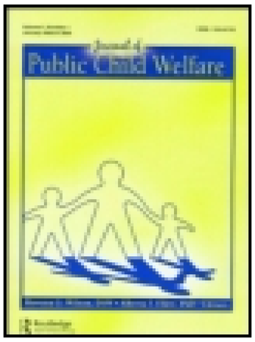

Journal of Public Child Welfare

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/wpcw20

Physiological evidence of escalating stress during COVID-19: a longitudinal assessment of child welfare workers

Austin Griffiths, Kim Link, Kara Haughtigan, Oliver W. J. Beer, Lindsey Powell & David Royse

To cite this article: Austin Griffiths, Kim Link, Kara Haughtigan, Oliver W. J. Beer, Lindsey Powell & David Royse (2023): Physiological evidence of escalating stress during COVID-19: a longitudinal assessment of child welfare workers, Journal of Public Child Welfare, DOI: 10.1080/15548732.2023.2182396

To link to this article: https://doi.org/10.1080/15548732.2023.2182396

Published online: 22 Feb 2023.

JOURNAL OF PUBLIC CHILD WELFARE
https://doi.org/10.1080/15548732.2023.2182396

Physiological evidence of escalating stress during COVID-19: a longitudinal assessment of child welfare workers

Austin Griffiths [a,b], Kim Link [b,c], Kara Haughtigan [c], Oliver W. J. Beer [b,d], Lindsey Powell [a,b], and David Royse [e]

[a]Department of Social Work, Western Kentucky University, Bowling Green, KY, USA; [b]LifeSkills Center for Child Welfare Education and Research, College of Health and Human Services, Western Kentucky University, Bowling Green, Kentucky, United States; [c]School of Nursing and Allied Health, Western Kentucky University, Bowling Green, KY, USA; [d]School of Health Professions, The University of Plymouth, Plymouth, England; [e]Professor Emeritus, College of Social Work, University of Kentucky, Lexington, KY, USA

ABSTRACT

Studies have shown that stress has contributed to employee turnover and retention problems for agencies, and at the individual level, chronic stress has been associated with coronary heart disease, anxiety, depression, and many other negative effects. In the past, the extent of stress one has felt has been measured by subjective paper-and-pencil instruments; however, recent technological advances have improved our ability to obtain accurate biofeedback assessments from wearable instruments. The Kentucky Child Welfare Workforce Wellness Initiative is the first known study to explore physiological stress in a sample (n = 32) of child welfare professionals using biometric technology (Firstbeat Bodyguard 2) and the first to report that data longitudinally over a four-month period. The study revealed that a variable associated with the strength of the Autonomic Nervous System (RMSSD) remained below the norms for a healthy population as participants experienced consistent and prolonged physiological stress. When examined relatively to the agency's lifting of COVID restrictions and returning to face-to-face service delivery, stress levels began to further rise almost to significant levels (p < .10) and the participants' ability to achieve a state of physiological relaxation significantly decreased. Future research employing biometric technology is also suggested.

ARTICLE HISTORY
Received 11 August 2022
Revised 7 February 2023
Accepted 13 February 2023

KEYWORDS
Child welfare; longitudinal; health; biomarkers; job stress

Introduction and presenting problem

In 2020, child welfare workers responded to approximately 3.9 million referrals alleging the maltreatment of 7.1 million children in the United States ((U. S. Department of Health & Human Services, 2022). These professionals are an essential safety mechanism for society addressing prevailing safety concerns, connecting families with services, and promoting positive outcomes. Yet,

CONTACT Austin Griffiths austin.griffiths@wku.edu Department of Social Work, Western Kentucky University 1906 College Heights Blvd, Bowling Green, 42101 KY, USA

a national study identified these professionals only stay in their positions for less than 2 years and estimates of turnover are reported to range from 15% to 40% (Boyas, Wind, & Ruiz, 2013; Edwards & Wildeman, 2018). Research has shown that stress associated with working in this field is responsible for employee turnover and negative outcomes for families and children (Griffiths, Desrosiers, Gabbard, Royse, & Piescher, 2019a; Royse & Griffiths, 2019), and the heightened stress associated with the COVID-19 pandemic may further contribute to this national problem (Gallup, 2021; Magruder, Wilke, Radey, Cain, & Yelick, 2022).

Literature review

Implications of occupational stress

Stress has been defined as a nonspecific response of the body to a problematic demand. Over time, the body's response to stress can result in poor health. Lifetime subjection to stress and limited physical activity are associated with coronary heart disease, poor survival from cardiac events, and changes to the immune and nervous systems (Stults-Kolehmainen, Tuit, & Sinha, 2014). Impacting workers both mentally and physically, stress has also been associated with anxiety, depression, difficulty sleeping, undesired weight changes, diabetes, and musculoskeletal disorders (American Psychological Association, 2021; Auten & Fritz, 2019; Kivimäki & Kawachi, 2015; Soteriades, Psalta, Leka, & Spanoudis, 2019).

Further, the National Institute for Occupational Safety and Health (NIOSH) defined occupational stress as the negative psychological and physiological responses that occur when an individual's job requirements do not align with the individual's needs, resources, and abilities (Sauter et al., 1999). Occupational stress can lead to the same diagnoses as lifetime stress (NIOSH, 2014). According to the World Health Organization, job-related stress may result in distressing emotions by challenging the employee's coping skills (Houtman, Jettinghof, & Cedillo, 2007). Thus, job-related stress can lead to significant costs to both employers and society (Hassard, Teoh, Visockaite, Dewe, & Cox, 2018). Due to the impact of occupational stress on the well-being of employees, it is both a global concern and a public health hazard.

Occupational stress in child welfare

Research has focused on the occupational stress of child welfare workers as they are responsible for providing vital services in their communities and have a direct connection with vulnerable populations. Given the direct connection between the presence of occupational stress in this position and increased turnover, decades of research have focused on outcomes associated with contributing factors of stress. Child welfare workers regularly work around the clock and for agencies that often face difficulties in obtaining resources (Beer, Phillips, Letson, & Wolf, 2021; Kim, Ji, & Kao, 2011). Also, research has identified that case severity, public perception, moral distress, and amount of time needed to spend with clients all contribute to stress (Kothari et al., 2021; Lawrence, Zeitlin, Auerbach, Chakravarty, & Rienks, 2018; Stahlschmidt, He, & Lizano, 2021; Zeitlin, Chakravarty, Lawrence, & DeCristofano, 2019). While the body of the literature examining factors that contribute to stress in child welfare is robust, a meta-analysis by Kim and Kao (2014) categorized all relevant factors leading to turnover into four domains including demographic predictors, work-related predictors, work environment, and attitudes/perceptions. Their study found that stress and burnout had a medium to high influence on turnover in child welfare.

Occupational stress on child welfare leads to consequential rates of high turnover, negatively affecting families and children through issues with service delivery and affecting the continuity of care due to the constant cycle of hiring and training new employees (Lizano, He, & Leake, 2021; Pharris, Munoz, & Hellman, 2022). High turnover is costly for agencies, forcing them to continually advertise new positions, interview candidates, and retain new employees. Thus, the National Child Welfare Workforce (NCWWI, 2016) institute estimates that it costs child welfare agencies around $54,000 for each worker that leaves the agency. High turnover in child welfare also places an elevated pressure on agency staff, resulting in negative outcomes in their lives. Research has reported that high rates of stress in child welfare are associated with decreased time with family, isolation, withdrawal, unhealthy work–life balance, and negative coping strategies (Beer et al., 2021; Griffiths, Royse, & Walker, 2018).

