there was a greater occurrence of sleep duration under four hours per night on at least two days per week among addicted gamers compared to regular gamers (58.0% versus 4.3%, $p<0.001$) (Ko et al., 2020). None of the studies that reported on sleep specifically discriminated between nocturnal and diurnal sleep time. The sleep quality of gamers was reported subjectively in five studies using the PSQI (total scores range: 4.56 ± 2.66 to 10.5 ± 3.0) (Akcay & Akcay, 2020; Altintas et al., 2019; Exelmans & Van den Bulck, 2015; Mario et al., 2014; Wong et al., 2020). All studies reporting PSQI total scores, apart from Exelmans & Van den Bulk (2015) (PSQI total score: 4.56 ± 2.66), reported total scores greater than 5, thus indicating poor sleep quality.

2.3.4 Sleep and gaming volume, duration, and intensity

Exelmans & Van den Bulck (2015) estimated gaming volume by (i) multiplying the volume of gaming during an average weekday (Mon - Thurs) by four and weekend day (Sat and Sun) by two; (ii) summing the average measures of volume on weekdays, weekend days and Fridays; and finally (iii) dividing the result by seven to produce an average estimate game playing time (as hours per day). Weak but significant relationships between gaming volume with PSQI ($r=0.109$, $p<0.01$) and BIS ($r=0.104$, $p<0.01$) total scores, as well as bedtime ($r=0.172$, $p<0.01$), and rise time ($r=0.189$, $p<0.01$) were observed. Hierarchical cluster analysis further explained that an increasing volume of gaming was associated with worsened sleep quality (PSQI score: $\beta=0.145$, $p<0.001$), increased symptoms of insomnia (BIS score: $\beta=0.120$, $p<0.01$), as well as delayed bedtime ($\beta=0.100$, $p<0.01$) and rise times

(β=0.168, p<0.001). Each additional hour of gaming per day delayed bedtime by 6.9 min (95% CI: 2.0-11.9 min), rise time by 13.8 min (95% CI: 7.8-19.7 min), and increased the odds of having poor sleep quality (defined as having a PSQI total score > 5) by 31.0% (95% CI: 1.09-1.57, p<0.01). Compared to those who did not play games, gamers playing >1 h per day had a greater chance of having poor sleep quality (Odds ratio (OR): 2.746, 95% CI: 1.596-4.723, p<0.001), with 29.5% of the prevalence of poor sleep quality being attributed to gaming. Relatedly, these gamers were also more likely to have sleep latency (OR: 3.379, 95% CI: 1.699-6.720, p<0.01) and sleep efficiency (OR: 2.776, 95% CI: 1.202-6.413, p<0.01) PSQI sub-component scores of 2 (rather than 0) and were 2.29 times more likely to perceive their sleep quality as "rather bad," than "very good," compared to those who did not play games (p<0.05). All models were adjusted for gender, age, educational level, hours of exercise, and perceived stress (1st step), and video gaming (2nd step).

Two studies found no association between gaming behavior and sleep parameters (Mario et al., 2014; Rudolf et al., 2020). One of these studies calculated total video game playing (measured as hours per week) by summing the recorded hours of gaming over the last year in an average week (Mario et al., 2014). No significant association was found between total game playing and PSQI-measured sleep quality (rho=0.23, p>0.05) (Mario et al., 2014). The other study reported no associations between gaming duration (measured in hours per week) with self-reported sleep quality and duration (rho<0.10, p>0.05) (Rudolf et al., 2020).

2.3.5 Sleep and gaming addiction

Achab et al. (2011) used the DAS to determine if gamers screened positive (DAS+) or negative (DAS-) for gaming addiction and were subsequently allocated to their respective groups. After adjusting for age, sex, and educational level, the DAS+ group was more likely to have shorter sleep duration (OR: 0.78, CI: 0.66-0.93, p=0.004) and less restful sleep (OR: 0.23, 95% CI: 0.14-0.38, p<0.001) compared to the DAS- group. There was also a greater frequency of sleep deprivation due to gaming (OR: 2.83, 95% CI: 1.83-4.38, p<0.001) and daytime sleepiness (OR: 3.10, 95% CI: 1.92-5.00, p<0.001) in the DAS+ group.

Altintas et al. (2019) did not find significant correlations between total PSQI scores and gaming variables (gaming duration: r=-0.035, p>0.05; the intensity of video game playing: r=-0.093, p>0.05). Hierarchical cluster analysis was used to identify high sleep quality profiles (HSQ group; 60.83% of participants) and low sleep quality profiles (LSQ group; 39.17% of participants) among participants.

After comparing PSQI subcomponent scores between these two groups, Altintas et al., (2019) showed that the LSQ group was characterized by having lower scores of subjective sleep quality (2.84 ± 0.75 versus 1.66 ± 0.56, p=0.01) and sleep efficiency (0.51 ± 0.84 versus 0.11 ± 0.33, p=0.01); greater scores of sleep latency (2.04 ± 0.73 versus 0.60 ± 0.55, p=0.01), sleep disturbance (1.25 ± 0.55 versus 0.78 ± 0.53, p=0.01) and sleep medication use (0.37 ± 0.88 versus 0.03 ± 0.27, p=0.01). The LSQ group also had greater video game duration (19.12 ± 21.85 h • wk^{-1} versus 17.52 ± 14.87 h • wk^{-1}, p=0.01) and intensity of video game playing total scores (44.33 ± 16.86 versus 37.21 ± 11.51, p=0.01), compared to the HSQ group. Furthermore, in logistic regression analysis, high-intensity video game playing was associated with a greater risk of having low sleep quality (OR: 0.969, 95% CI: 0.946-0.993, p=0.01) when sleep quality profile was used as the dependent variable.

A recent study by Akçay & Akçay (2020) reported positive correlations between GAS-SF scores and various self-reported or subjective parameters of sleep, including daily average sleep duration (measured in hours; r=0.118, p<0.001), wake-up time (r=0.114, p=0.001) and total scores for PSQI (r=0.247, p<0.001) and ESS (r=0.066, p=0.048). More extended periods of gaming (β=0.108, p<0.001) and the presence of technology in the bedroom (β=0.203, p<0.001) were also associated with poorer PSQI-measured sleep quality. Together, these two factors independently contributed to 38% of the variance in the study after controlling for age, sex, family income, tertiary education year, place of residence, consumption of caffeinated drinks, alcohol, substance abuse, and smoking. Similarly, participants who indicated the presence of a technological device in the bedroom also had lower average sleep duration (7.4 ± 1.1h versus 7.6 ± 0.9h, p=0.015) and higher mean GAS-SF (21.1 ± 10.5 versus 15.4 ± 7.6, p<0.001), total scores for PSQI (10.3 ± 3.0 versus 8.0 ± 2.4, p<0.001) and ESS (4.9 ± 4.3 versus 2.6 ± 3.6, p<0.001), compared to those who did not.

Evren et al. (2019) used the ISI to discriminate the presence or absence of probable insomnia (using the ISI total score > 14) among students engaged in esports or gaming. Stepwise linear regression analysis demonstrated positive associations (β=0.107, p<0.001) between insomnia and internet addiction severity (measured with the YIAT-SF) after adjusting for anxiety, depression, neuroticism, and dimensions of attention deficit hyperactivity disorder (inattentiveness; hyperactivity or impulsivity). Additionally, the group with a presence of probable insomnia was characterized by greater YIAT-SF internet addiction severity total scores compared to the group without insomnia (31.71 ± 9.38 versus 26.48 ± 8.23, p<0.001).

Wong et al. (2020) explored the relationship between IGD severity with sleep quality and emotional distress in young adults and reported positive correlations between IGDS9-SF and PSQI total scores ($r=0.249$, $p<0.001$). Furthermore, this relationship was independently maintained ($\beta=0.157$, $p<0.050$) even after adjusting for age, gender, time spent on smartphones, time spent on social media, and time spent gaming in multiple regression analyses.

Ko et al. (2019) investigated delayed sleep phase syndrome (DSPS) and insomnia in gamers and healthy controls. DSPS and Insomnia Disorder were confirmed based on standardized criteria during face-to-face interviews with an experienced psychiatrist specializing in internet gaming disorder. Chi-squared analysis revealed that there was a greater occurrence of DSPS (43.5% versus 2.9%, $p<0.001$) and insomnia disorder (17.4% versus 4.3%, $p<0.05$) among gamers with internet gaming addiction (IGD group; classified by DSM-V criteria), compared to healthy controls. These results were mirrored in gamers with gaming disorder (GD group; classified by ICD-11 criteria), who also had a greater occurrence of DSPS (36.4% versus 2.9%, $p<0.001$) and insomnia disorder (22.7% versus 4.3%, $p<0.01$) when compared to healthy controls.

2.3.6 Sleep and physical health

Altintas et al. (2019) also assessed physical health and was the only study to report associations between sleep quality and physical health. Sleep quality was assessed using PSQI total scores, and physical health was assessed with the 36-item Short Form (SF-36) generic health survey (Ware & Sherbourne, 1992). No significant relationship was found between PSQI total scores and physical health ($r=0.049$, $p>0.05$). Likewise, no relationships were found using logistic regression analyses with either high or low sleep quality profiles and physical health (OR: 1.005, 95% CI: 0.964-1.048, $p=0.81$).

2.3.7 Gaming behavior and cardiometabolic disease risk

This section characterizes outcome measures that do not align with the primary narrative but provide insight into gamers' current health and lifestyle behaviors.

BMI was reported in six of the included studies (King & Delfabbro, 2009; Mario et al., 2014; Rudolf et al., 2020; Thomas et al., 2019; Thomée et al., 2015; Wong et al., 2020). Only two of these studies objectively measured anthropometric outcomes (Mario et al., 2014; Thomas et al., 2019); the rest of the studies relied on self-reported data. BMI ranged from 20.52 ± 2.64 kg $\cdot$ m^{-2} (Wong et al., 2020) to 25.60 ± 3.44 kg $\cdot$ m^{-2} (Thomas et al., 2019). The prevalence of being overweight among gamers was reported to be as high as 31.0% and 38.0% (King & Delfabbro, 2009; Thomée et al., 2015). In a different study, only 51.3% of the population was classified as normal weight (Rudolf et al., 2020).

One study reported that frequent gamers (i.e., playing >7 $h \cdot wk^{-1}$) had greater waist circumferences (median: 84.5, IQR: 77.7-101.3 cm, p=0.04), fat masses (median: 12.3, IQR: 7.2-19.9 kg, p=0.04) and heart rates (median: 85.6, IQR: 69.0-97.3 bpm, p=0.007) compared to infrequent gamers (median: 81.8, IQR: 77.6-86.5 cm; median: 9.5, IQR: 8.0-13.0 kg; median: 76.5, IQR: 63.0-80.6 bpm, respectively) (Mario et al., 2014). No between-group differences were observed for body weight, height, and systolic or diastolic blood pressure (Mario et al., 2014). Similarly, another study found no differences in BMI between professional, former professional, amateur regular, and occasional gamers (Rudolf et al., 2020). Compared to a prospective cohort study population at baseline, however, it was indicated that the mean BMI of both male (24.2 ± 4.1 $kg \cdot m^{-2}$, p<0.05) and female (24.1 ± 4.9 $kg \cdot m^{-2}$, p<0.01) "high gamers" (i.e., playing games >2 $h \cdot day^{-1}$) was significantly greater than the male and female "low gamers," respectively (Thomée et al., 2015).

Three studies described associations between gaming behavior with health and physical activity (Mario et al., 2014; Rudolf et al., 2020; Thomée et al., 2015). Mario et al., (2014) reported that total video game playing time ($h \cdot wk^{-1}$) correlated positively with body mass index (BMI; rho=0.30, p<0.050), waist circumference (rho=0.42, p<0.01), fat mass (rho=0.47, p<0.01) and heart rate (rho=0.47, p<0.010). Total vigorous physical activity (measured as metabolic equivalent minutes per week; MET $min \cdot wk^{-1}$) was negatively correlated with total video game playing time (rho=-0.30, p<0.050).

Rudolf et al. (2020) reported similar (albeit weaker) positive correlations between video gameplay time ($h \cdot wk^{-1}$) with BMI (rho=0.11, p<0.01) and sedentary behavior (rho=0.15, p<0.01) after adjusting for age, gender, and education. Additionally, the group observed a negative association between video gameplay time and self-reported health status (rho=-0.12, p<0.01) after adjusting for BMI and sedentary behavior.

Thomée et al. (2015) assessed associations between leisure computer use among "high gamers" (i.e., playing >2 h per day) and prevalence of overweight (i.e., BMI ≥ 25 $kg \cdot m^{-2}$) at baseline and follow-up, 1-5 years later. At baseline, the prevalence of overweight was 38% and 32% in males and females, respectively. In cross-sectional logistic analyses adjusting for age, occupation, physical activity, social support, and sleep duration, the prevalence of overweight at baseline was greater in the "high gamers" males (OR: 1.70, 95% CI: 1.30-2.26, p-value not reported) and females (OR: 1.70, 95% CI: 1.06-2.74, p-value not reported), compared to “low gamers.” Similarly, the prevalence of obesity (BMI ≥ 30 kg • m^{-2}) at baseline was higher in the “high gamer” males (OR: 1.8, 95% CI: 1.02-3.04) and females (OR: 2.1; 95% CI: 1.02-4.47) compared to the “low gamers.” For prospective analyses, participants with baseline BMI ≥ 25 kg • m^{-2} were excluded. In adjusted models, at baseline, female “high gamers” were more likely to be overweight at 1-year follow-up (OR: 3.2, 95% CI: 1.23-8.12). This was associated with new cases of being overweight at a 5-year follow-up (OR: 3.0, 95% CI:1.29-6.83) after adjusting for occupation and physical activity. Accounting for BMI changes, this translated to a total increase in BMI from baseline to a 5-year follow-up of 2.12 BMI units in female “high gamers.” These associations were not seen amongst male “high gamers.”

Outcomes of health and physical activity were reported in six of the included studies (King & Delfabbro, 2009; Ko et al., 2020; Mario et al., 2014; Rudolf et al., 2020; Thomas et al., 2019; Thomée et al., 2015). Ko et al. (2019) reported a higher frequency of poor health and lifestyle behaviors among addicted gamers (IGD group) compared to those with no gaming addiction (CON group). This was characterized by a greater occurrence of overweight and obesity (defined as BMI>27 kg • m^{-2}; 27.5% versus 14.5%, $p<0.01$), irregular diet (13% versus 2.9%, $p<0.05$), increased body weight (11.6% versus 1.4%, $p<0.05$), and unhealthy behavior (defined broadly as problems resulting from online gaming engagement; 95.7% versus 15.9%, $p<0.001$) in the IGD compared to CON group. In addition, more gamers in the IGD group (40.6%) reported no exercise for more than three weeks compared to the CON group (0%, $p<0.001$), and more gamers in the IGD group (73.9%) reported being sedentary for more than 4 hours on three or more days per week, compared to the CON group (2.9%, $p<0.001$).

Similar results were reported in other studies involving frequent or high-volume gamers (Mario et al., 2014; Thomée et al., 2015). In one study (Mario et al., 2014), frequent gamers (i.e., playing >7 h • wk^{-1}) were found to engage in less total vigorous physical activity (MET min • wk^{-1}) compared to infrequent gamers (median: 0, IQR: 0-3800 versus median: 960; IQR: 0-3720, $p=0.04$). Another study reported that the subgroups of male and female “high gamers” (i.e., playing more than two h per day) reported less time spent doing regular or vigorous physical activity (males: 33% versus 49%, females: 17% versus 41%, $p<0.001$) activity and more time being physically inactive (males: 34% versus 17%, females: 40% versus 13%, $p<0.001$), compared to the entire study group (Thomée et al., 2015).

Interestingly, most gamers reported themselves to be in either good (38.6%), very good (38.2%), or excellent (18.2%) health (Rudolf et al., 2020). In this study, only a small group of gamers reported having poor (4.8%) or very poor (0.2%) health status. More than two-thirds (66.9%) of gamers in this study reported engaging in moderate to vigorous physical activity lasting more than 2.5 h • wk^{-1} and reported mean sedentary behavior time was 7.7 ± 3.6 h • day^{-1} across the entire cohort. There were no significant differences in sedentary behavior time between the different types of gamers (p=0.34). The sporting activities that these gamers reported engaging in were diverse, ranging from yoga and Pilates (1.9%) to jogging (28.3%) and fitness training (36.0%). Only 16.5% of gamers reported not participating in any sporting activity at all. The study also reported no statistically significant or relevant (rho <0.10) associations between video gameplay time and physical activity.

Similarly, in a separate study with heavy gamers (defined as those "(a) playing for over 30 hours per week, (b) playing for at least four days per week, and (c) playing for an average duration of three hours in a typical sitting") one in five (20%) reported exercising for at least 30 minutes on three or four days per week, while one in four (24%) exercised less than once per week (for 30 minutes), and nearly one in five (18%) did not exercise at all (King & Delfabbro, 2009). In comparison, elite esports players reported exercising at a frequency of 4.2 ± 1.7 days per week (Thomas et al., 2019).

2.4 Discussion

Based on the reviewed evidence, it appears that excessive gaming activity is broadly associated with worsened parameters of sleep. Gamers with high gaming addiction scores were vulnerable to poor sleep and were more likely to have shorter sleep duration, poorer quality sleep, and greater daytime sleepiness and insomnia scores than gamers with low gaming addiction scores and non-gamers. These findings were mirrored in gamers with high gaming volume and duration, who were likelier to have worsened sleep quantity and quality, in addition to delayed sleep timing and a greater prevalence of insomnia. Therefore, it is apparent that sleep problems may not be limited to addicted gamers but could be the culmination of various factors related to gaming exposure in general.

Exelmans & Van den Bulk (2015) indicated that decrements in sleep quality became most profound after gaming exceeded a volume of one hour per day. Akçay & Akçay (2020) corroborated these findings, demonstrating unfavorable effects on sleep resulting from gaming for more than two hours per day. This was in line with a previous study conducted on adolescents, which showed that playing games for 50 minutes per day resulted in nearly no disruption of initiation or maintenance of sleep, with no changes to sleep structure (Weaver et al., 2010). Consequently, these results point toward a lack of consensus regarding the dose at which gaming becomes problematic. Moreover, these results highlight the heterogeneity in these studies since it may not be possible to arrive at the same dose-dependent association regarding the effect of gaming on sleep in adults and adolescents, whose reward networks are still maturing (Reichelt, 2016).

It is also speculative whether sleep decrements attributed to gaming exposure exhibit a cumulative (rather than an acute) effect or whether other factors related to gaming behavior are involved. Altintas et al. proposed the concept of gaming intensity, highlighting that it may be a more salient predictor of sleep quality than gaming duration (Altintas et al., 2019). In traditional sports, athletes engaged in high-intensity sports were characterized by significant differences in sleep patterns (including better sleep structure and sleep continuity) compared to those engaged in low-intensity sports (Suppiah et al., 2015). It is, therefore, arguable whether this extends to gamers engaged with high-intensity gaming, such as esports athletes. Indeed, these gamers may not match the levels of physical exertion experienced by traditional athletes; however, the level of intensity may be comparable to the cognitive effort (or "mental fitness") required to maintain their proficiency and competitive status (Kemp et al., 2020). While this is speculative, it is likely that novel performance metrics, such as actions per minute, which measure game input commands, could be used as an objective proxy for gaming intensity in the future (Bonnar et al., 2019b). Of course, the intensity of their lifestyle and rigorous training schedules could also explain sleep issues, which is apparent from the high rates of burnout and fatigue reported amongst these gamers (ESPN, 2015).

Realistically, the mechanisms driving the adverse effects on sleep may involve the coupled interaction of behavioral and physiological factors related to gaming activity. Most noteworthy is the inhibitory effect that short, blue wavelength light emitted from device screens has on melatonin. The suppression of nocturnal melatonin secretion from the pineal gland delays the sensation of sleepiness and the onset of sleep (Gooley et al., 2011). This effectively reduces sleep quality by increasing sleep onset latency time. Sleep structure is also impaired because of nighttime light exposure, thereby further impairing the quality of sleep (Blume et al., 2019). However, it is speculative whether the efficacy of these interactions is more or less profound during daytime gaming, which questions the extent to which the timing (rather than duration) of gaming sessions contributes to problematic sleep. Likewise, light sources (from screen devices) attached to gaming modalities may also presumably exhibit varying effects on the circadian clock and, thus, sleep, depending on the inclusion of light sources that are most stimulatory for photoentrainment.

Similarly, gamers exposed to light sources emitting greater intensity light, or gamers situated near such light sources, may presumably experience more remarkable chronobiological effects and thus be at greater risk for problematic sleep. This could be explained by artificial light sources having variable spectral profiles in terms of the distribution of short- and long wavelength light (Blume et al., 2019). The size or configuration of screen devices may also affect the light fluence received by gamers (Lei et al., 2013). These factors have not been explored and warrant further investigation.

Physiological arousal resulting from gaming activity may also be a factor and has previously been proposed as an underlying mechanism involved in difficulty initiating and maintaining sleep (Exelmans & Van den Bulck, 2015). Indices of physiological arousal that may be negatively affected by gaming activity include respiratory rate, blood pressure, and heart rate (Exelmans & Van den Bulck, 2015). Furthermore, since gaming intensity is complementary to gaming duration in its deleterious effect on sleep (Altintas et al., 2019), it is possible that certain games (e.g., those that could be considered more intense or stimulating) would exhibit stronger effects on arousal (and thus sleep), compared to other games. For instance, games with high actions per minute may be faster-paced and thus induce greater alertness and require greater attention. Therefore, cognitive alertness may also be a key factor impairing efforts to initiate sleep. This effect was demonstrated by Mathiak & Weber (2006), who used functional magnetic resonance imaging to show heightened cognitive alertness in a cohort of experienced gamers playing a first-person shooter game.

Interestingly, sleep was not associated with cardiometabolic health in the single study that considered it. Indeed, a robust relationship may exist between sleep and cardiometabolic disease risk in gamers, although the relatively young age of gamers may also mask this (i.e. since cardiometabolic diseases typically present with aging). The few studies that reported on health parameters (independent of sleep) characterized gamers as having poorer health and more unhealthy lifestyle behaviors. Among these unhealthy behaviors were reported lower levels of physical activity and higher levels of sedentary behavior, although the dose, frequency, and intensity of physical activity varied across the included studies. Gaming duration was also positively associated with BMI, waist circumference, fat mass, and heart rate. Addicted and “heavy” (or frequent) gamers appeared to be the most sedentary relative to other groups of gamers, which would be expected given their high volume of gaming activity. Conversely, most esports players met the WHO’s global recommendations for physical activity (World Health Organization, 2010) despite reporting as much as 24.4 ± 15.9 hours of gaming per week (Rudolf et al., 2020).

Sedentary behavior is recognized as an independent determinant of poor health and has previously been associated with insomnia and sleep disturbances (Martínez-Ramos et al., 2018; Yang et al., 2017).

Prolonged sitting time from gaming could, therefore, explain the adverse health outcomes reported. Coupled with poor sleep, sedentarism, and poor lifestyle behaviors, it may only act to exacerbate the long-term cardiometabolic risk in an already vulnerable population. This is explained by a population where as much as 38% of gamers were overweight (Thomée et al., 2015). Moreover, particular groups of gamers, including addicted gamers, heavy or high-volume gamers, and female high-volume gamers, were identified as vulnerable risk groups for adverse health outcomes. Therefore, targeted interventions such as educational awareness, health prevention, and behavior change programs would be beneficial and necessary in mitigating associated health deficits in these cohorts. Finally, none of the included studies reported any associations between sleep and gaming performance, indicating a major literature gap. We echo that, indeed, the performance of gamers and esports athletes may be vulnerable to the adverse effects of short and poor-quality sleep (Bonnar et al., 2019b). Therefore, future work should seek to identify the factors involved and establish informed, evidence-based recommendations or programs to support the performance management of these gamers (Bonnar et al., 2019b).

2.4.1 Limitations of reviewed studies

Despite the suggestive nature of these findings, it is essential to acknowledge and address the limitations related to the design of the included studies. The first major limitation present in nearly all studies involved the use of self-report instruments (not including validated subjective tools like the PSQI) to measure sleep parameters. Consequently, the findings presented in these studies are subject to several potential issues, including both social desirability and recall biases. This is particularly the case for self-reported sleep duration, where there is a rich history of over-reporting (Girschik et al., 2012). Considering that sleep was seldom the primary outcome of interest in the reviewed studies, it is sensible that a low-cost, practical alternative was employed over objective measures, such as actigraphy or polysomnography. However, the use of self-report instruments is discouraged since it may reduce the ability to identify significant causal or associative relationships between sleep with gaming behavior and health. Likewise, this issue also extrapolates to self-reported gaming behaviors (particularly gaming duration and exposure). On the one hand, gamers may inadvertently over-report their daily playing time, failing to discriminate between active engagement and idle gaming time (e.g., in lobbies, matchmaking queues, and during pause time). On the other hand, gamers may deliberately over-report or under-report their gaming time for social favor or to protect the public image of gaming, respectively.

The second limitation was the use of cross-sectional study designs, which do not allow for causal inferences. Most observational studies employed the sole use of online or paper-based survey data collection methods, which further reduces the integrity of the reported data for reasons previously discussed. Additionally, data collection methods solely using online surveys could be subject to deliberate and fraudulent false reporting owing to the anonymity of the online surveys used. A recent study highlighted a growing issue where respondents may intentionally submit fraudulent data by submitting duplicate, inconsistent, or low-quality responses (Pozzar et al., 2020). The same research group also indicated sophisticated ways in which "fraudsters" could distort data by using robotic automation (or "botting"), virtual private networks, and server farms to generate mass fraudulent responses (Pozzar et al., 2020). While the occurrence of fraudulent data may be rare, researchers should be mindful of such threats to the validity of their sample and, thus, the integrity of their data.

The third limitation included the use of convenience samples and sampling methods that reduced the generalizability and representativeness of the participants. Researchers should use random sampling methods to ensure that their study populations are broadly representative and transferable to other age groups, sexes, and nationalities. This may also reduce the risk of social desirability and sampling biases, especially when sampling individuals in non-clinical settings. Relatedly, the relatively small share of female gamers among the considered study populations of the reviewed studies is of particular concern. This methodological oversight creates a reporting bias that limits the applicability of evidence to clinical recommendations for both sexes. Beyond this, it also perpetuates the false narrative that females comprise a minority of the general gaming cohort, where, in fact, they comprise nearly half of the general gaming demographic (Entertainment Software Association, 2021).

A fourth limitation concerns the variability in the outcomes related to sleep reported in each of the studies. For example, only PSQI and sleep duration were consistently reported. Therefore, miscellaneous sleep metrics should be interpreted with caution. This is particularly the case for metrics that were not based on validated questionnaires.

The fifth limitation relates to self-reported sleep duration. Based on the reviewed evidence, gamers would appear to meet the recommended guidelines for sleep duration between 7 and 9 hours for adults, as outlined by the National Sleep Foundation (Hirshkowitz et al., 2015). While these findings do not appear clinically significant, it is essential to note that these data do not discriminate between (and may thus represent a composite of) diurnal and nocturnal sleep time. Therefore, the interpretation of these findings is cautioned since the purported sleep duration may not reflect nocturnal sleep.

The sixth limitation regards the lack of results concerning circadian disruption. Again, the methodological oversight by studies not employing objective tools, such as actigraphy, arguably restricts researchers' ability to develop a holistic understanding, particularly regarding the respective roles of other contributing factors on problematic sleep and the potential downstream effects on health and performance. In particular, the pervasive phase-delaying and melatonin-suppressing effect of light from gaming at nighttime may adversely affect circadian rhythms, the sleep-wake cycle, and sleep (Blume et al., 2019; Ceranoglu, 2014); and cannot be quantified by subjective means.

Lastly, studies did not discriminate between the different types of gamers and often assumed homogeneity across their gaming populations. This major limitation is discussed in more depth in the following section, which aims to provide direction to researchers involved in future research.

2.4.2 Future direction for studies involving gamers or esports players

Gaming addiction tests appear to be criterion methods to discriminate between pathological and non-pathological gaming behavior. However, this may be confounded by competitive gamers (such as esports athletes) who may engage in prolonged periods of online gaming without functional impairment. Therefore, researchers should apply the appropriate tools to their respective study populations to limit bias and erroneous reporting. Beyond this, it is apparent that there is a great deal of heterogeneity in the instruments used to assess gaming and internet addiction, which provoked the call for the validation of standardized procedures toward the identification and management of these gamers (Costa & Kuss, 2019). Achab et al. (2011) highlighted that there is also a need for validated tools in determining internet and genre-specific gaming addiction, arguing that previous studies do not differentiate between internet use in general (e.g., browsing, social media, and other general internet-use activities) and online games, nor between different types of online games. Another research group concluded that addicted and non-addicted gamers demonstrated varying physiological arousal deficits, depending on the game genre that was played (Metcalf & Pammer, 2013). Ultimately, appropriating effective research methodology may improve researchers' understanding of the etiology of gaming addiction and comorbid sleep problems, which may assist with the early discovery of pathological gaming habits, education around "healthy" gaming practices, interventions, and other related treatment strategies.

Researchers should also endeavor to describe their gaming cohorts more coherently. In the case of studies using heterogeneous gaming cohorts, researchers should consider prior years of gaming exposure, current frequency, duration, and intensity of gameplay, in addition to the current level of competitive involvement (i.e., social, amateur, novice, semi-professional, or professional) of players as potential factors that may affect outcomes of interest. For example, esports athletes may have greater overall skill and exposure to gaming than social gamers. Esports athletes may also embark on frequent transmeridian travel or engage in online events scheduled for a different time zone from where they live, which may invariably confound outcomes related to sleep and circadian rhythms. Moreover, these gamers may also have little to no restrictions on their playtime and may not curtail sleep in favor of gaming practices or matches, compared to non-professional gamers who have (in addition to gaming) other lifestyle commitments, such as work or studies. Therefore, a cohort comprising both social gamers and esports athletes may yield dampened significance or confounded findings.

By extension, researchers are also cautioned against including heterogeneous cohorts comprising gamers playing on disparate gaming platforms (i.e., computer, console, or mobile). Although gamers playing on a single modality may represent a proportionately small group of gamers, it is unknown how individual differences between each gaming platform impact sleep, circadian rhythms, and other related physiological outcomes. For example, gamers playing on computers, consoles, mobile, or even virtual reality devices may experience varying chronobiological effects based on their (i) proximity to screen devices, (ii) viewing geometry, (iii) dose and intensity of light exposure from screens. Thus, the corresponding effects on sleep patterns may also differ. In addition, gameplay time may also be differently affected; for example, mobile gamers may be limited in gaming time by the battery span of their mobile devices, while PC and console gamers are not. Likewise, virtual reality gaming, in addition to increased light exposure from the headset, may offer greater immersion in the game than other gaming modalities, which may augment physiological arousal and contribute to worsened sleep.

It is clear from the synthesis of evidence that further longitudinal research is warranted to establish causal inferences with gaming on sleep, cardiometabolic health, and performance. Additionally, longitudinal studies may be more effective in informing the direction of developmental trends regarding gaming behaviors and problematic sleep. Research may also benefit from describing gamers' sleep in more detail, including using multiple validated questionnaires combined with objective sleep monitoring. Employing objective sleep monitoring, such as actigraphy or polysomnography, and using clinical health measures may benefit researchers by reducing the intrinsic biases associated with subjective data collection methodology. This may assist in establishing a better empirically grounded understanding of the mechanics driving problematic sleep through gaming behavior, which is currently lacking because of the heterogeneity in the reporting of sleep parameters by the included studies. Likewise, future research is encouraged to use sleep diaries through which study participants may detail their sleep, daily gaming activities, caffeine consumption, physical activity, medication, and supplement use to reduce recall bias and to provide a greater level of detail regarding participants' free-living behaviors and the factors influencing their sleep. Finally, researchers should seek a more representative and generalizable cohort of gamers, with a more accurate share of female gamers, to improve the application of evidence toward treatment strategies, future studies, and policymaking. The present body of evidence lacks sufficient credence to warrant the establishment of policies or recommendations for esports practice and regular engagement with gaming. Instead, researchers are encouraged to appropriate the suggestions above, develop training strategies that include sleep hygiene education and awareness, and incorporate exercise or related techniques to improve sleep. Incorporating cognitive behavioral therapy for insomnia framework is also recommended as a solution to prevent and treat sleep disturbances in high-volume gamers and esports players.

2.4.3 Limitations of the systematic review

Beyond the limitations previously discussed, we also acknowledge the limitations of the present systematic review. The first limitation was the sole inclusion of studies published in the English language. It is possible that related studies, which may have been published elsewhere in other languages, may not have been accounted for. This is particularly the case since gaming and esports have both been globally received in recent years. The second limitation is that the search strategy employed in the present review may not include all relevant studies related to gaming and esports, especially in cases where they have been described differently. This follows the condition that there is a lack of consensus regarding esports' proper definition and spelling. While attempts were made to use globally inclusive search terms previously used to describe esports (such as 'cybersports'), other terms may have been missed. Lastly, the present review only included studies involving adults. There is a plethora of research on gaming involving children and adolescents; therefore, these findings may be limited to only adult gaming cohorts.

2.5 Conclusion

We corroborate the findings reported in previous systematic reviews that excessive gaming is associated with worsened sleep parameters. We contribute to the existing literature by providing evidence related to adults habitually engaging with gaming (rather than children and adolescents) and offer direction for future work in this field. We also draw attention to esports and encourage researchers to explore this rapidly growing phenomenon. In addition, we encourage researchers to explore further the coupled interaction involving poor quality and quantity of sleep with cardiometabolic health and gaming performance in adult gamers, as well as the relative contribution (and associated risk) that various games, game genres, and timing of the gaming activities have on sleep. Finally, we note that the growing access to technology and media (particularly in the bedroom at nighttime), and not only gaming, appears to have a substantial impact on the development of problematic sleep among young adults. Therefore, researchers are encouraged to explore interventions that may attenuate related deficits, particularly in vulnerable cohorts, such as high-volume and addicted gamers.

Chapter 3

Assessing the validity and reliability and determining cut-points of the Actiwatch 2 in measuring physical activity

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3.1 Introduction

Wearable devices have gained increasing popularity in health research for their ability to return continuous objective measures of various health-related outcomes in free-living, habitual settings (Bassett Jr et al., 2012). Among these outcomes are physical activity and sleep, which are important factors in preventing and managing chronic diseases, including obesity, hypertension, and type 2 diabetes (Ndahimana & Kim, 2017). Currently, there are many devices that can measure sedentary behavior, physical activity, and sleep independently. Although it is possible to use multiple devices to measure sleep and physical activity parameters independently, it is not ideal. Thus, a major challenge has been to identify a single valid and reliable monitoring device capable of measuring two or more of these variables concurrently (Neil-Sztramko et al., 2017; Quante et al., 2015).

Accelerometers are favored as valid and reliable alternatives to traditional methods of objective physical activity and energy intake monitoring for their practical and non-invasive designs (Hills et al., 2014; Sylvia et al., 2014). Among the most used accelerometer devices for monitoring physical activity are the Actigraph GT1M and GT3X model devices (Actigraph, Pensacola, Florida, U.S.) (Hills et al., 2014). Accelerometers are typically small wearable devices fixed to various points on the body (including the waist, wrist, hip, thigh, or ankle) and can detect gross bodily movement in up to three orthogonal planes: anteroposterior, mediolateral, and vertical (Sylvia et al., 2014). Since the wearer typically receives no visual feedback about their measured physical activity, the risk of participants inadvertently altering or manipulating their habitual activity patterns is thought to be low (Ainslie et al., 2003). The use of accelerometers is considered a gold-standard approach in the direct assessment of waking (total volume) movement behavior in free-living settings (Lambiase et al., 2014). In addition to wake-time physical activity, accelerometers are now also used to indirectly monitor sleep patterns in free-living settings (Lambiase et al., 2014).

Despite differences in placement (hip-worn for measuring waking movement versus wrist-worn for measuring sleep) (Ancoli-Israel et al., 2003), the mechanics of sleep and physical activity monitoring by accelerometry are identical. The devices produce acceleration forces which, after being converted into voltage signals, are integrated as an average or peak acceleration according to a user-defined interval (or epoch) and are finally reported as arbitrary units called counts (Rowlands & Stiles, 2012; Sasaki et al., 2016). The conversion of raw accelerations into counts is done by manufacturer-specific algorithms, which may either be proprietary or open-source. Proprietary algorithms incur additional research challenges as raw data are often unavailable, meaning counts from one device may not be interpretable or comparable to those from other devices (Sasaki et al., 2016). The premise of these algorithms in physical activity monitoring is to estimate physiological outcomes, including energy expenditure and the dose of physical activity exposure at various intensities (i.e., sedentary, light, moderate, or vigorous) (Strath et al., 2013). For sleep monitoring, these algorithms are used to determine sleep-wake intervals by assessing whether gross motion is indicative of the wearer being awake, using the magnitude and duration of the acceleration signal (Cheung et al., 2018).

The Actiwatch 2 (AW2; Philips Respironics, Bend, Oregon, U.S.) is widely used for research to measure sleep parameters in free-living settings directly and has been validated against polysomnography (Cheung et al., 2018; Chow et al., 2016; Lambiase et al., 2014). However, while the AW2 can also measure physical activity using the native (albeit proprietary) algorithm to produce activity counts, there is limited evidence supporting its validity in physical activity. To the best of our knowledge, only a few studies have attempted to validate the AW2 for physical activity monitoring. For example, Neil-Sztramko et al. (2017) validated the AW2 in a convenience sample of mostly older, lean, active female shift workers; and Lee et al. (2019) validated it using a task menu comprising only treadmill running activities. However, the extrapolation of these findings to a broader demographic, the general population, or across a wide range of activities is limited.

This study aimed to test the validity of a single monitoring device (AW2), usually applied to measure sleep patterns, to quantify sedentary behavior and physical activity. This study expands upon the work by Neil-Sztramko et al. (2017) by including both males and females, encompassing a younger age range with wide variation in physical fitness. The aims were to (i) validate the AW2 as a tool for assessing sedentary behavior and physical activity by comparing its physical activity counts to both a reference physical activity monitor (Actigraph GT3X) and energy expenditure using indirect calorimetry, (ii) determine the AW2-derived count cut-points, maximizing sensitivity and specificity, for sedentary, light, moderate and vigorous physical activity using metabolic equivalent (MET) and count data, and Receiver Operating Characteristic (ROC) Curve analyses and (iii) assess the reliability of the AW2 to measure physical activity by comparing the physical activity counts across two independent assessment periods.

3.2 Methods

3.2.1 Participants

Apparently healthy males and females were eligible to participate in the study if they were between 18 and 60 years of age. Fifty participants with varying levels of physical activity were recruited through media posting (**Appendix A**). Participants first underwent health screening using the American College of Sports Medicine Exercise Pre-Participation Screening criteria (Riebe et al., 2015) to ascertain participant safety during moderate to vigorous physical activity (**Appendix B**). Participants who answered "Yes" to any of the questions during the screening process and pregnant females were excluded due to health risks and for the integrity of cardiometabolic data. Ethical approval was obtained from the University of Cape Town's Human Research Ethics Committee (HREC No. 334/2017; **Appendix C**), and all participants provided written informed consent (**Appendix D**). This study was conducted in accordance with the ethical principles of the Declaration of Helsinki (General Assembly of the World Medical Association, 2014).

3.2.2 Procedures

An overview of the study procedures is depicted in Figure 3.1. All testing was performed at the Division of Exercise Science and Sports Medicine, University of Cape Town, with data collection sessions scheduled between 07:00 and 11:00 to control for diurnal intra-individual variability. Participants were asked not to eat or drink (except water) at least two hours before testing, not to consume caffeine at least three hours before testing, and to avoid moderate to vigorous physical activity at least six hours before testing. Participants completed the Global Physical Activity Questionnaire (Armstrong & Bull, 2006) to characterize their habitual physical activity (**Appendix B**). Outcome variables were moderate-to-vigorous physical activity metabolic equivalent hours per week (MET $h \cdot wk^{-1}$). The investigator measured each participant's height (to the nearest 0.1 cm) and weight using a stadiometer and digital scale, respectively. Waist circumference measurements (at the level of the umbilicus) were taken in triplicate using a standard tape measure and averaged. Waist circumference measurements were missing for four participants. Anthropometric outcome variables were height (m), weight (kg), waist circumference (cm), and body mass index ($kg \cdot m^{-2}$).

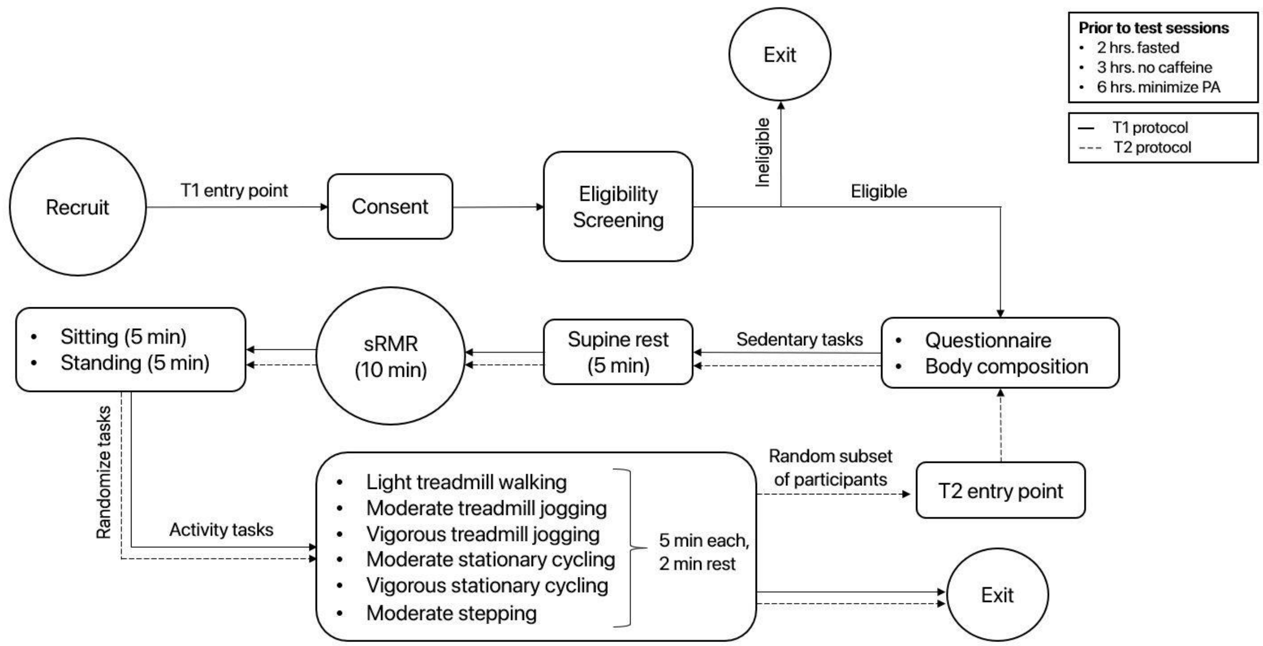

Figure 3.1. Study procedures overview. PA: physical activity; sRMR: simulated resting metabolic rate test; T1: session 1; T2: session 2.