COVID-19 and child welfare

A state of national emergency was declared in the United States in March 2020 due to the COVID-19 pandemic, immediately changing the landscape of the child welfare system and impacting those who are responsible for providing services to children. Child welfare professionals were required to pivot from a face-to-face practice modality to working remotely and communicating with clients through virtual approaches – contributing a new set of stresses. System-wide shortcomings associated with technology, infrastructure, and the need for improved training became increasingly evident (Loria et al., 2021; Schwab-Reese, Drury, Allan, & Matz, 2020; Seay & McRell, 2021). Concerns about the pandemic's impact on child welfare practice (e.g., increased levels of maltreatment and placements, etc.) and whether child maltreatment was being adequately reported remain (Brown, Orsi, Chen, Everson, & Fluke, 2022; Merritt

& Simmel, 2020; Metcalf et al., 2022; Nugyen 2021; Wong, Ming, Maslow, & Gifford, 2020).

Given the potential impact on child welfare professionals, researchers have begun to explore the effects of stress during COVID. While limited, a study of 1996 child welfare workers found elevated stress levels on the COVID-19 Peritraumatic Distress Index, indicating that participants experienced mild to severe distress (Miller, Niu, & Moody, 2020). Further, Magruder et al. (2022) used open-ended responses to examine proximal and distal factors that influenced the well-being of 532 health and human service workers, who reported intrapersonal, interpersonal, and organizational factors affecting their well-being. Julien-Chinn, Katz, and Wall (2021) surveyed the coping techniques of over 250 child welfare workers and their relationship with the intention to leave. The study findings indicated that the coping skills used most often were diverse social supports, use of humor, physical self-care, hobbies, and mindfulness of vicarious trauma (Julien-Chinn et al., 2021). These preliminary explorations have set the table for a more comprehensive assessment of the stresses associated with working in child welfare during COVID-19. While it is unclear if the coronavirus will ever "disappear," what is clear is that agencies are tasked with transitioning back to service delivery in a format that is not entirely virtual. A better understanding of the effects during this transition period will assist child welfare agencies in responding.

Measuring occupational stress

There is a great agreement about the importance of the health and wellness of the child welfare workforce (Lizano et al., 20021; Bowman, 2022), yet little research has focused on the physical health of child welfare workers, and even fewer studies have used objective measures to collect physiological data (Griffiths, Royse, Flaherty, & Collins-Camargo, 2020). As of 2020, there were no frameworks or guidelines considering the dimensions of child welfare worker well-being (Lizano et al., 2021). A statewide study in Kentucky examined the attributions of various unhealthy habits that child welfare 117 supervisors and 511 frontline workers attributed to the stresses of their positions (Griffiths, Harper, Desrosiers, Murphy, & Royse, 2019b; Griffiths et al., 2018). These personal accounts provided details about how the stress of their positions were a catalyst for substance use, self-neglect, unhealthy eating, etc. Respondents attributed weight gain, high blood pressure, hair loss, and other physical and mental health issues to job stress. While this connection between occupational stress and health implications may not be a surprise to those with experience in child welfare, relying exclusively on the subjective self-reported accounts of those who are experiencing this stress may not be the most accurate or comprehensive approach. More objective and accurate data is needed to enhance our knowledge base and assess the implications of occupational stress, a significant problem that continues to impact the field of child welfare.

Objectively identifying and addressing the physiological response associated with elevated stress is imperative, as its prolonged chronic occurrence can be detrimental (Dickson et al., 2022). Historically, the stress has been measured subjectively (Jeon & Kim, 2018; Ravalier, 2019; Soteriades et al., 2019). More recently, researchers are using objective measurements (e.g., heart rate and heart rate variability (HRV)) to understand the physiological effects of stress (Endukuru & Tripathi, 2016; Järvelin-Pasanen, Sinikallio, & Tarvainen, 2018; Kim, Cheon, Bai, Lee, & Koo, 2018; Verkuil, Brosschot, Tollenaar, Lane, & Thayer, 2016; Wettstein, Kühne, Tschacher, & La Marca, 2020). HRV is provides a reliable reflection of the heart's response to functions of the ANS, and it is an objective indicator for measuring conditions associated with mental health and stress (Kim et al., 2018; Rajendra Acharya, Paul Joseph, Kannathal, Lim, & Suri, 2006; Ritvanen, Louhevaara, Helin, Väisänen, & Osmo Hänninen, 2006; Van Amelsvoort, Schouten, Maan, Swenne, & Kok, 2000; Verkuil et al., 2016). With respect to its interpretation, an increased HRV is associated with efficient autonomic nervous system function, and a decreased HRV is concerning due to its association with poor health outcomes (e.g., anxiety disorders, cardiovascular diseases, diabetes) (Benichou et al., 2018; Chalmers, Quintana, Abbott, & Kemp, 2014; Patel et al., 2017; Schiweck, Piette, Berckmans, Claes, & Vrieze, 2019). There are different approaches to measuring HRV, but the primary time-domain measure for detecting changes in HRV is the root mean square differences of successive intervals between heartbeats (RMSSD) (Shaffer & Ginsberg, 2017).

Approaches to managing occupational stress

Along with objectively measuring occupational stress, approaches to managing occupational stress must also be considered. Occupational stress can be overwhelming. When attempting to offset this stress, some approaches have been developed to promote workforce wellbeing in a general context. While not intended to be an inclusive list, current approaches that attempt to manage overwhelming occupational stress include exercise-based interventions, Total Worker Health, resilience-based interventions, and psychological interventions. The Occupational Safety and Health Administration (OSHA) offers guidelines for employers who want to assist their employees in stress management, titled *Safe Workplace, Good Headspace* (OSHA, 2022). Guidelines under the program include considerations for supervisors, such as empathy, access to coping resources, awareness of emotional load, and factors that can make work more difficult. Further, the National Institute for Occupational Safety and Health (NIOSH) created a holistic approach for employers to use that is adaptable to organizational needs, known as Total Worker Health. Formally launched in 2011, the Total Worker Health program touches on workplace strategies including community supports, policies, compensation, and chronic illness prevention to support overall workforce wellness (CDC, 2020). Since 2011, Total Worker Health has become one of the most researched workforce wellness approaches.

In the realm of child welfare agencies, there is less congruence related to the adoption of approaches for occupational wellness. Recent research has continued to examine the impact of self-care, supervision, and work-life balance on the child welfare worker wellness (Mack, 2022; Miller, 2020). However, the necessary development of practical frameworks for child welfare workforce wellness programs may benefit from a better understanding of the depth and magnitude of the stress experienced by these professionals.

Purpose of study

On June 11th, 2021, child welfare workers in Kentucky were notified that the agency was lifting restrictions on face-to-face contact with families. This correspondence was a directive from the Governor's Office and the Department for Public Health. Until this time, the previous 14 months consisted of agency restrictions where child welfare workers used virtual means of contact to initiate investigations and facilitate monthly home visit with families and children in out-of-home care. While this change in policy reflects a shift in expectations for service delivery, it did not alter the requirements for the location of employees related to their workstation. Agency staff were still able to continue to work either 100% remotely or operate from a county-specific plan where they would report to the local office for a pre-determined number of days per week. Regardless, resuming face-to-face contact immediately as it relates to the initiation of referrals, home visits, visitations with children in out-of-home care, regular foster home visits, and visitation between children and their families brought back the challenges of working in this position (e.g., required travel, home visits, safety risks, contact with collateral and community partners, etc.). Uniquely, it also added new pandemic-related factors as well (e.g., risk of exposure to COVID-19 from entering client homes, etc.). The purpose of this study is to use biometric analytic technology to examine the physiological impact of working in child welfare during COVID-19 over time. The focus will be on the assessment of physiological stress before and after the implementation of this policy change on June 11th, 2021.

Research question

1: Using relevant metrics from the Firstbeat Bodyguard 2, what is the biometric profile of a sample of child welfare professionals over a four-month span (e.g., May through August) in 2021?

2: Based on the biometric feedback from the Firstbeat Bodyguard 2, did the physiological stress of child welfare workers significantly increase over the 3 months (e.g., June through August of 2021) following the removal of COVID-19 restrictions?

3: Based on the biometric feedback from the Firstbeat Bodyguard 2, did the physiological relaxation of child welfare workers significantly decrease over the 3 months (e.g., June through August of 2021) following the removal of COVID-19 restrictions?

Methodology

Sample

A total of 81 child welfare professionals in a public child welfare agency were employed in positions as frontline workers and supervisors in the spring of 2021 across the region of interest. An effort was made to communicate with all of these prospective individuals through a preliminary e-mail and subsequent zoom information sessions where the protocol and criteria for exclusion from the study were described (e.g., pregnancy or the use of medications that could affect the biometric assessments). Additionally, criteria for inclusion limited participants to only these frontline service workers with client contact who did not work in an administrative or an auxiliary support role (e.g., CPS investigators, CPS ongoing workers, and CPS frontline supervisors). The recruitment process lasted for around 45 days, resulting in Cohort 1 of the study consisting of 32 frontline child welfare workers in south central Kentucky. Informed consent documentation was signed electronically using Qualtrics. Table 1 displays the demographic characteristics of the 24 participants in Cohort 1 who finished the final biometric screening in August 2021.

Demographic variables revealed minimal gender, racial, or ethnic diversity. Participants primarily identified as white (70.8%) and female (95.8%), while a small percentage identified as male (3.1%). The remaining percentage of nonwhite participants was African American (16.6%) and Biracial or Multiracial (12.5%). Participants' ages ranged from 22 to 60 and averaged 37.52 years (SD = 10.62). Participants' years of service at the agency ranged from 1 to 27 years, at an average of 9.42 years of service (SD = 8.33). Related to sexual orientation, most identified as heterosexual (83.3%), while one identified as lesbian (4.2%), two preferred not to respond (8.3%), and one selected "other" (4.2%). Regarding marital status, most participants stated that they were either married (50.0%) or never married (41.7%), while two reported that

Table 1. Sample characteristics of cohort 1 frontline child welfare workforce (n = 24).

Worker characteristics	*F* (Valid%)	Range	M (SD)
Age		22–60	37.52 (10.62)
Years worked for the agency		1–27	9.42 (8.33)
Gender			
Female	23 (95.8)		
Male	1 (4.2)		
Racial/ethnic identity			
White	17 (70.8)		
African American	4 (16.6)		
Biracial or multiracial	3 (12.5)		
Marital status			
Married	12 (50.0)		
Never married	10 (41.7)		
Divorced	2 (8.3)		
Current sexual orientation			
Heterosexual/straight	20 (83.3)		
Lesbian	1 (4.2)		
Prefer not to respond	2 (8.3)		
Other	1 (4.2)		
Highest degree earned			
Undergraduate degree, social work	12 (50.0)		
Undergraduate degree, other (not social work)	6 (25.0)		
Graduate degree, social work	5 (20.8)		
Graduate degree, other (not social work)	1 (4.2)		
*In general, would you say your health is:			
Poor	0 (0.0)		
Fair	7 (29.2)		
Good	14 (58.3)		
Very good	2 (8.3)		
Excellent	1 (4.2)		

*Item taken from the PROMIS (Hays et al., 2009).

they had been divorced (8.3%). Additionally, participants responded to an item related to their perceived general health (Hays et al., 2009). Responses revealed that many participants felt “good” about their overall health (n = 14; 58.3%), while a portion reported that their health was “fair” (n = 7; 29.2%). Two reported that their health was “very good” and one stated that it was “excellent.”

Design and data collection

The exploratory and longitudinal research design (Schober & Vetter, 2018) of the Kentucky Child Welfare Workforce Wellness Initiative (KCWWWI) utilized a series of sequential (e.g., repeated) subjective and objective measures, focused on collecting data related to occupational stress and salient variables known to influence working in child welfare (e.g., job satisfaction, burnout, and anxiety). Facilitated across 2 years, the project was approved by the IRB at the university (#21–201) and by an IRB/IEC Authorization Agreement with the state’s child welfare agency. The interdisciplinary research team included nursing and social work faculty employed by the university, and not the state agency, ensuring the protection of data. Fully supported by the child welfare agency, employees were given work time to participate in the project. An essential component of the project is the integration of biometric analytic technology and a custom designed mindfulness-based intervention. The initiative included two separate cohorts of frontline child welfare professionals. Cohort 1 began data collection in the spring of 2021, and after its completion, cohort 2 began the process in early 2022. While future efforts will explore additional data from this initiative, this manuscript will examine the objective biometric data assessments from cohort 1 collected between May and August 2021.

The Firstbeat Bodyguard 2 was used in this project to collect biometric data. The Bodyguard 2 is a mobile, lightweight, minimally invasive device that attaches directly to the chest through two small electrodes. It has been found to be an effective, reliable, and valid means for collecting extensive information about the functions of the human body based on heartbeat measurements (Palmer, Distefano, Leneman, & Berry, 2021; Parak & Korhonen, 2015; Umair, Chalabianloo, Sas, & Ersoy, 2021). Mobile electrocardiography (ECG) devices such as the Bodyguard 2 have been identified as accurate and viable indicators of measuring Heart Rate Variability (Esco, Fedewa, & MacDonald, 2017). Further, the Bodyguard 2 collects RMSSD over a 24-h period. When compared to short-term data collection, 24-h HRV recordings are known as the "gold-standard" for clinical assessments (Kleiger, Stein, & Bigger Jr, 2005; Shaffer, McCraty, & Zerr, 2014). The Bodyguard 2 is also an effective and valid approach for measuring variations in sleep stages (Kuula & Pesonen, 2021).

Participants received specific instructions on how to wear the devices from the research team, who were available for consultation throughout the protocol. For Cohort 1, participants were asked to wear the devices every 4th week, during a 72-h timeframe during the workweek (Tuesday morning through Friday morning). Each data collection week, the research team would drop off devices on Mondays and work to collect them on Friday afternoons. After cleaning the devices, the research team would upload and sync user data to Firstbeat's cloud-based software system and move forward with data collection, storage, and analysis (Firstbeat Technologies, Ltd, 2019a, 2019b). Data for this manuscript will only include biometric data collection for Cohort 1 across the 4 months of May, June, July, and August of 2021. After the first data collection point in May 2021, the agency notified staff of the lifting of COVID-19 restrictions that had been in place for approximately 14 months and the requirement to resume face-to-face service delivery.

Physiological measures

The Firstbeat Bodyguard 2 collects extensive biometric information about the individual, much of which is beyond the purpose of this manuscript (e.g., oxygen levels, physical activity, etc.). In this investigation, a focus is on the salient variables related to the dimensions of the participant's physiological autonomic nervous system (ANS) and their Heart Rate Variability (HRV). Firstbeat's analysis server uses these biometric indicators as collected by the Firstbeat Bodyguard 2 device, and seven key continuous physiological measures will be examined and reported as an average for each assessment. Given the nature of their positions and the focus on collecting complete data related to participant sleep, the research team did not determine a uniform "24-h day" for data collection (e.g., 7am Monday to 7am Tuesday, etc.). Rather, an individualized approach was utilized, and each daily split began when the person awoke each morning.