All participants were fitted with the AW2, worn on their non-dominant wrist. They were also fitted with a GT3X, worn around the waist on an adjustable belt at hip level, in line with the midline of the thigh. Participants were also fitted with a mask connected to a cardiopulmonary gas analyzer (CPET; Cosmed CPET, Rome, Italy) to collect metabolic data. The CPET was calibrated before each data collection session with a 3 L calibration syringe and a standard gas mixture of 16% oxygen, 4% carbon dioxide, and the balance nitrogen (BOC Special Gas, Afrox, Cape Town, South Africa).

Sedentary testing included 5 min of supine rest followed by 10 min of a simulated resting metabolic rate (sRMR) test for normalization and 5 min each of sitting and standing. Participants were not permitted to speak, although they could listen to music and use their mobile phones during the supine rest, sitting, and standing tasks. During the sRMR test, participants were required to remain awake while lying still and listening to white noise. Respiratory exchange ratio data during supine rest were used to confirm fasting states.

Following the sedentary testing, a battery of six randomized physical activity tasks was performed. Participants exercised at self-selected paces eliciting light, moderate, or vigorous intensities based on their rating of perceived exertion (RPE) scores during the task using the Borg 20-point scale (Borg, 1998). RPE scores of 8±1, 12±1, and 15±1 were used for light, moderate- and vigorous-intensity exercise, respectively (Borg, 1998). Activity tasks comprised self-paced walking (light intensity) and jogging (moderate and vigorous intensities) on a treadmill (HP Cosmos treadmill, LE500CE, Nussdorf-Traunstein, Germany), stationary cycling (moderate and vigorous intensities) on a cycle ergometer (Wattbike Pro Trainer, Wattbike Ltd., Nottingham, England) and stepping up and down a two-step 21 cm stepping block (moderate intensity). Each activity was performed for 5 min with at least 2 min of rest preceding each task for a total data collection time of approximately 2 hours. A subset (n=18) of participants, chosen at random, were asked to return to the laboratory to repeat baseline and physical activity tasks to assess the reliability of the AW2 in measuring physical activity. These repeat sessions (T2) were scheduled 7±1 days after each participant's initial laboratory session. Participants had to comply with the same pre-test inclusion criteria as the initial session (T1).

Oxygen consumption (VO_2, mL • kg^{-1} • min^{-1}) was measured continuously using the CPET, and values for each task for each participant were subsequently converted to MET values and normalized using their resting metabolic rate derived from the sRMR test. Both the AW2 and GT3X count data were collected in 15-sec epochs and reported as counts per minute (CPM) for physical activity measurements after processing using Philips Actiware v.6.0.2 (Philips Respironics, Bend, Oregon, U.S.) and ActiLife v.6.10.4 (Actigraph, Pensacola, Florida, U.S.) software packages, respectively. Finally, data from the AW2 were synchronized with the GT3X and Cosmed using event markers, creating timestamps in the data.

3.2.3 Data and statistical analyses

Descriptive statistics are presented as mean ± standard deviation or median and interquartile range. Normality was assessed using the Shapiro-Wilk test. Differences between gender groups were analyzed using a Mann-Whitney U test. Data during the activity tasks were collected in 15-sec epochs, and only data from the 4th and 5th minute of each task were used to ensure steady state of metabolic data (Kaminsky & Ozemek, 2012). Correlations were performed using Spearman's rho tests. Receiver operating characteristic (ROC) curve analysis was used to calculate the area under the ROC curve (AUC) so that count cut-points for the AW2, which maximized sensitivity and specificity, could be determined for sedentary, light, moderate, and vigorous activities, defined as ≤ 1.5 METs, 1.5 - 3.0 METs, ≥ 3.0 METs, and ≥ 6.0 METs, respectively. Count cut-points were subsequently confirmed with Youden's J statistic (Youden, 1950). Quantification of predictive accuracy was determined using effect size equivalencies for AUC, Cohen's d, and r (Rice & Harris, 2005). Pairwise comparisons were also calculated to determine differences between the AUC under independent ROC curves at varying intensities. Differences in accelerometry and metabolic data between sessions T1 and T2 were analyzed using a paired-sample t-test or Wilcoxon matched-pair sign-ranked test. Repeatability of the AW2 to measure physical activity was performed using Bland-Altman analyses. Significance was accepted at $p<0.05$. All data were analyzed using SPSS (IBM Corp., IBM SPSS Statistics, Version 20.0. Armonk, New York, U.S.).

3.3 Results

Descriptive characteristics of the 50 participants are presented in Table 3.1. Their ages ranged from 19 to 59 years, and males were taller ($p<0.01$), heavier ($p<0.01$), and had greater waist circumferences ($p<0.05$) than females. The self-reported levels of moderate-to-vigorous physical activity during the week were similar among males and females (female range: 0 - 74 MET $h \cdot wk^{-1}$, male range: 0 – 44 MET $h \cdot wk^{-1}$).

Table 3.1. Descriptive characteristics of the participants.

	All (n=50)	Males (n=28)	Females (n=22)	p value
Age (y)	29.5 (18.0)	29.5 (18.0)	29.0 (20.0)	0.822
Weight (kg)	69.9 (15.2)	75.1 (18.2)	67.8 (16.4)	0.004
Height (m)	1.71 ± 0.09	1.77 ± 0.07	1.63 ± 0.05	<0.001
BMI ($kg \cdot m^{-2}$)	24.1 (5.5)	24.1 (5.6)	23.9 (5.7)	0.922
Waist circumference (cm)	78.5 (12.2) [a]	82.5 (13.8) [b]	74.5 (12.6) [c]	0.027
MVPA (MET $h \cdot wk^{-1}$)	10.0 (8.7)	10.0 (9.4)	10.0 (8.5)	0.645

Data are presented as mean ± standard deviation or median (interquartile range). BMI: body mass index; MVPA: moderate-to-vigorous physical activity; MET: metabolic equivalent. The p-value represents the gender comparison tested using an independent t-test or Mann-Whitney U test. Waist circumference available for a subset: [a] n=46; [b] n=26; [c] n=20.

MET and count data for each task, as well as correlations between the device counts and METs, and between the devices themselves, are presented in Table 3.2. While the purpose of the study was to validate the AW2 device, the correlations between the GT3X counts and MET are presented as a comparator for the AW2 vs. MET correlation. AW2 activity counts were positively correlated to MET values for the sitting (p=0.007), standing (p=0.007), light treadmill walking (p=0.010), moderate treadmill jogging (p<0.001), vigorous treadmill jogging (p=0.009), and vigorous stationary cycling (p=0.028) tasks. GT3X activity counts were positively correlated with MET values for sitting (p=0.020), light treadmill walking (p<0.001), moderate treadmill jogging (p<0.001), vigorous treadmill jogging (p=0.001), and moderate stepping (p=0.009) tasks. AW2 and GT3X counts were positively correlated for the moderate treadmill jogging (p=0.002) and moderate stepping (p=0.011) tasks. In most cases, the AW2 correlations were weak but significant, except for correlations for moderate treadmill jogging, which were all moderate and significant.

Table 3.2. Metabolic and count data measured during each task and their correlations.

Task	Predicted MET	Measured MET	AW2 (CPM)	GT3X (CPM)	AW2 vs. MET	GT3X vs. MET	AW2 vs. GT3X
					Spearman's rho (p value)		
Supine rest	1.3	1.1 ± 0.1	8.5 (23.1)	0.0 (0.0)	-0.024 (0.869)	0.146 (0.311)	0.014 (0.925)
Sitting	1.5	1.2 ± 0.1	34.8 (68.1)	0.0 (4.1)	0.377 (0.007)	0.328 (0.020)	0.220 (0.126)
Standing	1.8	1.2 ± 0.2	37.8 (79.3)	0.0 (1.0)	0.377 (0.007)	0.177 (0.219)	0.106 (0.465)
Light treadmill walking	3.5	3.3 ± 0.6	484.3 (248.8)	2131.0 (1413.0)	0.359 (0.010)	0.590 (<0.001)	0.063 (0.665)
Moderate treadmill jogging	>6.0	6.8 ± 1.4	1749.0 (1529.3)	7601.8 (3497.5)	0.570 (<0.001)	0.574 (<0.001)	0.428 (0.002)
Vigorous treadmill jogging	>6.0	8.3 ± 1.9	2610.1 ± 1140.9	7509.1 ± 2106.6	0.364 (0.009)	0.440 (0.001)	0.120 (0.407)
Moderate stationary cycling	6.8	4.9 (1.8)	80.0 (119.0)	74.8 (685.8)	0.058 (0.687)	-0.081 (0.576)	0.033 (0.820)
Vigorous stationary cycling	8.8	6.8 (3.2)	219.5 (193.6)	891.5 (1509.1)	0.312 (0.028)	-0.045 (0.755)	0.100 (0.490)
Moderate stepping	7.5	6.0 ± 1.2	712.2 ± 332.2	3206.1 ± 720.1	0.114 (0.431)	0.368 (0.009)	0.355 (0.011)

Data are presented as mean ± standard deviation, median (interquartile range), or Spearman's rho. MET: metabolic equivalent; AW2: Actiwatch 2; GT3X: Actigraph GT3X; CPM: counts per minute. Correlations were determined using Spearman's rho test. Significance was accepted at $p<0.05$.

Figure 3.2 displays the correlations for all tasks combined between AW2 and GT3X counts (A and B), AW2 counts and METs (C and D), and GT3X counts and METs (E and F, for comparison purposes). The left panel (A, C, E) includes all activities, while the right panel excludes the cycling tasks (B, D, F) since the intensity of the cycling tasks was poorly estimated by both devices (Table 3.2). The counts measured by the AW2 were positively correlated with counts measured by the GT3X regardless of whether cycling was included (Figure 3.2A, $p<0.001$) or excluded (Figure 3.2B, $p<0.001$) from the analyses. Counts measured by the AW2 were positively correlated with task METs for analyses including (Figure 3.2C, $p<0.001$) and excluding (Figure 3.2D, $p<0.001$) the cycling tasks. Similarly, counts measured using the GT3X were positively correlated with task METs for analyses including (Figure 3.2E, $p<0.001$) and excluding (Figure 3.2F, $p<0.001$) the cycling tasks. In all cases, the strengths of the correlations were improved through the removal of the cycling tasks.

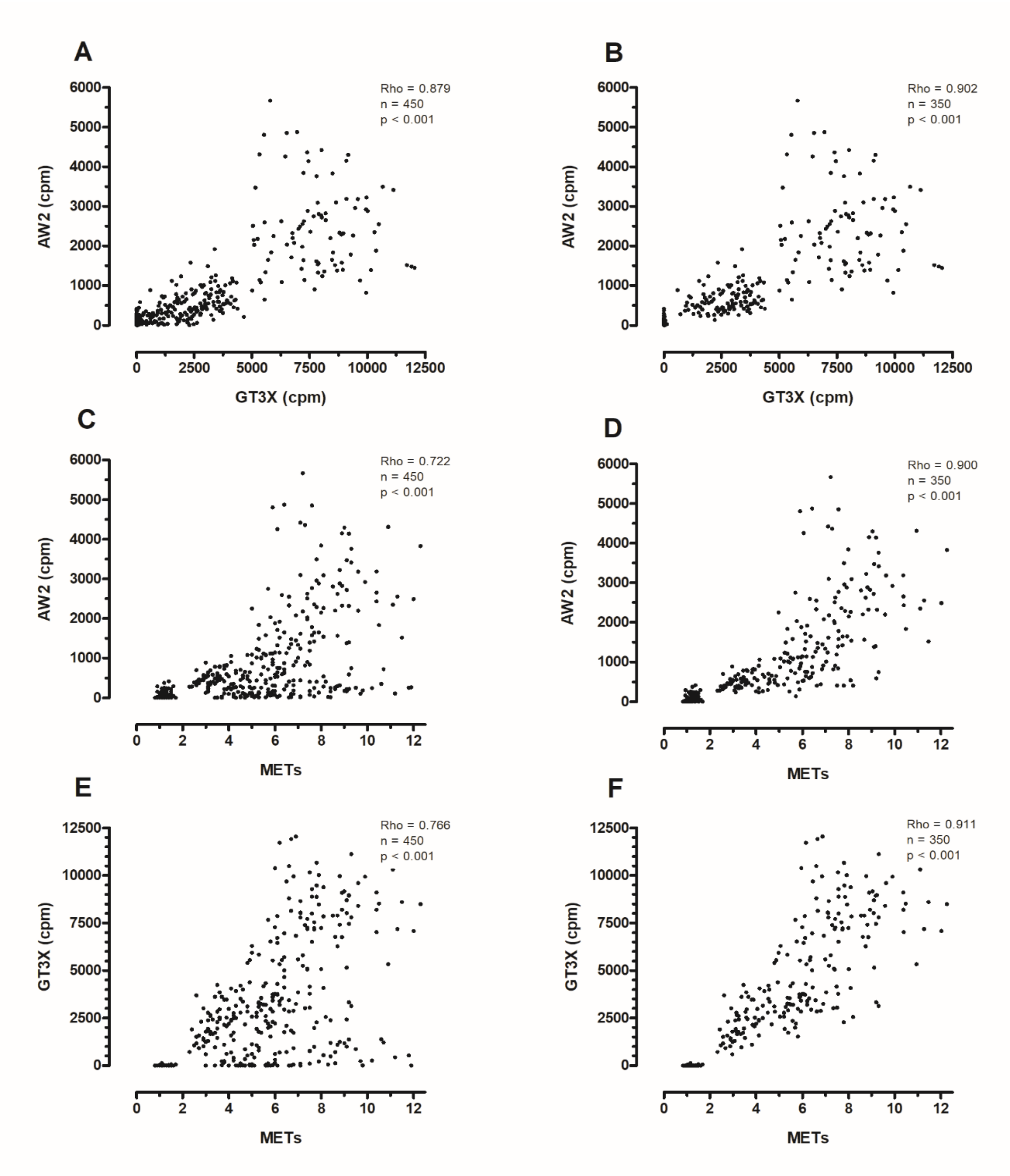

Figure 3.2. Correlations between counts measured by the AW2 and GT3X accelerometers (A, B), AW2 counts and task MET (C, D), and GT3X counts and task MET (E, F). The left panel includes all tasks **(A, C, E),** while the cycling tasks are omitted from the right panel graphs **(B, D, F)**. CPM: counts per minute; MET: metabolic equivalents. Correlations were determined using Spearman's rho test.

ROC analysis revealed that the AW2's ability to characterize sedentary activity was strong (AUC=0.93, 95% CI: 0.90 to 0.95, p<0.001) and that using a count cut-point of 99 CPM produced 85.5% sensitivity and 86.6% specificity (Figure 3.3A). The ability of the AW2 to characterize light activity was weak (AUC=0.47, 95% CI: 0.38 to 0.55, p=0.600), and a cut-point of 578 CPM elicited a 90.9% sensitivity but 33.9% specificity (Figure 3.3C). AW2 characterization of moderate activity was also weak (AUC=0.58, 95% CI: 0.53 to 0.63, p=0.007), and a count cut-point of 259 CPM gave 63.0% sensitivity and 56.5% specificity, indicative of high false-positive rates (Figure 3.3B). While vigorous activity characterization by the AW2 was acceptable (AUC=0.84, 95% CI: 0.80 to 0.88, p<0.001), a count cut-point of 400 CPM yielded 72.3% sensitivity and 73.5% specificity (Figure 3.3D). Based on the poor sensitivity and specificity for the characterization of light activity, the ability of the AW2 to reliably determine the cut-points for light activity intensity was not justified, and is therefore not reported.

The ability of the GT3X to characterize sedentary activity was almost perfect (AUC=0.97, 95% CI: 0.95 to 0.98, p<0.001) using a cut-point of 42 CPM, yielding 99% sensitivity and 89.5% specificity (Figure 3.3A). In contrast, the ability of the GT3X to characterize light activity was weak (AUC=0.52, 95% CI: 0.45 to 0.60, p=0.699) using a cut-point of 2328 CPM, produced 90.9% sensitivity and 39.7% specificity (Figure 3.3C). Moderate activity was weakly characterized by the GT3X (AUC=0.62, 95% CI: 0.56 to 0.67, p<0.001) using a cut-point of 1442, producing 66.7% sensitivity and 62.5% specificity. The ability of the GT3X to characterize vigorous activity (AUC=0.86, 95% CI: 0.82 to 0.89, p<0.001) was acceptable, and using a cut-point of 2836 CPM resulted in 68.2% sensitivity and 84.8% specificity. Pairwise comparison of AW2 and GT3X ROC curves indicated that there were no differences between the AUC for light (p=0.522), moderate (p=0.419), or vigorous (p=0.531) cut-points, except for the AUC for sedentary (p=0.036) cut-points which were significantly different.

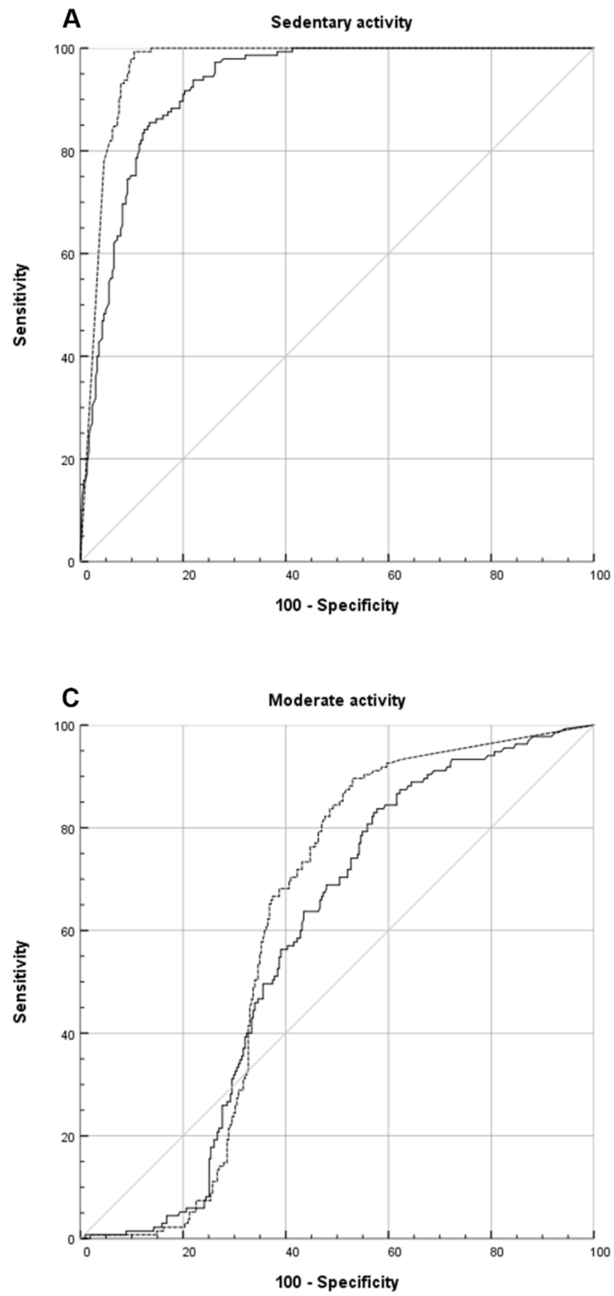

Figure 3.3. Receiver operating characteristic (ROC) analyses for sedentary, light, moderate, and vigorous activities for the Actiwatch 2 (solid line) and Actigraph GT3X (dashed line) devices.

Removing cycling tasks from the sample pool improved the ability of the AW2 to characterize sedentary activity to nearly perfect (AUC=0.99, 95% CI: 0.98 to 1.00, $p<0.001$) with a count cut-point of 256 CPM, giving 97.9% sensitivity and 96.6% specificity (Figure 3.4A). Characterization of light activity using the AW2 remained weak (AUC=0.46, 95% CI: 0.38 to 0.54, $p=0.548$) with a cut-point of 273 CPM, giving 81.0% sensitivity and 45.0% specificity (Figure 3.4C). AW2 characterization of moderate activity improved but remained weak (AUC=0.66, 95% CI: 0.60 to 0.71, $p<0.001$), with a count cut-point of 418 CPM producing 80.5% sensitivity and 59.7% specificity (Figure 3.4B). Characterization of vigorous activity using the AW2 was almost perfect (AUC=0.95, 95% CI: 0.93 to 0.97, $p<0.001$) with a count cut-point of 720 CPM, yielding 88.2% sensitivity and 85.1% specificity (Figure 3.4D).

Similarly, with the cycling tasks removed, the ability of the GT3X to characterize sedentary activity remained nearly perfect (AUC=0.99, 95% CI: 0.98 to 1.0, $p<0.001$) with a cut-point of 46 CPM, giving 99.3% sensitivity and 97.8% specificity (Figure 3.4A). GT3X characterization of light activity remained weak (AUC=0.44, 95% CI: 0.37 to 0.50, $p=0.341$) with a cut-point of 655 CPM, producing 71.4% sensitivity and 44.1% specificity (Figure 3.4C). Characterization of moderate activity with the GT3X improved but remained weak (AUC=0.65, 95% CI: 0.60 to 0.71, $p<0.001$) using a count cut-point of 1585 CPM, producing 93.9% sensitivity and 60.1% specificity (Figure 3.4B). Vigorous activity (AUC=0.96, 95% CI: 0.95 to 0.98, $p<0.001$) was characterized almost perfectly using the GT3X using a cut-point of 3707 CPM, giving 86.3% sensitivity and 91.9% specificity (Figure 3.4D).

Pairwise comparison of AW2 and GT3X ROC curves with the cycling tasks excluded yielded no differences between the AUC for sedentary ($p=0.471$), light ($p=0.800$), moderate ($p=0.922$), or vigorous ($p=0.384$) cut-points.

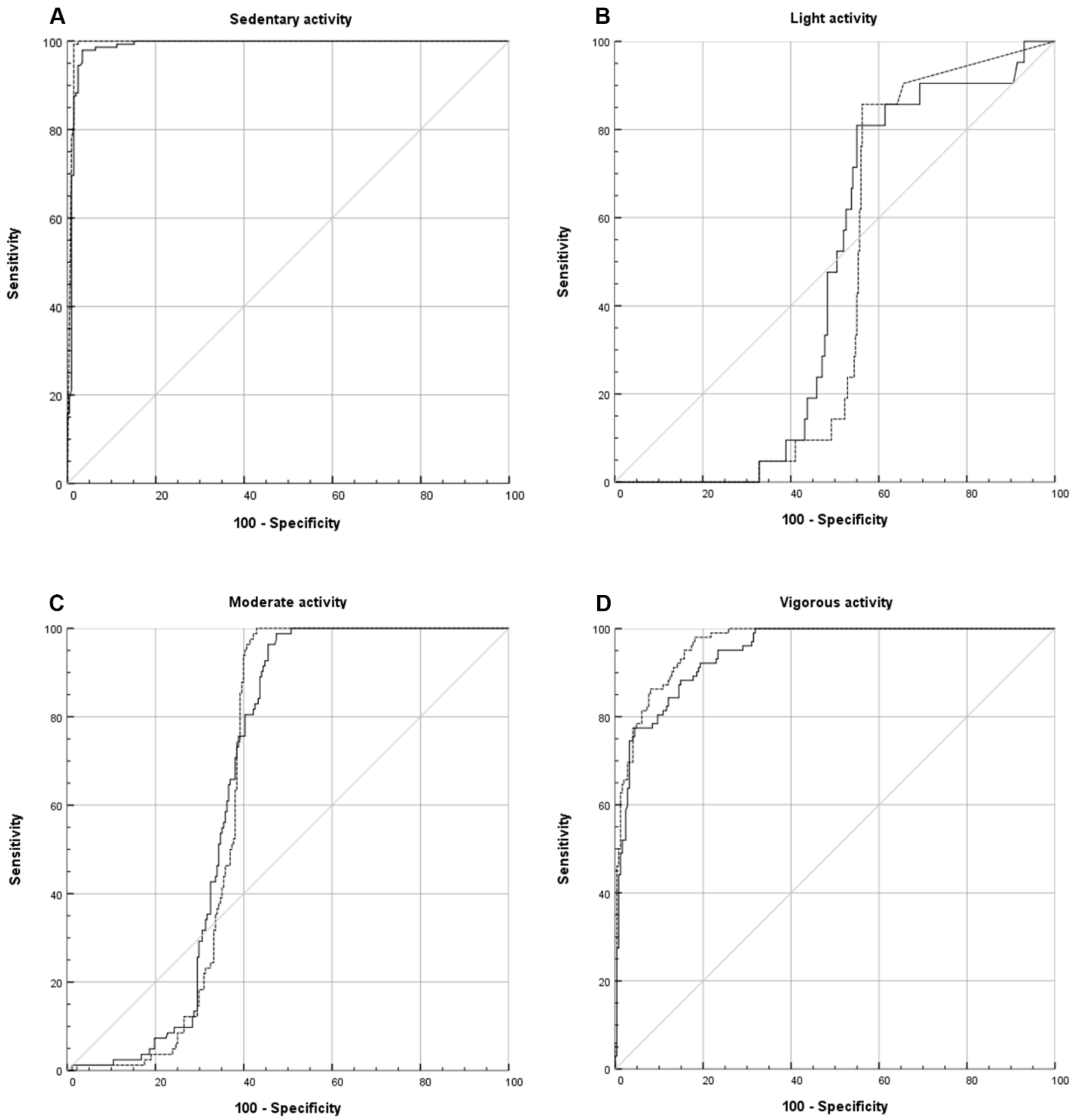

Figure 3.4. Receiver operating characteristic (ROC) analyses for sedentary, light, moderate, and vigorous activities for the Actiwatch 2 (solid line) and Actigraph GT3X (dashed line) devices with cycling activity tasks omitted.

A comparison of metabolic and AW2 count data measured on two separate occasions (T1 and T2) is presented in Table 3.3. There were no differences in MET values or AW2 counts measured between T1 and T2. Bland-Altman analyses (Figure 3.5A – 3.5I) illustrate the agreement of AW2 counts in the activity tasks.

Table 3.3. Comparison of metabolic and Actiwatch 2 count data measured on two occasions (T1 and T2) in a subset of participants (n=18).

Tasks	MET			AW2 (CPM)		
	T1	T2	p value	T1	T2	p value
Supine rest	1.1 ± 0.1	1.1 ± 0.1	0.668	15.0 (30.5)	20.8 (43.0)	0.647
Sitting	1.2 (0.2)	1.1 (0.2)	0.557	35.3 (99.9)	48.8 (63.9)	0.472
Standing	1.2 ± 0.2	1.2 ± 0.2	0.750	35.3 (41.4)	38.5 (73.5)	0.246
Light treadmill walking	3.5 ± 0.5	3.7 ± 0.7	0.205	518.4 ± 179.0	518.5 ± 132.7	0.998
Moderate treadmill jogging	6.9 ± 1.2	7.3 ± 1.6	0.232	2115.0 (1567.5)	2001.5 (1021.1)	0.983
Vigorous treadmill jogging	8.2 ± 1.4	8.5 ± 1.8	0.408	2609.0 (1349.8)	2367.8 (1152.6)	0.845
Moderate stationary cycling	5.1 ± 1.1	5.3 ± 1.3	0.621	64.0 (211.1)	104.0 (214.6)	0.420
Vigorous stationary cycling	6.9 ± 1.8	6.7 ± 1.9	0.658	204.0 (247.0)	178.5 (284.3)	0.396
Moderate stepping	6.1 ± 1.0	6.1 ± 1.0	0.810	720.8 (383.8)	581.3 (307.1)	0.828

Data are presented as mean ± standard deviation or median (interquartile range). MET: metabolic equivalent; AW2: Actiwatch 2 (presented in counts per minute; CPM). Significance was determined using either a paired t-test or a Wilcoxon matched-pair signed-rank test. Significance was accepted at $p<0.05$.

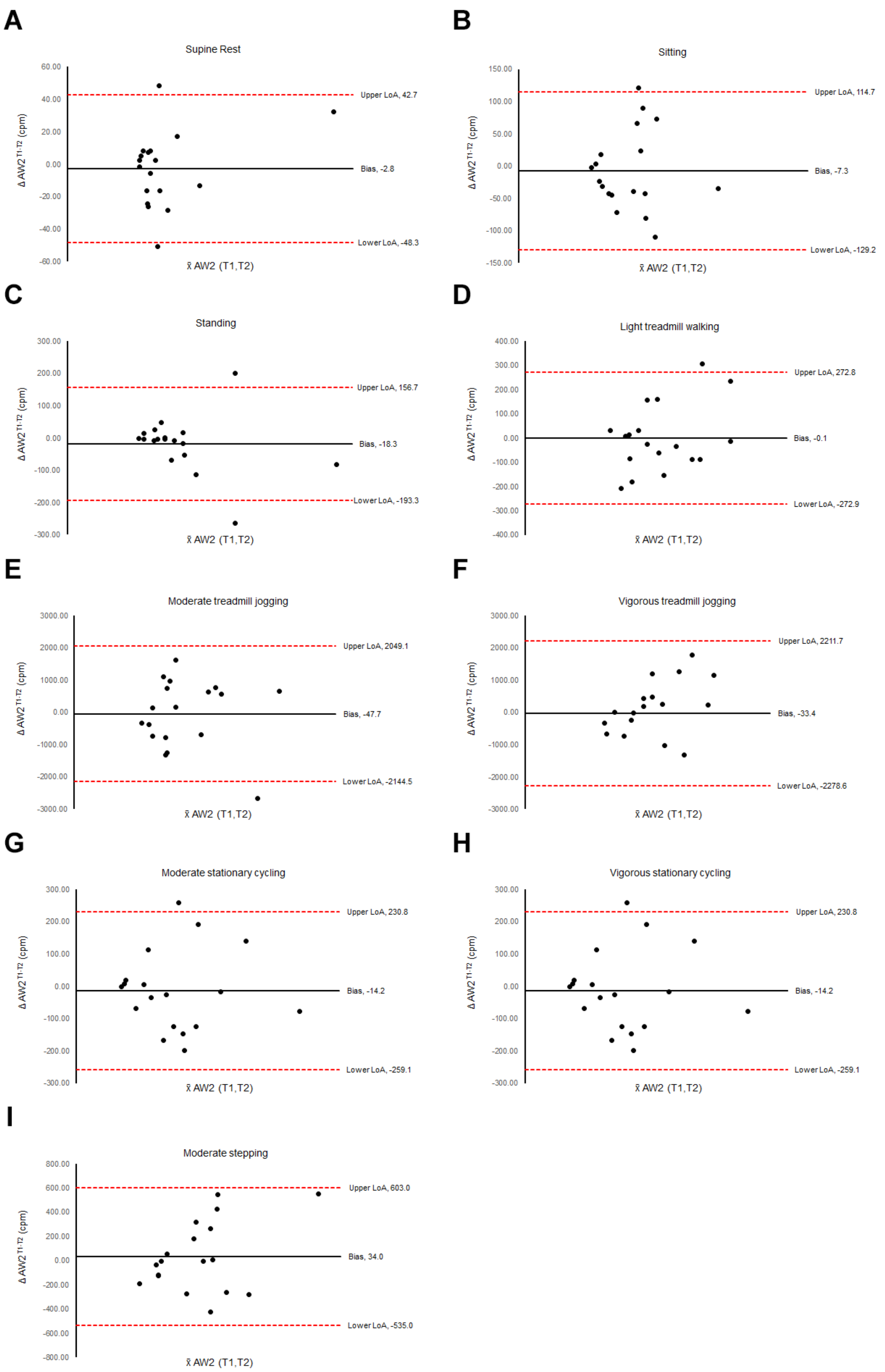

Figure 3.5. Bland-Altman plots demonstrating agreement in AW2 count data (counts per minute; CPM) across two independent assessment periods (T1, session 1; T2, session 2) during supine rest (A), sitting (B), standing (C), light treadmill walking (D), moderate treadmill jogging (E), vigorous treadmill jogging (F), moderate stationary cycling (G), vigorous stationary cycling (H) and moderate stepping (I) activity tasks. The solid line represents the mean (bias), while the dotted lines represent the upper and lower limits of agreement (LoA, ± 1.96 SD). The difference in AW2 activity counts is plotted on the y-axis, and the mean of the AW2 activity counts across are plotted on the x-axis.

3.4 Discussion

The present study performed calibration and validation of the AW2 by comparing AW2-derived physical activity outcomes (counts per minute) against objectively measured oxygen consumption (MET) and physical activity outcomes of a reference device (GT3X). The calibration component of the study was performed using ROC curve analyses and AUC to determine count cut-points using the native algorithm typically used in the analysis of sleep parameters. Additionally, this study assessed the reliability of the AW2 to measure physical activity outcomes in an array of tasks over two independent assessment periods, using Bland-Altman analyses.

Using the native sleep algorithm to predict physical activity outcomes at varying intensities, the AW2 may be an effective tool to report on sleep and physical activity behavior in a research setting concurrently. This may provide physical activity researchers with a broader understanding of the relationship between sleep and activity during wakeful periods, including the combined effect of time spent in sleep, sedentary activity, light, and moderate-to-vigorous physical activity intensities, and dose of the activity exposure. Moreover, the ability of the AW2 to concurrently deliver meaningful information comparable to criterion approaches of sleep, physical activity, and energy expenditure measurements is important to minimize participant burden and measurement bias.

A limited number of studies have assessed physical activity using the AW2 device (Lee, Paul & Tse, 2019; Neil-Sztramko et al., 2017). While one study has reported AW2 count cut-points for the measurement of physical activity at sedentary, light, moderate, and vigorous intensities, the findings are limited to predominantly older (40.0 ± 14.9 years), lean (22.4 ± 3.1 kg $\cdot$ m^{-2}), active (37.5 ± 24.5 MET h $\cdot$ wk^{-1}) female shift-workers (Neil-Sztramko et al., 2017). The present study sought to expand upon the work of Neil-Sztramko et al. (2017) by including both male and female participants of varying degrees of cardiorespiratory fitness from the general population. Moreover, the present study employed an alternative menu of physical activity tasks (including sedentary and stationary cycle tasks) and used stronger methodological steps, namely the inclusion of an objective parameter of activity task intensity using the Borg 20-point scale (Borg, 1998); using an sRMR to determine baseline oxygen consumption in normalizing metabolic data during ROC analysis to determine MET values (versus using the Harris-Benedict predicted resting metabolic rate); and confirming participants' fasted states in real-time using the CPET to minimize the thermic effect of feeding for metabolic integrity.

The data reported in the present study suggest that the AW2 count cut-points were acceptable for characterizing sedentary activity (256 CPM) and vigorous (720 CPM) intensity activity. However, the ability of the AW2 to characterize moderate (418 CPM) intensity activity was weak, and it was unable to characterize light activity. Overall, count data between both AW2 and GT3X monitoring devices were acceptably correlated with each other and objective energy expenditure measurements (MET), suggesting that the AW2 is comparable to a valid and reliable reference activity monitor, despite differences in the anatomical placement (i.e., wrist- versus waist-worn) of the respective monitoring devices. Moreover, the AW2 illustrates a high level of reproducibility in its ability to predict physical activity outcomes during sedentary and active tasks in a laboratory environment.

Neil-Sztramko et al. (2017) reported AW2 physical activity count cut-points for sedentary activity and moderate and vigorous activity intensity of 145 CPM, 274 CPM, and 597 CPM, respectively. Light intensity count cut-points were reported to be 145 – 274 CPM. These cut-points are lower than the cut-points reported in the present study and have a stronger ability to discriminate between light and moderate activity intensities. However, the present study reported count cut-points with a stronger ability to discriminate sedentary behavior and vigorous-intensity activity. Additionally, correlations reported in the present study were stronger between AW2 and Actigraph (GT3X/+) counts and MET values than in the study by Neil-Sztramko et al. (2017). While the present study did report positive correlations between individual activity tasks, it is noted that these correlations were mostly weak, as were similarly reported by Neil-Sztramko et al. (2017).

This study also reported count cut-points for the Actigraph GT3X as a qualitative assessment of count data. The Freedson VM3 (Sasaki et al., 2011) count cut-points are among the most frequently used in physical activity research. The corresponding count cut-points for physical activity at either light (0 - 2690 CPM), moderate (2691 – 6166 CPM), or vigorous (>6167 CPM) intensity are 655 CPM, 1585 CPM, and 3707 CPM, respectively. While Freedson-reported count cut-points are higher than those measured, it is thought that discrepancies may be attributed to the study's small sample size, population bias, or procedural differences. For instance, cycling tasks distorted physical activity count data (and consequently, physical activity intensity and energy expenditure) in both AW2 and GT3X monitoring devices, possibly owing to the static nature of the cycling task and variability of reported activity by each device. This is substantiated by an improvement in the strength of correlations between AW2 and GT3X activity counts with METs, respectively (Figure 3.2), after cycling tasks were omitted from the analysis. In hindsight, substituting cycling tasks with alternative habitual lifestyle activity tasks (such as lifting or carrying tasks) may have yielded superior findings.

The methodological steps employed in this study followed best practice recommendations (Freedson et al., 2012). These included using criterion approaches for energy expenditure (via indirect calorimetry), using a broad age range of participants, including both males and females with a range of body mass index and cardiorespiratory fitness, as well as a menu of activity tasks spanning a MET range of 1.1 to 10 METs to discriminate sedentary activity, light, moderate and vigorous physical activity. In addition, a key methodological step was using a personalized and device-derived independent variable to compare AW2 and GT3X count data, which was afforded via indirect calorimetry.

Another methodological strength was comparing AW2 physical activity count data with a waist-worn (GT3X) monitor, which is the preferred approach for detecting moderate to vigorous physical activity intensities (Trost et al., 2005). The AW2 demonstrated the ability to discriminate vigorous activity tasks acceptably despite being wrist-worn. However, both AW2 and GT3X devices poorly discriminated light and moderate-intensity activity tasks. It is thought that the inclusion of additional lower-intensity activity tasks may have provided stronger compliance by both devices within these lower MET ranges (i.e., 1.5 - 6.0 METs).

A major limitation of this study is due to the small sample size, which resulted in a loss of statistical power. While efforts were made to maintain homogeneity between male and female participants, the cohort was not normally distributed. Moreover, it was not possible to verify participants' cardiorespiratory fitness using the subjective physical activity questionnaire, meaning the broad range of MVPA (MET $h \cdot wk^{-1}$) may be the result of misrepresentation of habitual physical activity. Future work should employ a larger cohort of participants, comprising a broader distribution of age and habitual physical activity (or cardiorespiratory fitness). Another major limitation includes using cut-point methods (ROC-AUC) to define intensity categories. Future work should embrace alternative analytical techniques (such as pattern recognition analysis) for predicting energy expenditure, which utilizes components of raw acceleration signals and minimizes the over-representation or under-representation of energy expenditure (Freedson et al., 2012).

Given the variability of tasks performed over 24 hours or over multiple days, it is also recommended that future research determine the ability of the AW2 to measure waking movement behavior in free-living settings. Given the stringency of controlled laboratory conditions, natural human movement patterns may have been restricted and were not properly reflected in this study as in a free-living setting.

3.5 Conclusion

In conclusion, the count cut-points reported in the present study provide promising evidence for using the AW2 to discriminate between sedentary behavior and moderate-to-vigorous physical activity intensities in apparently healthy adult males and females. However, it is crucial to recognize that while our findings provide valuable insights, they may primarily be generalizable to population groups that share similar demographic profiles to our study's cohort. Accordingly, more work is required to confirm these findings and refine best practice recommendations for concurrent sleep and physical activity data collection in the general population and niche cohorts. Further cross-validation of the AW2 to concurrently measure physical activity of varying intensities and parameters of sleep would also aid in broadening the understanding of the combined effect of sleep and dose exposure to physical activity intensities during wake periods.

Chapter 4

Sleep, cardiometabolic health, and neurocognitive performance in esports players

4.1 Introduction

The competitive realm of video gaming (i.e., esports) has ballooned into a billion-dollar industry with massive global reach (Newzoo, 2021). Despite its commercial success, esports has been challenged with concerns regarding the adverse lifestyle behaviors associated with excessive gaming: short sleep, excessive sedentary behavior, and their potentially deleterious effects on gaming performance and future cardiometabolic health (Arnaez et al., 2018; Bonnar et al., 2019a; DiFrancisco-Donoghue et al., 2019). Although current research has identified some of these factors and others, such as stimulant use, as being related to the acute effects of gaming, findings have typically been limited to child and adolescent social gamers (Holden et al., 2018; Turel et al., 2016). As a result, there is a gap regarding these factors in adults engaged habitually with competitive games (Kemp et al., 2021), namely, esports players, who coincidentally now also represent the majority of gamers in general (Entertainment Software Association, 2020).

There is evidence that some gamers may spend up to 10 hours per day playing games, which is considered a sedentary behavior, and just 5.5 hours per night sleeping within 24 hours (DiFrancisco-Donoghue et al., 2019; Turel et al., 2016). This short sleep may be attributed to gaming-related physiological arousal and light exposure from screens (Hale & Guan, 2015), both of which can lengthen sleep onset latency, reduce sleep opportunity (Exelmans & Van den Bulck, 2015), and inadvertently disrupt the circadian clock. Bright short-wavelength 'blue' light from screens can suppress and delay melatonin secretion acutely and dose-dependently, leading to delayed sleep onset timing, a reduced sleep opportunity, and ultimately reduced sleep quality (Cajochen et al., 2011; Chang, Anne-Marie et al., 2015; Hatori et al., 2017). Thus, chronic light exposure from screens at night likely induces a circadian phase delay (Chinoy et al., 2018), which may manifest as social jetlag, characterized by discrepant sleep timing between work and non-work days (Wittmann et al., 2006).

While there is broad consensus that short, poor quality sleep is associated with a myriad of health deficits, including a greater risk for obesity, hypertension, type 2 diabetes, and all-cause mortality rates (Chaput et al., 2020), the coupled effect of short sleep with excessive sedentary behavior (from prolonged periods of seated gaming), may exacerbate the risk of these underlying comorbidities. In addition, the long-term effects of social jetlag parallel those attributed to short sleep, such as an increased prevalence of obesity, diabetes, insulin resistance, and cardiovascular disease (Cajochen et al., 2011; Hatori et al., 2017; Koopman et al., 2017; Roenneberg et al., 2012; Xi et al., 2014). It is also believed that short sleep, insulin resistance, and obesity are interacting epidemics perpetuated by a vicious cycle, with circadian dysfunction contributing to the development of cardiometabolic disease risk and exacerbating these negative effects (Lucassen et al., 2012).

In contrast, research has suggested that higher levels of gaming proficiency may be associated with superior neurocognitive performance in domains such as processing speed, memory, decision-making, and problem-solving (Buelow et al., 2015; Pallavicini et al., 2018). Given the intense cognitive load of certain commercial games, it has even been proposed that computer games may be used as a proxy to study cognitive epidemiology at a global level (Kokkinakis et al., 2017). Gaming relies heavily on an array of elementary and executive cognitive processes (Bonnar et al., 2019a). These processes may include alertness, vigilance, reaction time, problem-solving, decision-making, and working memory (Bonnar et al., 2019a), which may be selectively impaired by inadequate sleep (Lowe et al., 2017). Since sleep potentiates skill acquisition and improves attention and problem-solving ability (Nusbaum et al., 2018), it is thought that sleep may be a key determinant of gaming performance (Bonnar et al., 2019a). The extent to which inadequate quantity or quality of sleep may impact gaming performance or limit cognitive benefits remains unclear. Managing sleep to either preserve or improve performance may be an appealing motive for esports players to reconsider their lifestyle choices and potentially offset any adverse consequences associated with excessive gaming behavior.

Most earlier studies involving gamers have typically included any person who plays games without necessarily accounting for their level and experience of competitive involvement, habitual gaming practices (training and competition), or timing of gaming activities, nor did they discriminate gamers by their primary gaming platform (console, mobile, or computer gaming) (Kemp et al., 2021). There is also a clear gap in objectively describing the sleep-wake patterns of gamers engaged competitively with esports, including their health profiles and the relationship between their sleep habits with cardiometabolic health and performance. This study aims to bridge this gap by characterizing and exploring the associations between habitual sleep patterns, cardiometabolic disease risk factors, and neurocognitive performance in adult esports players. It is hypothesized that esports players will exhibit (i) worse sleep profiles, (ii) worse cardiometabolic health profiles, and (iii) superior neurocognitive performance compared to a control group of non-gamers, and that short sleep duration and poor-quality sleep will be associated with worsened cardiometabolic health and worse cognitive performance.

4.2 Methods

4.2.1 Study design and participants

The present study employed a cross-sectional observational design, comprising a group of 31 adults who either primarily played video games on the computer or self-identified as "computer gamers" (Esports players) and an age- and sex-matched group of 28 non-gamers (Control). These individuals were sampled randomly from around Cape Town in South Africa using social media posts and a press release advertised on general and gaming-specific online groups and forums (**Appendix E**). The study was approved by the University of Cape Town's Human Research Ethics Committee (HREC Ref. No.: 266/2018; **Appendix F**), and all participants provided written informed consent (**Appendix G**). Experimental procedures were conducted in accordance with the ethical principles of the Declaration of Helsinki (General Assembly of the World Medical Association, 2014).

Participants were eligible for inclusion in the study if they were: (i) aged between 18 and 30 years and (ii) employed in a regular, full-time job or enrolled as full-time students. The latter criterion was to standardize potential time constraints between participants, thereby ensuring consistency in the balance between work or study commitments, sleep, and daily gaming activities. Both male and female participants were eligible to participate in this study; however, only males were included in the final analysis since only two eligible female participants (Esports players: n=1, Control: n=1) enrolled in the study. During the recruitment phase, it became clear that female representation among esports players was exceptionally low, despite exhaustive efforts to balance the groups by sex. Therefore, female participants were excluded in the final analysis to maintain the scientific rigor and internal validity of the study. This decision was crucial to avoid overstating findings from an unrepresentatively small subgroup and to preserve the generalizability and integrity of the study. In addition, participants were required to satisfy group-specific inclusion criteria. To ensure participants in the Esports players group were habitually engaged with competitive gaming, they were required to (i) have at least five years of competitive gaming experience in amateur or semi-professional esports leagues; (ii) play either action- or strategy-genre esports games for at least 14 hours per week, of which a minimum of 2 x 30-minute sessions must occur on a weekday; and (iii) not have been disengaged from their gaming activities in the three months prior to their involvement in the study. Control group participants were included if they: (i) had never played computer games before or (ii) had no prior exposure to competitive gaming and did not play games (regardless of platform) for more than two hours per week in the two months prior to their involvement in the study.

Exclusion criteria included: (i) pregnant females, (ii) night or rotating shift work (in the three months prior to enrollment), (iii) any chronic medication known to affect either sleep, circadian rhythms, or the central nervous system (including but not limited to: sleep medication, supplemental melatonin, stimulants, and antidepressants) taken within the three months preceding enrollment, (iv) persons medically diagnosed with a psychiatric or mental illness known to affect sleep (e.g., depression), (v) substance abuse (i.e., drug or alcohol abuse), (vi) persons on vacation during the data collection period, (vii) console or mobile gamers, (viii) recreational (i.e., non-competitive) gamers, and (ix) individuals caring for children aged under four years.

4.2.2 Coronavirus impact statement

The data presented in this study were collected (and concluded) before any government-mandated lockdowns or related coronavirus disease (COVID-19) policies. This study was, therefore, neither directly nor indirectly affected by the coronavirus pandemic.

4.2.3 Experimental procedure

An overview of the study procedure is presented graphically in Figure 4.1. All testing was performed in the Chronobiology and Sleep Laboratory at the Health through Physical Activity, Lifestyle, and Sport Research Centre at the University of Cape Town between October 2018 and March 2020. In addition, participants were required to attend two testing sessions at the laboratory, which were scheduled 7±1 days apart.

4.2.3.1 Session 1

The first testing session was scheduled to start between 08:00 and 11:00 to limit circadian-related effects on clinical measurements. Participants were asked to arrive overnight-fasted (i.e., at least 10 hours) to ensure the integrity of metabolic blood markers. Upon arriving, an investigator explained the study's purpose and the risks and benefits of participation. Participants who agreed to take part in the study provided written informed consent before being screened to determine their eligibility.

During the screening process, participants completed a series of electronic questionnaires detailing their demographics, family medical history, occupation, overall and psychosocial health, medication use, and gaming activity histories (**Appendix H**). They also completed the Drug Abuse Screening Test (Yudko et al., 2007), Alcohol Use Disorders Identification Test – Consumption (Bush et al., 1998), and Patient Health Questionnaire Version 9 (Kroenke et al., 2001) to determine if they met the exclusion criteria for substance abuse and depression, respectively (**Appendix H**). Participants who passed the screening process were allowed to continue with the main study. For detailed information on the inclusion and exclusion criteria applied during the screening process, please refer to **Section 4.2.1.**

Eligible participants completed a further set of electronic questionnaires as part of the main study, designed to determine their (i) levels of video gaming addiction using the Video Gaming Addiction Scale – Short Version (VGAQ) (Lemmens et al., 2009), (ii) chronotype using the Horne-Östberg Morningness-Eveningness Questionnaire (HÖMEQ) (Horne & Ostberg, 1976), (iii) subjective sleep quality using the Pittsburgh Sleep Quality Index (PSQI) (Buysse et al., 1989), and (iv) daytime sleepiness using the Epworth Sleepiness Scale (ESS) (Johns, 1991) (**Appendix I**). Participants were classified as having video game addiction for VGAQ scores ≥ 4 (Lemmens et al., 2009), as being evening-types for HÖMEQ scores of 16-41, neither-types for HÖMEQ scores of 42-58, and morning-types for HÖMEQ scores of 59-86 (Horne & Ostberg, 1976), as having poor sleep quality if PSQI scores >5 (Buysse et al., 1989) and as having excessive daytime sleepiness if their ESS scores >10 (Johns, 1991).

The investigator then measured each participant's standing height (to the nearest 0.5 cm) and weight (to the nearest 0.1 kg) using a calibrated stadiometer and digital scale (BW-150, UWE Scales, Cape Town, South Africa), respectively. Waist circumference (cm) was measured at the level of the umbilicus (in triplicate) using a standard tape measure. After resting in a seated position for at least five minutes, the average of three systolic and diastolic blood pressure (mmHg) and resting heart rate (bpm) measures were taken at 1-minute intervals using an automated blood pressure monitor (Omron HEM-907, Omron Healthcare Co., Ltd., Kyoto, Japan).

A trained phlebotomist subsequently drew blood samples, which were sent to an accredited medical diagnostic laboratory (Lancet Laboratories, Cape Town, South Africa) to measure fasting glucose (mmol • L-1) and insulin (mU • L-1) using standard methods. Insulin resistance was determined using the Homeostasis Model of Assessment of Insulin Resistance (HOMA-IR) using the formula below (Matthews et al., 1985):

$$HOMA - IR = \frac{glucose\ (mmol \cdot L^{-1})\ *\ insulin\ (mU \cdot L^{-1})}{22.5}$$

Participants were familiarized with a task battery of three computerized cognitive tests designed to assess components of neurocognitive performance understood to be relevant to gaming. These tests each formed part of the open-source Psychology Experiment Building Language (PEBL) - Version 2.0 software suite (Mueller & Piper, 2014) and comprised a trial-based (120-trial limit) Psychomotor Vigilance Test (PVT) to measure sustained attention and vigilance; the Berg Card Sorting Test (BCST) to measure problem-solving, abstract thinking, and cognitive set-shifting ability; and a one-dimensional n-back (n=1,2,3) task to measure working memory and reaction time. Participants were each allowed up to two minutes to practice each task, the order of which was randomized for each participant.

Finally, participants were given an Actiwatch-2 or Actiwatch Spectrum device (Philips Respironics, Bend, Oregon, U.S.) to wear continuously for seven consecutive days on their non-dominant wrist to measure habitual sleep, physical activity, and white light exposure in a free-living setting. Notably, per confirmation by the device manufacturers, there were no algorithmic differences between these device models regarding the measurement of variables of interest. As a result, both models were employed in the present study due to limited supply. During the wear period, participants pressed a marker button to indicate the start and end of both nocturnal sleep periods and daytime naps. They also kept an adapted version of the Consensus Sleep Diary (Carney et al., 2012), detailing sleep timing, gaming, physical activity, caffeine, medication, and supplement use (**Appendix J**). In addition, participants were asked not to adjust their habitual gaming, sleep, eating, or physical activity behaviors during this time.

4.2.3.2 Session 2

This session took place seven days after session one. It was scheduled to start between 09:00 and 12:00 as it was thought that offering a circadian-neutral time frame, in which participants could choose a "personally optimal time" for peak functionality (i.e., without favoring any one chronotype), would be best to reduce time-of-day effects on cognitive performance (Evans et al., 2017). Participants were also instructed not to consume caffeine for at least ten hours before the testing session. Upon arrival, each participant completed the Positive and Negative Affect Schedule (PANAS; **Appendix I**) before completing the neurocognitive tests to control for the effects of mood on neurocognitive performance.

The order of the tests was randomized, and participants were instructed to turn their mobile phones to silent mode to avoid potential distractions.

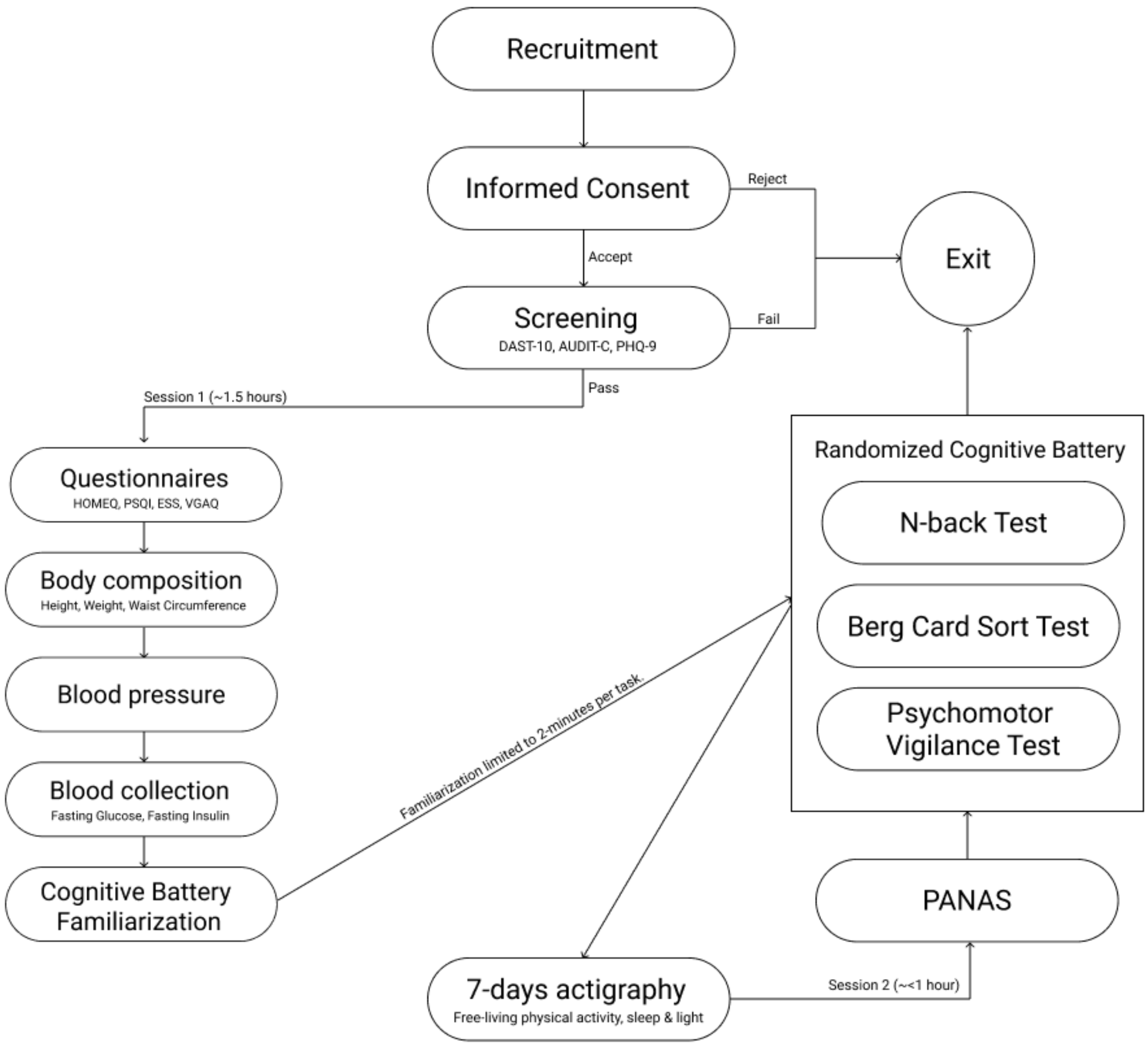

Figure 4.1. Study overview. DAST-10: Drug Abuse Screening Test; AUDIT-C: Alcohol Use Disorders Identification Test; PHQ-9: Patient Health Questionnaire; HÖMEQ: Horne-Östberg Morningness-Eveningness Questionnaire; PSQI: Pittsburgh Sleep Quality Index; ESS: Epworth Sleepiness Scale; VGAQ: Video Gaming Addiction Questionnaire; PANAS: Positive and Negative Affect Schedule.

4.2.4 Data and statistical analyses

4.2.4.1 Analysis of sleep using actigraphy

Actiwatch devices were configured and analyzed using Philips Actiware v.6.0.9 (Philips Respironics, Bend, Oregon, U.S.). Sleep patterns were analyzed in 15-second epochs using the 'medium' wake threshold parameter. Data were included in the analysis if at least four weekdays (i.e., Sunday to Thursday) and at least one weekend day (i.e., Friday to Saturday) were captured. Periods of non-wear time were marked as 'excluded' intervals and were omitted from the final analysis. Non-wear periods were defined as continuous intervals of 60 minutes where the Actiwatch recorded zero activity counts per minute (CPM), allowing brief interruptions of 1-2 minutes that recorded between 0-100 CPM (Troiano et al., 2008). Two independent investigators manually established the timing of sleep periods based on published guidelines (Chow et al., 2016). In addition to standard Actiwatch-derived sleep parameters, bedtime and wake-up time ranges were defined as the difference between the latest and earliest bedtimes and wake-up times for each person over the monitoring period, respectively. Social jetlag was calculated as the absolute difference between the average sleep midpoints on weekend nights (i.e., Friday and Saturday) and weeknights (i.e., Sunday to Thursday) for each person. Finally, bedtime and wake-up time regularity were defined as the standard deviation around bedtime and wake-up time for each person over the monitoring period, respectively; larger values described a greater degree of dispersion (i.e., more irregularity). Outcome variables included: bedtime, wake-up time, time-in-bed (h), total sleep time (h), sleep onset latency (min), sleep efficiency (%), wake after sleep onset (min), and arousal index (number of awakenings per hour total sleep time), bedtime range (h), wake-up time range (h), social jetlag (h), bedtime regularity (h), and wake-up time regularity (h). Long sleep onset latency was defined as a sleep onset latency >30 min and poor sleep efficiency as a sleep efficiency of <85%.

4.2.4.2 Cardiometabolic disease risk composite score

Cardiometabolic disease risk composite scores are typically used as an alternative to traditional individual clinical risk indices and were constructed to assess overall cardiometabolic disease risk (Carroll et al., 2014). The continuous cardiometabolic disease risk score used in the present study was previously validated for adult cohorts and is comparable to Framingham Risk Scores (Carroll et al., 2014). The composite score indicated below is calculated by summing the standardized (z) scores of six dimensions, each representing risk factors for metabolic syndrome, including fasting plasma glucose (Glu), fasting insulin (Ins), waist circumference (WC), body mass index (BMI), systolic blood pressure (SBP) and diastolic blood pressure (DBP). The scoring formula used in the present is a modified version of the formula used by (Kanagasabai & Chaput, 2017); the triglyceride and high-density lipoprotein dimensions were omitted since they were not measured in the present study. A higher score indicates a greater risk of cardiometabolic disease.

$$Cardiometabolic\ Disease\ Risk\ Score\ =\ zGlu\ +\ zIns\ +\left(\frac{zWC\ +\ zBMI}{2}\right)+\ \left(\frac{zSBP\ +\ zDBP}{2}\right)$$

4.2.4.3 Sleep health composite score

Recently, researchers have been exploring the use of a composite sleep health score by operationalizing key related dimensions of sleep, including but not limited to duration, timing, regularity, satisfaction, alertness, and efficiency (Buysse, 2014; Knutson et al., 2017). Since sleep is a multidimensional concept, this novel approach to assessing sleep is considered superior to examining individual sleep outcome measures and their associations with physical and mental health (Chung et al., 2021; DeSantis et al., 2019; Dong et al., 2019). This study employed six sleep dimensions, including actigraphy-derived sleep duration (total sleep time), sleep efficiency, sleep duration regularity, and sleep timing regularity measured over the free-living monitoring period, and subjective measures of sleep quality and daytime dysfunction extracted from the Pittsburgh Sleep Quality Index (PSQI). Sleep duration regularity ($\text{Duration}_{\text{reg}}$) and sleep timing regularity ($\text{Timing}_{\text{reg}}$) were defined as the standard deviations of total sleep time and sleep midpoint, respectively, derived from seven days of actigraphy data for each individual. Subjective sleep quality (Quality) and daytime dysfunction (Dysfunction) were defined using scores from question 6 and sub-component 7 (defined as the sum of scores for questions 8 and 9) of the PSQI, respectively. Sleep efficiency refers to the percentage of time spent asleep compared to the total time spent in bed, calculated as total sleep time divided by time-in-bed (in hours, measured by actigraphy), multiplied by 100.

Since sleep duration exhibits a U-shaped relationship with cardiometabolic disease risk (Xi et al., 2014), creating a standardized linear score for sleep duration is not ideal. Instead, a substitute variable (transformed sleep time, or 'TrST') was introduced as a better-suited metric. Total sleep times falling within the 6.5 – 8.5 h range were assigned a z-score of zero. For sleep times outside this range, the z-score was calculated as the absolute difference between the total sleep time value and the closest bound of the optimal range (either 6.5 or 8.5 hours). The total sleep time range of 6.5 - 8.5h was based on current guidelines for optimal sleep duration (7 to 9 hours per night) in adults (Hirshkowitz et al., 2015), adjusted for "good sleep efficiency" (estimated to be 90-95% in healthy young adults). This results in an effective sleep duration range of 6.5 to 8.5 hours, representing 92.5% of the recommended sleep duration. The sleep health score was calculated by summing the standardized scores of each dimension using the formula below; higher scores indicate poorer sleep health.

$$Sleep\ Health = zTrST - zEfficiency + zDuration\ reg + zTiming\ reg + zQuality + zDysfunction$$

This sleep health composite score differs from previous binary scores as the individual dimension scores and composite scores are continuous. We believe this improves the score since it is not overly reliant on cut points to score dimensions as good or poor.

4.2.4.4 Statistical analyses

Unless otherwise stated, descriptive data are presented as the mean ± standard deviation, median (interquartile range), or count (percentage). Data were assessed for normality using the Shapiro-Wilk test, and Levene's test was used to assess the homogeneity of variance. The between- and within-group differences were analyzed using the independent and dependent t-test for parametric data or the Mann-Whitney U test and the Wilcoxon matched-pair signed-rank test for non-parametric data, respectively. Differences between frequency counts or categorical variables were analyzed using a Chi-squared test for expected frequencies greater than five; otherwise, Fisher's Exact Test was used. Data from the Esports players and Control groups were pooled for correlation analyses. Only variables that were homogenous across groups or observed a parametric distribution after pooling were included in correlation analyses. Otherwise, data transformation was attempted in non-parametric distributions to achieve approximate normality. Transformation of non-parametric variables was performed according to the Tukey ladder of powers. Correlations were determined using Pearson's Product-Moment Correlation test for continuous parametric data for the purposes of identifying candidates for linear regression. Variables that exhibited multicollinearity were visually indicated by shading in gray. Variables that underwent reciprocal transformation (i.e., x to 1/x) were also reflected in the y-axis to generate a negative reciprocal (-1/x) to preserve the variable order during data interpretation. Linear regression models were used to examine further significant relationships between sleep (total sleep time, PSQI total score, bedtime, wake-up time, and wake-up time regularity), cardiometabolic health (HOMA-IR, systolic blood pressure, and cardiometabolic disease risk score), and neurocognitive performance (1-back reaction time and 3-back reaction time) variables per correlation analyses in **Appendix K** (Suppl. Tables 5 and 6). Models were adjusted for group (categorized as 0: Control; 1: Esports players), as well as potential confounders: smoking (defined as the response to the question: "Are you a smoker?" and categorized as 0: no; 1: yes), and chronotype (defined by HÖMEQ total score classification and categorized as 1: morning-type, 2: neither-type, 3: evening-type). Group interaction terms with each sleep variable were created to test for interaction effects. Since no significant interaction effects were found, data were pooled for analyses. Covariates (chronotype and smoker) were tested for contribution to models, but since their contributions were negligible, the regression models were run without covariates to maximize power. Smoking and chronotype covariates were selected *a priori* because of their known associations with cardiometabolic and sleep-related outcomes. The strength of associations and effect sizes were characterized according to Cohen's classifications (Cohen, 1988; Cohen, 1992). Statistical significance was accepted if $p<0.05$. All data were analyzed using Stata v.15 (StataCorp, College Station, Texas, U.S.). Graphical plots were created using GraphPad Prism v.8.0.0 for Windows (GraphPad Software, San Diego, California, U.S.).

4.3 Results

4.3.1 Descriptive characteristics

The descriptive characteristics of the Esports players and Control groups are presented in Table 4.1. The prevalence of overweight (defined by BMI ≥ 25 $kg \cdot m^{-2}$) in the Esports players (41.9%) and Control (39.3%) groups was similar ($p=0.836$). The only difference between the groups was that more Esports players were smokers than Control participants ($p=0.035$).

Table 4.1. Physical and cardiometabolic disease characteristics.

	Esports players (n=31)	Control (n=28)	p value
Age (y)	23.6 ± 3.7	23.3 ± 3.2	0.661
Weight (kg)	73.7 (28.2)	75.9 (20.3)	0.549
Height (m)	1.75 (0.15)	1.79 (0.15)	0.579
Body mass index (kg • m^{-2})	24.6 (7.1)	24.1 (5.5)	0.355
Waist circumference (cm)	84.0 ± 11.3	79.9 ± 7.8	0.117
Resting systolic blood pressure (mmHg)	119.1 ± 9.7	118.2 ± 9.9	0.738
Resting diastolic blood pressure (mmHg)	78.6 ± 7.3	76.4 ± 7.2	0.254
Resting heart rate (bpm)	70.4 ± 10	67.1 ± 10	0.200
Fasting glucose (mmol • L^{-1})	4.8 ± 0.3	4.9 ± 0.4	0.232
Fasting insulin (mmol • L^{-1})	6.4 (5.2)	5.5 (2.1)	0.125
HOMA-IR	1.4 (1.1)	1.1 (0.5)	0.249
Cardiometabolic disease risk score	0.3 ± 2.8	-0.2 ± 2.4	0.431
Smoker (yes)	12 (42.9%)	4 (14.3%)	**0.035 ***

Data are presented as mean ± standard deviation, median (interquartile range), or count (percentage). HOMA-IR: Homeostatic Model Assessment of Insulin Resistance. P-values were determined using independent t-, Mann-Whitney U, and Pearson's chi-squared tests. * Significance was accepted at $p<0.050$.

4.3.2 Gaming behavior characteristics

Most participants in the Esports players group reported playing games competitively at an amateur level (71.0%), while the rest played at a semi-professional level (29.0%). During monitoring, these players reported gaming for 3.2 ± 1.5 hours per day. In addition, the most frequently played esports games included *Counterstrike Global Offensive* (Valve Corporation, U.S.), *League of Legends* (Riot Games, U.S.), and *Dota 2* (Valve Corporation, U.S.). These games corresponded to two major game genres: first-person shooter (FPS, 54.8%) and massive online battle arena (MOBA, 45.2%) games. As expected, Esports players were found to have greater scores of video gaming addiction compared to Controls (3.5 ± 1.9 versus 0.3 ± 0.08, $p<0.001$), with a prevalence of gaming addiction of 45.2% among the Esports players.

4.3.3 Sleep and chronotype characteristics

Chronotype and sleep data are presented in Table 4.2. The Esports players group had a lower HÖMEQ score than the Control group ($p<0.001$). Chronotype distribution differed between the groups (Figure 4.2), with post hoc analysis revealing that more Esports players were evening-types (45.2% versus 7.1%, $p=0.001$), and fewer were morning-types (6.4% versus 50.0%, $p<0.001$) compared to the Control group. No participants were classified as having excessive daytime sleepiness, but nearly half of the participants in each group had poor sleep quality (Esports players: 45.2%; Control: 42.9%).

Table 4.2. Chronotype, daytime sleepiness, and sleep quality.

	Esports players (n=31)	Control (n=28)	p value
HÖMEQ score	43.4 ± 8.8	56.5 ± 8.5	**<0.001 ***
ESS score	4.0 (3.0)	4.0 (2.0)	0.945
PSQI score	5.0 (3.0)	5.0 (4.5)	0.505

Data are presented as mean ± standard deviation or median (interquartile range). HÖMEQ: Horne-Östberg Morningness-Eveningness Questionnaire, ESS: Epworth Sleepiness Scale, PSQI: Pittsburgh Sleep Quality Index. Between-group differences were detected using an independent t-test or Mann-Whitney U test. * Significance was accepted at p<0.050.

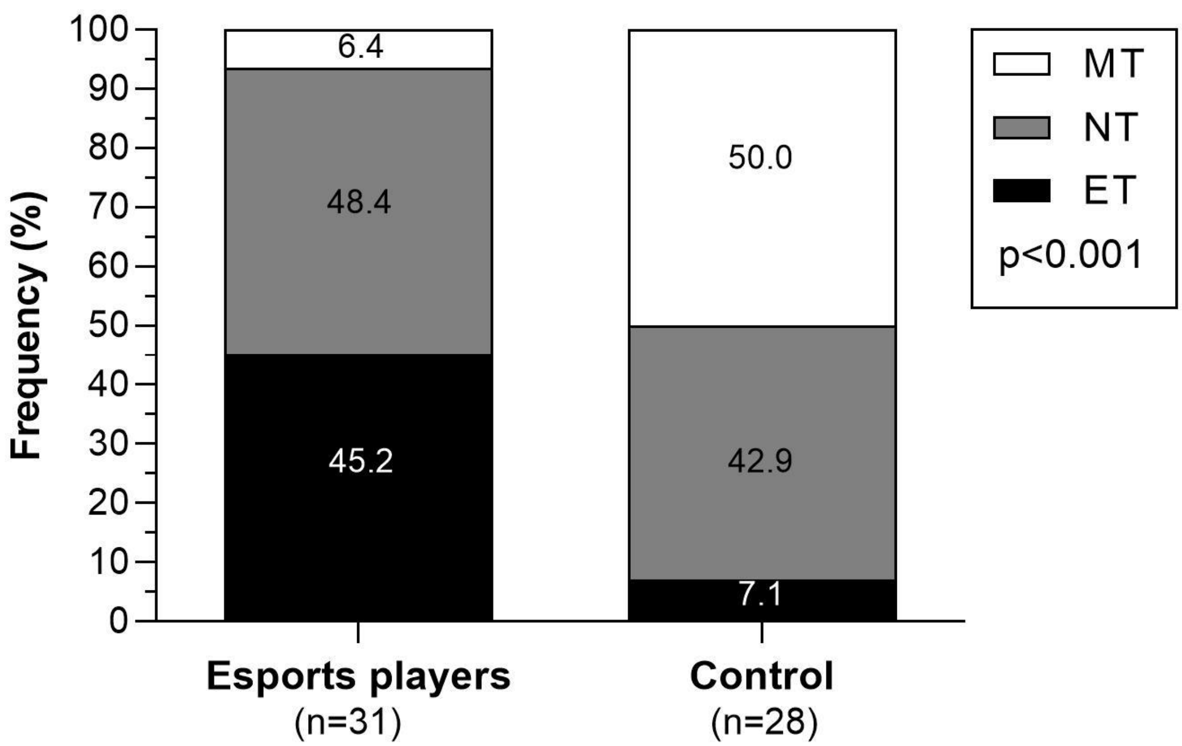

Figure 4.2. Chronotype frequency distributions of the Esports players and Control groups. MT: morning-type; NT: neither-type; ET: evening-type. Between-group differences were determined using Pearson's Chi-squared test, followed by post hoc analysis using Fisher's Exact test. Significance was accepted at p<0.050.

Valid actigraphy data were obtained from all participants, based on an average of 6.7±0.6 nights per participant, with 4.8±0.5 being week nights and 1.9±0.2 being weekend nights. Nocturnal actigraphy-derived sleep characteristics are illustrated in Figure 4.3. The Esports players group had later bedtimes and wake-up times (Figure 4.3 A-B: p=0.001 and p=0.004, respectively), with a correspondingly delayed midpoint of sleep (Figure 4.3 E: p=0.001) relative to the Control group. Only one-fifth of both the Esports players (n=6, 19.4%) and Control (n=6, 21.4%, p=0.843) groups achieved at least 7 hours of total sleep time, per the lower limit of the National Sleep Foundation's sleep duration guidelines for adults (Hirshkowitz et al., 2015). The Esports players group also had a shorter sleep onset latency (Figure 4.3 F: p=0.014) and better sleep efficiency (Figure 4.3 H: p=0.036) than the Control group. The proportion of participants in the Esports players (6.5%) and Control (10.7%) groups with long (>30min) sleep onset latencies was similar (p=0.661). Similarly, there were no significant differences in the proportion of Esports players (19.4%) and Control (39.3%) groups with poor (<85%) sleep efficiencies (χ^2=2.849, p=0.091). Approximately half of the Esports players (n=17, 54.8%) and Control (n=15, 53.6%, p=0.565) groups reported napping during the daytime, but daily average nap time-in-bed (p=0.001) and total sleep time (p=0.007) were longer in the Esports players than the Control group (Table 4.3). Accordingly, Esports players who napped had significantly longer 24-hour time-in-bed (9.1 ± 0.8 vs. 8.1 ± 0.7 h, p=0.001) and 24-hour total sleep time (7.8 ± 0.8 vs. 6.8 ± 0.9 h, p=0.003) compared to the Control group. There was no difference in sleep health scores between groups.

No group differences were observed in the bedtime and wake-up time ranges or sleep regularity indices (Table 4.3). A similar proportion of the Esports players (n=20, 64.5%) and Control (n=16, 57.1%) groups were classified as having ≥1h of social jetlag (χ^2=0.336, p=0.562). Although one-third of Esports players (n=10, 32.3%) and one-fifth of Controls (n=6, 21.4%) were classified as having ≥2h of social jetlag (χ^2=0.873, p=0.350), this proportion was not different between the groups.

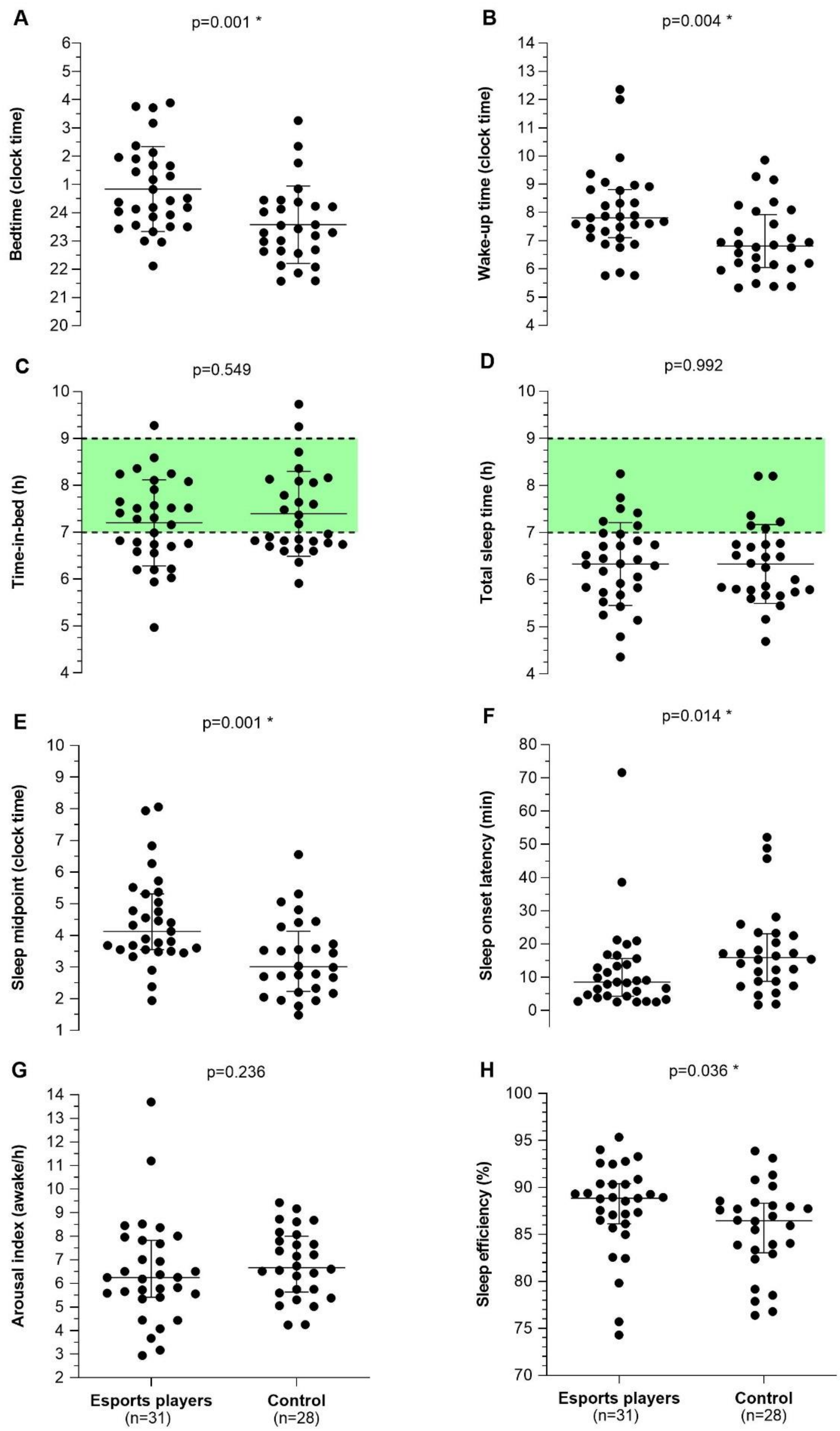

Figure 4.3. Scatter plots of nocturnal actigraphy-derived sleep characteristics of the Esports players and Control groups. Individual data points are presented as black circles (●) with either the mean or median (long horizontal line) and standard deviation or interquartile ranges (short horizontal lines). Green zones between dashed lines represent the National Sleep Foundation's recommended sleep duration for adults. Between-group differences were determined with an independent t-test (A, D) or Mann-Whitney U test (B, C, E-H). * Significance was accepted at p<0.050.

Table 4.3. Habitual napping, sleep timing and regularity indices as measured by actigraphy.

	Esports players (n=31)	Control (n=28)	p value
Nap time-in-bed (h) [a]	1.7 ± 0.7	1.0 ± 0.5	**0.001 ***
Nap total sleep time (h) [a]	1.4 ± 0.7	0.7 ± 0.6	**0.007 ***
Bedtime range (h)	3.7 ± 1.8	3.0 ± 1.6	0.120
Wake-up time range (h)	3.4 (2.5)	2.9 (2.1)	0.104
Social jet lag (h)	1.3 (1.8)	1.1 (1.2)	0.693
Timing regularity (h)	1.1 (0.7)	0.9 (0.5)	0.071
Duration regularity (h)	1.3 ± 0.7	1.2 ± 0.4	0.402
Bedtime regularity (h)	1.3 (1.0)	0.9 (0.7)	0.104
Wake-up time regularity (h)	1.3 (1.2)	1.1 (0.9)	0.060
Sleep health score (h)	-0.4 (3.0)	-0.2 (3.3)	0.574

Data are presented as mean ± standard deviation and median (interquartile range). Between-group differences were detected using an independent t-test or Mann-Whitney U test. [a] Nap data are based on a subset of participants who reported napping (Esports players: n=17, Controls: n=15). * Significance was accepted at p<0.050.

Table 4.4 compares week- and weekend-nocturnal sleep characteristics between and within the Esports players and Control groups. Compared to the Control group, the Esports players group had later bedtimes and wake-up times on both week (p=0.002; p=0.014, respectively) and weekend (p=0.012; p=0.004, respectively) nights. As a result, the Esports players group also had more delayed sleep midpoints than the Control group over both week and weekend nights (p=0.003; p=0.004, respectively). Within-group analyses revealed that the Esports players group exhibited a greater delay in bedtime (median: 30, IQR: 26 min, p=0.003) and wake-up time (median 86, IQR: 2 min, p<0.001) on weekend nights versus weeknights. Similarly, bedtime and wake-up times on weekend nights were significantly delayed in the Control group by a median of 57 min (IQR: 42 min) and 68 min (IQR: 29 min), respectively, compared to weeknights (both p<0.001). The Esports players and the Control group consequently had delayed sleep midpoints between the week and weekend nights (both p<0.001). In addition, sleep onset latency was shorter in Esports players over weeknights (p=0.007) and weekend nights (p=0.034) than in the Control group.

Table 4.4. Habitual nocturnal sleep characteristics as measured by actigraphy on weekday and weekend nights.

	Weekday nights			Weekend nights			Within-groups	
	Esports players (n=31)	Control (n=28)	p value	Esports players (n=31)	Control (n=28)	p value	Esports players p value	Control p value
Bedtime (hh:mm)	00:17 (02:17)	23:08 (01:35)	**0.002 ***	00:47 (01:51)	00:05 (02:17)	**0.012 ***	**0.003 ***	**<0.001 ***
Wake-up time (hh:mm)	07:18 (01:46)	06:22 (02:12)	**0.014 ***	08:44 (01:48)	07:30 (01:43)	**0.004 ***	**<0.001 ***	**<0.001 ***
TiB (h)	7.0 ± 1.0	7.4 ± 1.0	0.156	7.2 ± 1.4	7.7 ± 1.3	0.184	0.461	0.204
TST (h)	6.1 ± 1.0	6.3 ± 0.9	0.565	6.3 ± 1.4	6.6 ± 1.1	0.386	0.444	0.102
SOL (min)	7.9 (11.6)	15.8 (17.6)	**0.007 ***	6.0 (12.9)	15.5 (20.4)	**0.034 ***	0.493	0.509
SE (%)	88.0 (5.4)	86.0 (6.9)	0.092	88.7 (6.6)	85.5 (5.5)	0.118	0.597	0.909
WASO (min)	23.5 (15.2)	27.0 (15.3)	0.172	23.8 (18.0)	28.8 (18.2)	0.268	0.518	0.285
Awakenings (count)	40.1 ± 15.3	43.5 ± 10.9	0.338	42.7 ± 15.2	45.5 ± 13.2	0.450	0.195	0.398
Arousal Index (awake/h)	6.4 (3.1)	7.0 (2.7)	0.213	6.4 (2.2)	7.1 (2.8)	0.585	0.126	0.495
Sleep midpoint (hh:mm)	03:51 (01:55)	02:37 (01:45)	**0.003 ***	05:03 (01:50)	03:45 (01:24)	**0.004 ***	**<0.001 ***	**<0.001 ***

Data are presented as mean ± standard deviation or median (interquartile range). Between-group differences were detected using an independent t-test or Mann-Whitney U test; within-group differences were detected using a dependent t-test or Wilcoxon matched-pair signed-rank test. TiB: time-in-bed, TST: total sleep time, SOL: sleep onset latency, SE: sleep efficiency, WASO: wake after sleep onset. * Significance was accepted at p<0.050.

4.3.4 Neurocognitive performance characteristics

Esports players had more correct responses ($p<0.001$) and fewer attentional lapses ($p<0.001$) in the PVT test compared to the Control group (Table 4.5). Esports players also demonstrated better accuracy during the 3-back paradigm of the n-back task than the Control group ($p=0.009$). Esports players had a lower total error (median: 2.0, IQR: 0.9 versus median: 2.6, IQR: 5.0, $p=0.045$) and lower perseverative error scores (median: 1.3, IQR: 0.4 versus median: 1.7, IQR: 3.2, $p=0.013$) in the BCST compared to Control group. The PANAS was used to ensure that the psychological state was similar between groups, reducing the likelihood of neurocognitive performance being confounded by the psychological state of participants. No differences between groups for either positive or negative affect were observed ($p=0.741$ and $p=0.106$, respectively).

Table 4.5. Neurocognitive performance parameters in cognitive tests.

	Esports players (n=31)	Control (n=28)	p value
Psychomotor Vigilance Test			
False starts	0.0 (1.0)	1.0 (3.0)	0.054
Correct responses	117.0 (6.0)	108.0 (12.0)	**<0.001 ***
Attentional lapses	3.0 (5.0)	9.5 (14.5)	**<0.001 ***
N-back Test			
1-back reaction time (ms)	521.8 (123.5)	547.6 (159.9)	0.114
1-back accuracy (%)	100.0 (9.5)	95.2 (11.9)	0.197
2-back reaction time (ms)	628.3 (203.7)	614.4 (336.9)	0.682
2-back accuracy (%)	95.5 (13.6)	90.9 (11.4)	0.266
3-back reaction time (ms)	831.9 (519.8)	868.4 (238.1)	0.564
3-back accuracy (%)	82.6 (13.0)	78.3 (13.0)	**0.009 ***
Berg Card Sorting Test [a]			
Total error rate	2.0 (0.9)	2.6 (5.0)	**0.045 ***
Perseverative error rate	1.3 (0.4)	1.7 (3.2)	**0.013 ***
Non-perseverative error rate	0.8 (0.6)	1.0 (1.9)	0.075

Data are presented as median (interquartile range). [a] Error rates were normalized against the total number of categories completed; therefore, error rates are presented as a rate per category completed. Between-group differences were determined using the Mann-Whitney U test. * Significance was accepted at p<0.050.