Variables included in this analysis are the average session assessment (in hours), which reflects the amount of time each day devices were collecting data during the 72-h window. Heart rate is also utilized, as averages of both the minimum and maximum values per daily assessment. Related to measuring the presence of stress, Firstbeat indicates the percentage of each person's daily session assessment attributed to an increased activation in the body where the sympathetic nervous system dominates the parasympathetic nervous system (e.g., physiological stress). Related to physiological relaxation, Firstbeat uses two biometric indicators associated with sleep. These are the amount of sleep time in hours and the average of RMSSD during sleep per daily session assessment. Finally, Firstbeat indicates the percentage of each person's daily session assessment attributed to a decreased activation in the body where the parasympathetic nervous system dominates the sympathetic nervous system (e.g., relaxation).

Data analysis process

Data analysis was preceded by the ongoing data collection of the Firstbeat Bodyguard 2 device, the collection and cleaning of the devices by the research team, and the uploading and syncing of the individual devices to the Firstbeat analysis server (Firstbeat, 2019b). Then, raw data was exported to SPSS Version 28 for cleaning, preparation, and analysis. Decisions were made to only include participant contributions that met the following conditions: (1) Each daily assessment session must have logged 1224 minutes or 85% of a 24-h data collection period (Firstbeat Technologies, Ltd, 2019a); (2) The participant must have worked at the agency during the day of data collection; (3) The participant must have experienced some sleep during their daily assessment session (e.g., not stayed up 24 hours).

Results

Individual and group means were calculated to identify the physiological presence of stress, relaxation, and sleep in a sample of child welfare workers across a four-month period. Table 2 provides group means, based on

Table 2. Descriptive physiological indicators of the sample across 4 months (M, SD).

	May (*n* = 29)	June (*n* = 28)	July (*n* = 21)	August (*n* = 24)
Session totals (h)	23.83 (0.57)	23.74 (0.38)	23.65 (0.79)	23.79 (0.88)
Heart rate (Min)	61.32 (8.96)	62.10 (9.64)	62.93 (8.47)	60.70 (8.82)
Heart rate (Max)	145.98 (15.00)	139.27 (14.59)	143.21 (15.29)	139.33 (12.47)
Sleep time (h)	7.73 (1.13)	7.59 (1.02)	7.60 (1.33)	7.55 (1.18)
RMSSD sleep	31.91 (21.22)	34.40 (27.35)	31.10 (22.88)	34.12 (31.93)

individual mean contributions per assessment session. While there was some attrition in the sample, participation numbers across all 4 months also reflected individuals taking vacations during data collection weeks (e.g., July). Despite the rather invasive nature of this innovative health project (e.g., wearing a device on your person for 72 hours, every 4th week), the dedication of these participants resulted in 24 of the 32 participants finishing the fourth biometric data assessment in August 2021. Of note, two participants chose to leave the project just before biometric data collection began in May 2021.

The session time totals across all 4 months averaged from 23.65 to 23.83 hours. This is within a few minutes of the "gold-standard" of data collection at 24 hours, and the start and stop times on the daily assessments were determined organically to ensure the complete collection of data related to sleep for each participant (e.g., not to cut off an assessment during a participant's sleep so that it was on two separate assessment periods).

Research question 1

1: Using relevant metrics from the Firstbeat Bodyguard 2, what is the biometric profile of a sample of child welfare professionals over a four-month span (e.g., May through August) in 2021?

Heart rate minimums across the four-month protocol averaged between 60.70 and 62.93, and heart rate maximums averaged between 139.27 beats per minute and 145.98 beats per minute. Sleep time remained consistent across the 4 months, averaging between 7.55 and 7.73 hours per assessment. However, this measure does not speak to sleep quality or actual recovery (relaxation); it simply speaks to the amount of time that an individual is asleep. RMSSD is the primary time-domain HRV indicator, and increased stress has been associated with lower RMSSD. Recognizing that this is a report of group means and that variations are expected within the sample, the range of RMSSD during sleep across the 4 months (31.10 ms to 34.40 ms) fell concerningly well below prior RMSSD sleep research norms on "healthy" participants ranging between 43 ms to 38.2 ms depending on gender (Beckers, Verheyden, & Aubert, 2006; Nunan, Sandercock, & Brodie, 2010).

Table 3. Average % of assessment associated with physiological stress states (n= 17).

Month	*Mean (%)*	SD
May 2021	66.98	9.15
June 2021	68.85	12.45
July 2021	70.41	9.85
August 2021	73.73	12.90

Of additional concern, lower levels of RMSSD are associated with increased stress (Endukuru & Tripathi, 2016; Järvelin-Pasanen et al., 2018; Shaffer & Ginsberg, 2017; Wettstein et al., 2020).

Research question 2

2: Based on the biometric feedback from the Firstbeat Bodyguard 2, did the physiological stress of child welfare workers significantly increase over the 3 months (e.g., June through August of 2021) following the removal of COVID-19 restrictions?

The results of a one-way repeated-measures ANOVA identified a continuous increase in the average percentage of the assessment associated with physiological stress, per participant, over 4 months. Mauchly's Test of Sphericity was conducted, and the assumption was met (x^2 = 6.79, p = .238). While close, results were not statistically significant at the .05 level (F (3,48) = 2.225, p = .097). A total of 17 child welfare professionals participated in all four biometric assessments and were included in the analysis. See Table 3.

Research question 3

3: Based on the biometric feedback from the Firstbeat Bodyguard 2, did the physiological relaxation of child welfare workers significantly decrease over the 3 months (e.g., June through August of 2021) following the removal of COVID-19 restrictions?

The results of a one-way repeated-measures ANOVA showed a significant main effect and continuous decline in the average percentage of the assessment associated with physiological relaxation, per participant, over 4 months (F(3,48) = 2.884, p = .045). Mauchly's Test of Sphericity was conducted, and the assumption was met (x^2 = 1.741, p = .884). Given the significant F-statistic and the conservative nature of the Bonferroni adjustment (Lee & Lee, 2018), Fisher's least significant difference (LSD) test was utilized as the post hoc method to assess for significant mean differences across points in time. Fisher's LSD test identified a significant decrease between the relaxation levels between both May (M = 11.70, SD = 7.71) and July (M = 8.75, SD = 7.15, p = .043) and May and August (M = 7.86,

Table 4. Average % of assessment associated with physiological relaxation states (n= 17).

Month	*Mean (%)*	SD
*May 2021	11.70	7.71
June 2021	11.20	10.83
*July 2021	8.75	7.15
*August 2021	7.86	8.74

Note. $*p < .05$

SD = 8.74, p = .031). Consistent with Research Question 2, a total of 17 child welfare professionals participated in all four biometric assessments and were included in the analysis. See Table 4.

Discussion

This study is the first to collect biometric data from a sample of frontline child welfare workers over time. There are several salient contributions from this manuscript, related to the data collection process and the results themselves. However, it is important to remember the context of this novel approach with frontline child welfare workers. The participants were from one agency, located in the southcentral region of one southern state, and data collection occurred during 4 months of the summer in 2021 – while COVID risk levels were in a consistent decline. It is recognized that there are personal and environmental factors that were not measured that could have influenced the ongoing physiological stress of the child welfare worker. However, the intention of this pilot study was to address a gap in the literature and to serve as a catalyst for immediate improvement. With all of that said, there are several contributions from this study as it pertains to the child welfare workforce literature.