4.3.5 Linear regression models

Based on significant correlations (Suppl. Tables 5 and 6, Appendix K), associations between sleep measures with markers of cardiometabolic disease and neurocognitive performance were explored further using linear regression modeling. Since no significant interaction effects were observed in any of the models between group and the sleep variable of interest, data from both groups were pooled for these analyses. Unadjusted regression models showed that higher PSQI total scores were associated with higher cardiometabolic disease risk scores (Figure 4.4 A, $\boldsymbol{\beta}$=0.268; 95% CI: 0.054, 2.309, p=0.040), systolic blood pressure (Figure 4.4 B, $\boldsymbol{\beta}$=0.293; 95% CI: 0.655, 9.061, p=0.024) and

HOMA-IR values (Figure 4.4 C, $\boldsymbol{\beta}$=0.296; 95% CI: 0.016, 0.209, p=0.023). In addition, the PSQI total score contributed to 7.2%, 8.6%, and 8.8% of the variance in each model, respectively. Later bedtimes (Figure 4.4 D, $\boldsymbol{\beta}$=-0.257; 95% CI: -179.973, -0.070, p=0.0498) and later wake-up times (Figure 4.4 E, $\boldsymbol{\beta}$=-0.284; 95% CI: -64.883, -3.551, p=0.029) were each associated with lower systolic blood pressure and explained 6.6% and 8.1% of the variance in systolic blood pressure, respectively. In addition, more irregular wake-up times were associated with higher HOMA-IR values (Figure 4.4 F, $\boldsymbol{\beta}$=0.274; 95% CI: 0.019, 0.548, p=0.036) and explained 7.5% of the variance in HOMA-IR. Higher PSQI total scores were associated with faster 3-back reaction times (Figure 4.5 A, $\boldsymbol{\beta}$=-0.259; 95% CI: -0.127, -0.001, p=0.048) and explained 6.7% of the variance in 3-back reaction time. Conversely, shorter total sleep time was associated with slower 1-back reaction time (Figure 4.5 B, $\boldsymbol{\beta}$=-0.290; 95% CI: -<0.001, -<0.001, p=0.026) and explained 8.4% of the variance in 1-back reaction time. Regression models with independent variables PSQI total score and total sleep time were adjusted for chronotype and smoking, while models with bedtime, wake-up time, and wake-up time regularity as independent variables were adjusted for smoking. None of the adjusted linear regression models retained significance (Table 4.6).

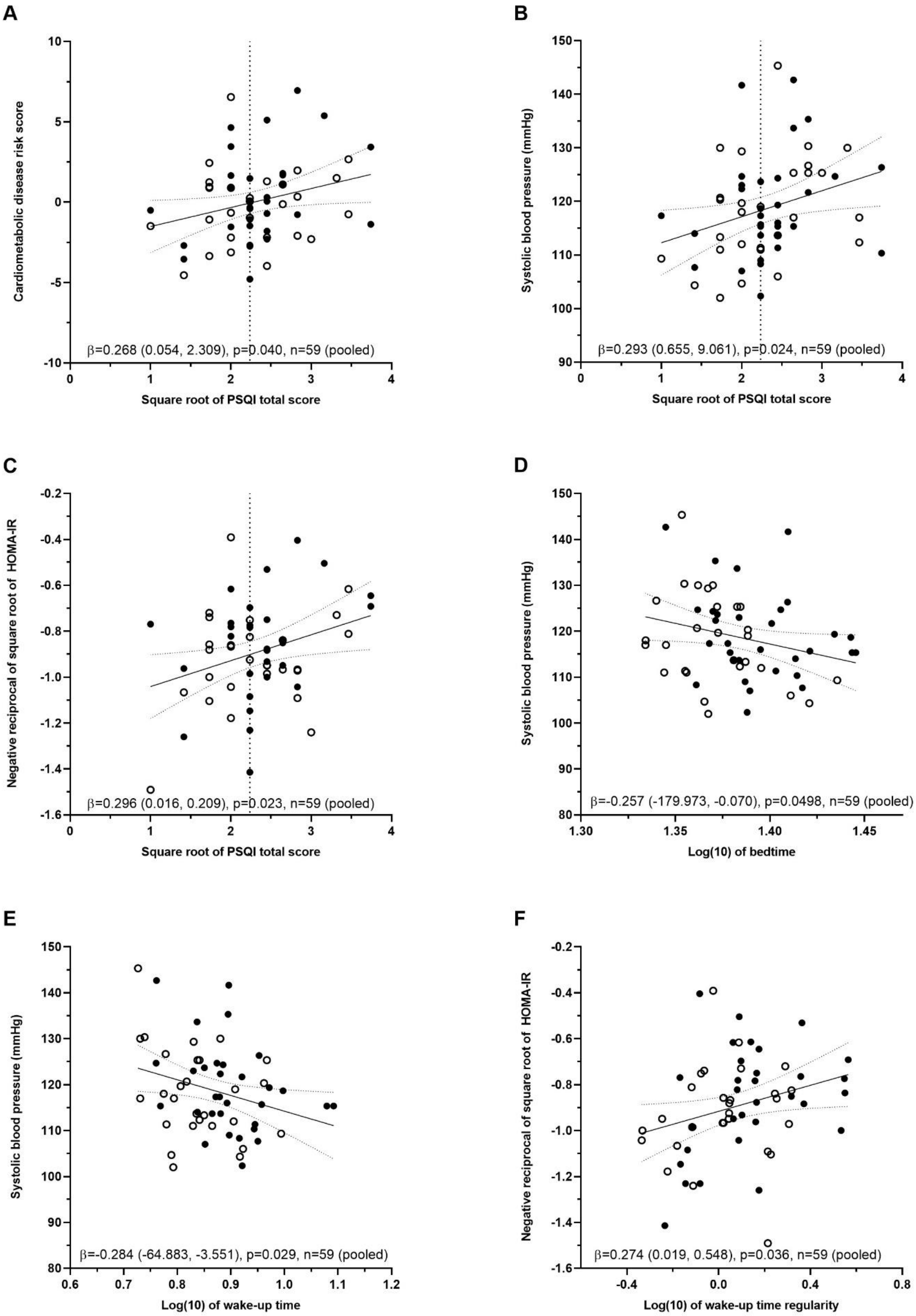

Figure 4.4. Linear regression plots of the unadjusted relationships between sleep variables and markers of cardiometabolic disease: (A) PSQI total score and cardiometabolic disease risk score, (B) PSQI total score and systolic blood pressure, (C) PSQI total score and HOMA-IR, (D) bedtime and HOMA-IR, (E) wake-up time and systolic blood pressure, and (F) wake-up time regularity and HOMA-IR. Esports players: closed circles (●); Controls: open circles (○); dotted vertical line (A-C): PSQI total score cut-off for poor sleep quality; solid line: goodness of fit line; dashed lines: 95% confidence intervals. PSQI: Pittsburgh Sleep Quality Index, HOMA-IR: Homeostatic Model Assessment of Insulin Resistance. Overall linear regression model data are presented as beta coefficients (95% confidence interval) for pooled datasets. Significance was accepted at p<0.050.

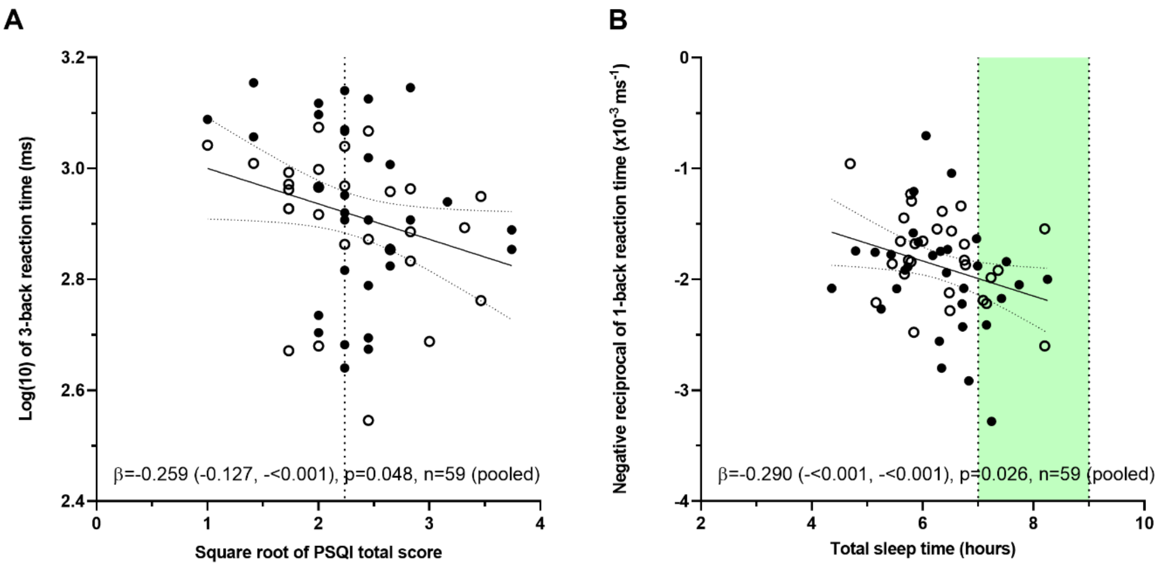

Figure 4.5. Linear regression plots of the unadjusted relationships between sleep measures and neurocognitive performance: (A) PSQI total score and 3-back reaction time and (B) total sleep time and 1-back reaction time. Esports players: closed circles (●); Controls: open circles (○); dotted vertical line (A): PSQI total score cut-off for poor sleep quality; green zone between vertical dotted lines (B): National Sleep Foundation guidelines for the recommended sleep duration for young adults; solid line: goodness of fit line; dashed lines: 95% confidence intervals. PSQI: Pittsburgh Sleep Quality Index. Data are presented as beta coefficients (95% confidence interval) and p values, determined using linear regression analysis. Significance was accepted at $p<0.050$.

Table 4.6. Adjusted linear regression models exploring relationships between sleep measures and markers of cardiometabolic disease and neurocognitive performance in all participants (n=59).

Model	Independent variable	Dependent variable	Regression coefficient (β)	95% confidence interval	R^2	Adjusted R^2	p value
1	PSQI total score	CMD risk score	0.291	0.072, 2.499	0.090	0.022	0.272
2	PSQI total score	Systolic blood pressure	0.277	0.098, 9.099	0.113	0.047	0.161
3	PSQI total score	HOMA-IR	0.367	0.038, 0.242	0.132	0.068	0.100
4	PSQI total score	3-back reaction time	-0.219	-0.122, 0.013	0.096	0.029	0.234
5	Total sleep time	1-back reaction time	-0.246	-<0.001, <0.001	0.152	0.089	0.059
6	Bedtime	Systolic blood pressure	-0.260	-181.155, -1.273	0.084	0.051	0.086
7	Wake-up time	Systolic blood pressure	-0.270	64.126, -2.455	0.092	0.060	0.067
8	Wake-up time regularity	HOMA-IR	0.269	0.012, 0.545	0.081	0.048	0.095

PSQI: Pittsburgh Sleep Quality Index; CMD: Cardiometabolic disease; HOMA-IR: Homeostatic Assessment Model of Insulin Resistance. Variables were transformed as follows: PSQI: square root; HOMA-IR: negative reciprocal square root; 3-back reaction time: log; 1-back reaction time: negative reciprocal; bedtime: log; wake-up time: log; wake-up time regularity: log. Models 1 – 5 were adjusted for smoking (0: no, 1: yes) and chronotype (1: morning-type, 2: neither-type as baseline comparator, 3: evening-type). Models 6-8 were adjusted for smoking. Variables total sleep time, bedtime, wake-up time, and wake-up time regularity are actigraphy-derived. Overall model statistics are presented, with significance accepted at $p<0.050$.

4.4 Discussion

This study characterized and compared the sleep, cardiometabolic health, and neurocognitive performance profiles of esports players and non-gamers and explored the associations between these factors. The Esports players had a later sleep timing, were more evening-oriented, and smoked more than the Controls. In addition, although the Esports players had more efficient nocturnal sleep, they fell asleep faster at night and napped for longer during the day than the Controls. As hypothesized, the neurocognitive performance of Esports players was superior across nearly all task parameters versus Controls. Among all participants, unadjusted linear regression analyses identified associations between poor self-reported sleep quality and higher wake-up time irregularity with worsened indices of cardiometabolic health. Furthermore, short sleep duration was associated with worse reaction time performance in the 1-back task despite the fact that poorer self-reported sleep quality was associated with improved reaction time performance in the 3-back task. These findings are discussed in detail in the following sections.

4.4.1 Sleep measures of Esports players

Although no group differences were observed in actigraphy-derived nocturnal sleep duration, only one-fifth of participants in both groups met the National Sleep Foundation's sleep duration guidelines for adults (Hirshkowitz et al., 2015). This finding is congruent with previous research highlighting a rising prevalence of short sleep among young adults (Althakafi et al., 2019; Steptoe et al., 2006). Similarly, while there were also no group differences in self-reported sleep quality, nearly half of the participants in this study were categorized as "poor sleepers" based on their PSQI scores (Buysse et al., 1989). This result is aligned with a meta-analysis reporting that roughly a third of adults from low-middle-income countries reported poor subjective sleep quality (Simonelli et al., 2018). The high prevalence of poor sleep observed among the Esports players in this study also aligns with the findings from **Chapter 2**, where habitual adult video gamers were frequently found to have poor sleep quality, based on PSQI total scores ranging from 4.56 ± 2.66 to 10.5 ± 3.0. However, the findings in this study suggest that poor sleep quality may not be exclusive to the gaming community. Perhaps it is rather a phenomenon typical of this younger age group of adults. Given the similarity between groups concerning device-derived sleep duration and PSQI-measured sleep quality, it is speculated that Controls may have displaced their sleep time with disparate non-gaming screen activities near bedtime, such as engaging with social media, general internet browsing, or streaming entertainment media. While this is not something measured in the present study, it is plausible since other studies have demonstrated that a dose-dependent relationship with electronic device use near bedtime is associated with poorer sleep quality, sleep insufficiency, and daytime dysfunction (AlShareef, 2022; Hartley et al., 2022; Pham et al., 2021).

While the later sleep timing in the Esports players group was expected, an unexpected observation was that they also did not exhibit shorter, poorer quality sleep than Controls. A previous multi-national study using actigraphic sleep monitoring in young adult males (aged 20.0 ± 3.5 years) who were professional esports athletes reported a total sleep time (median: 6.8 h) and sleep efficiency (median: 86.4%) (Lee et al., 2021) that was comparable to the Esports players in this study. This again suggests that the shorter sleep observed in this study is not a unique phenomenon among gamers. Interestingly, the delay in sleep timing observed in the present study was less than that reported by the professional esports players (median bedtime: 03:43 (IQR: 02:28–05:06), median wake-up time: 11:24 (IQR: 10:19–12:14) in the study by Lee et al. (2021). A noticeable difference is that, in addition to exhibiting shorter sleep onset latency than Controls, Esports players in the present study had remarkably shorter sleep onset latencies than the professional esports players (median: 20.4 min) in the study by Lee et al. (2021). Although the Esports players group had higher nocturnal sleep efficiency than the Controls in this study, this difference (while statistically significant) falls within what is typically considered the acceptable range for sleep efficiency (85-90%). When combined with the data on sleep onset latency, these findings suggest that Esports players might actually have marginally better sleep quality than Controls.

Noteworthy is a possible age-dependent influence on the effects of pre-sleep gaming activities. A study exploring the effect of pre-sleep gaming on sleep parameters in adolescents (mean age: 16.6±1.1 years) (Weaver et al., 2010) observed shorter sleep onset latency (median: 7.5, IQR: 7.8 min) than a study in younger school-age children (mean age: 13.5±1.0 years; sleep onset latency: 32.5±26.0 min) (Dworak et al., 2007) but longer sleep onset latency than a study in older adult male students (mean age: 24.7±5.6 years; sleep onset latency: median 6.2, IQR: 2.0 min) (Higuchi et al., 2005). Importantly, neither of these studies explicitly stated that participants were regular gamers, but participants in the study by Higuchi et al. (2005) reportedly "liked playing computer games" (p. 268). Together, these findings suggest that with age, the impact of pre-sleep gaming on sleep onset latency may diminish, possibly indicating an age-dependent response, with older individuals being less susceptible to the delaying effects of pre-sleep gaming on sleep onset latency compared to younger individuals (Weaver et al., 2010). In the case of younger individuals, particularly children, it is thought that they may be more sensitive to the suppressive effects of blue light exposure on melatonin production than adults, which may lead to greater difficulty falling asleep (Lee et al., 2018). For the adult Esports players in this study, however, an alternate explanation is postulated: an acute sleep insufficiency, possibly due to the displacement of sleep time for game training or competitive matches during late evening hours to the point of exhaustion (this point is touched on again later). This argument is supported by their shorter sleep onset latency, greater sleep efficiency, and longer napping duration than Controls.

While the prevalence of napping was similar (roughly 50%) in both groups, Esports players had a longer average nap duration than the Controls, suggesting that Esports players reduce their sleep debt through "catch-up" sleep (i.e., napping) during the daytime rather than by sleeping in over the weekend. This is marked by no differences in sleep duration between weekend and weekday nights, despite Esports players having more freedom to engage in longer gaming activities on the weekends, which encroaches on sleep opportunities at night. While no indications of excessive daytime sleepiness were present from ESS total scores, sleep debt could be ameliorated by regular and excessive stimulant use throughout the day, such as caffeine consumption and smoking. Participants were asked to record caffeine consumption in the sleep diaries; however, these data were not reliably collected and consequently were not examined. On the other hand, more Esports players were smokers (42.9%, n=12), which could infer that smoking is used to stay awake and more alert during gaming sessions, thereby delaying sleep timing and leading to shorter sleep duration. This logic is congruent with previous research demonstrating an association between short sleep with current and prior smoking status, particularly considering the higher risk of dependence among males and individuals with evening chronotypes (Broms et al., 2012; Patterson et al., 2016) (discussed further in **Section 4.4.2.**).

While both the Esports and Control groups displayed later sleep timing on weekends compared to weekdays, the Controls had a larger delay in weekend bedtime than the Esports players, who themselves had a larger delay in weekend wake-up time. This observation is likely explained by the groups' chronotype and habitual weekday bed- and wake-up times. In the case of Esports players, this delayed sleep-wake timing could be attributed to their stronger propensity for eveningness (Donato et al., 2022). A clinically relevant median social jetlag of 1.3 hours and 1.1 hours was also observed in Esports players and Controls, respectively. Previously, it has been established that for each additional hour of social lag, the risk of being overweight and obesity and cardiovascular disease increases by as much as 33% and 11%, respectively (Roenneberg et al., 2012). This confers substantial chronic metabolic risk to both groups over time (Lucassen et al., 2012), particularly since most Esports players and Controls do not meet the National Sleep Foundation's sleep duration guidelines (Hirshkowitz et al., 2015).

A study of 133 gamers (aged 24.9 ± 5.3 years) revealed that age impacts the timing of video gaming, with older gamers preferring to play at night compared to younger gamers. This preference was thought to reflect a greater incentive for longer periods of uninterrupted, multi-cooperative play during the nighttime hours (Triberti et al., 2018). While formal esports match timing data was not collected from participants, anecdotal information gathered through conversations with the esports players in this study suggests that competitive matches are usually scheduled in the evenings (from 20:00 to 23:00) to accommodate players who work full-time during the day. As such, this scheduling may explain the later sleep-wake behavior observed in the Esports players group. Likewise, the same esports players mentioned anecdotally that they also play "scrims" (practice matches) and engage recreationally in other screen-based activities (e.g., casual games, social media, or video streaming) before and after their matches. In this regard, delayed sleep timing could be facilitated by these extrinsic factors, which could manifest in prolonged wakefulness combined with greater exposure to light at night. A previous study on professional esports players supported this notion, demonstrating that players whose training sessions ended later at night had much later bedtimes compared to players who ended training earlier that same day (Lee et al., 2021).

Realistically, later sleep-wake timing is likely multifaceted, involving a combination of behavioral and physiological factors (including having a late chronotype, response to light-induced melatonin suppression, and physiological arousal). Beyond this, it could be argued that individuals with a later chronotype are more likely to choose and adhere to gaming activities that align more closely with their biological preferences. This suggests that gaming may be particularly appealing to late chronotypes due to the timing of the activity being better suited to their natural sleep-wake cycle. Indeed, individuals with evening chronotypes have slower sleep pressure kinetics and, therefore, have a slower build up of sleepiness during extended periods of wakefulness, enabling them to stay up later (Taillard et al., 2003). Alternatively, it might be argued that esports players become conditioned to later sleep-wake behaviors resulting from extensive chronic gaming exposure and years of habituation.

4.4.2 Cardiometabolic health of Esports players

Cardiometabolic health parameters were not significantly different between the groups. Despite this, all measured health indices apart from weight and glucose were tacitly raised in Esports players versus Controls. The absence of significant adverse clinical health indications could be attributable to the group's relatively young age. In this regard, it is speculated that continued engagement with esports or high-volume gaming activity, which is highly sedentary, may translate to increased cardiometabolic disease risk over time. Interestingly, more than half (58.1%) of the Esports players sampled were classified as 'normal weight' (defined as BMI < 25 $kg \cdot m^{-2}$), which is less than males aged 20-24 (75.7%) and 25-34 years (66.0%) in the general population (National Department of Health: Statistics South Africa, 2017). A study in an international cohort of esports players highlighted that higher ranked players were more likely to have lower self-reported BMIs ($r=-0.11$, $p<0.01$) despite engaging more frequently with esports ($r=-0.01$, N.S.) (Trotter et al., 2020). Since esports rankings were not explicitly recorded in the present study, it is not possible to show whether higher rankings were associated with lower BMI. Alternatively, nutrition and physical activity (not examined in this study) are among the most frequently reported correlates of body weight changes and might also explain the similarities in body composition between the groups. For example, previous research has demonstrated that non-exercising individuals with poor diets are highly susceptible to unhealthy weight gain (Paixão et al., 2020; van Baak et al., 2021).

Another explanation may be smoking, which is widely understood to lower body weight and decelerate age-related weight gain; this is primarily mediated by nicotine, which increases energy expenditure and reduces appetite via a systemic release of catecholamines and neurotransmitters in the brain respectively (Audrain-McGovern & Benowitz, 2011). This argument is supported by Esports players having a higher prevalence of smokers compared to both the Control group in this study and the general male population (Reddy et al., 2015). Accordingly, Esports players' relatively strong evening phenotype (ET: 45.2%) versus Controls' stronger morning phenotype (MT: 50.0%) could be partially explained by the high occurrence of smokers among the Esports players, who might also choose to smoke due to insufficient sleep and needing to stay up late to engage with gaming activities. This rationale is supported by studies demonstrating that short sleep is linked with current or prior smoking status and higher cigarette use in adults from industrialized settings (Krueger & Friedman, 2009; Mehari et al., 2014; Phillips & Danner, 1995). Prior studies have linked smoking with a greater propensity for eveningness, coffee and alcohol consumption, and delayed wake-up times between weekdays and weekends (Donato et al., 2022). Similarly, late chronotypes have also demonstrated greater odds of being a smoker than early chronotypes (Patterson et al., 2016). This association could be attributed to nicotine's stimulatory effect on the central nervous system, characterized by increased alertness and decreased sleepiness (Patterson et al., 2016; Zhang et al., 2006).

On the other hand, the high prevalence of smokers among Esports players could be related to the fact that almost half of them were classified as 'addicted gamers' based on the VGAQ. This is further supported by the observation that two-thirds of Esports players who smoked also met the criteria for addiction, according to the VGAQ. A study examining the interaction between smoking and game addiction on local spontaneous brain activity concluded that smoking and gaming addiction interact dependently in the brain, especially in reward and motivation-related brain regions (Qiu et al., 2020). These findings suggested that addicted gamers are more likely to be smokers, with internet addiction being more easily predicted in smokers than healthy controls. Beyond this, there is some speculation that "glamorizing" imagery of smoking in certain video games could normalize real-world smoking behavior; however, this relationship has not been well established (Forsyth & Malone, 2016). While smoking may be worth exploring further in future research, it would be premature to draw any definitive conclusions about smoking potentially playing a functional role in areas such as sleep, health, and gaming addiction based on the current evidence. That said, smoking cessation may still be beneficial in ameliorating negative behaviors associated with gaming addiction when weighed against the known negative effects of smoking on overall health and well-being, emphasizing the importance of avoiding smoking to cope with gaming-related stress or addiction.

4.4.3 Associations between sleep measures and cardiometabolic health

Poorer self-reported sleep quality was associated with worse indices of cardiometabolic disease risk, specifically higher systolic blood pressure, HOMA-IR, and cardiometabolic disease risk score. These findings are congruent with previous research linking sleep quality with metabolic syndrome and multiple cardiometabolic disease risk factors: waist circumference, BMI, body fat percentage, serum insulin, glucose, and glycated hemoglobin concentrations, as well as insulin resistance (Cappuccio et al., 2010; Jennings et al., 2007; Knutson, 2010; Zhu et al., 2017). Similarly, higher HOMA-IR values (indicative of increased insulin resistance) were also associated with more irregular wake-up time. This observation is supported by previous research linking greater irregularity around sleep patterns to heightened cardiometabolic disease risk and is consistent across cross-sectional and prospective analyses, independent of lifestyle, socioeconomic, or sleep-related factors (Full et al., 2023; Huang & Redline, 2019; Ogura et al., 2022; Zuraikat et al., 2020).

While the mechanisms underlying the link between sleep quality and sleep regularity on heightened cardiometabolic disease risk are not fully understood, it is believed that circadian disruption may be a key facilitator of metabolic dysfunction by triggering a cascade of negative physiological pathways at a cellular, humoral, and behavioral level (Full et al., 2023; Huang & Redline, 2019). This is because the regulation of nearly every cardiovascular process begins at the level of the circadian clock genes (He et al., 2016; Škrlec et al., 2020). However, the downstream transcriptional activity of these genes extends to several key hormones, such as cortisol or insulin, which are directly involved in energy metabolism, but also hormones like melatonin that indirectly modulate energy balance by regulating circadian rhythms (Drăgoi et al., 2017; Qaid & Abdelrahman, 2016). Therefore, it is only natural that disrupting or uncoupling these finely-tuned physiological processes could lead to pathological health outcomes. At a behavioral level, night-to-night variability in sleep-wake patterns may also promote circadian disruption; this may directly lead to insulin resistance and glycemic dysregulation by reducing melatonin production, a key regulator of energy metabolism (Zuraikat et al., 2020). Over time, this is believed to result in a greater risk of cardiometabolic diseases like metabolic syndrome and type 2 diabetes. Notably, limited evidence in adults suggests that poor diet quality and irregular patterns in food consumption could also facilitate sleep variability and circadian disruption. As a result, diet (not examined) could mediate an association between sleep variability and increased adiposity. In this case, downstream effects on insulin and glucose metabolism could also worsen chronic cardiometabolic disease outcomes (He et al., 2015; Zuraikat et al., 2020).

In addition to sleep regularity, another factor that can disrupt sleep-wake behaviors and, consequently, downstream metabolic processes is increased light exposure at night. Previous research has demonstrated that nighttime light exposure at 100 lux during a single night of sleep increased insulin resistance the morning after and increased sympathovagal balance during sleep in healthy adults (Mason et al., 2022). While nighttime light exposure is known to affect circadian rhythms by suppressing or phase-shifting melatonin (Gooley et al., 2011; Zeitzer et al., 2000), the researchers supported the possibility that light-induced sympathetic activation might also directly or indirectly mediate sleep disruption and thus cascading negative health outcomes. In this regard, chronic nighttime light exposure might be an important factor to consider in future research exploring its long-term effects on cardiometabolic health, particularly in vulnerable population groups like esports players, who are commonly engaged with screen-based digital technologies at night.

Noteworthy, conflicting findings concerning sleep timing at night with blood pressure were reported in this study. In particular, later bedtimes and wake-up times were associated with lower systolic blood pressure, which were not expected. These results are, however, consistent with a U-shaped association between bedtime and systolic blood pressure reported in a previous study of over 7600 adults from the National Health and Nutrition Examination Survey (NHANES), where blood pressure decreased gradually with later bedtimes to the lowest point at midnight before steadily increasing with further delayed bedtimes (Su et al., 2021). In addition, a separate study of over 2000 children and adolescents (age range: 9.5 to 18 years) replicated the U-shaped association between bedtime and blood pressure, demonstrating that earlier bedtimes (i.e., before 21:00) were linked with a higher risk of elevated blood pressure, and bedtimes after 22:00 were associated with higher blood pressure (Jansen et al., 2020). Moreover, these associations persisted even after adjusting for wake-up time and other factors: age, sex, maternal education, screen time, depression, and alcohol consumption. While the biological mechanism of the relationship between sleep timing and blood pressure is still a matter of debate, circadian disruption characterized by a mismatch between sleep-wake and endogenous biological timing (independently of sleep duration) is thought to be at least partly responsible (Morris et al., 2017; Scheer et al., 2009).

The present study found no associations between short sleep duration and cardiometabolic health parameters despite numerous prior studies linking short sleep with poorer cardiometabolic health outcomes (Dejenie et al., 2022; Jansen et al., 2018). However, the lack of association may reflect the young age of the study population, in which case a significant cardiometabolic disease phenotype may not have occurred yet and thus only become apparent later in life. In addition, the study participants' sleep duration was not restricted to such a severe extent that robust associations with cardiometabolic disease factors would be apparent. Supporting this explanation is a meta-analysis of 17 studies demonstrating that child and adult short sleepers (<10 h per night and <5 h per night, respectively) had a greater risk of obesity, with a higher risk observed in children (pooled OR: 1.89, 95% CI: 1.46–2.43) than in adults (pooled OR: 1.55, 95% CI: 1.43–1.68) (Cappuccio et al., 2008). On the other hand, a lack of statistical power or the presence of other effect modifiers may have dampened the strength of this relationship. For example, there is evidence to suggest that associations between sleep and cardiometabolic health risk may be linked to racial and socioeconomic disparities (neither measured nor adjusted for) and may vary by geographical location and sex (Grandner et al., 2014; Kanagasabai & Chaput, 2017; Rae et al., 2020). Separately, lifestyle factors like alcohol consumption, caffeine, physical activity, and diet (neither measured nor adjusted for) may also modify the relationship between sleep and cardiometabolic health (Jansen et al., 2018; Magee et al., 2008). A prospective cohort study found that the addition of sufficient sleep duration (≥7 h per night) to four healthy lifestyle factors (regular physical activity, a healthy diet, moderate alcohol consumption, and non-smoking) resulted in a lower composite (HR: 0.35, 95% CI: 0.23-0.52) and fatal cardiovascular disease risk (HR 0.17, 95% CI: 0.07-0.43) compared to when only one or no healthy lifestyle factors were maintained (Hoevenaar-Blom et al., 2014). Taken together, the results of this study suggest that rather than sleep duration, disparate components of sleep health – namely, sleep quality and sleep regularity – appear to be more closely related to cardiometabolic disease risk. As such, future analyses are warranted to explore the interactions between sleep factors and cardiometabolic health, adjusting for the lifestyle factors potentially modifying these relationships.

4.4.4 Neurocognitive performance of Esports players

The reason for assessing neurocognitive performance in the participants in this study was to evaluate whether any aspects of gamers' sleep might affect markers of cognitive performance understood to be relevant to gaming performance. As hypothesized, Esports players outperformed the Controls in computer-based tasks requiring sustained attention, accuracy, and quick reaction times. These findings were comparable to previous research examining various neurocognitive parameters in gamers and esports players, including demonstrably improved attention, spatial processing, and multi-tasking ability, among other cognitive processes (Palaus et al., 2017; Sousa et al., 2020). Interestingly, group differences in n-back task performance were only evident with increasing paradigm difficulty, suggesting superior adaptation and reactivity among Esports players to conditions with scaling complexity. One might hypothesize that this observation relates to the fact that success in esports requires a large degree of cognitive flexibility to adapt to unique, dynamic circumstances within each match. For example, in MOBA games like *Dota 2* (Valve Corporation, U.S.) or *League of Legends* (Riot Games Inc., U.S.), teams comprise a unique composition of five player-controlled "heroes" or "champions," each with different abilities and item combinations, which are uniquely synergic to the 'meta' (i.e., referring to the optimal playstyle and strategy) of each game. This would explain why Esports players also exhibited superior performance in executive function tasks like the BCST, typically viewed as a proxy measure for adaptive behavior.

Intrinsically, group differences may be attributed to game training effects on cognitive processes (Buelow et al., 2015; Pallavicini et al., 2018); however, other factors may also be involved. For example, esports players may experience enormous stress before and during their competitive matches, much like in traditional competitive sports. Naturally, this stress might differ from traditional sports since esports players rely more on their cognitive ability (rather than gross anatomical movement) to perform. In many cases, there might also be a strong drive to "prove oneself," as players may fear becoming obsolete or dismissed from their respective teams. As a result, even minor mistakes may lead to game-changing and real-life outcomes, such as losing sponsorship deals or failing to qualify for certain tournaments. Likewise, esports players may require a great deal of emotional resilience to cope with stress and maintain their composure and proficiency in the game. A recent study on elite esports players found a partial overlap in mental toughness and stress-coping mechanisms between esports players and high-performance athletes in traditional sports (Poulus et al., 2020). Since it is established that mood may have a pervasive effect on cognition (Chepenik et al., 2007), regulating one's emotions in the game may be the differential factor between winning and losing at elite levels (since skill at these levels may be more closely matched than in amateur divisions). Esports matches may also last several hours in real-world scenarios, with little to no time for breaks; this means that esports players must also be highly resistant to cognitive fatigue. Although the present study controlled for the effect of mood on neurocognitive performance, prior research identified that esports players with higher levels of emotional control were able to reduce the intensity of perceived stressors (Poulus et al., 2020). The same study cited that esports players may appraise stressors as a challenge rather than a threat (Poulus et al., 2020).

In hindsight, employing tools that include scales to measure perceived stress and emotional regulation may have improved the interpretability of neurocognitive outcomes. These may be more salient factors influencing esports players' cognitive (and thus gaming) performance. As discussed in **Section 1.8.1,** it is important to note that the computerized format of the cognitive test battery may have favored Esports players independently of participants in both groups being familiar with using computers. This rationale follows gamers often honing skills like reaction time during gameplay sessions, in which case the interpretation of these results is cautioned. While paper-based testing may have mitigated potential method bias, the appropriateness of testing cognitive parameters as a proxy of gaming ability may have been limited, especially given that computerized tasks offer greater precision to measure game-specific outcomes like reaction time (Noyes & Garland, 2008). Moreover, each test utilized in the cognitive test battery was previously validated for its ecological validity in non-gaming cohorts (Dinges & Powell, 1985; Berg, 1948; Kirchner, 1958), which justified its use in this study. Still, further research is needed to investigate the potential impact of testing format on cognitive performance in this population.

4.4.5 Associations between sleep measures and neurocognitive performance

Linear regression analyses indicated that shorter actigraphy-derived nocturnal sleep duration was associated with slower reaction time in the 1-back test. This finding is not surprising and is consistent with previous research linking short sleep duration with impaired cognitive function, particularly in the areas of memory, attention, and processing speed (Lowe et al., 2017). However, an unexpected association was found between poorer self-reported sleep quality and faster reaction time in the more challenging 3-back task. Moreover, in both cases, adjusting for smoking and chronotype resulted in a loss in overall model significance. A likely explanation for the weak associations between sleep and cognitive performance could be that Esports players achieved better sleep duration and quality than originally anticipated, which may have led to a negligible impact on their cognitive performance. Previous research has demonstrated that 7 to 8 hours of sleep is optimal for overall cognitive performance and that deviating from these sleep timings can lead to depreciated cognitive performance, regardless of age (Wild et al., 2018). Given the similarity in sleep duration and quality between Esports players and controls, it seems plausible that the relationship between sleep and neurocognitive performance was overshadowed by the advantage the Esports players had with the computerized tasks. This includes their familiarity with the computerized format of the tasks, which these players may have viewed as mimicking the likeness of video games. In this regard, having the Controls perform a single familiarization session with the computerized tasks may not have been sufficient to offset the range of cognitive benefits attributed to the Esports players through years of regular video gameplay (Buelow et al., 2015; Pallavicini et al., 2018). However, as discussed in **Section 1.8.1**, limiting the method bias associated with computer-based cognitive performance tests is challenging when measuring game-specific cognitive outcomes in a standardized format. Although computerized tests offer improved precision in measuring parameters like reaction time and are less prone to human error (Noyes & Garland, 2008), they may also inadvertently favor individuals with extensive computer experience. Future studies could aim to level the playing field by scaling up the difficulty of cognitive tasks to better discern the impact of sleep on neurocognitive performance while minimizing the advantage experienced by Esports players due to their familiarity with video gaming.

While the PANAS was used to assess participants' affective experiences in this study, other factors, such as motivation, stress, and emotional regulation, may also have influenced cognitive results, particularly in the context of more complex task paradigms. This is supported by Esports players with higher mental toughness generally being more resilient at handling stress (Gerber et al., 2018; Kou & Gui, 2020; Poulus et al., 2020), which might enable them to maintain cognitive performance despite having poor sleep quality. Likewise, Esports players may have been more motivated to excel in the cognitive task based on their familiarity with outperforming the competition. This motivation might have led to Esports players achieving better reaction time performance regardless of having poorer sleep quality, in which case their motivation could have overshadowed the anticipated cognitive deficits. In retrospect, using tools like the Difficulties in Emotion Regulation Scale (Gratz & Roemer, 2004) to assess an individual's ability to regulate emotions directly may have provided greater resolution regarding the potential influence of emotions on these findings. In contrast, the n-back tasks could not have been challenging enough to detect the effect of short duration and poor quality sleep. In this regard, an extension of neurocognitive testing protocols, with longer duration and more difficult task parameters, would have potentially highlighted more striking differences between these groups, with more robust and interpretable associations with sleep measures.

4.4.6 Study limitations

The first limitation relates to the cross-sectional design of the present study, which limits the possibility of making any causal inferences. Furthermore, since only adult male esports players engaged at amateur and semi-professional levels were sampled in the experimental group, the results may not extend to females, casual gamers, or professional esports athletes. Additionally, since the Esports player group comprised only computer gamers, the results may not extend to those playing on disparate gaming platforms (e.g., console or mobile). These results should, therefore, be interpreted with caution when generalizing to the broader gaming or esports population. It should also be cautioned that esports players specializing in specific games or genres may exhibit differential sleep or neurocognitive performance outcomes. For example, esports players specializing in high-intensity games or genres could experience higher rates of burnout and fatigue and thus be characterized by more frequent episodes of problematic sleep relative to players specializing in low-intensity games or genres. Likewise, the same players may also demonstrate superior performance in neurocognitive tests assessing processes specific to that game or genre. Elite esports athletes specializing in a real-time strategy (RTS) game, for example, reported making game input actions (i.e., mouse clicks or keystrokes) up to ten times every second (Wong, 2014). Other slower-paced game genres, like certain MOBA games, may involve substantially lower actions per unit of time. Despite this, the present study did not stratify Esports players by their primary game genre, owing to the difficulty in recruiting from an already niche target population. Instead, the experimental group of esports players comprised an approximately equal spread of gamers engaged with either predominantly FPS or MOBA games.

Another limitation is the absence of specific quantification of player ranking within the Esports players group. While participants competed in amateur and semi-professional leagues, specific player ranks were not explicitly measured or reported. This omission is primarily due to the varied ranking structures across different games and genres, combined with the challenges inherent in recruiting from a niche pool of eligible candidates. Although it was broadly understood that these divisions were comparable in terms of skill level, future research should endeavor to explicitly control for individual player rankings, which could provide a more nuanced understanding of performance variations across different levels of competitive play. Given the lack of empirical evidence, it is speculative whether the differences observed among elite esports athletes would extend to players engaged at amateur and semi-professional levels or to those specializing in other game genres. This is less of a concern, however, since most players typically have at least some degree of experience playing several different games and genres concurrently. Still, it is an important limitation and potentially confounding factor that should be addressed and explored in future research.

It is also important to acknowledge the inherent limitations of the Actiwatch. Specifically, this includes its inability to differentiate between specific sources of artificial light, including light emitted from screen devices such as televisions, computers, tablets, and smartphones. Additionally, the Actiwatch lacks the capability to discern how individuals engage with these devices, such as whether they are browsing the internet, watching videos, or engaging with gaming activities. This limitation could lead to a generalized interpretation of light exposure data that may not accurately reflect the complex impacts of different light qualities and intensities on sleep patterns and circadian rhythms. To address this gap, future research should include detailed daily activity logs or use more sophisticated light measurement tools that can identify and categorize light sources.

Finally, although participants were required to abstain from caffeine for 10 hours prior to testing, the absence of empirical caffeine consumption data restricted the ability to fully account for its confounding effects on the relationships between sleep, cardiometabolic disease risk, and neurocognitive performance. Participants were initially asked to record their caffeine consumption; however, the inconsistency in the collected data was not reliable for formal analysis or inclusion into the regression model as a covariate. Future studies should consider more reliable methods of quantifying caffeine intake, such as using standardized caffeine intake questionnaires administered at regular intervals or by employing objective measures like blood serum levels to ensure more accurate and consistent data collection.

4.4.7 Study strengths

A major strength of the present study included using a control group and objective measures to assess sleep and cardiometabolic health in esports players, a small but well-defined and understudied group of gamers in the sampled region of Cape Town. Previous research on esports players has been limited by the reliance on online surveys, which are inherently biased due to self-reporting. By employing a random (rather than convenience) sampling technique, this study improves the overall generalizability of the findings to esports players in the region. In addition, while the sample size was small relative to the total population of esports players, the well-defined nature of the group allowed for a more detailed and precise analysis of their characteristics around sleep, cardiometabolic disease risk, and neurocognitive performance.

4.5 Conclusion

This study provides important insights regarding the sleep and cardiometabolic health status of young adult esports players, including the importance of promoting healthy sleep habits to mitigate future cardiometabolic disease risk. Accordingly, the findings suggest that despite their later sleep-wake patterns, Esports players and Controls in this study had largely comparable sleep, with no significant between-group differences in cardiometabolic disease risk factors. In addition, Esports players were characterized by better cognitive performance; however, this is likely attributed to extensive and prolonged engagement with video gaming over the years. Still, the observed associations between poor sleep habits and cardiometabolic disease risk in both groups raise some concern, particularly given the young age of the participants. This finding warrants further investigation, including whether esports players manage their sleep appropriately or if non-gaming lifestyle behaviors by participants in the Control group are limiting their sleep. Overall, the collective findings regarding the relationship between sleep factors and cardiometabolic disease risk in these groups are a clinical indicator of potential future health complications and represent a developing challenge among young adults (rather than esports players alone), with profound public health implications over time.

While the precise mechanisms underlying the relationship between sleep factors and cardiometabolic disease risk are not fully understood, they likely involve several co-occurring factors, such as obesity, physical inactivity, alcohol and caffeine consumption, and poor nutrition (Knutson, 2010). One consideration may involve the clustering of unhealthy behaviors and antecedents of cardiometabolic disease with the challenges of living in a fast-paced digital world. This includes scenarios where light from screen technologies infiltrates bedrooms to displace sleep time, exercise is replaced for sedentary leisure activities, and unhealthy calorie-dense foods are the staple diet. Given that young adults may be particularly vulnerable to the effects of short sleep and circadian disruption on cardiometabolic health (Zitting et al., 2018), interventions targeting behaviors that specifically disrupt sleep must be appropriated to mitigate potentially disastrous chronic health outcomes in these young individuals.

Future research could benefit from using qualitative methods like interviews and focus groups to broaden understanding of the complex interplay between sleep, lifestyle, and gaming behaviors in esports players. Longitudinal studies would also be useful in establishing causal links between the various factors contributing to cardiometabolic disease, including the role of gaming in this relationship. This may assist competitive gamers to be more conscious of the factors influencing their sleep and health and provide a support framework for the provision of healthier gameplay standards and improved gaming performance, which the latter may be more attractive for other esports players to adopt. Furthermore, researchers can gain insights into the experiences and perspectives of the players, as well as the social, cultural, and environmental factors that affect them over time, which may help inform the development of more effective interventions to improve the health and well-being of esports players. Lastly, the contribution of nighttime general screen technology use (i.e., television watching, social media networking, online video streaming, etc.), rather than standalone gaming behavior, should be explored further in future research.

Chapter 5

Diurnal patterns of light exposure and physical activity in esports players

5.1 Introduction

Circadian rhythms are fundamental for health and well-being, temporally governing many biological processes necessary for life. The synchronization of these processes to the external light environment is achieved via the central circadian oscillator in the brain located in the suprachiasmatic nucleus (SCN) (Blume et al., 2019). Beyond its role in permitting vision, light is the dominant entrainer and synchronizes internal biological rhythms with planetary timing via a complex interconnected signaling system (Vetter et al., 2011). Light can thus modify the sleep-wake cycle by delaying the timing of sleep initiation and wakefulness states, thereby influencing sleep duration, sleep quality, and the homeostatic response to sleep loss (Blume et al., 2019; Cajochen et al., 2019). However, pervasive changes to the light environment, such as using screen technologies and electrical lights during the nighttime, have dramatically challenged the circadian system and are linked to several downstream health outcomes, ranging from depression to cardiometabolic disease (Böhmer et al., 2021).

A striking 96% of adults under 30 years of age surveyed in the U.S. reported using light-emitting technology in the hour before bedtime, which is typically regarded as a critical time for inducing circadian phase delays (Gradisar et al., 2013). This behavior is concerning as it may increase the risk of developing "screen insomnias," as characterized by reports of difficulty falling asleep and achieving unrefreshing sleep after engaging with stimulating electronic devices before bedtime (Gradisar et al., 2013). Notably, persistent nighttime technology use can exacerbate these negative effects through circadian desynchrony, manifested as social jetlag or chronodisruption, which independently confers deleterious effects on sleep and metabolic health (Caliandro et al., 2021). Beyond this, there are growing concerns regarding young people in industrialized societies achieving insufficient doses of natural bright light, with many people in the U.S. spending up to 90% of their waking hours indoors (U.S. Environmental Protection Agency, 1989). Low doses and irregular timing of daylight exposure may adversely affect chronobiological health and sleep, impacting mental health, performance, and productivity (Blume et al., 2019; Boubekri et al., 2014). For example, researchers demonstrated that lower levels of morning circadian-effective light were linked with higher sleep onset latencies, lower phasor magnitudes, and sleep quality, with similar effects on sleep and mood in response to deficient daylight exposure (Figueiro et al., 2017).

On the other hand, physical activity is a powerful non-photic entraining agent that influences circadian-regulated processes, independently of the SCN, with time-of-day effects that encourage chronobiological homeostasis and play a vital role in physical and mental performance, health, and disease (Lewis et al., 2018). Physical activity and exercise are widely understood to ameliorate sleep-related problems and reduce the risk of diseases like cancers, heart disease, obesity, and diabetes, ultimately improving the overall quality of life (Warburton & Bredin, 2017). There is also substantial evidence characterizing the interrelationship between sleep and exercise. Physical activity can exhibit phase-shifting effects on the sleep-wake cycle, either advancing or delaying it, depending on the time of day (Dolezal et al., 2017; Miyazaki et al., 2001). Beyond this, there appears to be an independent link between daylight exposure and physical activity, such that greater daylight exposure translates to greater levels of moderate-to-vigorous intensity physical activity (MVPA) and less sedentary behavior (Aggio et al., 2015). Reports indicate that many young people in the U.S. fail to achieve the recommended allotment of exercise and lead sedentary lifestyles, introducing additional circadian and cardiometabolic health challenges (Zenko et al., 2019).

Esports players may be especially vulnerable to these pervasive health effects, given the implicit indoor, sedentary nature of gaming activities coupled with the proclivity for competitors to curtail sleep in favor of competitive tournaments or playlists lasting several hours into the night. In addition, since most esports players balance their gaming habits with work or academic commitments, sedentary gaming is often compounded with other sedentary behaviors, such as prolonged seated office work or studying and extended periods of non-gaming screen time. While light from screen devices and the alerting response from gaming are thought to be at the center of problematic sleep for gamers, the dose, timing, and rhythmicity of movement behavior and light exposure patterns may also play a role in circadian phase-shifting responses, sleep disturbances and consequently, chronic health deficits in these individuals.

Therefore, the aims of this study were to describe and compare the physical activity levels and degree of white light exposure as well as their respective diurnal patterns between young adult esports players and a non-gaming control group. Accordingly, it is hypothesized that esports players will exhibit (i) higher levels of sedentary behavior with correspondingly lower levels of MVPA and (ii) lower quantitative doses of bright outdoor light with correspondingly higher doses of dim indoor light across waking hours, but especially at night, compared to the control group.

5.2 Methods

5.2.1 Study design, setting, and participants

This cross-sectional observational study used the same 59 adult male participants described in **Section 4.2.1**, namely 31 esports players and a control group of 28 non-gamers recruited from Cape Town, South Africa. The same inclusion and exclusion criteria described in **Chapter 4** applied to this study. The study was approved by the University of Cape Town's Human Research Ethics Committee (HREC #266/2018), and all participants provided written informed consent. Experimental procedures were conducted according to the Declaration of Helsinki (General Assembly of the World Medical Association, 2014).

5.2.2 Coronavirus impact statement

The data collection presented in this study was conducted (and concluded) before enforcing any lockdowns or related coronavirus disease (COVID-19) policies. Therefore, the coronavirus pandemic did not directly or indirectly affect this study.

5.2.3 Study overview

The experimental procedures for this study are identical to those described in the previous chapter (**Section 4.2.3**). The study was conducted at the Chronobiology and Sleep Laboratory at the Health through Physical Activity, Lifestyle, and Sport Research Centre at the University of Cape Town between October 2018 and March 2020. Briefly, and of relevance to this study, following screening and consenting, eligible participants were given an Actiwatch-2 or Actiwatch Spectrum device (Philips Respironics, Bend, Oregon, U.S.) to wear continuously for seven consecutive days on their non-dominant wrist to measure free-living sleep, ambulatory physical activity, and white light exposure. During this monitoring period, participants each kept an adapted version of the Consensus Sleep Diary (Carney et al., 2012), detailing their sleep, gaming and physical activity, caffeine, medication, and supplement use. In addition, participants were instructed not to adjust their habitual gaming, sleep, eating, or physical activity behaviors during the monitoring period. Actigraphy-derived measures of movement behavior (activity counts) and exposure to white light (lux) were the primary outcome variables of interest.

In an effort to minimize differences in day-length related light exposure due to seasonal variations, a conscious effort was made to enroll and measure a Control participant at the same time as an Esports player. Within the Esports players group, 7 participants were recruited in Autumn (April to June), 9 in Winter (July to September), 11 in Spring (October to December), and 4 in Summer (January to March). Among the Control participants, 6 were recruited in Autumn, 7 in Winter, 11 in Spring, and 4 in Summer. There was no significant difference in the season distribution for data collection between the two groups (χ^2= 0.175, p=0.982).

5.2.4 Data processing and analyses

Actiwatch devices were configured and analyzed using Philips Actiware v.6.0.9 (Philips Respironics, Bend, Oregon, U.S.). A dataset was deemed valid if the Actiwatch was worn for a minimum of five days, including at least four weekdays (i.e., Sunday to Thursday) and at least one weekend day (i.e., Friday or Saturday). To be considered valid, a 24-hour period required a daily wear time of ≥ 10 hours (Troiano et al., 2008). Intervals identified as non-wear time were marked as 'excluded' intervals and omitted from the analysis. Non-wear periods were defined as continuous intervals of 60 minutes where the Actiwatch recorded zero activity counts per minute (CPM), allowing brief interruptions of 1-2 minutes that recorded between 0-100 CPM (Troiano et al., 2008). Noteworthy, one participant in the Esports players group was eliminated from the final analysis after only wearing the Actiwatch device during the nighttime. Each day's nocturnal sleep period and daytime naps were scored as described in the previous chapter (**Section 4.2.4.1**). Raw actigraphy data for all valid days were exported to Excel for analyses, including distinct columns for the clock time, activity counts, white light lux, and sleep/wake status of each 15-sec epoch recorded. These 15-sec epochs were subsequently integrated into 60-sec epochs, generating new variables representing the total activity counts and white light exposure (lux) per minute.

5.2.4.1 Physical activity data

Only activity counts at epochs corresponding to wake were used to assess daily physical activity levels between wake-up time and bedtime for each participant, with naps excluded from analyses. Each 60-sec epoch of activity data was then classified according to the physical activity level count cut-points established in **Chapter 3**: ≤256 CPM for sedentary behavior (SB), 257 CPM ≤ x ≤ 417 CPM for light-intensity (LIPA), 418 CPM ≤ x ≤ 719 CPM for moderate-intensity (MPA), and ≥720 CPM for vigorous-intensity (VPA) physical activity, respectively (Kemp et al., 2020). The time spent in SB, LPA, MPA, and

VPA for each monitoring day for each participant was averaged for all valid days to determine the absolute time spent in SB, LPA, MPA, and VPA ($h \cdot day^{-1}$) while awake. To account for interindividual differences in total waking time, the activity data were also normalized to the total waking time recorded per participant and presented as relative time spent in SB, LPA, MPA, and VPA (% of the total waking time).

Data binning was employed in the analysis of 24-hour physical activity pattern data. A total of 24 one-hour bins (representing each absolute clock hour) were generated by averaging each participant's physical activity counts every hour of every valid monitoring day, thus spanning sleep and wake periods. Data were subsequently log-transformed, successfully producing parametric and homoscedastic data for the mixed model analyses.

5.2.4.2 White light exposure data

Both Actiwatch models used in this study were equipped with photodiode sensors capable of measuring white light exposure in lux and were processed by the same proprietary algorithm. White light data were analyzed by following and adapting a previously established methodology (Scheuermaier et al., 2010). Briefly, only lux data corresponding to epochs classified as 'wake' were used to assess daily light exposure levels during waking hours. Each 60-sec epoch was assigned a light exposure category based on the following threshold categories: <10 lux (very dim light), 10 to <100 lux (dim light), 100 to <1000 lux (moderate light), and ≥1000 lux (bright light). These thresholds correspond to typical levels of light exposure throughout the waking day. For example, light measuring 0.1 lux corresponds to moonlight, 50 lux to dim indoor lighting, 350-500 lux to typical office lighting, and 1000 lux to light levels on an overcast day (Dautovich et al., 2019).

Scheuermaier et al. (2010) noted that epochs of white light measuring under 1 lux could indicate artifact data produced by the occlusion of photodiode sensors (e.g., wearing long-sleeved clothing). Owing to the difficulty in discriminating artifact data from actual dim light data (e.g., those originating from technological sources used during the nighttime), it was decided that epochs measuring under 1 lux would be retained in the final analysis. Time spent in each light exposure level category was determined for each day for each participant and then averaged over the monitoring period to determine absolute time spent in very dim, dim, moderate, and bright light during waking hours ($hours \cdot day^{-1}$). Relative time spent in each category was also determined by expressing absolute time spent in each category as a percentage of time spent awake each day.

As for physical activity count data, data for white light exposure were binned into 24x 1-hour periods. These hourly averages were log-transformed to preserve the contribution of brief periods of very bright light (Scheuermaier et al., 2010) and to obtain parametric and homoscedastic data suitable for mixed model ANOVA repeated measures analyses. Two additional time periods were created: 'pre-bedtime' (i.e., the last three hours preceding bedtime, i.e., BT -1h, -2h, -3h) and 'post-wake-up time' (i.e., the first three hours following wake-up time, i.e., WT +1h, +2h, +3h) since these times are sensitive to circadian photoentrainment (Burgess & Molina, 2014; Gooley et al., 2011).

5.2.4.3 Statistical analysis

Descriptive data are presented as mean ± standard deviation or standard error of measurement or median (interquartile range). Data were assessed for normality using the Shapiro-Wilk test, and Levene's test was used to assess the homogeneity of variance. Analysis of between-group differences was performed using the independent t-test for parametric data or the Mann-Whitney U test for non-parametric data. Differences between frequency counts or categorical variables were analyzed using a Chi-squared test for expected frequencies greater than five; otherwise, Fisher's Exact Test was used. Physical activity patterns and white light exposure over 24-hour periods were analyzed using a mixed-model analysis of variance (ANOVA) with a repeated-measures approach. The two independent variables were group (Esports players vs. Controls) and time (24x 1-hour clock time intervals). Statistical significance was accepted if $p<0.05$. All data were analyzed using Stata v.15 (StataCorp, College Station, Texas, U.S.). Graphical plots were created using GraphPad Prism v.8.0.0 for Windows (GraphPad Software, San Diego, California, U.S.).

5.3 Results

The descriptive and sleep characteristics of participants are described in the previous chapter (**Sections 4.3.1** to **4.3.3**). Owing to one invalid physical activity dataset, data on only 30 esports players are presented.

5.3.1 Habitual physical activity behaviors and patterns

While both groups spent a similar amount of time awake each day, movement behavior during the wake period differed significantly between the Esports players and Controls (Table 5.1 and Figure 5.1). Esports players spent an average of 1.8 hours more of their waking time in sedentary behavior and medians of 0.8 and 0.9 hours less of their waking time in moderate- and vigorous-intensity physical activity, respectively, compared to the Controls (Table 5.1, all $p<0.001$). In relative terms, Esports players spent a greater proportion of their waking time in sedentary behavior (Figure 5.1: median: 74.1, IQR: 14.7% versus median: 61.9, IQR: 11.9%, $p<0.001$), and a smaller proportion of this time engaged in light- (Figure 5.1: median: 11.6, IQR: 4.3% versus median: 13.9, IQR: 5.7%, $p<0.001$), moderate- (Figure 5.1: median: 9.6, IQR: 5.1% versus median: 14.8, IQR: 4.3%, $p<0.001$), and vigorous-intensity physical activity (Figure 5.1: median: 4.1, IQR: 5.5% versus median: 9.8, IQR: 6.1%, $p<0.001$) compared to Controls.

Table 5.1. Free-living waking movement behavior characteristics as determined by actigraphy.

	Esports players (n=30)	Controls (n=28)	p value
Total waking time (h • day^{-1})	15.8 (1.1)	15.1 (2.0)	0.503
Sedentary behavior (h • day^{-1})	10.9 ± 1.9	9.1 ± 1.6	**<0.001 ***
Light-intensity physical activity (h • day^{-1})	1.8 ± 0.4	2.1 ± 0.5	**0.048 ***
Moderate-intensity physical activity (h • day^{-1})	1.4 (0.7)	2.2 (0.6)	**<0.001 ***
Vigorous-intensity physical activity (h • day^{-1})	0.6 (0.7)	1.5 (0.9)	**<0.001 ***

Data are presented as mean ± standard deviation or median (interquartile range). Between-group differences were detected using an independent t-test for parametric data or the Mann-Whitney U test for non-parametric data. Significance was accepted at $p<0.050$.

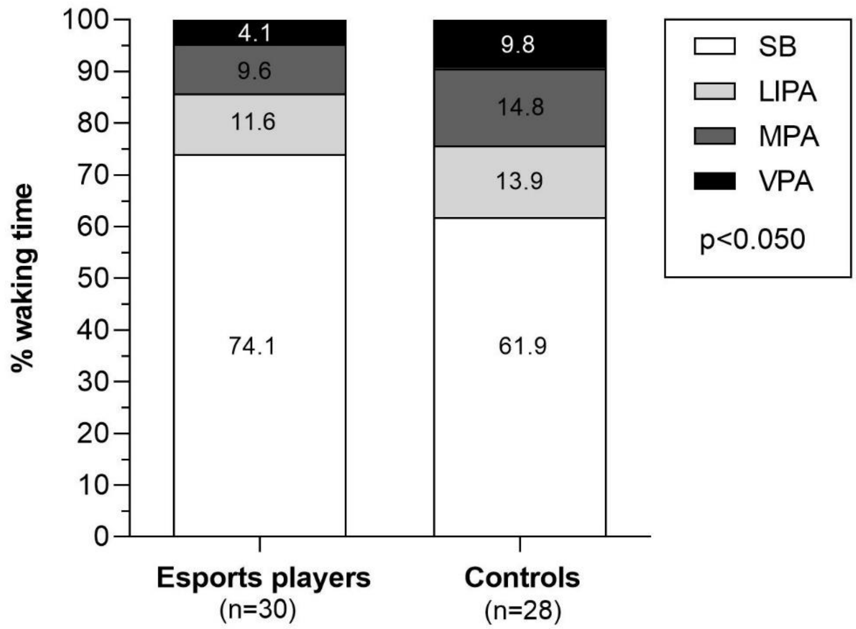

Figure 5.1. Relative time spent in sedentary behavior and light-, moderate- and vigorous-intensity physical activity in Esports players (n=30) and Controls (n=28). Between-group differences were detected with the Mann-Whitney U test. SB: sedentary behavior; LIPA: light-intensity physical activity; MPA: moderate-intensity physical activity; VPA: vigorous-intensity physical activity. Significance was accepted at $p<0.050$.

Twenty-four-hour free-living physical activity patterns of Esports players and Controls were examined using a mixed model ANOVA with a repeated measures approach (Figure 5.2). A significant main effect for the factor 'group' was identified, demonstrating significantly higher mean activity levels in the Control group (122.1 ± 3.7 CPM) compared to the Esports players group (90.0 ± 3.7 CPM, $p<0.001$) over 24 hours. In addition, a significant main effect for 'time' ($p=0.001$) was observed, with activity levels increasing steadily throughout the day. There was also a significant 'group x time' interaction effect ($p<0.001$), with post hoc analyses indicating that physical activity levels were significantly higher in the Control group (versus the Esports players group) between 05:00 and 08:00 ($p<0.001$) and at 09:00 ($p=0.044$), 18:00 ($p=0.049$), and 20:00 ($p=0.048$) clock times. In addition, physical activity levels were significantly higher at 00:00 in the Esports players group compared to the Controls ($p=0.033$). Esports players spent, on average, nearly all their time in sedentary behavior over the entire 24-hour period. In contrast, Controls spent most of their time in sedentary behavior after 20:00 and before 09:00.

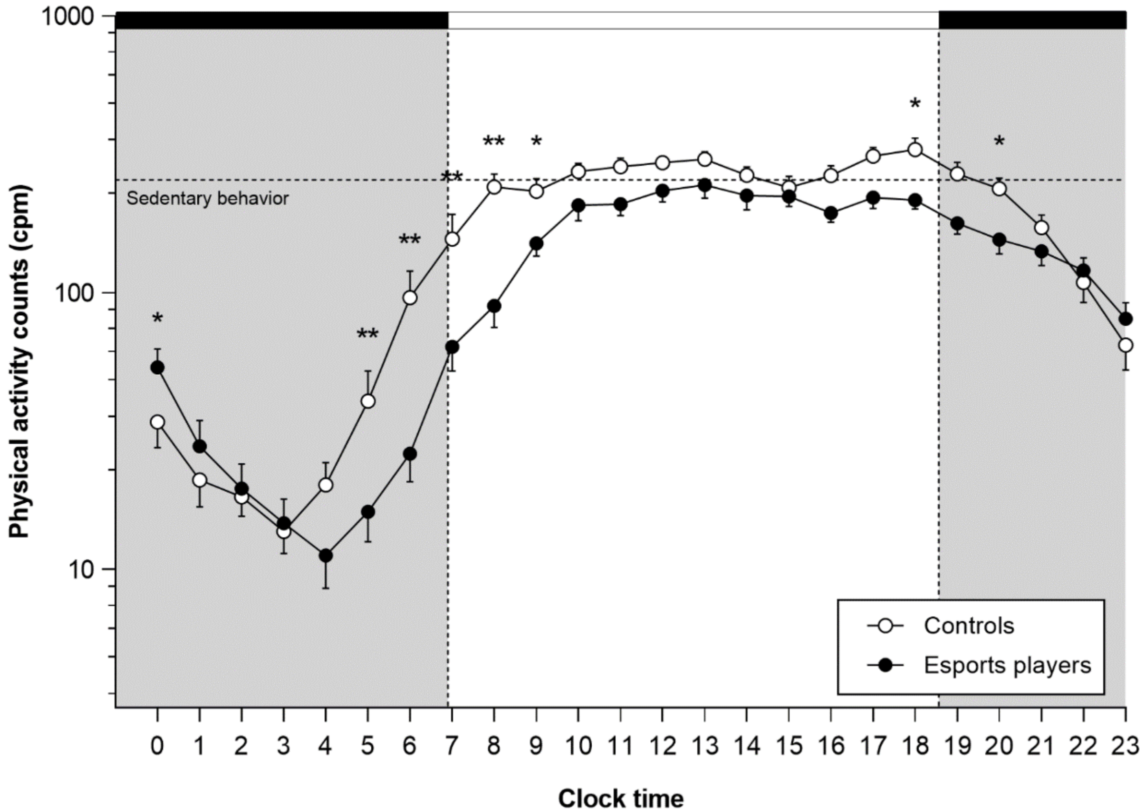

Figure 5.2. 24-hour physical activity patterns of Esports players (n=30) and Controls (n=28) measured during the 7-day free-living monitoring period. Data are presented as the logarithmic mean ± standard error of measurement. Clock time is presented as 24-hour local clock time; vertical dashed lines: mean sunrise and sunset times; gray zones: nighttime; white zone: daytime; horizontal dashed line: count threshold for sedentary behavior (256 CPM). Data were analyzed using mixed models ANOVA with repeated measures. Interaction effect: $p<0.001$, 'group' effect: $p<0.001$, 'time' effect: $p=0.001$. Post hoc interaction effect differences between groups are represented by * $p<0.050$ and ** $p<0.010$.

5.3.2 Free-living white light exposure levels and patterns

Table 5.2 displays both groups' absolute and relative white light exposure during waking hours. On average, Esports players spent more of their absolute waking time in very dim light (<10 lux) (p=0.024) and less of their waking time in moderate light (100-1000 lux) (p=0.004) compared to Controls (Table 5.2). Relative to the total waking hours measured, Esports players spend 11.8% more of their waking hours in very dim light (p=0.020) and 8.4% less of their waking hours in moderate light compared to Controls (p=0.004). Interestingly, bright light exposure (>1000 lux) comprised less than 5% of the total time in both groups. Neither Esports players nor Controls experienced light exposure levels greater than 10,000 lux over the monitoring period.

Table 5.2. Free-living white light exposure levels as measured by actigraphy during waking hours.

	Esports players (n=30)	Controls (n=28)	p value
Absolute light exposure time (h • day^{-1})			
Very dim light (<10 lux)	9.5 ± 3.1	7.7 ± 2.9	**0.024 ***
Dim light (10 to <100 lux)	3.0 (3.1)	4.3 (2.2)	0.096
Moderate light (100 to <1000 lux)	1.3 (1.2)	2.5 (1.9)	**0.004 ***
Bright light (>1000 lux)	0.4 (0.5)	0.7 (0.8)	0.123
Relative light exposure time (% waking time)			
Very dim light (<10 lux)	62.8 ± 19.5	51.0 ± 18.2	**0.020 ***
Dim light (10 to <100 lux)	22.9 ± 13.3	27.4 ± 10.4	0.160
Moderate light (100 to <1000 lux)	8.4 (8.6)	16.8 (13.9)	**0.004 ***
Bright light (>1000 lux)	2.6 (2.9)	4.7 (5.0)	0.099

Data are presented as mean ± standard deviation or median (interquartile range). Between-group differences were determined using an independent t-test or the Mann-Whitney U test. Significance was accepted at p<0.050.

Twenty-four-hour white light exposure patterns of both groups are shown in Figure 5.3. Mixed model ANOVA with a repeated measures analysis revealed no significant main effect for 'group' such that the Controls were exposed to similar mean daily levels of white light compared to Esports players (8.0 ± 31.9 lux versus 10.0 ± 44.5 lux, p=0.382) over 24 hours (Figure 5.3). A significant main effect for 'time' was observed (p<0.001), with white light exposure increasing steadily from approximately 06:00 until noon before tapering from approximately 18:00 onwards (Figure 5.3). There was a significant 'time x group' interaction effect (p<0.001), with post hoc analyses indicating greater light exposure between 06:00 to 08:00 (p<0.001) and at 09:00 (p=0.049) and lower light exposure between 23:00 to 01:00 (p<0.001) and at 02:00 (p=0.027) in the Control group compared to the Esports player group (Figure 5.3).

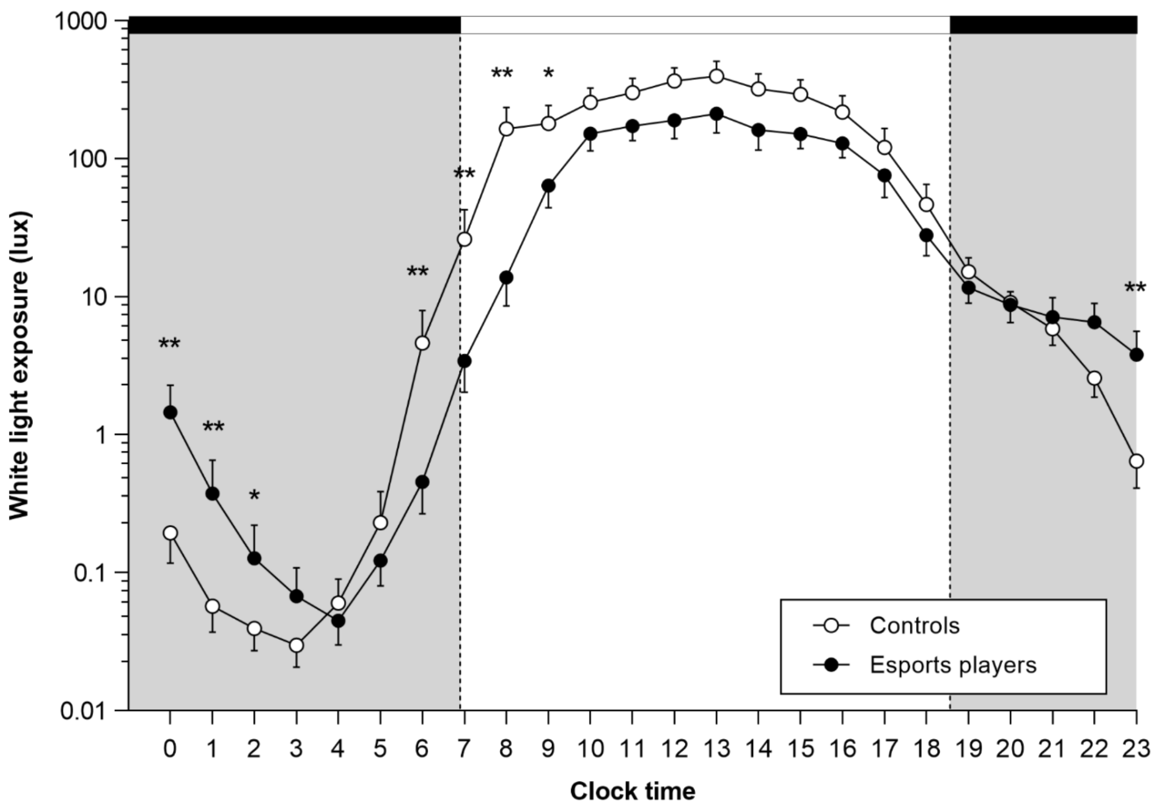

Figure 5.3. 24-hour white light exposure patterns of Esports players (n=30, missing: n=1) and Controls (n=28) are plotted on a logarithmic scale. Data are presented as the logarithmic mean ± standard error of measurement. Clock time is presented as 24-hour local clock time; vertical dashed lines: mean sunrise and sunset times; gray zones: nighttime; white zone: daytime. Data were analyzed using mixed models ANOVA with repeated measures. Interaction effect: p<0.001, 'group' effect: p=0.382, 'time' effect: p=0<0.001. Post hoc interaction effect differences between groups are represented by * p<0.050 and ** p<0.010.

Analysis of white light exposure, with respect to the three-hour period prior to bedtime, revealed a significant main effect for time, with white light decreasing steadily over the three hours prior to bedtime (p<0.001) (Figure 5.4). There was no main effect for 'group' (p=0.969) or any 'group x time' interaction effect (p=0.073). Likewise, a significant main effect for 'time' was observed in the three hours following wake-up time, whereby white light levels increased (p<0.001) (Figure 5.4), but there was no main effect for 'group' (p=0.248) and no 'group x time' interaction effect (p=0.621).

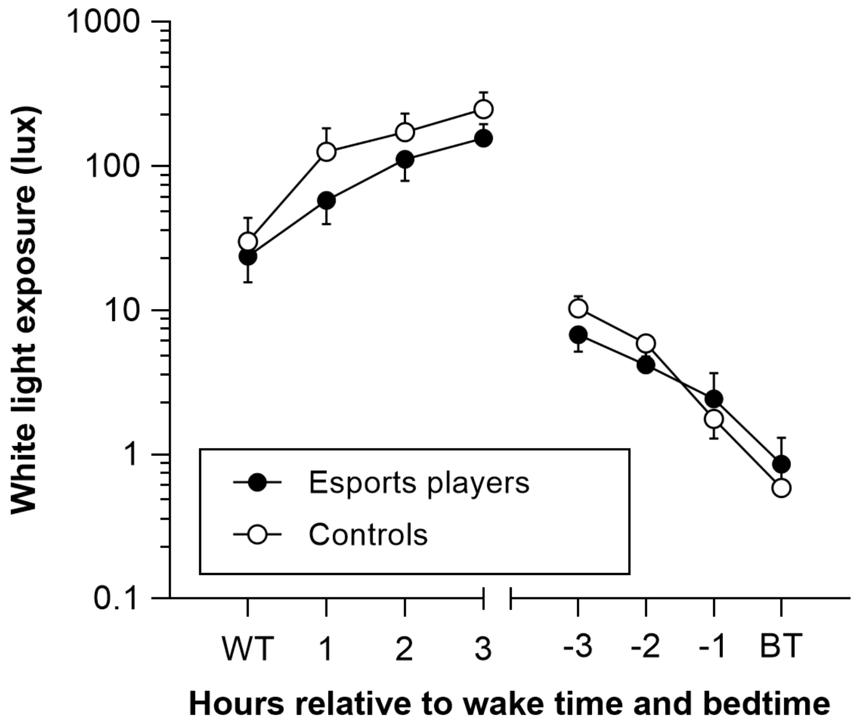

Figure 5.4. White light exposure patterns of Esports players (n=30) and Controls (n=28) during the 3 hours after wake-up time and the 3 hours prior to bedtime. Lux data are presented as logarithmic means (± SEM). WT: wake-up time; BT: bedtime. For reference: 0.1 lux = moonlight, 50 lux = dim indoor lighting, 350-500 lux = office lighting, 1,000 lux = overcast day, and 10,000 lux = clear day. Significance was accepted at p<0.050.

5.4 Discussion

The present study compared the quantitative levels and 24-hour pattern rhythmicity of movement behavior and white light exposure between Esports players and an aged-matched non-gaming Control group. These findings confirmed the hypothesis that Esports players exhibit higher levels of sedentary behavior and lower levels of moderate-to-vigorous intensity physical activity than Controls. Notably, this study identified interesting temporal differences in movement behaviors between the groups, illustrated by Esports players becoming more active later during the day than the Controls. Likewise, Esports players exhibited overall lower levels of light exposure each day, with specifically more time spent in dim light and less time in moderate light conditions, and a robust phase-delay in their white light exposure profile than the Controls. However, there were no statistical differences in white light exposure in the three hours after wake-up time or before bedtime between the groups. These findings are discussed in the subsequent sections.

5.4.1 Sedentary behavior

Movement behavior data showed that Esports players allocated a concerning proportion (74.1% or 10.9 hours) of their waking time to sedentary behavior each day. This magnitude of sedentary time is significantly greater than Controls (61.9% of waking time or 9.1 hours per day) and comparatively higher than what has been described in the general population of other industrialized countries. To illustrate, the total sedentary time of Canadian adults (aged 18-34 years), as measured by actigraphy, ranged from 9-9.5 hours per day, with leisure screen time consuming 2.8-3.8 hours per day (Prince et al., 2020). Similarly, university students (aged 18-20 years) in the U.S. have also been shown to be highly sedentary, engaging in 10.0 ± 1.2 hours of sedentary time per day (Peterson et al., 2018). Given these comparisons, it is speculated that the elevated sedentary behavior observed among Esports players in this study is likely attributable to their involvement with excessive seated gaming activity, averaging 3.2 ± 1.5 hours per day, as reported in **Section 4.3.2** of the previous chapter. Specifically, it is inferred that the Esports players' gaming time may displace time that would otherwise involve more movement, such as performing exercises, household chores, or leisure-type activities, thus leading to greater total waking sedentary time.

This interpretation is consistent with the prevailing trend of sedentarism, with nearly one-third of adults and four-fifths of adolescents achieving insufficient physical activity levels (World Health Organization, 2022). It is also congruent with global trends around screen-based activities in recent years, evidenced by the rise in the average amount of screen time per person each day, from 9 hours in 2012 to 11 hours in 2019 (Harvey et al., 2022). The propensity for sedentarism is likely related, at least in part, to the ubiquity of digital media (reflected by the surge in social media usage and streaming entertainment like Netflix and YouTube) and the broad accessibility to electronic screen devices (Moreno-Llamas et al., 2020). Still, the potential long-term implications of such pronounced sedentary behavior measured in the Esports players group are worrisome. In particular, the high volume of sedentary time, coupled with the prolonged engagement with the screen time (i.e., gaming time) they log, could confer a greater risk of all-cause mortality and adverse cardiovascular health outcomes, as demonstrated in previous studies (Stamatakis et al., 2011; Wang et al., 2019). Notably, a meta-analysis identified that sedentary behavior exceeding a threshold of 8 hours per day was associated with a significantly increased risk (relative risk: 1.04, 95% C.I.: 1.03-1.05 per additional hour) for all-cause mortality, independent of physical activity volume (Patterson et al., 2018). This seminal finding raises important long-term health concerns for the Esports players and Control groups, who both exhibit sedentary behavior beyond this 8-hour threshold (Patterson et al., 2018). In this case, the issue of excessive sedentarism and its known potential health implications might instead represent a broader problem affecting young adults as a whole. This concept is discussed further under **Section 5.4.3** on movement behavior patterns.

5.4.2 Physical activity

Esports players spent 9.6% (1.4 hours) and 4.1% (0.6 hours) of their daily waking time in moderate- and vigorous-intensity physical activity (MVPA), respectively, or 13.7% (2.0 hours) in MVPA. In contrast, Controls spent nearly a quarter (24.6% or 3.8 hours) of their waking time in MVPA per day. The divergent MVPA duration observed between these groups was expected and is likely explained by Esports players' prolonged gameplay. Likewise, this finding also aligns with previous device-based research, demonstrating that collegiate esports players were significantly less active than age-matched non-gaming counterparts (DiFrancisco-Donoghue et al., 2022). Still, these MVPA doses far exceed the WHO physical activity guidelines, which recommend that adults should achieve weekly aerobic and muscle-strengthening physical activity volumes of 150-300 minutes or 75-150 minutes (2.5-5 hours or 1.25-2.5 hours) at a moderate or vigorous intensity, respectively (Bull et al., 2020).

However, it is important to mention that the reported MVPA values in this study represent a spectrum of daily living movement behaviors in a free-living setting, delineated by the accumulation of minute-by-minute activity counts meeting a defined MVPA threshold over the waking day. This is a notable distinction from earlier physical activity guidelines based on sustained 10-minute bouts of aerobic exercise (World Health Organization, 2010). While these guidelines have been updated to include any duration of physical activity (Bull et al., 2020), considerable work is still needed to elucidate device-based guidelines, especially when occupational and household activities might account for as much as 78% of total daily MVPA (Saint-Maurice et al., 2021; Troiano et al., 2020). An earlier study established that counting every minute above the moderate threshold versus strictly considering sustained periods of MVPA over ten or more minutes resulted in proportionally fewer (i.e., 68% versus 11%, respectively) participants achieving activity levels consistent with previous WHO physical activity guidelines (McVeigh et al., 2016). Accordingly, these researchers argued there was an absence of harmony regarding evidence generated from accelerometers (which collect minute-by-minute physical activity data) with physical activity guidelines (typically based on self-reported MVPA), which are each also functionally different (McVeigh et al., 2016). This argument remains valid despite decades of evolving science around the establishment of physical activity guidelines and raises important questions regarding device-based MVPA measures and their implications on cardiovascular disease morbidity and mortality (Troiano et al., 2020).

Another important distinction is that the monitoring device used to capture MVPA in this study was calibrated using a menu of ambulatory and daily lifestyle activities, a protocol recognized to yield substantially higher MVPA estimates than ambulatory protocols alone (Matthews et al., 2018). In this regard, the total MVPA values of Esports players were consistent with device-based MVPA estimates of U.S. adults (1.99 – 2.39 hours per day) across all life domains in prospective studies and calibration studies (Matthews et al., 2016; Matthews et al., 2018; Saint-Maurice et al., 2021). On the other hand, Controls in the current study had an MVPA volume nearly double that which was observed in the Esports players group in the current study and U.S. adult population estimates (Matthews et al., 2016; Matthews et al., 2018; Saint-Maurice et al., 2021). Albeit speculative, this result could point to a moderate-intensity cut-point that is too low, in which case light-intensity physical activity might be erroneously misclassified as moderate-intensity physical activity, leading to an overestimation of total MVPA volume (i.e., false positives). Indeed, this explanation is plausible, given that the cut-points used to discriminate moderate-intensity physical activity (AUC=0.66, cut-point: 418 CPM) exhibited weak classification accuracy (Kemp et al., 2020). While further device cross-validation is a potential solution to establishing more accurate cut-points (and thus physical activity doses), there is broad recognition that cut-point calibration methods are inferior to artificial intelligence-based methods capable of discriminating domain-specific behaviors using raw acceleration signals (Trost, 2020). This argument is substantiated by the fact that even robust cut-points may underestimate energy costs, resulting in the misclassification of physical activity intensities by as much as 40% of the time (Trost et al., 2011; Trost, 2020). Anchored by these contrasting findings and the absence of device-based physical activity guidelines, these data highlight the limitation of MVPA data obtained via cut-point methods and the need to elucidate the optimal dose of device-measured MVPA and its implications on cardiovascular disease risk, particularly in young adult esports players.

5.4.3 Movement behavior patterns

The analysis of the Esports players and Control groups' daily physical activity patterns provided greater temporal granularity regarding their free-living movement habits. As expected, both groups demonstrated a steady increase in activity levels in the early morning hours, plateauing over typical office hours (09:00 -17:00). Activity levels peaked briefly during the late afternoon (17:00-18:00) in the Control group before tapering off in the evening. In contrast, Esports players remained consistently sedentary throughout the day, with activity levels declining only toward late evening hours. Except for Esports players' unique proclivity for consistent sedentarism, this diurnal physical activity pattern is unremarkable compared to other population studies exploring 24-hour movement behavior (McVeigh et al., 2016). The occupational or academic status of participants in both groups could partially explain these movement behavior trends over the waking period.

Previous research indicates that being a student or a full-time worker often accounts for a significant proportion of an individual's waking sedentary time. Specifically, a recent systematic review and meta-analysis revealed that university students spend an average of 9.8 sedentary hours per day, as measured by accelerometers, with computer use outstripping other forms of screen time (Castro et al., 2020). Similarly, another review examining device-measured physical activity, sedentary behavior, and cardiometabolic health and fitness across different occupational groups demonstrated that approximately 60% of work hours were spent in sedentary activities, with office workers having the highest proportion of sedentary time compared to other occupations (72.5% vs. 49.7%) (Prince et al., 2019). These historical data suggest that workplace and societal norms could be significant factors driving the highly sedentary behavior observed among the general public – and, by extension – the participants in this study. However, it is important not to overlook the accumulation of sedentary time outside of work or academic hours. Leisure time, which might be spent on various discretionary sedentary activities, also contributes to total daily sedentary time. Therefore, it is conceivable that, while Esports players might dedicate their free time to gaming, the Control group may also allocate a considerable part of their waking hours to other forms of non-gaming screen time, such as browsing social media, watching television, streaming media, and engaging in similar leisure activities (as speculated in **Section 4.4.1** of **Chapter 4**).

An interesting observation was the delayed phase shift in the diurnal patterning of Esports players and Controls' movement behavior. Specifically, Controls were more active than Esports players in the early morning and late afternoon; the peak physical activity dose was observed among Controls at 18:00 and is presumably explained by post-work exercise or gym sessions (data not measured or reported). However, from 22:00 onwards, the Esports players became more active than the Controls, presumably reflecting their engagement with nocturnal gaming or esports matches. These differences are strongly suspected to be attributed to inherent chronotype differences between the groups. In particular, the Controls were characterized with mostly morning-type chronotypes and shared a stronger propensity for earlier rise times, while the Esports players were identified as having mostly evening-type chronotypes (**Section 4.3.3**). However, there is also a possibility that these disparate temporal differences might be related to the acute melatonin suppression from light emitted by screen devices at nighttime, which may strongly influence sleep-wake timing (Blume et al., 2019; Cajochen et al., 2019). This conjecture is discussed further in **Section 5.4.4**.