The Kentucky Child Welfare Workforce Wellness Initiative is the first to use wearable biometric analytic devices to track physiological indicators of job stress in child welfare workers. The Firstbeat Bodyguard 2 collects 24-h continuous physiological data on the human body, the "gold-standard" for HRV data collection, and this occurred across 4 months without any substantial operational or logistical concerns shared by the participants. While the cost of these devices might be cost-prohibitive, they can be reused by participants, and there is a return on investment. Specifically, the Firstbeat BodyGuard 2 collects substantial information in a noninvasive way. The research team can basically remain detached from the participants throughout, as they are only generally responsible for replacing the used electrodes on the device each day and then handing the devices back to the team after the assessment. The ease of use, collection of robust and ongoing physiological data, and the logistic feasibility as it relates to involving a unique sector of public service employees were all noted as major successes of this approach.

While there were initial concerns about participants being worried about an invasion of their privacy on behalf of sharing confidential health data, these concerns were never relayed to the research team. This voluntary and confidential study used a series of steps to assure the ongoing protection of data, and participants voiced that their profound interest in participation outweighed any concerns of this nature, and they had confidence the research team and the interdisciplinary team comprised experienced medical professionals. Moving forward, researchers should consider integrating comprehensive ECG devices such as the Firstbeat Bodyguard 2 when assessing the health of their staff and also when designing employee wellness interventions with child welfare workers.

Additionally, this study uniquely collected biometric health data on child welfare workers. While progress has been made in other fields with respect to using biomarkers to measure stress (e.g., PET scans, cortisol levels, etc.) (Bremner et al., 2017; Brown, Coogle, & Wegelin, 2016; Reilly-Spong, Reibel, Pearson, Koppa, & Gross, 2015), the collection of biometric data remains a major gap in child welfare research. The utilization of biometric feedback provides objective, unbiased data, which is a novel advancement in the field of child welfare research. Previous research has demonstrated that stress among child welfare workers is continuously self-reported. Concerningly, prior studies focused on physiological data have identified discrepancies in both the way data is measured and reported when it comes to comparing the use of both self-reported and objective measures (Liu, Eaton, Driban, McAlindon, & Lapane, 2016). To be clear, this is not to discredit or minimize the value of surveys or subjective reports but to acknowledge the feasibility, effectiveness, and added value of the objective physiological data in addition to these common historical approaches used to measure stress.

Additionally, moving from the cross-sectional design to a longitudinal approach and using repeated measures is essential when examining workforce health. While only a few child welfare studies have taken this approach (Hermon & Chahla, 2019; Kim & Barak, 2015; Kim et al., 2011), there is value in the comprehensive assessment of participants over time. Recognizing the challenges in facilitating a longitudinal project of expense and use of employees' time for reporting, establishing community partnerships, and incentivizing participation may help to obtain "buy-in." In the future, researchers may consider using longer approaches for biometric data collection (e.g., longer than 4 months) while balancing the potential to offset any negative implications (e.g., participant attrition).

With respect to the results of the study, much can be learned from this comprehensive four-month collection of physiological data. As noted, just 2 weeks after the first assessment session in May 2021, an agency-wide directive lifted COVID-19 restrictions and required staff to move from remote and virtual service delivery back to face-to-face service for the first time in approximately 14 months. The current study shows the workforce experienced escalated stress and less relaxation time when examined in May and over the next 3 months. The percentage of stress per assessment in this pilot study session increased each month from May to August and was almost significant at $p = .097$. When placing these findings into hours and considering only the month of August, child welfare workers in the sample averaged about 17.5 hours per day where they were in a state of elevated stress. This reveals that they were not fully entering a physiological state of recovery even when sleeping.

There was also a statistically significant decrease in the percentage of relaxation per assessment session from May to August ($p = .045$). With respect to hours per day, for August child welfare workers in the sample averaged about 1.87 hours per day where their body was in a state of relaxation. During that same month, they averaged 7.55 hours of sleep per day, but the HRV data suggest that they were not actually in a state of recovery. Prior research suggests that these professionals are using caffeine, being called out to homes or fielding phone calls at night, eating unhealthy meals to cope (Griffiths et al., 2019b, 2018). It may take the body time to "unwind" from this daily cycle and to finally enter a restorative state, if at all.

The National Association for Social Workers mandates self-care as a professional obligation (Murray, 2021) and the wellness of the workforce has been described as an "ethical imperative" (Bowman, 2022). Further, Lizano et al. (2021) have developed a biopsychosocial framework for the wellbeing of the child welfare worker. While attention is increasing on the effects of occupational stress on child welfare workers, it is important to note the difference between eustress and distress. Eustress involves a positive response to stress, including feelings of meaningfulness and satisfaction, while distress involves a negative response (e.g., fatigue, anger; Nelson & Simmons, 2011). Previous research has shown that employees with high perceived distress experience greater workday fatigue than employees with lower perceived stress (Parker & Ragsdale, 2015). It is also important to consider the contribution of the environment, as team climate has been shown to influence occupational eustress, distress, and levels of exhaustion (Kozusznik, Rodríguez, & Peiró, 2015). Unfortunately, employees facing high levels of distress may struggle to recover from stress, resulting in an increased risk of burnout (Caliskan & Kargın, 2022). Related to the environment, an effort must be made to sample more geographically diverse child welfare professionals to know if there are differences in urban versus rural areas. We also need to learn how child welfare agencies are intervening to address the stresses on their employees. Could it be that NIOSH's Total Worker Health or OSHA's *Safe Workplace, Good Headspace* are the best approaches to improving the health and wellness of the frontline child welfare workforce? The utilization of biometric data may be integral in the evaluation of these types of programs as child welfare agencies make decisions about investing in their workforce.

It is time to consider systematic solutions during this changing environment of pandemic-related restrictions (Metcalf et al., 2022). According to Pisani-Jacques (2020) the child welfare system is now in crisis, and the workforce is feeling these effects. Other frontline professions, including nurses and paramedics, have experienced elevated stress, issues with sleep, and depression during COVID-19 (Aydin Sayilan, Kulakac, & Uzun, 2021; Roberts et al., 2021; Tselebis et al., 2020). The results from the current study add to and enhance prior efforts to identify stress in child welfare workers during COVID-19 (Julien-Chinn et al., 2021; Magruder et al., 2022; Miller et al., 2020) and illustrate a connection between occupational stress and possible deteriorating physiological health, over time. Further, the repeated measures approach supports the notion that changes in policy may contribute to a change in the worker's health. As stated by Shaffer and Ginsberg (2017), establishing HRV and RMSSD norms and findings related to "specialized populations" is an important step in building the evidence base. Researchers should consider prioritizing techniques such as utilizing wearable biometric devices and repeatedly measuring data through a longitudinal design when planning future child welfare workforce wellness studies.

Limitations

Limitations of this study are primarily associated with the geographical region of the study, the limited diversity of the participants, and the small sample size. Additionally, the generalizability of findings may also be influenced by the chosen sampling approach, inclusion criteria, recruiting process, and perceived invasive nature of collecting participant biometric data collection. While this pilot study sought to collect novel health data on the physiological stress of child welfare workers, it is recognized that additional external factors may contribute to these findings (e.g., genetics, lack of exercise, unhealthy habits, external stressors, quality of social support systems, weight of assigned cases, policies and procedures, and quality of supervision). Asking frontline child welfare professionals to repeatedly wear biometric devices to collect continual health data on their person, for 72 hours at a time, is noted as both a significant advancement and as a logistical challenge. For this reason, data collected within these 72-h assessment periods is not intended to be representative of time outside of the measurement window. Further research should build upon this pilot study, examining differences such as the contribution of marital status, age, the impact of stress based on service location, additional external stressors (e.g., COVID-19 and caregiving responsibilities), and the potential stress-related benefits of working remotely. The contribution of a qualitative approach may also assist by providing a deeper understanding of this phenomenon as well.