All things considered, it is also important to recognize some methodological challenges regarding how the 24-hour movement behavior patterns were analyzed. The first point pertains to the process of data binning, which broadly assumes that all activity undertaken within the given one-hour period is equally representative of the participants' movement behavior during that same period (and across the different monitoring days) (Baranowski et al., 2008). However, this may not always be true, as substantial intra-hour variation may exist, as previously acknowledged in a separate study involving older adults (Jansen et al., 2018). Using an example, the researchers highlighted that although mean activity levels declined in the evening, some participants in their study still demonstrated peaks of physical activity at these times (Jansen et al., 2018). In spite of the implicit limitation in accelerometers' inability to distinguish between specific activity modalities, a likely explanation for this phenomenon rests in the interindividual differences regarding how participants might spend their time on any particular day. These activity peaks may not be reflected in the hourly bin if their occurrence is not frequent enough in the study group.

Another important point relates to the log transformation process, which was employed to stabilize variance and normalize 24-hour physical activity data distribution. The geometric mean, which is the anti-log of the mean of the log-transformed data, is particularly sensitive to skewness and outliers (Feng et al., 2014). As such, the calculated average for each hourly bin might not fully reflect the central tendency of the original, non-transformed data cluster. This sensitivity is particularly notable when the original data exhibits high skewness or contains extreme outliers, which may occur during specific parts of the day when variability is naturally very high. This issue underscores how individual variations in daily routines might influence physical activity data, such as differences in wake-up routines or other movement-related behaviors (e.g., whether an individual drives to work or not), particularly if these routines vary significantly from day to day (Baranowski et al., 2008). It also raises the question of how well an overall average can represent disparate routines, such as activity patterns on weekdays versus weekend days.

Therefore, while the methodology provides a simplified representation of the 24-hour physical activity patterns of Esports players and Controls, it might not fully account for the nuances and complexities of their actual daily movement behaviors, potentially limiting the accuracy and representativeness of these findings. In this regard, the 24-hour movement behaviors must be interpreted with caution. Future research could benefit from larger sample sizes and superior modeling techniques, providing a more detailed picture of the 24-hour movement behaviors. The inclusion of qualitative research could also shed light on why individuals choose to engage in specific physical activity or sedentary behavior tasks at particular times or days. Further to this, supplementing accelerometer data with other data collection methods, such as daily activity logs, could more accurately capture the complexities of individual behavior patterns. Overall, these potential improvements should aid in designing time-specific interventions that could promote physical activity and reduce sedentary behavior, enhancing the practical relevance and impact of this research on esports players in the real world.

However, considering the high levels of sedentary behavior of Esports players observed in this study, there is reason to expect poorer cardiometabolic health status among these individuals in the future, especially if these patterns persist and are not counterbalanced by adequate physical activity. This follows the fact that sedentary behavior is widely recognized as an independent determinant of health, with substantial evidence linking excessive sedentary time with a greater incidence of non-communicable diseases like cardiovascular disease, type 2 diabetes, and cancer (Dempsey et al., 2020). At the same time, achieving guideline doses of regular and sustained muscle-strengthening or aerobic physical activity is broadly understood to reduce all-cause and cause-specific mortality (Zhao et al., 2020), conferring several notable health benefits, including improvements to body composition, cardiorespiratory fitness, lipid profiles, glycemic regulation, and blood pressure (Ruegsegger & Booth, 2018; Warburton et al., 2006).

As a corollary, limiting prolonged sitting time and participating in regular exercise would be an immediately practical and effective preventative strategy for esports players and young adults in general to employ. Strong evidence supports the cardioprotective effects derived from the reallocation of sedentary behavior to MVPA, with the trade-off resulting in up to 25% improvement in cardiovascular disease risk biomarkers per 30 minutes of reallocation (Buman et al., 2014). Likewise, historical data on low-activity U.S. adults highlighted an 18% and 42% reduction in mortality when one hour of sedentary behavior was replaced with light-intensity physical activity or MVPA, respectively (Matthews et al., 2016). There is also evidence to support that disrupting prolonged periods of sedentary behavior may lead to favorable changes in body composition and cardiometabolic disease risk biomarkers (Saunders et al., 2020). As such, there should be greater advocacy for esports players to integrate intermittent breaks into their sedentary gaming sessions. Utilizing these intervals to participate in low-intensity non-exercise activities can be particularly beneficial during extended periods of seated screen time and relatively easy to incorporate during "pause" time, matchmaking, or in idle lobbies (i.e., "in-game waiting rooms"). This strategy, especially if used in tandem with regular physical exercise, might be effective in lowering a number of cardiometabolic disease risk factors, including glucose levels, type 2 diabetes, triglycerides, and HDL cholesterol, independently of MVPA (Hamilton et al., 2007). Taken together, it is clear that efforts to promote more movement and less sedentary time may help to lower future cardiometabolic disease risk and improve overall well-being and quality of life in Esports players.

5.4.4 White light exposure of esports players

The Esports players in this study were found to spend more time, both absolute and relative, in very dim (<10 lux) light, yet less time in moderate (100 to <1000 lux) light during waking hours than the Control group. Given the characterization of Esports players being highly sedentary, as previously highlighted in **Section 5.4.1**, a plausible assumption could be that a significant proportion of their time is spent indoors – a condition likely imposed by a contemporary lifestyle and the typical light environment associated with such. This interpretation aligns with the results of a previous study, which suggest a strong inverse relationship between light exposure and sedentary behavior (more light exposure, less sedentary time) and a separate direct relationship between light exposure and MVPA (more light exposure, more physical activity) (Aggio et al., 2015). It is also consistent with the condition of the modern lifestyle, whereby as much as 90% of individuals' waking time is spent indoors under relatively modest light conditions (Klepeis et al., 2001; Murray et al., 2017) and the prevailing global trend that as much as 11 hours per day is being spent in front of digital screens (Harvey et al., 2022). However, without qualitative data or activity logs, it is challenging to definitively attribute the increased time spent in very dim light to indoor screen-based activities. This identifies a potential oversight in our study's design— the lack of direct measurement of total daily screen time, which restricts the study's ability to draw firm conclusions about the direct influence of screen time on the observed light exposure patterns. Contrarily, the disparity in light exposure could also suggest that the Control group engaged in more varied daily routines, possibly including more outdoor activities or varied indoor tasks, compared to Esports players. This could explain the noticeable differences observed in the time spent in sedentary behavior and physical activity intensities between the groups.

Interestingly, there were no between-group differences regarding waking light exposure across the 10 to 100 lux and <1000 lux ranges. Further, neither group was exposed to substantial levels of bright light during the week-long monitoring period, suggesting that participants in both groups spent proportionally more time indoors than outdoors during waking hours. This supports the argument in the previous passage and is consistent with studies exploring natural light exposure in the general population. For example, an early study on young adults in the U.S. showed that roughly 15% (or 1.5 hours) of waking time was spent in light levels over 1000 lux (Savides et al., 1986). A later study demonstrated that young adults (aged 23.4 ± 4.6 years) spent only an average of 9% of their waking time in light levels over 1000 lux and 30% of their waking time in light levels under 10 lux (Scheuermaier et al., 2010). In contrast, participants in the present study achieved even lower levels of light measuring over 1000 lux (2.6% and 4.7%, respectively) and remarkably higher levels of light measuring under 10 lux (62.8% and 51.0%, respectively). The apparent diminishing level of bright outdoor light exposure in young adults is concerning, potentially representing a gradual change in the light environment that deviates from expected patterns, which may yield negative consequences on health over time. Specifically, suboptimal exposure to bright natural light is linked with later sleep timing and greater symptoms of depression, poor sleep quality (the latter of which is evident in both groups – see **Section 4.3.3**), and cognitive deficits (Harb et al., 2015; Roenneberg et al., 2003). These observations underscore the need for further research to substantiate this hypothesis and explore potential interventions to counteract these effects.

An unanswered question that emerges from this study is whether the temporal differences in light exposure seen among Esports players are driven by a natural predisposition for eveningness or the acute melatonin suppression from light emitted by screen devices related to nighttime gaming activities. This consideration follows the observation that there were no between-group differences regarding total light exposure, suggesting that divergent amounts of light observed among Esports players are likely attributable to temporal differences in hour-by-hour white light exposure. Notably, the gamers exhibited a robust delayed phase-shift pattern in light exposure, marked by lower morning-time and higher evening-time light exposure than the Controls. However, this did not translate to significant differences in the light levels relative to the groups' actual bedtime and wake-up times. These observations may support the argument that chronotype rather than melatonin suppression by light is driving these temporal differences, especially given that the delayed light exposure profile is reciprocated by the Esports players' apparent phase-delayed shift movement behavior patterns and preference for later bedtimes and wake-up times (as characterized in the previous chapter).

Indeed, there is a complex interaction between light exposure and chronotype. A previous study model demonstrated that increased exposure to daytime illuminances reduces individual differences in circadian timing, effectively lowering chronotype variations (Papatsimpa et al., 2021). Further, the model showed that extended exposure to light during the late evening shifts the population towards having a more evening-oriented phenotype and increases interindividual differences. The model predicted that a typical evening illuminance of 35 lux could lead more than 20% of the population to develop a later chronotype (Papatsimpa et al., 2021). This finding aligns with a separate experimental study, which showed that evening chronotypes had more significant circadian changes under natural light-dark conditions, such that phase advances were comparable to morning-type chronotypes (Wright et al., 2013). While the data in this study are insufficient to support a cause-effect relationship regarding light exposure on chronotype, the shift towards eveningness described in these previous studies may explain the many problems linked with late chronotypes in general, such as lower sleep quality (including difficulty initiating and maintaining sleep, nightmares, and insomnia symptoms) (Montaruli et al., 2021), diabetes and metabolic disorders (Yu et al., 2015), and increased tendency to smoke (Patterson et al., 2016) and consume alcohol and caffeinated drinks (Adan, 1994). It is also reasonable to speculate if a vicious cycle does, in fact, exist, in which the reduced exposure to natural bright light (possibly due to the delayed phase shifts in sleep-wake timing) is responsible for reinforcing eveningness. This could, in turn, alter the proportion of time spent in natural light (for example, significant phase shifts might result in less overall daylight exposure), potentially further reinforcing an evening phenotype. Future research must delve deeper into this intricate interaction to fully understand its implications and devise strategies to mitigate any adverse effects, particularly for populations like Esports players who may be at risk due to their unique light exposure patterns and lifestyle.

While photoentrainment by morning light exposure is understood to be dose-dependent (Dijk et al., 1989; Misiunaite et al., 2020), the morning-time light exposure relative to the wake-up time in both groups was low. Therefore, it is arguable whether either group's light exposure levels were sufficient to establish a robust circadian phase resetting response. Noteworthy, previous studies argue that exposure to an illuminance level of at least 1000 lux is sufficient to achieve robust circadian phase resetting (Chang et al., 2012; Zeitzer et al., 2000); however, the actual threshold for resetting may vary across individuals and different light exposure conditions, with the timing of exposure being a critical factor for the direction of the phase shift (Hou et al., 2022). Considering the similar levels of morning-time and evening-time light exposure relative to wake-up and bedtime across the groups, it is unlikely that the delayed sleep timing in Esports players is solely attributable to light-induced melatonin suppression. This is especially so since the light exposure before sleep primarily consisted of very dim light, which arguably did not have substantial suppressive effects on melatonin and subsequent sleepiness. However, for Esports players who experienced prolonged exposure to dim light (presumably from screen devices in the hours leading up to bedtime), it is plausible that they have developed a greater resilience against the acute melatonin-suppressing effects of the light emitted from their gaming and screen-related activities. As such, it is worth speculating whether it is not just the intensity but also the prolonged duration of light exposure over time that has conditioned the bodies of Esports players over time to better resist the potential sleep-disrupting effects of their screens at night. Beyond this, other inter-individual factors (e.g., genetic disposition, age, sex, and chronotype) may also influence photosensitivity and may differentially affect circadian entrainment by light and sleep-wake timing (Chellappa, 2021). These factors can possibly add an additional layer of complexity to the relationship between light exposure and sleep.

Finally, the absence of a strong photic stimulus is a key driver of delayed and problematic sleep-wake behaviors and could be related to a high level of sedentary behavior and physical inactivity among these individuals. For example, physically active individuals may naturally be exposed to greater levels of bright outdoor light through their engagement with sports or outdoor physical exercise. In contrast, individuals with a propensity for sedentariness would likely participate in fewer outdoor activities and presumably more sedentary indoor tasks. Therefore, it is imperative that concerted efforts are made to encourage esports players to spend more time outdoors, especially during daylight hours, to increase their exposure to bright natural light. A practical solution could involve balancing their substantial screen time with more outdoor activities during the daytime. This may include a wider variety of sports or exercises (like running, cycling, or hiking) and other outdoor pursuits (such as gardening) to increase MVPA and reduce sedentary behavior time. Alternatively, changes to the current work and home light environment could also be beneficial. For instance, arranging workstations near windows, making architectural adjustments to allow more natural light into interior spaces, and installing larger windows or cool white polychromatic light fixtures might be effective. Such interventions could promote better performance, productivity, physical activity, enhanced sleep quality, and overall quality of life (Boubekri et al., 2014).

5.4.5 Study strengths

A key strength of the present study was employing objective methods to measure habitual waking doses of sedentary behavior, physical activity, and white light exposure over seven days in a free-living setting among young adults engaged with esports since much of the previous research in this area has been predominantly based on self-report online surveys. Accelerometers are widely regarded as a criterion measure and superior to self-report tools, especially when predicting physical activity (Prince et al., 2008); moreover, the use of a 24-hour monitoring protocol additionally confers the ability to characterize the type of timing of physical activity and light exposure. As such, this feature is a major contribution to the literature since the 24-hour light exposure and movement behavior patterns of esports players have not (to the best of our knowledge) been reported before. Another strength was the inclusion of an age-matched control group and the employment of random (rather than convenience) sampling techniques, which reduces sampling bias and provides comparability regarding the unique behaviors of esports players versus the general population. Finally, the simultaneous measurement of sedentary behavior, physical activity, light exposure, and sleep patterns is another key strength that reduces measurement bias associated with using multiple monitoring devices. It also allows for a greater degree of interpretability with respect to cardiometabolic health and associations between these factors.

5.4.6 Study limitations

Although using wrist-worn accelerometers was a key methodological strength of the present study, it is important to acknowledge its limitations. First, the cut-point calibration method used to discriminate sedentary behavior and physical activity intensities, while considered the gold standard in its time, has more recently been surpassed by more advanced artificial intelligence-based physical activity classification models (Trost, 2020). These artificial neural-network-based models are based on the device's raw acceleration signal and offer more accurate estimates of time spent in sedentary behavior, physical activity, and domain-specific tasks (Trost et al., 2012). However, it was not possible to employ these classification techniques in the present study since machine-learning models rely on accessibility to the device's raw acceleration signal, which is unavailable in the Actiwatch proprietary algorithm.

Second, while wrist-worn devices typically offer greater wear compliance than hip-worn devices, this position is more likely to misclassify sedentary behaviors due to the inter-individual variability in participants' wrist movements versus static hip placement (Rosenberger et al., 2013; Scott et al., 2017). Having said this, the sedentary behavior cut points used in this study had 97.9% sensitivity and 96.6% specificity (Kemp et al., 2020). While implementing a 24-hour monitoring protocol provided greater temporal resolution regarding participants' daily hour-by-hour movement behavior patterns, extending the analysis to include epochs representing both waking behavior and sleep could result in misclassifying sleep as sedentary behavior and overestimating total sedentary time (Trost, 2020). Third, in the absence of device-based physical activity guidelines, it is not possible to elucidate Esports players' compliance in meeting recommended MVPA doses. In hindsight, this could have been overcome using objective monitoring in conjunction with validated physical activity questionnaires, which would have also helped contextualize the observed device-based physical activity estimates.

The fourth limitation involves the measurement of white light exposure. Light levels measured using wrist-worn devices may not reflect light fluence received at the retina since the photodiode sensors on these devices could be occluded (e.g., by clothing or angled such that light is not incident on it); thus, the light levels measured may be underrepresented. Another limitation was the difficulty discriminating artifact data (typically defined as light <1 lux) from true dim light exposure. However, it was ultimately decided that all light data, including light measuring <1 lux, would be included in the final analysis since omitting this data could potentially exclude dim light emitted from screen devices in the nighttime and result in underestimating true dim light levels.

Lastly, the study is limited by its cross-sectional design, which prohibits the establishment of causal inferences. In addition, the study sample also comprised only young adult males; therefore, the findings may not extend to other cohorts. Relatedly, Esports players were primarily engaged with computer-based gaming modalities, in which case findings might not extend to players engaged with mobile and console-based modalities.

5.5 Conclusion

Esports players were found to be significantly more sedentary, engaged in less physical activity of any level, and were exposed to more dim light levels than age-matched Controls. Analysis of 24-hour movement and light patterns revealed clear phase delays in activity and light exposure among the

Esports players group. This is consistent with observations from **Chapter 4**, in which the Esports players had delayed sleep timing and were identified as having a strong evening-oriented phenotype. On the one hand, this suggests that Esports players' proclivity for nighttime gaming behaviors may drive their phase-delayed behavior. Alternatively, their evening chronotype might attract them to a night-oriented pastime. These findings offer important implications for future interventions, particularly those aimed at improving physical activity levels and sleep in esports players and the timing thereof. Ultimately, the lack of adequate natural light exposure and proclivity for sedentarism amongst young adults is concerning and may present unique challenges as technology becomes increasingly omnipresent in contemporary society.

Chapter 6

General discussion and future considerations

The primary aim of this thesis was to characterize and explore the associations between device-derived sleep patterns, cardiometabolic health risk factors, and neurocognitive performance in adult esports players. In addition, the thesis aimed to describe the quantitative doses and 24-hour pattern profiles of physical activity and white light exposure in esports players. These aims were achieved in **Chapter 2** by first identifying key knowledge gaps and methodological limitations in the extant literature, which informed the subsequent chapters' structure and research questions. In particular, this included identifying the need for objective measures concerning sleep and physical and cardiometabolic health risk factors in esports populations. Relatedly, **Chapter 3** was an integral part of this thesis, exploring the validity and reliability of concomitantly using a single monitoring device (i.e., the Actiwatch) to measure sleep, light exposure, sedentary behavior, and physical activity at varying intensities (including a calibration study of the respective threshold values) in a general population of apparently healthy adults spanning a range of cardiorespiratory fitness for broad applicability. The ecological validity of using the Actiwatch to measure these parameters objectively was later confirmed and employed in a population of young adult esports players in **Chapter 4** and **Chapter 5**.

Accordingly, the primary finding of the thesis showed that esports players exhibited striking differences in sleep-wake behaviors compared to their non-gaming, age-matched counterparts. In these chapters, esports players were characterized by delayed bedtimes, wake-up times, and sleep mid-points, with a high occurrence of evening chronotypes. In addition, while sleep and cardiometabolic health characteristics were mostly unremarkable in comparison, esports players exhibited a greater prevalence of smoking and presented with high levels of sedentary behavior and short sleep duration, each with direct implications for cardiometabolic health (Patterson et al., 2016; Patterson et al., 2018; Xi et al., 2014). Interestingly, esports players did not demonstrate signs of excessive daytime sleepiness despite presenting with chronic sleep restriction; however, they did engage more frequently with "catch-up" sleep (napping) during the daytime. Furthermore, esports players were not broadly characterized by clinically relevant poor subjective sleep quality, but a substantial proportion (i.e., roughly half) of esports players could be described as "addicted gamers" or "poor sleepers." Finally, esports players were exposed predominantly to very dim light throughout the waking day, with proportionally low exposure to bright natural light. While the overarching explanation concerning these findings is arguably complex, several risk factors and ideas are discussed in the following sections.

6.1 Chronotype

This study's findings contribute to the existing body of literature by reinforcing the observation that esports players tend to align their sleep schedules with their inherent chronobiological preferences. This alignment is evidenced by the high proportion of evening-type chronotypes among these players, which is reflected in their correspondingly delayed bedtimes and wake-up times. Further examination showed that while sleep timing was significantly more delayed on weekends than on weekdays, it was driven more by a delay in wake-up times rather than bedtimes on the weekends. This finding likely follows the need to accommodate societal obligations (e.g., work or university) during the week. As a result, it is thought that esports players wake up out of sync with their biologically preferred sleep window during weekdays, leading to truncated sleep (total sleep time: 6.3 hours), thereby facilitating the need to nap to ameliorate the sleep deficit.

Despite this, there was no indication of excessive daytime sleepiness among esports players. However, it is postulated that the use of napping, caffeine consumption, and stimulants, such as nicotine, may be used to mitigate sensations of daytime sleepiness and fatigue resulting from mounting sleep debt. This may also explain the short sleep onset latency observed in esports players, suggesting that these individuals defer sleep beyond the point of exhaustion. Whether esports players delay sleep-wake timing because of a natural predisposition for eveningness or as a product of gaming habits is a multifaceted and complex matter for debate.

On the one hand, it is widely understood that genetic factors account for 40-50% of the variance in chronotype, mimicking the heritability of other complex traits like height and weight (Roenneberg et al., 2007). This implies that individuals with a greater genetic predisposition for eveningness may be more likely to become esports players due to the evening nature of gaming activities. This reasoning is reinforced by the fact that evening chronotypes typically exhibit slower sleep pressure kinetics, enabling prolonged wakefulness (Taillard et al., 2003), which might be complemented by esports training and match schedules that typically end late at night (discussed further in the next section).

On the other hand, the influence of habitual activity patterns on chronotype cannot be overlooked. As demonstrated in a separate study, individuals regularly engaged in rugby exhibited a higher proportion of morning-type chronotypes (47% versus 23%) and a lower proportion of evening-type chronotypes (3% versus 18%) than a control group of habitually low-activity individuals. This suggests that habitual athletic behavior shifted diurnal preferences to favor morningness tendencies independently of a chronotype-genotype relationship (Kunorozva et al., 2017). This could imply that the sedentary nature of gaming activities might further reinforce eveningness in esports players.

Beyond this, the excessive use of electronics and exposure to artificial lighting during gaming activities presumably also disrupts circadian rhythms, reduces sleep quality, and delays sleep by suppressing melatonin secretion (Cajochen et al., 2011). In this regard, esports players may develop evening tendencies as a consequence of their habitual gaming routines. This logic is supported by a landmark study, which showed that artificial lighting and industrialized settings contributed to delayed circadian clock timing, lower levels of natural daylight, and increased levels of evening light exposure compared to a natural midsummer light-dark cycle achieved during camping (Wright et al., 2013). In the study, participants were resynchronized with the environment (solar time), with evening-oriented individuals exhibiting significant advances in circadian timing to the point of aligning more closely with morning-oriented individuals after entrainment (Wright et al., 2013). This demonstrates the extent to which environmental factors can influence individual differences in circadian timing, particularly in the presence of electrical lighting at night and the absence of strong circadian time cues like sunlight. Additionally, evening-oriented individuals are also understood to be more prone to developing gaming addiction (Vollmer et al., 2014), which is congruent with the phenotype of esports players in this study. This may lead to a vicious cycle, where esports players' propensity for eveningness encourages more gaming, which in turn reinforces evening tendencies, later bedtimes, truncated and poor quality of sleep.

6.2 Esports matches and practice times

Although the circadian signals and sleep pressure kinetics of esports players may favor nighttime activities, it is not possible to rule out training schedules contributing to later timed sleep. This is particularly true for esports players in this study, who engaged with gaming for an average of 3.2 ± 1.5 hours per day and reported matches and practices ending late at night. It is speculated that esports players might experience difficulty initiating sleep due to the melatonin-suppressing effects of artificial light or electronic screen devices and the time delay for melatonin to acclimate to levels efficacious to induce sleepiness (discussed more later). This, coupled with the physical delay in bedtime due to the late end time of matches, may exacerbate trouble initiating sleep and result in poor sleep quality. However, in the absence of robust evidence to support when esports players participated in matches and practices, it is challenging to ascertain the relative contribution of these later-timed matches on sleep patterns.

Nevertheless, this logic is supported by prior research studies involving elite esports athletes, demonstrating that later and longer training schedules can delay sleep readiness. In particular, a multinational study of Korean, Australian, and American esports athletes reported that Korean players trained for an average of 13.4 ± 2.0 hours per day, between 13:07 and 04:45, with a resulting sleep onset time of 04:50. In contrast, the Australian and American samples trained for 4.8 ± 1.0 hours per day (17:30 to 22:15) and 6.1 ± 1.3 hours per day (11:48 to 18:12) respectively, with sleep onset times of 03:40 and 02:00 (Lee et al., 2021). Importantly, while later esports practice and match schedules were shown to displace sleep opportunities more readily than earlier-timed schedules, sleep-wake timing was still delayed in the Australian and American samples despite their earlier practice times in comparison to the Korean esports athletes (Lee et al., 2021). This observation further implies that other contributing factors, such as bedtime procrastination, may be involved in the delayed sleep timing of these individuals.

6.3 Bedtime procrastination

Bedtime procrastination is defined as "going to bed later than intended, without having external reasons for doing so." It is strongly linked with short quantity and poor sleep quality (Carter et al., 2016; Kroese et al., 2014, p. 2) and has previously been posited as a factor explaining later sleep times in esports players. In a qualitative study comprising esports athletes from five professional teams based in Korea (20.4 ± 2.4 years), researchers highlighted smartphones as a major facilitator of bedtime procrastination and delayed sleep. The study also identified other contributing factors: match and practice schedules, post-training hyperarousal, high stress levels, suboptimal sleep environments (e.g., outdoor noises, room temperature), and interpersonal factors (Lee et al., 2020).

In a separate study, a subset of "high bedtime procrastination" individuals from a general population (22.7 ± 2.9 years) was also shown to engage more with leisure and social activities (most notable being mobile phone use) during the day and in the hours prior to bedtime (Chung et al., 2020). The same study also demonstrated a link between bedtime procrastination with eveningness tendencies, delayed sleep-wake timing, higher rates of clinical insomnia symptoms, lower sleep quality, and more symptoms of depression and anxiety (Chung et al., 2020). In line with previous research, esports players in **Chapter 4** appeared to delay bedtimes beyond the supposed end times of practices and matches, which may support the argument that these individuals experienced bedtime procrastination, presumably of their own volition.

It is well established that chronotype may be a significant predictor of bedtime procrastination, with evening types displaying more bedtime procrastination, especially on work days. On the one hand, bedtime procrastination is thought to stem solely from individuals acting on impulse and their inability to exercise self-control (Chung et al., 2020; Kroese et al., 2014). However, other experts argue that bedtime procrastination results from the combined effect of biological preferences with societal and environmental demands, differentiating it from procrastination of tasks. In particular, the ability of late chronotypes to self-regulate may be blunted by the continuous demand of "forced circadian misalignment" (e.g., sleep-wake patterns that run contrary to biological preferences), compelling greater behavioral procrastination over time (Kühnel et al., 2018). This is supported by bedtime procrastination being viewed as an "intention-behavior gap" (i.e., when individuals fail to do what they set out to do), whereby late chronotypes fail to recognize their intentions to sleep earlier (Kroese et al., 2014; Kühnel et al., 2018). Accordingly, biological preferences (rather than an individual's inability to control their short-term desires) are thought to reinforce this, such as evening chronotypes having heightened alertness at night, which drives later evening activities and consequent sleep displacement (Kühnel et al., 2018).

Given the striking prevalence of digital media (especially social media) consumption in contemporary society and its established links with sleep complaints (Boer et al., 2020; Gradisar et al., 2013), it is argued that future research should employ qualitative techniques to understand the purpose behind bedtime procrastination practices to pave the way for establishing effective treatment strategies and interventions for these individuals. In hindsight, appropriating tools to measure bedtime procrastination coupled with better compliance around reporting esports match practice start and end times could have provided greater resolution regarding their relative contribution to delaying the sleep of esports players in this study.

6.4 Implications of sleep and chronotype on performance

Sleep and chronotype also have important combined implications for gameplay performance. In particular, esports players with greater evening tendencies might be less likely to report sleep problems and performance impairments, given the synchrony between their chronotype and peak levels of alertness with evening-timed gaming activities. However, morning-oriented players might experience suboptimal performance given that the timing of competitive activities contradicts their preferred sleep-wake preferences.

In this regard, it seems plausible that esports players pursue and excel in esports *because* it matches their chronotype. This logic is aligned with studies involving traditional sports, evidenced by the proportionally large amount of morning-oriented individuals engaged in morning sports (Kunorozva et al., 2017; Lastella et al., 2016). In a systematic review comprising ten studies, morning-type chronotypes typically reported a lower rating of perceived exertion in submaximal physical tasks and superior athletic performance in the mornings than individuals with neither- and evening-type chronotypes (Vitale & Weydahl, 2017). Another study described similar time-of-day effects on multiple cognitive performance measures (including reaction time and executive function tests), such that completing tasks during an individual's biological night resulted in worse performance (Facer-Childs et al., 2018).

While evening-oriented esports players would be more likely to perform optimally during evening-timed matches, there would arguably be greater performance deficits in these players during earlier matches. In this regard, screening processes that identify players' chronotypes could be a potentially beneficial performance tool, allowing coaches and team managers to match individual players and their chronotypes to competitive schedules to gain a competitive edge.

6.5 Light exposure

The results from **Chapter 5** indicate that esports spend an extraordinarily long time in low light conditions (<10 lux) during the hours preceding bedtime and throughout the day. This finding could be attributed to players spending a substantial proportion of their time indoors or in poorly lit environments, which increases their risk of developing circadian rhythm disorders and subsequently impacting their sleep, such as disrupting sleep-wake cycles or manifesting insomnia and fatigue (Wright Jr et al., 2013). Given that these conditions favor later sleep timing, it cannot be ruled out that the suppression of melatonin also plays a role in delaying the wakefulness of these players (Duffy & Wright Jr, 2005; Wright Jr et al., 2013).

Extensive research has established that aberrant light exposure, particularly light exposure in the hours preceding sleep and the lack of morning light exposure, contributes to later-timed and problematic sleep, attenuating sleep propensity by influencing both homeostatic and circadian processes in an intensity-dependent manner (Duffy & Wright Jr, 2005). In particular, artificial light exposure at night can prolong the photoperiod by delaying sleep phases, suppressing melatonin secretion, and increasing alertness. This process triggers a coordinated realignment of biological rhythms and sleep patterns, leading to circadian disruption and deleterious effects on sleep, including negative downstream effects on performance, mood, metabolism, and physical and mental health (Foster et al., 2013; LeGates et al., 2014; West & Bechtold, 2015). Noteworthy, preliminary evidence suggests that exposure to light as low as 5-10 lux at night can negatively affect sleep by reducing total sleep time and sleep efficiency; and promote shallower sleep by negatively altering sleep architecture. (Cho et al., 2016; Cho et al., 2018).

On the other hand, exposure to dim light or the lack of exposure to bright light (>1000 lux) during the day is also understood to influence sleep and circadian-regulated processes, with the duration of light exposure having a moderating role such that the effects of light vary in intensity and timing (Dautovich et al., 2019). In particular, light exposure informs circadian rhythms, which in turn regulates the release of cortisol, which is critical for maintaining wakefulness and alertness throughout the day (Gooley et al., 2011). Furthermore, prior research has also demonstrated that low light exposure during the daytime could reduce the amplitude of melatonin secretion in the evening and advance melatonin onset timing (Zeitzer et al., 2000). This raises questions about the efficacy of the morning light exposure experienced by esports players in eliciting a robust circadian phase-resetting response (Cajochen et al., 2011), which could suggest that esports players may not be exposed to light of sufficient intensity, duration, and spectral density during the day.

Likewise, large differences in light intensity can significantly affect physiological responses. For example, a previous study demonstrated that a history of exposure to very dim light levels (1 lux) during waking episodes amplified the circadian phase-shifting response to a sub-saturating light stimulus (90 lux) after 6.5 hours. The study's findings underscore the role of both light intensity and photic history in regulating circadian rhythms. However, it is currently unclear if this effect extends to brief or momentary changes in light exposure or switching between very dim light levels (e.g., shifting from 1 lux to 10 lux or 0.1 lux to 1 lux) (Chang et al., 2011). This point is especially relevant to esports players, whose light exposure might predominantly be artificial light from computer screens with varying intensity and spectral composition. The challenges of evaluating the effect of light history on sleep patterns in such scenarios are further exacerbated by the difficulties in accurately measuring and analyzing light data in esports players, including the lack of information about the spectral composition of the light (such as blue or red light), the intensity of screen light, size of the screen, and distance of eyes from the screen.

To address this problem, it may be beneficial to implement guidelines for lighting in esports training and competition environments and to educate esports players on how to optimize light exposure outside of these settings to promote healthy sleep. Additionally, more research is needed to better understand the specific light exposure experienced by esports players and its impact on their sleep and overall health, using methods such as time-use surveys and measuring the spectral composition of light exposure in future studies. By taking these steps, esports players might be able to maintain healthy sleep patterns, which can, in turn, improve their performance, mood, metabolism, and overall health.

6.6 Game culture and conditioning

Separately, it is speculated that esports players may be conditioned to delayed phase-shifted and short duration sleep due to dysfunctional beliefs and years of habituation to chronic gaming. Unlike traditional sports, there is little to no structure, governance, or oversight in esports (Kemp et al., 2020). In turn, there is no predefined or official pathway to becoming a professional esports athlete nor evidence-based "best practices" to adopt behaviors aimed at promoting or supporting esports performance. This lack of institutionalization and structure arguably permits the proliferation of ill-informed, dysfunctional beliefs like "sleep is for the weak" and the promotion of incessant "grinding" behaviors (i.e., excessive gaming of several hours per day) that is synonymous with gaming culture (Lewis et al., 2011). As a result, such habits may go unmodified into gamers' professional careers, compromising the health and sleep of these individuals, under the misconception that doing so might boost their gaming performance and overall prowess. Industry influencers (e.g., streamers) might also reinforce these dysfunctional beliefs by promoting the "play until you drop" behavior model (i.e., by engaging in lengthy broadcasts or "subathons" [2]), which arguably devalues the importance of sleep in the eyes of impressionable followers (Bonnar et al., 2019b). In this regard, challenging esports players' perspectives and debunking cultural beliefs regarding sleep is imperative to motivate healthier gaming habits. Moreover, in the case of elite-level esports athletes, modifying these dysfunctional behaviors might be the differential factor toward marginal performance gains needed to gain an advantage over their competitors; this might also be an attractive motivation for these players to adopt behavioral change.

6.7 Practical implications and recommendations

Taken together, the sleep profile of esports players in this thesis likely represents the combined effect of multiple contributing factors, ranging from an innate preference for eveningness, underpinned by a combination of physiological, genetic, and intraindividual factors (Chellappa, 2021) to extrinsic conditions (e.g., end times of matches and practices, bedtime procrastination) and other idiosyncratic

[2] A subathon is an online phenomenon describing a broadcast that lasts for as long as viewers subscribe to the channel. Every time a viewer subscribes, a set amount of time (e.g., 10 seconds) is added to the time required to remain live.

conditions unique to esports. These conditions might include family commitments; high levels of stress following long hours of game training or pre-competition anxiety (Poulus et al., 2020); pain resulting from musculoskeletal injuries resulting due to prolonged aberrant posture, screen time, and repetitive microtrauma (Emara et al., 2020); and even video gaming addiction, which is understood to have a bidirectional relationship with mood disorders, circadian rhythms, and problematic sleep (Lam, 2014).

As a result, establishing practical implications and recommendations for esports players, teams, coaches, organizations, and researchers is the first step toward cultivating a healthier environment for esports and general video gaming. While there are many factors underpinning delayed sleep timing, short duration, and poor quality sleep in esports players, we echo Kroese et al. in that "the hours of sleep may be limited 'simply' due to going to bed late" and that "going to bed is more a matter of 'when' rather than 'if'" (Kroese et al., 2014, p. 2). In this regard, carefully designed sleep interventions considering esports players' innate preference toward and purpose behind eveningness are also warranted.

In the next section, several recommendations are proposed based on existing literature to (i) challenge existing perspectives around sleep health, (ii) increase total sleep time and improve sleep health awareness, (iii) establish sleep timing regularity, (iv) promote physical activity, (v) reduce the cardiometabolic health burden of poor sleep behaviors, all while (vi) keeping performance optimization in mind.

6.7.1 Sleep intervention considerations

Sleep hygiene education is typically accepted as an effective first-step treatment strategy in the public health realm to improve sleep in the general population (Chung et al., 2018). While empirical evidence concerning individual components of sleep hygiene is limited in their appropriateness, sleep hygiene recommendations are generally regarded for their relative ease of implementation and inexpensiveness. Specifically, the deployment of sleep hygiene treatment strategies does not necessarily require the involvement of specialists in adults with nonclinical sleep issues and has a low risk of adverse effects, making its adoption broadly applicable (Chung et al., 2018; Irish et al., 2015). Accordingly, recommendations to improve sleep might include keeping to a regular sleep schedule, achieving regular physical exercise, stress management, avoiding caffeine, nicotine, and alcohol, maintaining a bedroom environment favorable for sleep (i.e., cool ambient temperatures with low noise), limiting daytime napping or appropriating short "power naps" during optimal circadian times, and avoiding bright light exposure and screen time before bedtime. In addition, achieving greater intensity of morning and daytime light exposure by spending more time outdoors is also suggested to regulate the sleep-wake cycle.

An extension of these recommendations might include informing about ‘healthy’ gaming behaviors, such as appropriating regular breaks to stretch and move, eating healthy foods, avoiding long periods of sitting and physical inactivity, employing a more ergonomic posture, and promoting a balanced lifestyle. Importantly, limiting continuous periods of gaming and adhering to winding down 1 hour before bedtime may also be an effective way to de-arouse and allow melatonin to acclimate to levels favorable for sleep; this could include restriction of technology usage and appropriating relaxation techniques (meditation, deep breathing, or stretching). In addition, in cases where the use of screen technology during the nighttime is unavoidable, using a blue light filtering protector panel, eyewear, or apps and dimming artificial lights and electronic screens should be encouraged where feasible.

Game publishers could also assist with sleep-promotion strategies by displaying warnings on-screen when gaming sessions reach unhealthy playing time levels. They could also passively display sleep hygiene tips during loading screens to improve overall sleep education awareness. Alternatively, games could include “opt-in” options for players to temporarily disable matchmaking or limit gaming during predetermined hours to dissuade problematic gaming behaviors. Improved sleep awareness and applying these sleep hygiene practices to esports training may be affordable and practical solutions to combat problematic sleep and public health issues.

It is important to note that the effectiveness of these recommendations has largely not been tested in an esports population, with research concerning the evaluation of sleep interventions or similar sleep-oriented health programs in these individuals being scant in the present body of literature. For instance, to our knowledge, only one study attempted a “brief low-intensity sleep intervention” to improve sleep, mood, and cognitive performance in esports players during the competitive season (Bonnar et al., 2022). The intervention lasted 14 days and comprised a 40-minute group sleep education class, 30-minute private one-to-one sessions with a clinical psychologist, and daily feedback. Accordingly, the study reported mixed findings, with modest improvements post-intervention in select subjectively-measured sleep parameters: shorter sleep onset latency, earlier sleep onset time, and improved sleep efficiency; device-derived sleep onset time also improved. In addition, while the study participants improved their sleep knowledge and saw a reduction in the severity of insomnia symptoms, they experienced greater sensations of sleepiness, with negligible changes in mood or performance (Bonnar et al., 2022). However, the researchers noted that the degree of increase in sleepiness, despite being statistically significant, did not reach a threshold that was deemed clinically meaningful and attributed this to potential lagged improvements in sleepiness levels.

Although the low-intensity sleep intervention trial was designed to accommodate the intense routines of professional esports athletes, the researchers conceded that a stepped-care model could be more effective in addressing these high-performance individuals' sleep needs. Specifically, they proposed risk screening esports players, assigning “high-risk” individuals requiring greater therapeutic attention to bespoke treatment solutions like CBT-I and “low-risk” players to brief low-intensity sleep interventions (Bonnar et al., 2022). This sentiment aligns with Irish and colleagues, who noted that sleep hygiene alone might not be sufficient to ameliorate chronic underlying sleep problems, especially when poor sleep hygiene practices manifest as a direct result of compensatory responses to sleep disorders like severe insomnia or sleep apnea. In these cases, the researchers argued that more bespoke treatments might be necessary, which should be employed under the consultation of a sleep medicine health practitioner (Irish et al., 2015).

6.7.2 Cognitive behavioral therapy for insomnia

Another consideration might include individualized cognitive behavioral therapy for insomnia specific to esports populations. CBT-I is generally regarded as a first-line treatment option for individuals battling with insomnias, with comparable efficacy and long-term benefits as pharmacological treatment approaches (Mitchell et al., 2012). The approach is particularly useful when the inability to sleep becomes a learned habit and the initial triggering stimulus is no longer present. It incorporates thought reframing around sleep coupled with sleep restriction therapy to create greater sleep pressure and more consolidated sleep. This is achieved through a combination of strategies, including sleep hygiene, stimulus control, relaxation training, sleep restriction, and cognitive therapy to alter negative perspectives and behaviors related to sleep. It is delivered over four to eight weekly sessions and is thought to be useful in preventing and treating problematic sleep in esports players (Bonnar et al., 2019b; Siebern et al., 2012).

However, the effectiveness of CBT-I in treating insomnia must be balanced against its appropriateness in professional and competitive settings like esports. While its efficacy largely depends on individual circumstances, some central elements of the treatment (such as nap avoidance and sleep restriction therapy) have been argued to be potentially incongruent or problematic with the training and competition schedules of professional athletes in traditional esports (Cook & Charest, 2023). By extension, this notion might also be applicable to competitive esports players, especially in cases where training schedules and intensities mirror that of traditional sporting counterparts. As evidenced in **Chapter 4**, esports players frequently engage in napping, a practice commonly observed in traditional sports. In the sporting realm, napping has been shown to improve cognitive and physical performance and is viewed as beneficial for managing sleep debt before competitions (Lastella et al., 2021; Mesas et al., 2023).

On the other hand, sleep restriction therapy might prove counterproductive for professional and highly competitive esports players who often require more sleep due to the intensive demands of their training routines and the necessity of maintaining mental acuity, which is critical in esports. Therefore, we echo and extend the sentiment by Cook & Charest (2023) that applying CBT-I universally, or at least in its typical clinical form, might be inappropriate for this group. Further research is needed to identify which aspects of CBT-I, if any, are relevant to esports players, as well as how (and when) these can be best integrated into a customized sleep treatment program.

6.7.3 Behavior therapy and performance counseling

A separate but related consideration is behavior therapy, which may be more appropriate for improving perspectives around sleep. Specifically, motivational interviewing could be integrated with CBT-I or employed as an adjunct therapy to address ambivalence to sleep and health behavior change, given its potential to improve treatment compliance, uptake, and clinical outcomes (Morton et al., 2015; Randall & McNeil, 2017). Accordingly, esports players who experience high levels of stress due to demanding schedules and intense competition might find this type of counseling approach particularly useful to optimize esports performance and reduce the risk of burnout.

Similar to traditional athletes, esports players competing at elite levels may also engage in frequent transmeridian travel to compete in offline tournaments, typically in geographically polarized parts of the world (Bonnar et al., 2019a). These regular changes in time zones lead many athletes to become fatigued and jetlagged, with the intensity and duration of jet lag symptoms intensifying with trans-latitudinal travel over three or more time zones (Janse van Rensburg et al., 2021). Specifically, during the peak competitive season, esports athletes may participate in several tournaments within a tight timeframe, in which case the time between esports events could be insufficient to optimally stabilize esports players' sleep-wake behaviors in new time zones.

This type of frequent travel may disrupt circadian rhythms if transmeridian travel is required, leading to chronodisruption and problematic sleep, which in turn may inflict negative changes to performance and compel negative sleep behaviors like excessive caffeine consumption to battle sleepiness. Performance counseling around the management of jetlag could be effective in teaching players how to adapt to new time zones and develop healthy sleep habits, even when traveling. Likewise, combining pharmacological (e.g., administering melatonin, melatonin analogs, sedatives, or stimulants) with non-pharmacological strategies (e.g., light therapy, exercise, and phase shifting of sleep-wake cycles) to facilitate circadian entrainment may allow esports players to pre-emptively advance or delay sleep timing before a competition and limit the effects of jetlag depending on their east- or westward travel (Janse van Rensburg et al., 2021).

6.7.4 Collective approaches to sleep health in esports

Although these considerations may be useful to ameliorate the decrements attributed to gaming (in general) and increase sleep duration, the efficacy of these strategies may depend on their applicability to either individual players or teams. In other words, what works for one player might not work for another. As noted by Bonnar et al., “game performance hinges on good teamwork strategies” (Bonnar et al., 2019b, p. 63). In this regard, appropriating sleep health promotion strategies in a group setting with team members could prove useful for improving uptake by individual players. Therefore, integrating behavior change techniques, such as teaching goal setting, action planning, and self-monitoring (Samdal et al., 2017), would be beneficial to increasing broad adoption and compliance by interested esports players. It is also worth noting that a sleep intervention might not be implementable or valuable to everyone. Therefore, identifying candidates who might benefit from such a program through appropriate risk screening and integrating motivational strategies in those most resistant to health behavior change is necessitated for ensuring a successful sleep intervention.

Further to this, esports athletes, leagues, and tournament organizers also have a responsibility to promote healthy lifestyles and sleeping practices to ensure the well-being of its players. This can be achieved through a "top-down" approach, where leaders and prominent figures within the esports community model advocate for healthy habits. By promoting healthy lifestyles and sleeping practices, esports brands and individuals can set a positive example for the wider esports community, including impressionable amateur and grassroots players who might be more likely to adopt these habits upon seeing influencers prioritizing their health and sleep. This can help change the prevailing notion in gaming culture that "sleep is for the weak" and shift the emphasis towards a healthier, more sustainable approach to esports.

6.7.5 Physical activity promotion

The adverse health outcomes associated with excessive sedentary behavior are well-established, ranging from increased risk of non-communicable diseases such as obesity, insulin resistance, and cardiovascular disease to premature mortality (Patterson et al., 2018; Whitaker et al., 2018). In addition, there is a belief among researchers that extended gaming sessions that involve being seated for extended periods may raise the risk of developing venous thromboembolism, aptly dubbed “gamer’s thrombosis” (Rambaran & Alzghari, 2020). For instance, a case-control study revealed that extended periods of immobility due to computer screen time yielded a 2.8 times higher risk of venothrombolic events, the downstream effects of which are potentially life-threatening (Healy et al., 2010). Therefore, substituting esports’ natural propensity for sedentarism with regular physical activity would mitigate the adverse health effects of prolonged physical inactivity and confer several other far-reaching benefits, including improved sleep, physical health, and mental well-being.

In particular, physical activity intervention programs specifically engineered to improve esports performance might be more alluring to esports players than generic health promotion strategies. This might include employing activities that encourage long-term compliance, such as exercises esports players might find enjoyable, team-based sports or gamified physical activity programs personalized for each esports player. Gamification has proven to be effective in promoting healthier behaviors, such as exercise, among esports players (González et al., 2018). For example, using contextual learning, new information and behaviors can be integrated into a familiar context that esports players might already understand, such as using gaming terminology and scoreboards for an element of competition. Exergaming, or active video games, can also be incorporated into existing esports platforms to enhance the motivation of players to be more physically active (Bonnar et al., 2022; González et al., 2018). Likewise, integrating interventions with augmented reality or virtual reality systems like the Oculus (Oculus, Irvine, CA) or Valve Index (Valve Corporation, Bellevue, WA) might offer gamers an immersive virtual reality environment in which to mimic real-life scenarios, including dancing, virtual sports (e.g., golf, tennis, baseball), promoting physical activity.

Additionally, exercise-based relaxation techniques may help to reduce stress and burnout commonly experienced by young gamers (Smith et al., 2022). Some other considerations include modifications to the workstation and posture to prevent computer-related injuries, such as eye strain, back pain, and neck pain. This can be achieved through ergonomic modifications to the gamer's chair and computer setup, as well as by implementing regular breaks for stretching and movement to mitigate the risk of gamer's thrombosis (Emara et al., 2020). In addition, strength-training exercises targeting the cervical, thoracic, and lumbar spine, the pectoralis and anterior shoulder muscles, the periscapular muscles, the quadriceps and hamstring muscles, and the gluteal and deep hip muscles are also recommended to maintain flexibility and reduce the risk of injury (Emara et al., 2020). Finally, promoting health-friendly gaming policies can encourage more physically active and sleep-friendly gaming behaviors. In particular, game developers can be encouraged to include physical activity and sleep-friendly features in their games, and gaming organizations and events can establish policies that limit playing time and promote physical activity and sleep health.

It is important to note that there is some disagreement regarding the compliance of the physical activity of esports players with the WHO Guidelines on physical activity and sedentary behavior for adults aged 18-64 years (Trotter et al., 2020) versus a different study where 33.1% of esports players did not meet these recommendations (Rudolf et al., 2020). In both cases, physical inactivity was higher than the worldwide prevalence of physical activity insufficiency at 27.5% (Guthold et al., 2018) despite the latter study reporting that esports players were engaged in various sporting activities, including classic fitness training (36.0%), jogging (28.3%), and endurance sports like soccer (17.6%) (Rudolf et al., 2020). Contrary to both of those studies, a study on elite esports players reported physical activity levels that were three times higher than the WHO recommendations (Kari & Karhulahti, 2016), but this might be linked to esports players' rankings. In particular, higher-ranking players are reportedly more physically active than lower-ranking or recreational players. This might be explained by elite players having more opportunities to be physically active, especially after considering that monetization of their gaming time is a major motivation for them to play.

Beyond this, esports players' motivation to engage in physical activity is more often with performance enhancement in mind versus most typical players who likely do so for general health benefits (Trotter et al., 2020). As such, future research should examine physical activity patterns over extended monitoring periods to account for variability in movement behavior between weekends and weekdays and specific days of the week. This is particularly important because there might be unique routines that influence esports players' proclivity to engage in activities of a sedentary nature. For example, esports players might be less active on weekends than on weekdays, given the opportunity to engage more with gaming, in contrast to non-gamers, who might be more active due to not being confined to office deskwork.

Researchers might also need to reevaluate the methodology by which physical activity is measured. As highlighted in a previous study, most physical activity estimates assume that day-to-day error is random and that any two days during the monitoring period are identical; however, this might not be true after considering other potential external factors influencing participants' movement (McVeigh et al., 2016). For example, low levels of perceived safety due to crime can significantly impede individuals' movement and propensity to engage in physical activity (Rees-Punia et al., 2018). Similarly, physical activity levels vary throughout the year, with seasonal effects like cold winter weather or extreme summer heat also likely to reduce physical activity volume (Arnardottir et al., 2017). Finally, qualitative research would be useful to understand how and when best to implement exercise or movement interventions, especially considering Esports players' implicit sedentary lifestyle habits and unique circumstances of needing to balance work and gaming habits.

6.8 Conclusion

The findings in this thesis indicate that esports players exhibit a strong evening-oriented phenotype, as characterized by delayed sleep patterns and significant exposure to artificial light during night hours. While it is possible that esports and video gaming may naturally attract individuals who already have strong eveningness tendencies, the lifestyle and demands of esports players, including frequent and prolonged late-night gaming sessions, might also play a significant role in further shaping or reinforcing these behaviors. In addition, device-derived light data demonstrated that esports players were exposed to limited bright natural light during the day, which raises several interesting considerations concerning its ability to influence the sleep-wake schedules of these players. Furthermore, esports players demonstrated high levels of sedentary behavior, presumably related to the unique condition of prolonged seated gaming activities. Finally, despite cardiometabolic disease risk factors being unremarkable at this stage, these young adult esports players were characterized by short sleep duration, sleep onset latency, and frequent daytime napping, which, coupled with a high prevalence of smoking and sedentarism, may have striking cumulative downstream effects on cardiometabolic health later in life. By employing qualitative approaches, researchers could develop a more comprehensive understanding of the various factors influencing the unique sleep-related behaviors of esports players. This may in turn help raise awareness in the esports community around the relationships between sleep, gaming performance and the long-term health of gamers. Ultimately, these data may be used to advocate for both healthier gameplay standards and improved gaming performance, the latter of which may be attractive for esports players to adopt. As such, these findings offer important implications for future sleep and behavior change interventions, including those aimed at improving physical activity levels in esports players.

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Appendices

Appendix A: Ch.3 – Recruitment Poster

Appendix B: Ch.3 – Contact Information and Questionnaire

CALIBRATION, VALIDATION AND RELIABILITY TESTING OF THE ACTIWATCH 2 MONITOR

Date: ______________ Code: ______________

CONTACT INFORMATION

PERSONAL DETAILS

Name: ____

Surname: ____

Postal address: ____

____

____________________________ Code: _______

Email address: ____

Phone number (h): ____________________ Cell phone: ____________

Version 1 • Approved • 26 Jun 2017

Code: ______________

QUESTIONNAIRE

CALIBRATION, VALIDATION AND RELIABILITY TESTING OF THE ACTIWATCH 2 MONITOR

Date: ___________________

Date of birth: ___________________ (dd/mm/yyyy) Age: ____________ (years)

Sex: ☐ Female ☐ Male

ACSM EXERCISE PRE-PARTICIPATION SCREEN

1. Are you sedentary? ☐ Yes ☐ No

   Note:

   Yes: You **do not** participate in structured, moderate intensity (30-60% of HRR) exercise of at least 30min per session, on three or more days per week, and have not done so for the past 3months.

   No: You **have been participating** in structured, moderate intensity exercise of at least 30min per session, three times per week, for the past three months.

2. Do you **currently**, or have you **ever** in the past, experienced any of these **medical conditions**?

Pre-existing condition screen	Yes	No
Heart attack		
Undiagnosed chest pain		
Heart failure		
Abnormal heart beat / arrhythmia		
Rheumatic fever		
Heart murmur		
Cardiomyopathy		
Myocarditis		
Inherited cardiac defect		
Coronary artery bypass surgery		
Coronary stent / balloon angioplasty		
Heart transplant		
Cardiac pacemaker insertion		

Version 1 · Approved · 26 Jun 2017

Diabetes mellitus / pre-diabetic state (i.e. fasting glucose >5.5mmol/l)		
Chronic lung disease (e.g. emphysema / chronic bronchitis)		
Chronic kidney disease		

3. Do you **currently** experience any **symptoms of heart or blood vessel disease**?

Current symptom screen	Yes	No
Pain when exercising (in the chest / neck / jaw / upper limbs / upper back)		
Swollen ankles (significant swelling)		
Abnormal shortness of breath at rest / on mild exertion / when lying flat		
Dizziness / fainting during or after exercise		
Abnormal heart beats (palpitations)		
Long standing leg / calf pain when exercising that is relieved by rest (other than due to injury)		

OTHER HEALTH AND MEDICAL

Do you suffer from any other medical condition or disease not mentioned above?

☐ Yes ☐ No

If yes, please provide the following information:

Name of condition/disease	Date diagnosed

What medication, if any, are you **currently** using?

Name of medication	Purpose	Years taken

What supplements, if any, are you **currently** using?

Name of medication	Purpose	Years taken

Females only: Are you pregnant? ☐ Yes ☐ No

PHYSICAL ACTIVITY

Describe your usual physical activity during the past **three months** using the table below:

Activity name	Days per week	Session duration (min)	Intensity*
e.g. swimming	3	45min	M
e.g. walking the dog	4	20min	L

*Intensity scale:

Very light	Seated activity
Light	Housework
Moderate	Light sweat, but still able to hold a conversation
Vigorous	Out of breath, and struggling to hold a conversation

GLOBAL PHYSICAL ACTIVITY QUESTIONNAIRE

Physical Activity

Next I am going to ask you about the time you spend doing different types of physical activity in a typical week. Please answer these questions even if you do not consider yourself to be a physically active person.

Think first about the time you spend doing work. Think of work as the things that you have to do such as paid or unpaid work, study/training, household chores, harvesting food/crops, fishing or hunting for food, seeking employment.

In answering the following questions 'vigorous-intensity activities' are activities that require hard physical effort and cause large increases in breathing or heart rate, 'moderate-intensity activities' are activities that require moderate physical effort and cause small increases in breathing or heart rate.

	Questions	Response	Code
	Activity at work		
1	Does your work involve vigorous-intensity activity that causes large increases in breathing or heart rate like *[carrying or lifting heavy loads, digging or construction work*] for at least 10 minutes continuously?	Yes 1 No 2 *If No, go to P 4*	P1
2	In a typical week, on how many days do you do vigorous-intensity activities as part of your work?	Number of days:	P2
3	How much time do you spend doing vigorous-intensity activities at work on a typical day?	Hours : minutes:	P3 (a-b)

4	Does your work involve moderate-intensity activity that causes small increases in breathing or heart rate such as brisk walking *[or carrying light loads]* for at least 10 minutes continuously?	Yes 1 No 2 *If No, go to P 7*	P4
5	In a typical week, on how many days do you do moderate-intensity activities as part of your work?	Number of days:	P5
6	How much time do you spend doing moderate-intensity activities at work on a typical day?	Hours : minutes:	P6 (a-b)
Travel to and from places			
The next questions exclude the physical activities at work that you have already mentioned. Now I would like to ask you about the usual way you travel to and from places. For example to work, for shopping, to market, to place of worship.			
7	Do you walk or use a bicycle (*pedal cycle*) for at least 10 minutes continuously to get to and from places?	Yes 1 No 2 *If No, go to P 10*	P7
8	In a typical week, on how many days do you walk or bicycle for at least 10 minutes continuously to get to and from places?	Number of days	P8
9	How much time do you spend walking or bicycling for travel on a typical day?	Hours : minutes	P9 (a-b)
Recreational activities			
The next questions exclude the work and transport activities that you have already mentioned. Now I would like to ask you about sports, fitness and recreational activities (leisure).			
10	Do you do any vigorous-intensity sports, fitness or recreational (*leisure*) activities that cause large increases in breathing or heart rate like [*running or football,]* for at least 10 minutes continuously?	Yes 1 No 2 *If No, go to P 13*	P10
11	In a typical week, on how many days do you do vigorous-intensity sports, fitness or recreational (*leisure*) activities?	Number of days:	P11
12	How much time do you spend doing vigorous-intensity sports, fitness or recreational activities on a typical day?	Hours : minutes:	P12 (a-b)
13	Do you do any moderate-intensity sports, fitness or recreational *(leisure*) activities that causes a small increase in breathing or heart rate such as brisk walking,(*cycling, swimming, volleyball*)for at least 10 minutes continuously?	Yes 1 No 2 *If No, go to P16*	P13
14	In a typical week, on how many days do you do moderate-intensity sports, fitness or recreational (*leisure*) activities?	Number of days:	P14
15	How much time do you spend doing moderate-intensity sports, fitness or recreational (*leisure*) activities on a typical day?	Hours : minutes:	P15 (a-b)
Sedentary behaviour			
The following question is about sitting or reclining at work, at home, getting to and from places, or with friends including time spent [sitting at a desk, sitting with friends, travelling in car, bus, train, reading, playing cards or watching television], but do not include time spent sleeping.			
16	How much time do you usually spend sitting or reclining on a typical day?	Hours : minutes:	P16 (a-b)

Appendix C: Ch.3 – Ethics Clearance

UNIVERSITY OF CAPE TOWN
Faculty of Health Sciences
Human Research Ethics Committee

Room E53-46 Old Main Building
Groote Schuur Hospital
Observatory 7925
Telephone [021] 406 6626
Email: shuretta.thomas@uct.ac.za
Website: www.health.uct.ac.za/fhs/research/humanethics/forms

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22 June 2017

HREC REF: 334/2017

Dr Dale Rae
Sport Science Institute
Human Biology

Dear Dr Rae

PROJECT TITLE: DETERMINING CUT-POINTS AND ASSESSING THE VALIDITY AND RELIABILITY OF THE ACTIWATCH2 IN MEASURING PHYSICAL ACTIVITY (BSc-candidate-C Kemp)

Thank you for submitting your study to the Faculty of Health Sciences Human Research Ethics Committee.

It is a pleasure to inform you that the HREC has **formally approved** the above-mentioned study.

Approval is granted for one year until the 30 June 2018.

Please submit a progress form, using the standardised Annual Report Form if the study continues beyond the approval period. Please submit a Standard Closure form if the study is completed within the approval period.
(Forms can be found on our website: www.health.uct.ac.za/fhs/research/humanethics/forms)

Please quote the HREC REF in all your correspondence.

Please note that the ongoing ethical conduct of the study remains the responsibility of the principal investigator.

Please note that for all studies approved by the HREC, the principal investigator **must** obtain appropriate institutional approval before the research may occur.

The HREC acknowledge that the student, Chadley Kemp will also be involved in this study.

Yours sincerely

PROFESSOR M BLOCKMAN
CHAIRPERSON, FHS HUMAN RESEARCH ETHICS COMMITTEE
Federal Wide Assurance Number: FWA00001637.
Institutional Review Board (IRB) number: IRB00001938
This serves to confirm that the University of Cape Town Human Research Ethics Committee complies to the Ethics Standards for Clinical Research with a new drug in patients, based on the Medical

HREC 334/2017

Appendix D: Ch.3 – Participant Information Sheet and Informed Consent Form

PARTICIPANT INFORMATION SHEET AND CONSENT FORM

DETERMINING CUT-POINTS AND ASSESSING THE VALIDITY AND RELIABILITY OF THE ACTIWATCH2 IN MEASURING PHYSICAL ACTIVITY

Dear Volunteer,

We would like to provide you with information about the above-mentioned study, which will be conducted by researchers from the University of Cape Town (UCT)'s Division of Exercise Science and Sports Medicine, Department of Human Biology, Faculty of Health Sciences.

Why are we doing this study?

Physical activity is a behaviour that we can change, and is understood to improve health and reduce our risk for non-communicable diseases (i.e. diseases that cannot be passed from one person to another). Today there are many wearable activity monitors on the market, such as pedometers, which measure steps, and accelerometers, which measure vertical accelerations associated with movement of any type. These monitors have made it possible for researchers to measure physical activity, inactivity and sleep patterns in outside of the laboratory.

Examples of these physical activity monitors include Fitbit, Jawbone, ActivPal, Actical, ActiGraph and Actiwatch. Each has its own strengths and weaknesses, making some types better suited to measure sleep, while others provide better measures of physical activity during waking hours, and still others better measures of sedentary behaviour (i.e. low activity tasks such as sitting). Usually the monitors provide a measure of physical activity known as "counts". The problem with counts is that one count from one monitor may not be the same as one count from another monitor. Therefore, to make physical activity data comparable between monitors, the counts need to be converted to a standardised output, such as energy expenditure.

The Actiwatch2 is a wrist-worn monitor best known for its ability to predict sleep variables. This study has been designed to test how well the Actiwatch2 is able to measure physical activity, as well as to make sense of the count data obtained from the monitor so that we can compare it to other monitors in the future.

Version 1 · 26 Jun 2017 · Approved

Who can take part in this study?

- Males and females
- Aged between 18 and 60 years
- Usually participate in at least one exercise session (of at least 20min in duration) on at least one day per week during the past three months

Unfortunately the following individuals will not be able to participate:

- Pregnant ladies
- Anyone for whom exercise is contra-indicated, based on the American College of Sports Medicine Exercise Pre-participation guidelines

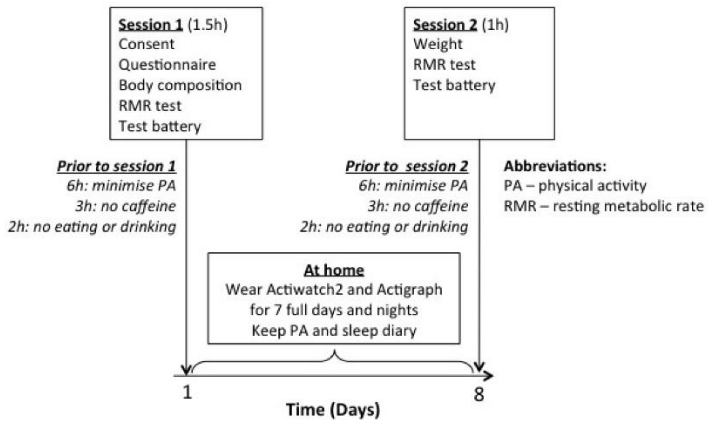
What will happen if you decide to take part in this study?

If you agree to participate in this study, we ask that you please read through this information sheet carefully, ask the investigator any questions you may have, and then sign the consent form. Participation in this study involves two visits to our laboratory at the Sports Science Institute of South Africa (SSISA) in Newlands for physical activity-related tests.

During the first visit, you will be asked to complete a questionnaire, following which the investigator will measure your height, weight and waist circumference. You will then lie quietly on a bed under a well-ventilated hood so that we can measure your resting energy expenditure. The investigator will then place the Actiwatch2 monitor on your wrist (the size of a small watch), the ActiGraph GT3X monitor around your waist (the size of a matchbox), a heart rate monitor around your chest, and a mask around your face, linked to a small backpack (the size of a lunchbox) holding a portable unit which will measure your energy expenditure. You will then be asked to perform the following tasks while we measure your heart rate, energy expenditure and counts (from the activity monitors).

	Task	Duration (min)	Intensity	Rest period (min)
1	Supine rest (awake)	5	-	0
2	Sitting	5	-	0
3	Standing	5	-	0
4	Treadmill walking	5	Light	2
5	Treadmill jogging	5	Moderate	2
6	Stair climbing	2 flights	Light	2
7	Stair descending	2 flights	Light	2
6	Stair climbing	2 flights	Moderate	2
7	Stair descending	2 flights	Moderate	2
8	Treadmill jogging	5	Vigorous	2
9	Cycling	5	Moderate	2
10	Cycling	5	Vigorous	2

During the week between the two visits, you will also be asked to wear the Actiwatch2 on your wrist and the ActiGraph GT3X around your waist for seven full days. These monitors will measure your physical activity and sleep patterns in your everyday routines. At the end of this week, you will be asked to return to the SSISA for the second testing session. This session will be identical to the first, with the exception that you will not be required to complete the questionnaire again. Below is an overview of the study:



How long will participation in this study take?

The first session will take approximately 1.5h. During the week between the first and second sessions we ask that you please continue to wear the two monitors – one on your wrist and one around your waist. The second session will take approximately 1h. In total, this study will span 8 days.

What are the risks and discomforts of this study?

There are no risks associated with completing a questionnaire or using the accelerometers to measure physical activity. There are minor risks associated with performing the physical activity tasks in this study, but these are no more than what one would experience while completing either regular activities-of-daily living or common exercise sessions. Also, the tasks are self-paced – which means that you will only work as hard as your current level of fitness allows. Only participants for whom exercise is considered safe using the ACSM's exercise pre-participation screening guidelines will be allowed to participate in these tests.

Are there any benefits to you for being in this study?

There are no direct benefits to you and you will not be remunerated for participating in this study. On completion of the study they will, however, receive general study feedback and a personal report containing information regarding your energy expenditure and sleep characteristics as measured during the study.

What are the other ethical considerations?

The University of Cape Town's Faculty of Health Sciences Human Research Ethics Committee (contact information below) has approved this study. The study will be performed in accordance with the principles of the Declaration of Helsinki (2013, Fortaleza, Brazil), International Conference on Harmonisation and the European Good Clinical Practice (GCP) guidelines, the South African GCP guidelines, and the laws of South Africa. The study will be covered by the University of Cape Town's no-fault insurance policy (more details below).

You will not be included in the study unless you have signed a consent form, after the investigator has provided substantial verbal and written explanation of the study, including risk factors. Participation in the study is entirely voluntary and you have the right to withdraw from the study at any time without stating a reason. The investigator may also withdraw you from the study at any time. All records and results generated from this study will be stored in a password-protected computer database to ensure your confidentiality and your information will not be passed on to any other parties. You will remain anonymous in any publication resulting from this study.

What happens if I get hurt taking part in this study?

This research study is covered by an insurance policy taken out by the University of Cape Town, in case you suffer a bodily injury because you are taking part in the study. The insurer will pay for all reasonable medical costs required to treat your bodily injury, according to the SA Good Clinical Practice Guidelines (2006). The insurer will pay without you having to prove that the research was responsible for your bodily injury. You may ask the study investigator for a copy of these guidelines.

If you are harmed and the insurer pays for the necessary medical costs, usually you will be asked to accept that insurance payment as full settlement of the claim for medical costs. However, accepting this offer of insurance cover does not mean you give up your right to make a separate claim for other losses based on negligence, in a South African court. It is important to follow the study investigator's instructions and to report straightaway if you have a become injured as a result of participation in this study.

Who do I speak to (or contact) if I have any questions about the study?

Should you have any ethical concerns or questions about the study, please contact the Human Research Ethics Committee:

Faculty of Health Sciences – Human Research Ethics Committee

Room E53-46, Old Main Building, Groote Schuur Hospital

Observatory, 7925

Tel: (021) 406 6338

Fax: (021) 406 6441

Email: nosi.tsama@uct.ac.za

Should you have any queries directly related to the study itself, please contact any of the investigators:

Principal investigator: Dr Dale Rae · 021 650 4577 · Dale.Rae@uct.ac.za

Co-investigator: Paula Pienaar · 021 650 4561 · PNRPAU001@myuct.ac.za

Student investigator: Chadley Kemp · 074 330 9617 · chadleyk@outlook.com

CONSENT FORM

I, the undersigned, have been fully informed about the study entitled "Determining cut-points and assessing the validity and reliability of the Actiwatch2 in measuring physical activity" to be conducted by researchers from the Division of Exercise Science and Sports Medicine within the Department of Human Biology, Faculty of Health Sciences at the University of Cape Town.

- I agree to complete a questionnaire disclosing my personal details and information relating to my medical, health and physical activity habits.
- I understand that my height, weight, waist circumferences and resting metabolic rate may be measured.
- I understand that I will be asked to complete the task battery described in the Information sheet above so that my heart rate and energy expenditures during each task may be measured on two separate sessions, separated by about one week.
- I agree to wear the **Actiwatch** on my wrist, the Actigraprh around my waist and to complete a **logbook** for seven consecutive days between sessions 1 and 2 logging my sleep and physical activity habits, as well as any illness I may suffer from, or medications / supplements I may use.

I have been informed about the risks involved in participating in this study. I understand that my personal details will be treated confidentially. I understand that I may (i) ask the investigator any questions about the tests and results of the study and (ii) withdraw from this study at any time without stating any reason. I also understand that the investigator may withdraw me from this study at any stage. I understand that I will receive general feedback regarding my personal results and that I will not be remunerated for participating in this study. I agree to participate in the study.

Participant:

________________________	__________________	__________________
Full name	Signature	Date

Investigator:

________________________	__________________	__________________
Full name	Signature	Date

Version 1 · 26 Jun 2017 · Approved

Appendix E: Ch.4-5 – Recruitment Poster and Press Release

Division of Exercise Science and Sports Medicine
Department of Human Biology, Faculty of Health Sciences
University of Cape Town, South Africa

HOW HEALTHY ARE COMPETITIVE COMPUTER GAMERS?

PARTICIPANTS WANTED FOR UCT RESEARCH

CARDIOMETABOLIC HEALTH AND NEUROCOGNITIVE PERFORMANCE IN COMPETITIVE COMPUTER GAMERS

The aim of this study is to characterize and compare the physical health and mental performance of competitive adult computer gamers to non-gamers.

If you:

- ✓ Are male or female between 18 and 30 years of age
- ✓ Reside in Cape Town
- ✓ Are a competitive computer gamer or are a non-gamer
- ✓ Are available to come to our laboratory on two occasions (1 week apart)
- ✓ have not been diagnosed with and are not on any medication known to influence sleep

You can volunteer for this study

What is involved?

- Complete a few questionnaires about your health and gaming history
- Have your height, weight, waist circumference and blood pressure measured
- Donate 3 teaspoons of blood to assess your risk for heart disease or diabetes
- Perform three computerized tests to assess your mental function
- Wear a small sleep monitor on your wrist and keep a sleep diary for 7 days

What are the benefits?

- Learn more about your own health and mental performance

If you are interested in taking part in the study and would like additional information, please contact:

Chadley Kemp
chadleyk@outlook.com
074 330 9617

Version 2 - Approved - 23 May 2018

MEDIA RELEASE
Sports Science Institute of South Africa
For immediate release

PARTICIPANTS REQUIRED FOR UCT RESEARCH STUDY:

HOW HEALTHY ARE COMPETITIVE COMPUTER GAMERS?

The Division of Exercise Science and Sports Medicine at the University of Cape Town is recruiting volunteers for a research study exploring the cardiometabolic health and neurocognitive performance of competitive computer video gamers. If you consider yourself to be a gamer and have ever wondered how gaming impacts your mental performance or physical health - this study is for you. We would like to compare the competitive gamers to non-gamers, so if you do not participate in regular or competitive computer gaming – this study is for you too.

All volunteers will be asked to visit the Sports Science Institute of South Africa (SSISA) on two occasions. During the first session they will complete questionnaires about their health and gaming habits. Body composition and blood pressure will be measured, and a small amount of blood drawn to assess risk for heart disease and diabetes. Participants will then wear a small sleep monitor on their wrist for the next 7 consecutive days while keeping a diary to assess their usual sleep habits. At the end of this week they will return to SSISA to complete a mood questionnaire and a battery of computerized tests to assess mental functioning and performance. The first session will take approximately 1.5h and the follow-up session about 1h.

Those interested in volunteering for this research should be/have:

- Male or female between the ages of 18 and 30 years old
- Resident in Cape Town
- Either a competitive computer gamer or a non-gamer
- Not suffer from any condition or take any medication known to affect sleep

Benefits of participating in the study include:

- Learn more about your own health and mental performance

To apply or for more information, please contact Chadley Kemp:

WhatsApp: 074 330 9617

E-mail: KMPCHA004@myuct.ac.za

Version 2 · Approved · 23 May 2018

Appendix F: Ch.4-5 – Ethics Clearance

ETHICS COMMITTEE
04 JUN 2022

UNIVERSITY OF CAPE TOWN

FACULTY OF HEALTH SCIENCES
Human Research Ethics Committee

FHS016: Annual Progress Report / Renewal

HREC office use only (FWA00001637; IRB00001938)			
This serves as notification of annual approval, including any documentation described below.			
☑ Approved	Annual progress report	Approved until/next renewal date	30.06.2023
☐ Not approved	See attached comments		
Signature Chairperson of the HREC/ Designee		Date Signed	5/6/2022

Note: Please email this form and supporting documents (if applicable) in a combined pdf-file to hrec-enquiries@uct.ac.za.
Please clarify your plan for research-related activities during COVID-19 lockdown.
Please use the latest form found on our website:
http://www.health.uct.ac.za/fhs/research/humanethics/forms

Comments to PI from the HREC

Principal Investigator to complete the following:

1. Protocol Information

Date (when submitting this form)	03/06/2022		
HREC REF Number	256/2016	Current Ethics Approval was granted until	30 May 2022
Protocol title	Sleep, cardiometabolic health and neurocognitive performance in competitive computer gamers		
Protocol number (if applicable)	N/A		
Are there any sub-studies linked to this study?	☐ Yes	✓ No	
If yes, could you please provide the HREC Reference number for all sub-studies? Note: A separate FHS016 must be submitted for each sub-study.			
Principal Investigator	Dr Dale Rae		
Department / Office Internal Mail Address	Division of Physiological Sciences, Department of Biology, Faculty of Health Sciences, University of Cape Town, 3rd Floor Sports Science Institute of South Africa Building, Boundary Road, Newlands. Email: Dale.Rae@uct.ac.za		

1.1 Does this protocol receive US Federal funding?	☐ Yes	✓ No

5 July 2021 Page 1 of 7 FHS016

(Note: Please complete the Closure form (FHS010) if the study is completed within the approval period)

Appendix G: Ch.4-5 – Participant Information Sheet and Informed Consent

PARTICIPANT INFORMATION SHEET AND CONSENT FORM

SLEEP, CARDIOMETABOLIC HEALTH AND NEUROCOGNITIVE PERFORMANCE IN COMPETITIVE COMPUTER GAMERS: A CROSS-SECTIONAL PILOT STUDY

Dear Volunteer,

We would like to provide you with information about the above-mentioned study, which will be conducted by researchers from the University of Cape Town (UCT)'s Division of Exercise Science and Sports Medicine, Department of Human Biology, Faculty of Health Sciences.

Why are we doing this study?

In recent years, the inception of competitive gaming (or "esports") has received mounting public interest. This comes after major investment into the scene, with most tournaments now offering millions of dollars in prize money. While similar to traditional sports in that esports is a professional industry with substantial commercial interest and public following, research interest is however, sorely lacking.

In South Africa, the circumstances are such that many gamers have regular daytime work, study and social commitments. Therefore, it is not uncommon for these gamers to spend many hours gaming at night. The result is that gamers may get significantly less sleep than is required. Beyond this, gaming before bed may also affect sleep quality, and make it harder to fall and stay asleep. Over time, poor sleep is also linked to an increased risk of developing obesity, heart disease and type 2 diabetes (i.e. blood sugar disease). Sadly, although we are beginning to understand the importance of sleep, we don't know what prolonged and excessive gaming might do to our health.

In addition to its health benefits, good quality sleep may also be critical for optimal gaming performance, since sleep is critical to brain function in general. This is especially true in learning and mental processes, which are important processes used in gaming. Although gaming may improve various aspects of mental function, it's not clear to what extent adequate quality and quantity of sleep may impact gaming performance. Beyond this, research findings have been inconsistent and gaming studies have generally been conducted in teenagers and children, and not in adults. Considering that short sleep is a major concern generally in young adults, one might argue that optimising sleep gamers may confer performance benefits.

The purpose of this pilot study is to characterize and understand the relationship between the health status, sleep patterns and mental performance of adult computer gamers.

Version 1 - 23 May 2018 - Approved

Who can take part in this study?

You can participate in this study if you:

- Are male or female
- Are aged between 18 and 30 years
- Have a regular, full-time job or are enrolled as a full-time student
- Are a competitive computer gamer OR are not a computer gamer (see criteria below)

If you are a competitive computer gamer, you can participate in this study if you:

- Have at least 5 years of competitive gaming experience in either amateur or semi-professional (ladder, 1st or 2nd tier) South African gaming leagues
- Play action- or strategy-based games (e.g. Dota 2, CSGO) more than 14 hours/wk
- Engage in gaming sessions (lasting at least 30 min) on at least 2 weekdays
- Have not been disengaged from gaming within the last 3 months

If you are NOT a computer gamer, you must have either:

- Have never played computer games before OR
- Have no prior exposure to competitive gaming **AND** you must not play games (regardless of platform - i.e. console or mobile) for more than **2 hours/wk,** in the last 6 months.

Unfortunately you will not be able to participate if you:

- Are pregnant
- Have worked any rotating or night-time shifts in the last 3 months
- Have taken any chronic medication for treatment of psychiatric or mental illness, such as antidepressants (Prozac, Zoloft, Celexa), stimulants (Adderall, Ritalin) and depressants (Xanax, Benzodiazepine, Cannabis) OR chronic medication known to affect sleep patterns, cortisol or circadian rhythms (such as, melatonin, prednisone, beta-blockers, blood pressure medication, and sleeping pills), in the last 6 months
- Have been medically diagnosed with any psychiatric or mental illness affecting sleep
- Struggle with substance abuse
- Are a console or mobile gamer
- Are a recreational (non-competitive) gamer
- Are on vacation or long-term leave
- Are caring for children living in your household under the age of 4 years.

What will happen if you decide to take part in this study?

If you agree to participate in this study, we ask that you please read through this information sheet carefully, ask the investigator any questions you may have, and then sign the consent form. Participation in this study involves two visits to our laboratory at the Sports Science Institute of South Africa (SSISA) in Newlands for health screening and mental performance testing.

In preparation for the first visit, we will ask you to fast overnight (i.e. no food or drinks beside water for at least 10 h prior to the visit). When you arrive, you will be asked to complete a series of electronic questionnaires detailing your personal details; medical history and current conditions; work; overall and mental health; habitual sleep; gaming activity; and video gaming addiction. The investigator will then measure your height, weight, waist circumference and blood pressure, before taking a small sample of your blood. Blood will be collected from your arm using a needle and be used to assess your risk of heart disease and diabetes by looking at the levels of glucose, insulin, HbA1c and blood lipids. After the blood draw, we will ask you to wear a small sleep monitor on your wrist and keep a diary for seven full days. The device will measure your sleep patterns and physical activity in your everyday routine.

At the end of this week, you will be asked to return to the SSISA for the second testing session. For this session you must not consume caffeine for 10 hours before the test. During this visit, you will complete a simple mood state questionnaire and then perform three computerized tests (whilst wearing a heart rate monitor) which measure various aspects of brain function (e.g. reaction time, alertness and vigilance; and executive function).

How long will participation in this study take?

The first session will take approximately 1 - 1.5 h. During the week between the first and second sessions we ask that you please continue to wear the sleep monitor on your wrist and maintain your diary each day. Do not change any of your usual daily behaviours, including your sleep, eating, physical and gaming activity. The second session will take approximately 1h. In total, this study will span 8 days.

What are the risks and discomforts of this study?

There are no risks associated with completing a questionnaire, using the sleep monitor or completing the computerized mental performance tests. There are minor risks associated with blood collection, including infection, delayed healing, swelling, physical pain, mental discomfort and injury to a nerve or a vessel. These risks are small and will be minimized via the use of trained phlebotomists, sterile techniques and disposable, single-use materials.

Are there any benefits to you for being in this study?

On completion of the study you will also receive general study feedback and a personal report containing information regarding your mental performance, health and sleep patterns as measured during the study.

Will I be compensated for taking part in this study?

You will receive monetary reimbursement of R150 towards your time and travel expenses.

What are the other ethical considerations?

The University of Cape Town's Faculty of Health Sciences Human Research Ethics Committee (contact information below) has approved this study. The study will be performed in accordance with the principles of the Declaration of Helsinki (2013, Fortaleza, Brazil), International Conference on Harmonisation and the European Good Clinical Practice (GCP) guidelines, the South African GCP guidelines, and the laws of South Africa. The study will be covered by the University of Cape Town's no-fault insurance policy (more details below).

You will not be included in the study unless you have signed a consent form, after the investigator has provided substantial verbal and written explanation of the study, including risk factors. Participation in the study is entirely voluntary and you have the right to withdraw from the study at any time without stating a reason. The investigator may also withdraw you from the study at any time. All records and results generated from this study will be stored in a password-protected computer database to ensure your confidentiality and your information will not be passed on to any other parties. You will remain anonymous in any publication resulting from this study.

What happens if I get hurt taking part in this study?

This research study is covered by an insurance policy taken out by the University of Cape Town, in case you suffer a bodily injury because you are taking part in the study. The insurer will pay for all reasonable medical costs required to treat your bodily injury, according to the SA Good Clinical Practice Guidelines (2006). The insurer will pay without you having to prove that the research was responsible for your bodily injury. You may ask the study investigator for a copy of these guidelines.

If you are harmed and the insurer pays for the necessary medical costs, usually you will be asked to accept that insurance payment as full settlement of the claim for medical costs. However, accepting this offer of insurance cover does not mean you give up your right to make a separate claim for other losses based on negligence, in a South African court. It is important to follow the study investigator's instructions and to report straight away if you have become injured as a result of participation in this study.

Who do I speak to (or contact) if I have any questions about the study?

Should you have any ethical concerns or questions about the study, please contact the **Human Research Ethics Committee:**

Faculty of Health Sciences – Human Research Ethics Committee
Room E53-46, Old Main Building, Groote Schuur Hospital
Observatory, 7925

Tel.: (021) 406 6338
Fax.: (021) 406 6441
Email: nosi.tsama@uct.ac.za

Should you have any queries directly related to the study itself, please contact any of the investigators:

Principal investigator:
Dr. Dale Rae
Tel.: (021) 650 4577
Email: dale.rae@uct.ac.za

Co-investigators:
A/Prof Laura Roden
Tel.: (021) 650 5322
Email: laura.roden@uct.ac.za

Dr. Gosia Lipinska
Tel.: (021) 650 3415
Email: gosia.lipinska@uct.ac.za

Student investigator:
Mr. Chadley Kemp
Cell.: 074 330 9617
Email: chadleyk@outlook.com

CONSENT FORM

I, the undersigned, have been fully informed about the study entitled "Sleep, cardiometabolic health and neurocognitive performance in novice & experienced gamers: a cross-sectional pilot study" to be conducted by researchers from the Division of Exercise Science and Sports Medicine within the Department of Human Biology, Faculty of Health Sciences at the University of Cape Town.

- I agree to complete questionnaires disclosing my personal details; medical history and current conditions; work; overall and mental health; habitual sleep; physical and gaming activity; and level of video gaming addiction.
- I understand that my height, weight, waist circumferences and resting blood pressure may be measured.
- I understand that I will be asked to donate a blood sample (approximately 3 teaspoons) to assess markers of my cardiometabolic health (including, fasting glucose and insulin, HbA1c, total cholesterol, HDL-C, LDL-C and triglycerides).
- I understand that I will be asked to complete a battery of mental performance tasks described in the Information sheet above so that aspects of my brain function may be measured.
- I agree to wear the Actiwatch 2 on my wrist and to maintain a diary for seven consecutive days between sessions 1 and 2, logging my sleep, physical and gaming activity habits, any illness I may suffer from, or medications / supplements I may use, as well as any caffeine I consume.

I have been informed about the risks involved in participating in this study. I understand that my personal details will be treated confidentially. I understand that I may (i) ask the investigator any questions about the tests and results of the study and (ii) withdraw from this study at any time without stating any reason. I also understand that the investigator may withdraw me from this study at any stage. I understand that I will receive general feedback regarding my personal results and that I will be reimbursed the amount of R150 towards my time and travel expenses related to participating in this study. I agree to participate in the study.

Participant:

Full name	Signature	Date

Investigator:

Full name	Signature	Date

Appendix H: Ch.4-5 – Screening Questionnaire

Contact Information

Please enter the relevant contact information in the fields below

* Required

1. **Email address** *

2. **What is your participant code?** *
   *Please ask the investigator to tell you what your code is.