Conclusions

This study provides a unique and comprehensive exploration of the physiological stress associated with working in child welfare during a global pandemic while at an agency facing what has been called a "crisis" in employee turnover. While some might argue that stress is an unfortunate expectation of this position, never has a study collected biometric health data from child welfare workers in this way or for this long. These professionals are tasked with speaking for those who do not have a voice and are responsible for making timely assessments and providing essential recommendations that have long withstanding consequences. The health and wellness of the child welfare workforce is critical, and the biometric data from this study suggest that we may not fully understand the gravity of the stress associated with working in this position. If not acknowledged or addressed, the accumulation of chronic stress in child welfare workers may lead to negative outcomes for families and children (e.g., poor service delivery, staff turnover, and physical wellbeing of staff).

The escalating stress of frontline child welfare workers creates an immediate call to action. Findings from this study provide a more comprehensive illustration of the impact of work-related stress and may assist in advocacy efforts. The utilization of biometric technology to collect physiological data can be an effective and feasible approach as the field begins to develop a robust evidence base. As professionals work to develop custom-designed wellness interventions for child welfare workers, the inclusion of objective and subjective measures is necessary. Furthermore, the importance of mutually beneficial interdisciplinary partnerships cannot be underestimated. Community partners, medical providers, the school, and legal system – these viable options should be prioritized as essential contributors when collaborators are designing projects to support the health of the child welfare workforce. Leveraging resources between agencies when appropriate might be a viable solution when there are financial or other needs (e.g., sharing biometric devices and sharing data for cross comparison between similar professions). Finally, the utilization of objective measures, longitudinal approaches, and experimental designs is the next step. Increasing the rigor of the child welfare research, with respect to the health of the workforce, is an ideal recipe for credibility, advocacy, and scientific progress.

Acknowledgments

Research reported in this publication was supported, in part, by the Cabinet for Health and Family Services, Department for Medicaid Services under Agreement titled “Kentucky Child Welfare Workforce Wellness Initiative.” Additional support was provided by the Kentucky Social Welfare Foundation, LifeSkills, Inc., and Western Kentucky University.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

Additional support was provided by the Kentucky Cabinet for Health and Family Services: Department for Medicaid Services, State University Partnership and the Kentucky Social Welfare Foundation.

Notes on contributors

Austin Griffiths has almost 16 years of combined professional practice experience in both child and adult protective services and in facilitating applied research. He is the Director of Western Kentucky University’s LifeSkills Center for Child Welfare Education and Research and is an Assistant Professor in the Department of Social Work.

Kim Link is an Associate Professor of Nursing at Western Kentucky University and an Associate for the LifeSkills Center for Child Welfare Education and Research. In addition to teaching and research, Dr. Link practices as a Psychiatric Mental Health Nurse Practitioner in the local community where she works with a variety of individuals and families with mental illness.

Kara Haughtigan is an Associate Professor of Nursing at Western Kentucky University. In addition to teaching and research, Dr. Haughtigan practices as a Nurse Practitioner in the local community.

Oliver W. J. Beer is an Associate Professor in the School of Health Professions at the University of Plymouth in the UK. Oliver’s research focuses on the health and well-being of the child protection workforce and introduces innovative approaches to prevent or reduce work-related stress.

Lindsey Powell is a Master of Social Work student at Western Kentucky University and is a Graduate Research Assistant for LifeSkills Center for Child Welfare Education and Research. Lindsey is passionate about both family and child welfare.

David Royse is a Professor Emeritus at the University of Kentucky. David has written many textbooks and manuscripts and has been a leader in social work research and education for several decades.

ORCID

Austin Griffiths http://orcid.org/0000-0002-6670-3150

Kim Link http://orcid.org/0000-0002-6687-7986
Kara Haughtigan http://orcid.org/0000-0002-5062-356X
Oliver W. J. Beer http://orcid.org/0000-0001-8581-3673
Lindsey Powell http://orcid.org/0000-0003-0626-646X
David Royse http://orcid.org/0000-0001-5327-0854

Disclaimer

The content is solely the responsibility of the authors and does not necessarily represent the official views of the Cabinet for Health and Family Services, Department for Medicaid Services, the Kentucky Social Welfare Foundation, LifeSkills, Inc., or Western Kentucky University.

References

American Psychological Association. (2021). Stress in America. *One year later, a new wave of pandemic health concerns*, Retrieved from https://www.apa.org/news/press/releases/stress/2021/sia-pandemic-report.pdfs

Auten, D., & Fritz, C. (2019). Mental health at work: How mindfulness aids in more ways than one. *Organizational Dynamics*, *48*(3), 98–104. doi:10.1016/j.orgdyn.2018.04.001

Aydin Sayilan, A., Kulakac, N., & Uzun, S. (2021). Burnout levels and sleep quality of COVID-19 heroes. *Perspectives in Psychiatric Care*, *57*(3), 1231–1236. doi:10.1111/ppc.12678

Beckers, F., Verheyden, B., & Aubert, A. E. (2006). Aging and nonlinear heart rate control in a healthy population. *American Journal of Physiology Heart and Circulatory Physiology*, *290* (6), H2560–2570. doi:10.1152/ajpheart.00903.2005

Beer, O. W. J., Phillips, R., Letson, M. M., & Wolf, K. G. (2021). Personal and professional impacts of work-related stress alleviation strategies among child welfare workers in child advocacy center settings. *Children and Youth Services Review*, *122*, 1–10. doi:10.1016/j.childyouth.2020.105904

Benichou, T., Pereira, B., Mermillod, M., Tauveron, I., Pfabigan, D., Maqdasy, S., & Dutheil, F. (2018). Heart rate variability in type 2 diabetes mellitus: A systematic review and meta–analysis. *PloS One*, *13*(4), e0195166–e0195166. doi:10.1371/journal.pone.0195166

Bowman, M. E. (2022). Child welfare worker wellness: An ethical imperative in the service of children. *Child Abuse Review*, *31*(5). doi:10.1002/car.2758

Boyas, J. F., Wind, L. H., & Ruiz, E. (2013). Organizational tenure among child welfare workers, burnout, stress, and intent to leave: Does employment-based social capital make a difference? *Children and Youth Services Review*, *35*(10), 1657–1669. doi:10.1016/j.childyouth.2013.07.008

Bremner, J. D., Mishra, S., Campanella, C., Shah, M., Kasher, N., Evans, S., . . . Carmody, J. (2017). A pilot study of the effects of mindfulness-based stress reduction on post-traumatic stress disorder symptoms and brain response to traumatic reminders of combat in Operation Enduring Freedom/Operation Iraqi Freedom combat veterans with post-traumatic stress disorder. *Frontiers of Psychiatry*, *8*, 157. doi:10.3389/fpsyt.2017.00157

Brown, K. W., Coogle, C. L., & Wegelin, J. (2016). A pilot randomized controlled trial of mindfulness-based stress reduction for caregivers of family members with dementia. *Aging & Mental Health*, *20*(11), 1157–1166. doi:10.1080/13607863.2015.1065790

Brown, S. M., Orsi, R., Chen, P. C. B., Everson, C. L., & Fluke, J. (2022). The impact of the COVID-19 pandemic on child protection system referrals and responses in Colorado, USA. *Child Maltreatment*, *27*(1), 3–11. doi:10.1177/10775595211012476

Caliskan, E., & Kargın, M. (2022). The relationship between coronavirus 19 fear and occupational fatigue, burnout and recovery levels in healthcare professionals in Turkey. *Archives of Environmental & Occupational Health*, *77*(9), 711–720. doi:10.1080/19338244.2021.2002796

Centers for Disease Control and Prevention. (2020). *NIOSH total worker health program*. Retrieved from https://www.cdc.gov/niosh/twh/default.html