3. **What is your first name?** *

4. **What is your surname?** *

5. **What is your physical address?** *

6. **What is your mobile number?**

7. **What is your landline number?**

Personal Information Questionnaire

* Required

1. **What is your participant code? ***

Demographics

2. **What is your current age in years? ***

3. **What is your date of birth? ***

   Example: December 15, 2012

4. **What is your sex? ***
   Mark only one oval.

   ◯ Female *Skip to question 5.*
   ◯ Male *Skip to question 6.*

5. **Are you currently pregnant? ***
   Mark only one oval.

   ◯ Yes *Skip to "Ineligible."*
   ◯ No *Skip to question 6.*

6. **Do you currently care for any children under 4 years of age living in your household? ***
   Mark only one oval.

   ◯ Yes *Skip to "Ineligible."*
   ◯ No *Skip to question 7.*

Employment Details

7. **What is your current employment status? ***
   Mark only one oval.

   ◯ Employed full time
   ◯ Employed part time *Skip to "Ineligible."*
   ◯ Self-employed full time
   ◯ Homemaker *Skip to "Ineligible."*
   ◯ Student full time *Skip to question 13.*
   ◯ Student part time *Skip to "Ineligible."*
   ◯ Unemployed or retired *Skip to "Ineligible."*

Employment Details

8. **What is your occupation? ***

9. **How many hours do you work per week?** *

Example: 4:03:32 (4 hours, 3 minutes, 32 seconds)

10. **What is your normal work start time?** *

Example: 8:30 AM

11. **What is your normal work end time?** *

Example: 8:30 AM

12. **Have you worked rotating or night time shifts in the last 3 months?** *

Mark only one oval.

- Yes *Skip to "Ineligible."*
- No *Skip to question 13.*

13. **Are you currently on vacation or long-term leave?** *

Note: if you took leave from work or studies just for today, then please select 'No'.
Mark only one oval.

- Yes *Skip to "Ineligible."*
- No *Skip to question 14.*

Mental Health

14. **Are you diagnosed with any mental or psychiatric condition?** *

This includes, but is not limited to: major depression, bipolar disorder, or personality disorder.
Mark only one oval.

- Yes *Skip to "Ineligible."*
- No

Overall and General Health

15. **Are you a smoker?** *

Mark only one oval.

- Yes
- No

16. **Has anyone in your immediate or extended family previously suffered or died from any of the following health conditions?** *

Check all that apply.

- [ ] Abdominal obesity
- [ ] High blood pressure (hypertension)
- [ ] High blood lipids (hypertriglyceridemia)
- [ ] High cholesterol (hypercholesterolemia)
- [ ] Diabetes (insulin-dependent)
- [ ] Diabetes (insulin-independent)
- [ ] Heart condition
- [ ] Stroke
- [ ] Heart attack
- [ ] Angina
- [ ] Bypass surgery

- [ ] Circulatory or peripheral vascular disease
- [ ] Coronary artery disease
- [ ] Do you have a history of sudden death in your family, under the age of 60 years?
- [ ] Other: ____________________

17. **Do you personally suffer from any of the following health conditions?** *
Check all that apply.

- [ ] High blood pressure (hypertension)
- [ ] High blood lipids (hypertriglyceridemia)
- [ ] High cholesterol (hypercholesterolemia)
- [ ] Diabetes (insulin-dependent)
- [ ] Diabetes (insulin-independent)
- [ ] Heart condition
- [ ] Stroke
- [ ] Heart attack
- [ ] Angina
- [ ] Bypass surgery
- [ ] Circulatory or peripheral vascular disease
- [ ] Coronary artery disease
- [ ] Other: ____________________

Supplements

18. **Are you currently taking any dietary supplements/vitamins?** *
Mark only one oval.

( ) Yes *Skip to question 19.*
( ) No *Skip to question 22.*

Supplements

19. **What supplements are you currently using?** *

____
____
____
____
____

20. **What is the purpose of you taking these supplements?** *

____
____
____
____
____

21. **How long have you been taking these supplements?** *

____

Medications

22. **Are you currently taking any prescribed medication?** *
Mark only one oval.

- ( ) Yes *Skip to question 23.*
- ( ) No *Skip to question 27.*

Medications

23. **Indicate if you have taken any one of the following medications within the last 6 months.** *
Mark only one oval.

- ( ) Antidepressants *After the last question in this section, skip to "Ineligible."*
- ( ) Antipsychotics *After the last question in this section, skip to "Ineligible."*
- ( ) Stimulants (Ritalin, Concerta) *After the last question in this section, skip to "Ineligible."*
- ( ) Sleep medication (Restoril, Ambien) *After the last question in this section, skip to "Ineligible."*
- ( ) Melatonin *After the last question in this section, skip to "Ineligible."*
- ( ) Corticosteroids (Prednisone) *After the last question in this section, skip to "Ineligible."*
- ( ) None of these

24. **What medication are you currently taking?** *

25. **What is the purpose of you taking this medication?** *

26. **How long have you been taking this medication?** *

Are you a gamer?

27. **Do you consider yourself a "gamer" in the broad sense?** *
Select 'Yes' if you are an occasional, recreational, or competitive gamer.
Mark only one oval.

- Yes *Skip to question 28.*
- No *Skip to question 38.*

Gaming Activity

28. **On what gaming platform do you play most frequently?** *
Mark only one oval.

- Computer
- Console (PlayStation, Xbox, Nintendo etc.) *Skip to "Ineligible."*
- Mobile *Skip to "Ineligible."*

29. **Which genre of games do you play most frequently?** *
If you play a combination of game genres, please select the genre you play most often. If you play Rocket League please select 'Other'.
Mark only one oval.

- Action games (Battlefield, Call of Duty, Counter Strike, Overwatch)
- Strategy games (Dota 2, League of Legends, Warcraft)
- Adventure games (Dark Souls, Amnesia) *Skip to "Ineligible."*
- Sports games (FIFA)
- Other: ____________________

30. **How many hours per week do you spend playing games?** *
This includes any matches and/or practices played during the week.
Mark only one oval.

- Less than 14 hours per week *Skip to "Ineligible."*
- About 14 hours per week
- More than 14 hours per week

31. **On which day(s) of the week do you usually play games?** *
Check all that apply.

- [ ] Monday
- [ ] Tuesday
- [ ] Wednesday
- [ ] Thursday
- [ ] Friday
- [ ] Saturday
- [ ] Sunday

32. **How many of your workday gaming sessions are at least 30 minutes in duration?** *
Mark only one oval.

- None, I don't play games on workdays *Skip to "Ineligible."*
- At least 1 *Skip to "Ineligible."*
- At least 2
- More than 2

33. **Have you been disengaged from your usual gaming routine within the last 3 months?** *

(Have you stopped your usual gaming routine for an extended period of time at anytime within the last 3 months?)

Mark only one oval.

- Yes *Skip to "Ineligible."*
- No

34. **Would you consider yourself a competitive gamer?** *

Select 'Yes' if you regularly play in any official gaming league (including ladder division). If you are a recreational gamer and play to socialize, then select 'No.'

Mark only one oval.

- Yes *Skip to question 35.*
- No *Skip to "Ineligible."*

Competitive Gaming Activity

35. **What division do you currently play in?** *

Mark only one oval.

- Amateur division (Ladder, 1st or 2nd division)
- Semi-professional division (Premiere division)
- Professional division (Masters division) *Skip to "Ineligible."*
- I represent South Africa on a national and/or international level *Skip to "Ineligible."*

36. **How long have you been exposed to competitive gaming?** *

Mark only one oval.

- Less than 5 years *Skip to "Ineligible."*
- About 5 years
- More than 5 years

37. **What game do you play most frequently, in your competitive capacity?** *

Mark only one oval.

- Dota 2 *Skip to "Submit Form."*
- Counter Strike *Skip to "Submit Form."*
- Overwatch *Skip to "Submit Form."*
- Battlefield *Skip to "Submit Form."*
- Call of Duty *Skip to "Submit Form."*
- League of Legends *Skip to "Submit Form."*
- Rocket League *Skip to "Submit Form."*
- Other: ______________________ *Skip to "Submit Form."*

Non-gamers

38. **Have you ever played in a competitive gaming league? ***
Mark only one oval.

- ⬭ Yes *Skip to "Ineligible."*
- ⬭ No

39. **Would you say you play games for more than 2 hours per week? ***
This includes games on any platform (computer or console) as well as mobile games like Candy Crush.
Mark only one oval.

- ⬭ Yes *Skip to "Ineligible."*
- ⬭ No *Skip to "Submit Form."*

Submit Form

You can now submit this form.

Stop filling out this form.

Ineligible

Sorry about that, but it seems that you are not eligible to participate in this study.

Psychosocial Health Screen Questionnaire

This questionnaire comprises four screening questionnaires. Please read and follow the instructions of each questionnaire very carefully.

* Required

1. **Please enter your participant code** *

Primary Care Post-traumatic Stress Disorder Screen (PC-PTSD)

(c) Cameron, R.P. and Gusman, D., 2003. The primary care PTSD screen (PC-PTSD): development and operating characteristics. Primary Care Psychiatry, 9(1), pp.9-14.

In your life, have you ever had any experience that was so frightening, horrible, or upsetting that, in the past month, you:

2. **1. Have had nightmares about it or thought about it when you did not want to?** *

   Mark only one oval.

   - Yes
   - No

3. **2. Tried hard not to think about it or went out of your way to avoid situations that reminded you of it?** *

   Mark only one oval.

   - Yes
   - No

4. **3. Were constantly on guard, watchful, or easily startled?** *

   Mark only one oval.

   - Yes
   - No

5. **4. Felt numb or detached from others, activities, or your surroundings?** *

   Mark only one oval.

   - Yes
   - No

Drug Abuse Screening Test (DAST-10)

The Drug Abuse Screen Test (DAST-10) was designed to provide a brief, self-report instrument for population screening, clinical case finding and treatment evaluation research. It can be used with adults and older youth.

Skinner HA (1982). The Drug Abuse Screening Test. Addict Behav 7(4):363-371. Yudko E, Lozhkina O, Fouts A (2007). A comprehensive review of the psychometric properties of the Drug Abuse Screening Test. J Subst Abuse Treatment 32:189-198.

Instructions

"Drug use" refers to (1) the use of prescribed or over-the-counter drugs in excess of the directions, and (2) any non-medical use of drugs.

The various classes of drugs may include cannabis (marijuana, hashish), solvents (e.g., paint thinner), tranquilizers (e.g., Valium), barbiturates, cocaine, stimulants (e.g., speed), hallucinogens (e.g., LSD) or narcotics (e.g., heroin).

These questions do NOT include alcoholic beverages.

Please answer every question. If you have difficulty with a statement, then choose the response that is mostly right.

These questions refer to drug use in the past 12 months...

6. **1. Have you used drugs other than those required for medical reasons?** *

   Mark only one oval.

   ◯ Yes

   ◯ No

7. **2. Do you use more than one drug at a time?** *

   Mark only one oval.

   ◯ Yes

   ◯ No

8. **3. Are you always able to stop using drugs when you want to?** *

   Mark only one oval.

   ◯ Yes

   ◯ No

9. **4. Have you had "blackouts" or "flashbacks" as a result of drug use?** *

   Mark only one oval.

   ◯ Yes

   ◯ No

10. **5. Do you ever feel bad or guilty about your drug use?** *

   Mark only one oval.

   ◯ Yes

   ◯ No

11. **6. Does your spouse (or parents) ever complain about your involvement with drugs?** *
Mark only one oval.

- Yes
- No

12. **7. Have you neglected your family because of your use of drugs?** *
Mark only one oval.

- Yes
- No

13. **8. Have you engaged in illegal activities in order to obtain drugs?** *
Mark only one oval.

- Yes
- No

14. **9. Have you ever experienced withdrawal symptoms (felt sick) when you stopped taking drugs?** *
Mark only one oval.

- Yes
- No

15. **10. Have you had medical problems as a result of your drug use (e.g., memory loss, hepatitis, convulsions, bleeding, etc.)?** *
Mark only one oval.

- Yes
- No

Alcohol Use Disorders Identification Test

The Alcohol Use Disorders Identification Test - Consumption (AUDIT-C) is a short three-item alcohol screen that is used to identify persons who are hazardous drinkers, or persons with active alcohol use disorders. This is a modified version of the 10-question AUDIT instrument.

(c) Bush, K., Kivlahan, D.R., McDonell, M.B., Fihn, S.D. and Bradley, K.A., 1998. The AUDIT alcohol consumption questions (AUDIT-C): an effective brief screening test for problem drinking. Archives of internal medicine, 158(16), pp.1789-1795.

16. **Are you male or female?** *
Mark only one oval.

- Male
- Female

17. **1. How often do you have a drink containing alcohol?** *
Mark only one oval.

- Never
- Monthly or less
- 2-4 times a month
- 2-3 times a week
- 4 or more times a week

18. **2. How many standard drinks containing alcohol do you have on a typical day?** *

Mark only one oval.

- 1 or 2
- 3 or 4
- 5 or 6
- 7 to 9
- 10 or more

19. **3. How often do you have six or more drinks on one occasion?** *

Mark only one oval.

- Never
- Less than monthly
- Monthly
- Weekly
- Daily or almost daily

Patient Health Questionnaire (PHQ-9)

(c) Kroenke K, Spitzer RL, Williams JB; The PHQ-9: validity of a brief depression severity measure. J Gen Intern Med. 2001 Sep 16(9):606-13.

20. **Over the last two weeks, how often have you been bothered by any of the following problems?** *

Mark only one oval per row.

	Not at all	Several days	More than half the days	Nearly every day
Little interest or pleasure in doing things?				
Feeling down, depressed, or hopeless?				
Trouble falling or staying asleep, or sleeping too much?				
Feeling tired or having little energy?				
Poor appetite or overeating?				
Feeling bad about yourself - or that you are a failure or have let yourself or your family down?				
Trouble concentrating on things, such as reading the newspaper or watching television?				
Moving or speaking so slowly that other people could have noticed?				
Being so fidgety or restless that you have been moving around a lot more than usual?				
Thoughts that you would be better off dead, or of hurting yourself in some way?				

Appendix I: Ch.4-5 – Questionnaires

Video Gaming Addiction Scale (Short Version)

The Gaming Addiction Scale measures the level of addiction. Game addiction is related to loneliness, anxiety, and depression, which are components that are measured by this questionnaire.

Lemmens, J.S., Valkenburg, P.M. and Peter, J., 2009. Development and validation of a game addiction scale for adolescents. Media Psychology, 12(1), pp.77-95.

1. **What is your participant code?** *

____

Video Gaming Addiction Scale

2. **How often during the last six months...** *

   Mark only one oval per row.

	Never	Rarely	Sometimes	Often	Very often
Did you think about playing a game all day long?	⬭	⬭	⬭	⬭	⬭
Did you spend increasing amounts of time on games?	⬭	⬭	⬭	⬭	⬭
Did you play games to forget about real life?	⬭	⬭	⬭	⬭	⬭
Have others unsuccessfully tried to reduce your game use?	⬭	⬭	⬭	⬭	⬭
Have you felt bad when you were unable to play?	⬭	⬭	⬭	⬭	⬭
Did you have fights with others (e.g., family, friends) over your time spent on games?	⬭	⬭	⬭	⬭	⬭
Have you neglected other important activities (e.g., school, work, sports) to play games?	⬭	⬭	⬭	⬭	⬭

Horne-Ostberg Morningness-Eveningness Questionnaire

An modified electronic version of the original questionnaire by Horne and Östberg, 1976. (c) Horne JA and Östberg O. A self-assessment questionnaire to determine morningness-eveningness in human circadian rhythms. International Journal of Chronobiology, 1976: 4, 97-100.

Instructions

a) Please read each question very carefully before answering.
b) Answer all questions as honestly as possible.
c) Answer questions in numerical order.
d) Each question should be answered independently of others.

DO NOT go back and check your answers

e) Your answers should reflect your ideal situations - as if you have no family, work and social pressures and are entirely free to choose behaviors that suit your body.

1. **Please enter your participant code** *

____

Questionnaire

2. **1. Approximately what time would you get up if you were entirely free to plan your day?** *
   Mark only one oval.
   - 5:00 AM – 6:30 AM
   - 6:30 AM – 7:45 AM
   - 7:45 AM – 9:45 AM
   - 9:45 AM – 11:00 AM
   - 11:00 AM – 12 noon

3. **2. Approximately what time would you go to bed if you were entirely free to plan your evening?** *
   Mark only one oval.
   - 8:00 PM – 9:00 PM
   - 9:00 PM –10:15 PM
   - 10:15 PM – 12:30 AM
   - 12:30 AM – 1:45 AM
   - 1:45 AM – 3:00 AM

4. **3. If you usually have to get up at a specific time in the morning, how much do you depend on an alarm clock?** *
   Mark only one oval.
   - Not at all
   - Slightly
   - Somewhat
   - Very much

5. **4. How easy do you find it to get up in the morning (when you are not awakened unexpectedly)?** *
Mark only one oval.

- Very difficult
- Somewhat difficult
- Fairly easy
- Very easy

6. **5. How alert do you feel during the first half hour after you wake up in the morning?** *
Mark only one oval.

- Not at all alert
- Slightly alert
- Fairly alert
- Very alert

7. **6. How hungry do you feel during the first half hour after you wake up?** *
Mark only one oval.

- Not at all hungry
- Slightly hungry
- Fairly hungry
- Very hungry

8. **7. During the first half hour after you wake up in the morning, how do you feel?** *
Mark only one oval.

- Very tired
- Fairly tired
- Fairly refreshed
- Very refreshed

9. **8. If you had no commitments the next day, what time would you go to bed compared to your usual bedtime?** *
Mark only one oval.

- Seldom or never later
- Less that 1 hour later
- 1 - 2 hours later
- More than 2 hours later

10. **9. You have decided to do physical exercise. A friend suggests that you do this for one hour twice a week, and the best time for him is between 7 - 8 AM. Bearing in mind nothing but your own internal "clock," how do you think you would perform?** *
Mark only one oval.

- Would be in good form
- Would be in reasonable form
- Would find it difficult
- Would find it very difficult

11. **10. At approximately what time in the evening do you feel tired, and, as a result, in need of sleep?** *
Mark only one oval.

- 8:00 PM – 9:00 PM
- 9:00 PM –10:15 PM
- 10:15 PM – 12:45 AM
- 12:45 AM – 2:00 AM
- 2:00 AM – 3:00 AM

12. **11. You want to be at your peak performance for a test that you know is going to be mentally exhausting and will last two hours. You are entirely free to plan your day.Considering only your "internal clock," which one of the four testing times would you choose?** *
Mark only one oval.

- 8 AM – 10 AM
- 11 AM – 1 PM
- 3 PM – 5 PM
- 7 PM – 9 PM

13. **12. If you got into bed at 11 PM, how tired would you be?** *
Mark only one oval.

- Not at all tired
- A little tired
- Fairly tired
- Very tired

14. **13. For some reason you have gone to bed several hours later than usual, but there is no need to get up at any particular time the next morning. Which one of the following are you most likely to do?** *
Mark only one oval.

- Will wake up at usual time, but will not fall back asleep
- Will wake up at usual time and will doze thereafter
- Will wake up at usual time, but will fall asleep again
- Will not wake up until later than usual

15. **14. One night you have to remain awake between 4 - 6 AM in order to carry out a night watch. You have no time commitments the next day. Which one of the alternatives would suit you best?** *
Mark only one oval.

- Would not go to bed until the watch is over
- Would take a nap before and sleep after
- Would take a good sleep before and nap after
- Would sleep only before the watch

16. **15. You have two hours of hard physical work. You are entirely free to plan your day. Considering only your internal "clock," which of the following times would you choose?** *
Mark only one oval.

- 8 AM – 10 AM
- 11 AM – 1 PM
- 3 PM – 5 PM
- 7 PM – 9 PM

17. **16. You have decided to do physical exercise. A friend suggests that you do this for one hour twice a week. The best time for her is between 10-11 PM. Bearing in mind only your internal "clock," how well do you think you would perform?** *

Mark only one oval.

- Would be in good form
- Would be in reasonable form
- Would find it difficult
- Would find it very difficult

18. **17. Suppose you can choose your own work hours. Assume that you work a five-hour day (including breaks), your job is interesting, and you are paid based on your performance. At approximately what time would you choose to begin?** *

Mark only one oval.

- 5 hours starting between 4 – 8 AM
- 5 hours starting between 8 – 9 AM
- 5 hours starting between 9 AM – 2 PM
- 5 hours starting between 2 – 5 PM
- 5 hours starting between 5 PM – 4 AM

19. **18. At approximately what time of day do you usually feel your best?** *

Mark only one oval.

- 5 – 8 AM
- 8 – 10 AM
- 10 AM – 5 PM
- 5 – 10 PM
- 10 PM – 5 AM

20. **19. One hears about "morning types" and "evening types." Which one of these types do you consider yourself to be?** *

Mark only one oval.

- Definitely a morning type
- Rather more a morning type than an evening type
- Rather more an evening type than a morning type
- Definitely an evening type

Pittsburgh Sleep Quality Index

Instructions

The following questions relate to your usual sleep habits during the past month only.

Your answers should indicate the most accurate reply for the majority of days and nights in the past month.

Please answer all questions.

1. **Please enter your participant code** *

Sleep and wake timing

2. **1. During the past month, what time have you usually gone to bed at night?** *

   Example: 8:30 AM

3. **2. During the past month, how long (in minutes) has it usually taken you to fall asleep each night?** *

4. **3. During the past month, what time have you usually gotten up in the morning?** *

   Example: 8:30 AM

5. **4. During the past month, how many hours of actual sleep did you get at night?** *

   Note: This may be different than the number of hours you spent in bed.

Sleep disturbances

For each of the remaining questions, select the one best response. Please answer all questions.

5. During the past month, how often have you had trouble sleeping because you ...

6. **a. Cannot get to sleep within 30 minutes** *

   Mark only one oval.

   - Not during the past month
   - Less than once a week
   - Once or twice a week
   - Three or more times a week

7. **b. Wake up in the middle of the night or early morning** *
Mark only one oval.

- Not during the past month
- Less than once a week
- Once or twice a week
- Three or more times a week

8. **c. Have to get up to use the bathroom** *
Mark only one oval.

- Not during the past month
- Less than once a week
- Once or twice a week
- Three or more times a week

9. **d. Cannot breathe comfortably** *
Mark only one oval.

- Not during the past month
- Less than once a week
- Once or twice a week
- Three or more times a week

10. **e. Cough or snore loudly** *
Mark only one oval.

- Not during the past month
- Less than once a week
- Once or twice a week
- Three or more times a week

11. **f. Feel too cold** *
Mark only one oval.

- Not during the past month
- Less than once a week
- Once or twice a week
- Three or more times a week

12. **g. Feel too hot** *
Mark only one oval.

- Not during the past month
- Less than once a week
- Once or twice a week
- Three or more times a week

13. **h. Had bad dreams** *
Mark only one oval.

- Not during the past month
- Less than once a week
- Once or twice a week
- Three or more times a week

14. **i. Have pain** *
Mark only one oval.

- Not during the past month
- Less than once a week
- Once or twice a week
- Three or more times a week

15. **j. Other reason(s), please describe...** *

16. **How often during the past month have you had trouble sleeping because of this?** *
Mark only one oval.

- Not during the past month
- Less than once a week
- Once or twice a week
- Three or more times a week

17. **6. During the past month, how would you rate your sleep quality overall?** *
Mark only one oval.

- Very good
- Fairly good
- Fairly bad
- Very bad

18. **7. During the past month, how often have you taken medicine to help you sleep (prescribed or "over the counter")?** *
Mark only one oval.

- Not during the past month
- Less than once a week
- Once or twice a week
- Three or more times a week

19. **8. During the past month, how often have you had trouble staying awake while driving, eating meals, or engaging in social activity?** *
Mark only one oval.

- Not during the past month
- Less than once a week
- Once or twice a week
- Three or more times a week

20. **9. During the past month, how much of a problem has it been for you to keep up enough enthusiasm to get things done?** *
Mark only one oval.

- No problem at all
- Only a very slight problem
- Somewhat of a problem
- A very big problem

21. **10. Do you have a bed partner or room mate?** *
Mark only one oval.

- No bed partner or room mate
- Partner/room mate in other room
- Partner in same room, but not same bed
- Partner in same bed

If you have a room mate or bed partner, ask him/her how often in the past month you have had . . .

22. **a. Loud snoring** *
Mark only one oval.

- Not during the past month
- Less than once a week
- Once or twice a week
- Three or more times a week

23. **b. Long pauses between breaths while asleep** *
Mark only one oval.

- Not during the past month
- Less than once a week
- Once or twice a week
- Three or more times a week

24. **c. Legs twitching or jerking while you sleep** *
Mark only one oval.

- Not during the past month
- Less than once a week
- Once or twice a week
- Three or more times a week

25. **d. Episodes of disorientation or confusion during sleep** *

Mark only one oval.

- Not during the past month
- Less than once a week
- Once or twice a week
- Three or more times a week

26. **e. Other restlessness while you sleep; please describe...** *

27. **How often during the past month have you noticed this?** *

Mark only one oval.

- Not during the past month
- Less than once a week
- Once or twice a week
- Three or more times a week

Epworth Sleepiness Scale

How likely are you to doze off or fall asleep, in contrast to just feeling tired? This refers to your usual way of life in recent times. Even if you haven't done some of these things recently, try to work out how they would have affected you. It is important that you answer each question as best as you can.

1. **Please enter your participant code** *

In the following situations, how likely are you to doze or fall asleep? ...

2. **Sitting and reading** *
   Mark only one oval.
   - Would never doze or sleep
   - Slight chance of dozing or sleeping
   - Moderate chance of dozing or sleeping
   - High chance of dozing or sleeping

3. **Watching TV** *
   Mark only one oval.
   - Would never doze or sleep
   - Slight chance of dozing or sleeping
   - Moderate chance of dozing or sleeping
   - High chance of dozing or sleeping

4. **Sitting inactive in a public place** *
   Mark only one oval.
   - Would never doze or sleep
   - Slight chance of dozing or sleeping
   - Moderate chance of dozing or sleeping
   - High chance of dozing or sleeping

5. **Being a passenger in a car for an hour** *
   Mark only one oval.
   - Would never doze or sleep
   - Slight chance of dozing or sleeping
   - Moderate chance of dozing or sleeping
   - High chance of dozing or sleeping

6. **Lying down in the afternoon** *
   Mark only one oval.
   - Would never doze or sleep
   - Slight chance of dozing or sleeping
   - Moderate chance of dozing or sleeping
   - High chance of dozing or sleeping

7. **Sitting and talking to someone** *

Mark only one oval.

- Would never doze or sleep
- Slight chance of dozing or sleeping
- Moderate chance of dozing or sleeping
- High chance of dozing or sleeping

8. **Sitting quietly after lunch (no alcohol)** *

Mark only one oval.

- Would never doze or sleep
- Slight chance of dozing or sleeping
- Moderate chance of dozing or sleeping
- High chance of dozing or sleeping

9. **Stopping for a few minutes in traffic while driving** *

Mark only one oval.

- Would never doze or sleep
- Slight chance of dozing or sleeping
- Moderate chance of dozing or sleeping
- High chance of dozing or sleeping

Positive and Negative Affect Schedule

This scale is a self-report measure of affect (emotion or desire as influencing behavior).

Instructions

a) This scale consists of a number of words that describe different feelings and emotions.
b) Read each item and then select how much you feel like this from the scale.
c) Indicate to what extent you feel IN GENERAL this way right now (i.e. at the present moment).

1. **Please enter your participant code** *

PANAS Questionnaire

2. **Indicate to what extent you feel this way right now.** *
   Mark only one oval per row.

	Very slightly or not at all	A little	Moderately	Quite a bit	Extremely
1. Interested					
2. Distressed					
3. Excited					
4. Upset					
5. Strong					
6. Guilty					
7. Scared					
8. Hostile					
9. Enthusiastic					
10. Proud					

3. **Indicate to what extent you feel this way right now.** *
   Mark only one oval per row.

	Very slightly or not at all	A little	Moderately	Quite a bit	Extremely
11. Irritable					
12. Alert					
13. Ashamed					
14. Inspired					
15. Nervous					
16. Determined					
17. Attentive					
18. Jittery					
19. Active					
20. Afraid					

Appendix J: Ch.4-5 – Sleep Diary

UCT Gaming Study - Diary **Name:**

Date:	Tuesday 27 Feb 2018							
Is this a **work day?**	Yes							
What time did you **get into bed?**	22h20							
What time did you try **to go to sleep?**	22h47							
What time did you **wake-up?**	06h30							
What time did you **get out of bed?**	06h45							
How would you rate the **quality** of your sleep?	☐Very poor ☐Poor ☐Average ✓ Good ☐Very good	☐Very poor ☐Poor ☐Average ☐Good ☐Very good	☐Very poor ☐Poor ☐Average ☐Good ☐Very good	☐Very poor ☐Poor ☐Average ☐Good ☐Very good	☐Very poor ☐Poor ☐Average ☐Good ☐Very good	☐Very poor ☐Poor ☐Average ☐Good ☐Very good	☐Very poor ☐Poor ☐Average ☐Good ☐Very good	☐Very poor ☐Poor ☐Average ☐Good ☐Very good
How **refreshed/ rested** did you feel when you woke up for the day?	☐Not at all ☐Slightly ☐Somewhat ✓ Well- ☐Very well-	☐Not at all ☐Slightly ☐Somewhat ☐Well- ☐Very well-	☐Not at all ☐Slightly ☐Somewhat ☐Well- ☐Very well-	☐Not at all ☐Slightly ☐Somewhat ☐Well- ☐Very well-	☐Not at all ☐Slightly ☐Somewhat ☐Well- ☐Very well-	☐Not at all ☐Slightly ☐Somewhat ☐Well- ☐Very well-	☐Not at all ☐Slightly ☐Somewhat ☐Well- ☐Very well-	☐Not at all ☐Slightly ☐Somewhat ☐Well- ☐Very well-
What time and for how long did you **nap or doze?**	17h30 (20min)							
Detail any **medication** or **supplements** you took today.	Name: Panado Dose: 500mg Time: 13h35	**Name:** Dose: Time:	**Name:** Dose: Time:	**Name:** Dose: Time:	**Name:** Dose: Time:	**Name:** Dose: Time:	**Name:** Dose: Time:	**Name:** Dose: Time:

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Version 1 - Approved - 23 May 2018

	Name: Herbex Dose: 1 caps Time: 07h00	**Name:** **Dose:** **Time:**	**Name:** **Dose:** **Time:**	**Name:** **Dose:** **Time:**	**Name:** **Dose:** **Time:**	**Name:** **Dose:** **Time:**	**Name:** **Dose:** **Time:**	**Name:** **Dose:** **Time:**
What exercises did you do today? **What time did you do this and how long?**	Gym; Jog 15h00 (1 hr); 18h00 (30 min)							
Rate the intensity of your exercise session on a scale of 1 to 5.	1 - Very difficult 2 - Difficult 3 - Moderate 4 - Easy 5 - Very easy							
What caffeinated products did you have? **What time was your last one?**	Red bull, coffee 18h50							
Did you play any games today? If so, what did you play? **Please also report what time you played each game and approximately for how long.** **Please be as accurate as possible.**	PUBG 20h30 (1h 20 min)							
	Dota 2 22h00 (3h)							
	N/A							
	N/A							

Appendix K: Ch.4 Supplementary Analyses

Correlation analyses in the combined cohort

Associations between sleep measures with markers of cardiometabolic health were examined. Cardiometabolic disease risk score (r=0.268, p=0.040), systolic blood pressure (r=0.293, p=0.024), and HOMA-IR (r=0.296, p=0.023) were each positively related to PSQI total score and were medium-strength correlations (Suppl. Table 1). Systolic blood pressure was negatively correlated with bedtime (r=-0.257, p=0.049) and wake-up time (r=-0.284, p=0.029), and HOMA-IR was positively related with wake-up time regularity (r=0.274, p=0.036) (Suppl. Table 2). Each of these relationships demonstrated associations that were medium in strength.

Associations were also performed to examine any relationships between sleep measures and parameters of neurocognitive performance. 1-back reaction time demonstrated a negative, medium-strength association with total sleep time (r=-0.290, p=0.026) (Suppl. Table 3). Additionally, 3-back reaction time was characterized by a negative medium-strength association with PSQI total score (r=-0.259, p=0.048) (Suppl. Table 3). No significant correlations were identified between sleep timing and regularity indices with neurocognitive performance outcome measures (Suppl. Table 4).

Suppl. Table 1. Correlation analysis matrix for sleep measures and markers of cardiometabolic health.

	1	2	3	4	5	6	7	8
1. Total sleep time [b]	-							
2. Sleep efficiency [a, b]	**0.375 ***	-						
3. PSQI total score [a]	-0.093	**-0.300***	-					
4. Cardiometabolic risk score	0.010	-0.104	**0.268 ***	-				
5. Body mass index [a]	-0.096	-0.062	0.141	**0.700 ***	-			
6. Systolic blood pressure	-0.055	-0.169	**0.293 ***	**0.539 ***	**0.352 ***	-		
7. Diastolic blood pressure	-0.131	0.007	0.255	**0.481 ***	0.250	**0.550 ***	-	
8. HOMA-IR [a]	-0.011	-0.040	**0.296 ***	**0.728 ***	**0.447 ***	0.210	**0.277 ***	-

Data are presented as Pearson's r correlation coefficient and were determined using Pearson's Product-Moment Correlation test. Sample size: n=59 (pooled). PSQI: Pittsburgh Sleep Quality Index; HOMA-IR: Homeostatic Model Assessment of Insulin Resistance. [a] Indicates data transformation (sleep efficiency: cubic transformation; PSQI total score: square root transformation; body mass index: log transformation; HOMA-IR: negative reciprocal square root transformation). [b] Indicates data is actigraphy-derived. The collinearity of variables is shaded in light gray. * Significance was accepted at p<0.050.

Suppl. Table 2. Correlation analysis matrix for sleep timing and regularity indices with markers of cardiometabolic health.

	1	2	3	4	5	6	7	8	9	10
1. Bedtime [a, b]	-									
2. Wake-up time [a, b]	**0.817 ***	-								
3. Sleep timing regularity [a, b]	**0.502 ***	**0.465 ***	-							
4. Bedtime regularity [a, b]	**0.464 ***	**0.383 ***	**0.775 ***	-						
5. Wake-up time regularity [a, b]	**0.438 ***	**0.427 ***	**0.791 ***	**0.353 ***	-					
6. Cardiometabolic risk score	-0.058	-0.037	0.068	0.039	0.141	-				
7. Body mass index [a]	0.012	-0.038	-0.056	-0.086	0.064	**0.700 ***	-			
8. Systolic blood pressure	**-0.257 ***	**-0.284 ***	-0.109	-0.061	-0.024	**0.539 ***	**0.352 ***	-		
9. Diastolic blood pressure	-0.064	-0.164	0.001	0.089	0.000	**0.481 ***	0.250	**0.550 ***	-	
10. HOMA-IR [a]	0.024	0.038	0.233	0.139	**0.274 ***	**0.728 ***	**0.447 ***	0.210	**0.277 ***	-

Data are presented as Pearson's r correlation coefficient and were determined using Pearson's Product-Moment Correlation test. Sample size: n=59 (pooled). HOMA-IR: Homeostatic Model Assessment of Insulin Resistance. [a] Indicates data transformation (bedtime: log transformation, wake-up time: log transformation, sleep timing regularity: log transformation, bedtime regularity: square root transformation, wake-up time regularity: log transformation, body mass index: log transformation, HOMA-IR: negative reciprocal square root transformation). [b] Indicates data is actigraphy-derived. The collinearity of variables is shaded in light gray. * Significance was accepted at p<0.050.

Suppl. Table 3. Correlation analysis matrix for sleep measures and neurocognitive performance.

	1	2	3	4	5	6	7
1. Total sleep time [b]	-						
2. Sleep efficiency [a, b]	**0.375 ****	-					
3. PSQI total score [a]	-0.093	**-0.300 ***	-				
4. 1-back reaction time [a]	**-0.290 ***	-0.170	0.185	-			
5. 2-back reaction time [a]	-0.101	0.039	-0.138	**0.273 ***	-		
6. 3-back reaction time [a]	0.064	0.157	**-0.259 ***	0.131	**0.408 ***	-	
7. 3-back accuracy [a]	-0.064	-0.135	-0.063	-0.232	0.047	0.049	-

Data are presented as Pearson's r correlation coefficient and were determined using Pearson's Product-Moment Correlation test. Sample size: n=59 (pooled). PSQI: Pittsburgh Sleep Quality Index. [a] Indicates data transformation (sleep efficiency: cubic transformation, PSQI total score: square root transformation, 1-back reaction time: negative reciprocal transformation, 2-back reaction time: negative reciprocal transformation, 3-back reaction time: log transformation: 3-back accuracy: cubic transformation). [b] Indicates data is actigraphy-derived. The collinearity of variables is shaded in light gray. * Significance was accepted at p<0.050

Suppl. Table 4. Correlation analysis matrix for sleep timing and regularity indices with neurocognitive performance.

	1	2	3	4	5	6	7	8	9
1. Bedtime [a]	-								
2. Wake-up time [a]	**0.817 ***	-							
3. Sleep timing regularity [a]	**0.502 ***	**0.465 ***	-						
4. Bedtime regularity [a]	**0.464 ***	**0.383 ***	**0.775 ***	-					
5. Wake-up time regularity [a]	**0.438 ***	**0.427 ***	**0.791 ***	**0.353 ***	-				
6. 1-back reaction time	-0.035	-0.169	-0.043	0.092	-0.059	-			
7. 2-back reaction time	0.172	0.119	0.126	0.172	0.016	**0.273 ***	-		
8. 3-back reaction time	0.133	0.155	-0.018	0.128	-0.171	0.131	**0.408 ***	-	
9. 3-back accuracy	0.100	0.115	0.103	0.255	0.028	-0.232	0.047	0.049	-

Data are presented as Pearson's r correlation coefficient. Correlations were determined using Pearson's Product-Moment Correlation test. Sample size: n=59 (pooled). All variables underwent data transformation (bedtime: log transformation, wake-up time: log transformation, sleep timing regularity: log transformation, bedtime regularity: square root transformation, wake-up time regularity: log transformation, 1-back reaction time: negative reciprocal transformation, 2-back reaction time: negative reciprocal transformation, 3-back reaction time: log transformation, 3-back accuracy: cubic transformation). [a] Indicates data is actigraphy-derived. The collinearity of variables is shaded in light gray. * Significance was accepted at p<0.050.

Suppl. Table 5. Correlations between sleep variables and markers of cardiometabolic health in all participants (n=59).

	CMD risk score		BMI [a]		SBP		DBP		HOMA-IR [a]	
	r	**Effect**	**r**	**Effect**	**r**	**Effect**	**r**	**Effect**	**r**	**Effect**
Total sleep time [b]	0.010	Negligible	-0.096	Small	-0.055	Small	-0.131	Small	-0.011	Negligible
Sleep efficiency [a, b]	-0.104	Small	-0.062	Small	-0.169	Small	0.007	Negligible	-0.040	Negligible
PSQI total score [a]	**0.268 ***	**Medium**	0.141	Small	**0.293 ***	**Medium**	0.255	Medium	**0.296 ***	**Medium**
Bedtime [a, b]	-0.058	Small	0.012	Negligible	**-0.257 ***	**Medium**	-0.064	Small	0.024	Negligible
Wake-up time [a, b]	-0.037	Negligible	-0.038	Negligible	**-0.284 ***	**Medium**	-0.164	Small	0.038	Negligible
Sleep timing regularity [a, b]	0.068	Small	-0.056	Small	-0.109	Small	0.001	Negligible	0.233	Small
Bedtime regularity [a, b]	0.039	Negligible	-0.086	Small	-0.061	Small	0.089	Small	0.139	Small
Wake-up time regularity [a, b]	0.141	Small	0.064	Small	-0.024	Negligible	0.000	Negligible	**0.274 ***	**Medium**

Data are presented as Pearson's r correlation coefficient and were determined using Pearson's Product-Moment Correlation test. Sample size: n=59 (pooled). The effect sizes presented are based on the strength of the correlation as assessed by the absolute value of the correlation coefficient (r), according to Cohen (1988). PSQI: Pittsburgh Sleep Quality Index; CMD: Cardiometabolic disease; BMI: body mass index; SBP: systolic blood pressure; DBP: diastolic blood pressure; HOMA-IR: Homeostatic Model Assessment of Insulin Resistance. [a] Indicates data transformation (sleep efficiency: cubic transformation; PSQI total score: square root transformation; bedtime: log transformation, wake-up time: log transformation, sleep timing regularity: log transformation, bedtime regularity: square root transformation, wake-up time regularity: log transformation, BMI: log transformation, HOMA-IR: negative reciprocal square root transformation). [b] Indicates data is actigraphy-derived. Effect sizes were characterized according to Cohen's classifications. * Significance was accepted at $p<0.050$.

Suppl. Table 6. Correlations between sleep variables and markers of neurocognitive performance in all participants (n=59).

	1-back reaction time		2-back reaction time		3-back reaction time		3-back accuracy	
	r	Effect	r	Effect	r	Effect	r	Effect
Total sleep time [b]	**-0.290 ***	**Medium**	-0.101	Small	0.064	Small	0.064	Small
Sleep efficiency [a, b]	-0.170	Small	0.039	Negligible	0.157	Small	-0.135	Small
PSQI total score [a]	0.185	Small	-0.138	Small	**-0.259 ***	**Medium**	-0.063	Small
Bedtime [a, b]	-0.035	Negligible	0.172	Small	0.133	Small	0.100	Small
Wake-up time [a, b]	-0.169	Small	0.119	Small	0.155	Small	0.115	Small
Sleep timing regularity [a, b]	-0.043	Negligible	0.126	Small	-0.018	Negligible	0.103	Small
Bedtime regularity [a, b]	0.092	Small	0.172	Small	0.128	Small	0.255	Medium
Wake-up time regularity [a, b]	-0.059	Small	0.016	Negligible	-0.171	Small	0.028	Negligible

Data are presented as Pearson's r correlation coefficient and were determined using Pearson's Product-Moment Correlation test. Sample size: n=59 (pooled). The effect sizes presented are based on the strength of the correlation as assessed by the absolute value of the correlation coefficient (r), according to Cohen (1988). PSQI: Pittsburgh Sleep Quality Index. [a] Indicates data transformation (sleep efficiency: cubic transformation; PSQI total score: square root transformation; bedtime: log transformation, wake-up time: log transformation, sleep timing regularity: log transformation, bedtime regularity: square root transformation, wake-up time regularity: log transformation, 1-back reaction time: negative reciprocal transformation, 2-back reaction time: negative reciprocal transformation, 3-back reaction time: log transformation: 3-back accuracy: cubic transformation). [b] Indicates data is actigraphy-derived. Effect sizes were characterized according to Cohen's classifications. * Significance was accepted at $p<0.050$.