Chalmers, J. A., Quintana, D. S., Abbott, M. J., & Kemp, A. H. (2014). Anxiety disorders are associated with reduced heart rate variability: A meta-analysis. *Frontiers in Psychiatry*, *5*, 80. doi:10.3389/fpsyt.2014.00080

Dickson, V. V., & Arabadjian, M., Scott, L., Zhanay, J., Leon, A., Zhanay, J., Leon, A. (2022). Measurement of stress amongst working adults with cardiovascular disease. *European Journal of Cardiovascular Nursing*, *21*(8), 848–856. doi:10.1093/eurjcn/zvac018

Edwards, F., & Wildeman, C. (2018). Characteristics of the front-line child welfare workforce. *Children and Youth Services Review*, *89*, 13–26. doi:10.1016/j.childyouth.2018.04.013

Endukuru, C. K., & Tripathi, S. (2016). Evaluation of cardiac responses to stress in healthy individuals - a non-invasive evaluation by heart rate variability and stroop test. *International Journal of Scientific Research*, *5*(7), 286–289. doi:10.36106/ijsr

Esco, M. R., Fedewa, M. V., & MacDonald, H. V. (2017). Accuracy of mobile HRV devices for measuring RMSSD: A systematic review and meta-analysis. *Medicine and Science in Sports and Exercise*, *49*(5S), 718–719. doi:10.1249/01.mss.0000518910.44424.8e

Firstbeat Technologies, Ltd. (2019a). Firstbeat analysis server for research use, 1–14.

Firstbeat Technologies, Ltd. (2019b). Firstbeat in research, 1–29.

Gallup. (2021). *State of the global workplace 2021 report*. Washington, D.C. Retrieved from https://www.gallup.com/file/workplace/349484/state-of-the-global-workplace-2021-download.pdfs

Griffiths, A., Desrosiers, P., Gabbard, J., Royse, D., & Piescher, K. (2019a). Retention of child welfare caseworkers: The wisdom of supervisors. *Child Welfare*, *97*(3), 61–83.

Griffiths, A., Harper, W., Desrosiers, P., Murphy, A., & Royse, D. (2019b). "The stress is indescribable": Self-reported health implications from child welfare supervisors. *The Clinical Supervisor*, *38*(2), 183–201. doi:10.1080/07325223.2019.1643433

Griffiths, A., Royse, D., Flaherty, C., & Collins-Camargo, C. (2020). Perceptions of workload and job impact as predictors of child welfare worker health status. *Child Welfare*, *98*(3), 97–120.

Griffiths, A., Royse, D., & Walker, R. (2018). Stress among child protective service workers: Self-reported health consequences. *Children and Youth Services Review*, *90*, 46–53. doi:10.1016/j.childyouth.2018.05.011

Hassard, J., Teoh, K. R. H., Visockaite, G., Dewe, P., & Cox, T. (2018). The cost of work-related stress to society: A systematic review. *Journal of Occupational Health Psychology*, *23*(1), 1–17. doi:10.1037/ocp0000069

Hays, R. D., Bjorner, J. B., Revicki, D. A., Spritzer, K. L., & Cella, D. (2009). Development of physical and mental health summary scores from the patient-reported outcomes measurement information system (PROMIS) global items. *Quality of Life Research*, *18*(7), 873–880.

Hermon, S. R., & Chahla, R. (2019). A longitudinal study of stress and satisfaction among child welfare workers. *Journal of Social Work*, *19*(2), 192–215. doi:10.1177/1468017318757557

Houtman, I., Jettinghof, K., & Cedillo, L. (2007). *Raising awareness of stress at work in developing countries*. Geneva, Switzerland: World Health Organization. Retrieved from https://www.who.int/occupational_health/publications/raisingawarenessofstress.pdf

Järvelin-Pasanen, S., Sinikallio, S., & Tarvainen, M. P. (2018). Heart rate variability and occupational stress-systematic review. *Industrial Health*, *56*(6), 500–511. doi:10.2486/indhealth.2017-0190

Jeon, S. W., & Kim, Y. K. (2018). Application of assessment tools to examine mental health in workplaces: Job stress and depression. *Psychiatry Investigation*, *15*(6), 553–560. doi:10.30773/pi.2016.10.24

Julien-Chinn, F. J., Katz, C. C., & Wall, E. (2021). An examination of coping strategies and intent to leave child welfare during the COVID-19 pandemic. *Child and Adolescent Social Work Journal*. doi:10.1007/s10560-021-00800-w

Kim, A., & Barak, M. E. M. (2015). The mediating roles of leader-member exchange and perceived organizational support in the role stress-turnover intention relationship among child welfare workers: A longitudinal analysis. *Children and Youth Services Review*, *52*, 135–143. doi:10.1016/j.childyouth.2014.11.009

Kim, H. G., Cheon, E. J., Bai, D. S., Lee, Y. H., & Koo, B. H. (2018). Stress and heart rate variability: A meta-analysis and review of the literature. *Psychiatry Investigation*, *15*(3), 235–245. doi:10.30773/pi.2017.08.17

Kim, H., Ji, J., & Kao, D. (2011). Burnout and physical health among social workers: A three-year longitudinal study. *Social Work*, *56*(3), 258–268. doi:10.1093/sw/56.3.258

Kim, H., & Kao, D. (2014). A meta-analysis of turnover intention predictors among US child welfare workers. *Children and Youth Services Review*, *47*, 214–223. doi:10.1016/j.childyouth.2014.09.015

Kivimäki, M., & Kawachi, I. (2015). Work stress as a risk factor for cardiovascular disease. *Current Cardiology Reports*, *17*(9), 630. doi:10.1007/s11886-015-0630-8

Kleiger, R. E., Stein, P. K., & Bigger Jr, J. T. (2005). Heart rate variability: Measurement and clinical utility. *Annals of Noninvasive Electrocardiology*, *10*(1), 88–101. doi:10.1111/j.1542-474X.2005.10101.x

Kothari, B. H., Chandler, K. D., Waugh, A., McElvaine, K. K., Jaramillo, J., & Lipscomb, S. (2021). Retention of child welfare caseworkers: The role of case severity and workplace resources. *Children and Youth Services Review*, *126*, 10. doi:10.1016/j.childyouth.2021.106039

Kozusznik, M. W., Rodríguez, I., & Peiró, J. M. (2015). Eustress and distress climates in teams: Patterns and outcomes. *International Journal of Stress Management*, *22*(1), 1–23. doi:10.1037/a0038581

Kuula, L., & Pesonen, A.-K. (2021). Heart rate variability and Firstbeat method for detecting sleep stages in healthy young adults: Feasibility study. *JMIR mHealth and uHealth*, *9*(2), e24704–e24704. doi:10.2196/24704

Lawrence, C. K., Zeitlin, W., Auerbach, C., Chakravarty, S., & Rienks, S. (2018). Measuring the impact of public perceptions on child welfare workers. *Journal of Public Child Welfare*, *13*(4), 401–418. doi:10.1080/15548732.2018.1508537

Lee, S., & Lee, D. K. (2018). What is the proper way to apply the multiple comparison test? *Korean Journal of Anesthesiology*, *71*(5), 353–360. doi:10.4097/kja.d.18.00242

Liu, S. H., Eaton, C. B., Driban, J. B., McAlindon, T. E., & Lapane, K. L. (2016). Comparison of self-report and objective measures of physical activity in US adults with osteoarthritis. *Rheumatology International*, *36*(10), 1355–1364. doi:10.1007/s00296-016-3537-9

Lizano, E. L., He, A. S., & Leake, R. (2021). Caring for our child welfare workforce: A holistic framework of worker well-being. *Human Service Organizations: Management, Leadership & Governance*, *45*(4), 281–292. doi:10.1080/23303131.2021.1932658

Loria, H., McLeigh, J., Wolfe, K., Conner, E., Smith, V., Greeley, C. S., & Keefe, R. J. (2021). Caring for children in foster and kinship care during a pandemic: Lessons learned and recommendations. *Journal of Public Child Welfare*, 1–24. doi:10.1080/15548732.2021.1965065

Mack, B. M. (2022). Addressing social workers' stress, burnout, and qualitative study with supervisors. *Social Work Research*, *46*(1), 17–28. doi:10.1093/swr/svab032

Magruder, L., Wilke, D., Radey, M., Cain, M., & Yelick, A. (2022). COVID-19′s social ecological impacts on health and human services worker well-being. *Social Work in Public Health*, *37*(3), 233–243. doi:10.1080/19371918.2021.1997864

Merritt, D., & Simmel, C. (2020, April). Barriers to child protection during COVID-19: Considering the impact on child maltreatment. *The Imprint: Youth and Family News*, Retrieved from https://imprintnews.org/child-welfare-2/covid-19-barriers-considering-the-impact-on-child-maltreatment/42632

Metcalf, S., Marlow, J. A., Rood, C. J., Hilado, M. A., DeRidder, C. A., & Quas, J. A. (2022). Identification and incidence of child maltreatment during the COVID-19 pandemic. *Psychology Public Policy and Law*, *28*(2), 267–279. doi:10.1037/law0000352

Miller, J. J. (2020). Developing self-care competency among child welfare workers: A first step. *Children and Youth Services Review*, *108*, 104529. doi:10.1016/j.childyouth.2019.104529

Miller, J. J., Niu, C., & Moody, S. (2020). Child welfare workers and peritraumatic distress: The impact of COVID-19. *Children and Youth Services Review*, *119*, 105508. doi:10.1016/j.childyouth.2020.105508

Murray, A. (2021). Code of ethics of the National Association of Social Workers (NASW) 2021 Amendments: Self-care and cultural competence. Retrieved from https://www.socialworkers.org/LinkClick.aspx?fileticket=UyXb_VQ35QA%3D&portalid=0

National Child Welfare Workforce Institute. (2016). *Why the workforce matters*. Retrieved from https://ncwwi.org/files/Why_the_Workforce_Matters.pdf

National Institute for Occupational Safety and Health [NIOSH]. (2014, June 6). *Stress . . . at work*. Retrieved from https://www.cdc.gov/niosh/docs/99-101/default.html#What%20Is%20Job%20Stress?

Nelson, D. L., & Simmons, B. L. (2011). Savoring eustress while coping with distress: The holistic model of stress. In J. C. Quick & L. E. Tetrick (Eds.), *Handbook of occupational health psychology* (pp. 55–74). Washington, DC: American Psychological Association.

Nguyen, L. H. (2021). Calculating the impact of COVID-19 pandemic on child abuse and neglect in the US. *Child Abuse & Neglect*, *118*, 12. doi:10.1016/j.chiabu.2021.105136

Nunan, D., Sandercock, G. R., & Brodie, D. A. (2010). A quantitative systematic review of normal values for short-term heart rate variability in healthy adults. *Pacing and Clinical Electrophysiology*, *33*(11), 1407–1417. doi:10.1111/j.1540-8159.2010.02841.x

Occupational Safety and Health Administration. (2022). Safe workplace, good headspace: Workplace stress. Retrieved from https://www.osha.gov/workplace-stress/employer-guidance

Palmer, A. R., Distefano, R., Leneman, K., & Berry, D. (2021). Reliability of the bodyguard2 (firstbeat) in the detection of heart rate variability. *Applied Psychophysiological Biofeedback*, *46*(3), 251–258. doi:10.1007/s10484-021-09510-6

Parak, J., & Korhonen, I. (2015). Accuracy of firstbeat bodyguard 2 beat-to-beat heart rate monitor.

Parker, K. N., & Ragsdale, J. M. (2015). Effects of distress and eustress on changes in fatigue from waking to working. *Applied Psychology, Health and Well-Being*, *7*(3), 293–315. doi:10.1111/aphw.12049

Patel, V. N., Pierce, B. R., Bodapati, R. K., Brown, D. L., Ives, D. G., & Stein, P. K. (2017). Association of holter-derived heart rate variability parameters with the development of congestive heart failure in the cardiovascular health study. *Journal of American College of Cardiology*, *5*(6), 423–431. doi:10.1016/j.jchf.2016.12.015

Pharris, A. B., Munoz, R. T., & Hellman, C. M. (2022). Hope and resilience as protective factors linked to lower burnout among child welfare workers. *Children and Youth Services Review*, *136*, 106424. doi:10.1016/j.childyouth.2022.106424

Pisani□jacques, K. (2020). A Crisis for a System in Crisis: Forecasting from the Short□ and Long□Term Impacts of COVID□19 on the Child Welfare System. *Family Court Review*, *58* (4), 955–964. https://doi.org/10.1111/fcre.12528

Rajendra Acharya, U., Paul Joseph, K., Kannathal, N., Lim, C. M., & Suri, J. S. (2006). Heart rate variability: A review. *Medical & Biological Engineering & Computing*, *44*(12), 1031–1051. doi:10.1007/s11517-006-0119-0

Ravalier, J. M. (2019). Psycho-social working conditions and stress in UK social workers. *The British Journal of Social Work*, *49*(2), 371–390. doi:10.1093/bjsw/bcy023

Reilly-Spong, M., Reibel, D., Pearson, T., Koppa, P., & Gross, C. R. (2015). Telephone-adapted mindfulness-based stress reduction (tMBSR) for patients awaiting kidney transplantation: Trial design, rationale and feasibility. *Contemporary Clinical Trials*, *42*, 169–184. doi:10.1016/j.cct.2015.03.013

Ritvanen, T., Louhevaara, V., Helin, P., Väisänen, S., & Osmo Hänninen, O. (2006). Responses of the autonomic nervous system during periods of perceived high and low work stress in younger and older female teachers. *Applied Ergonomics*, *37*(3), 311–318. doi:10.1016/j.apergo.2005.06.013

Roberts, R., Wong, A., Jenkins, S., Neher, A., Sutton, C., O'Meara, P., . . . Dwivedi, A. (2021). Mental health and well-being impacts of COVID-19 on rural paramedics, police, community nurses and child protection workers. *Australian Journal of Rural Health*, *29*(5), 753–767. doi:10.1111/ajr.12804

Royse, D., & Griffiths, A. (2019). *Child welfare and child protection: An introduction*. San Diego, CA: Cognella Academic Publishing.

Sauter, S., Murphy, L., Colligan, M., Swanson, N., Hurrell, J., Scharf, F., . . . Tisdale, J. (1999). Stress at work (DHHS (NIOSH) Publication No 99-101). OH: National Institute for Occupational Safety and Health: Cincinnati. Retrieved from https://www.cdc.gov/niosh/docs/99-101/pdfs/99-101.pdf?id=10.26616/NIOSHPUB99101

Schiweck, C., Piette, D., Berckmans, D., Claes, S., & Vrieze, E. (2019). Heart rate and high frequency heart rate variability during stress as biomarker for clinical depression. A systematic review. *Psychological Medicine*, *49*(2), 200–211. doi:10.1017/S0033291718001988

Schober, P., & Vetter, T. (2018). Repeated measures designs and analysis of longitudinal data: If at first you do not succeed—try, try again. *Anesthesia & Analgesia*, *127*(2), 2. doi:10.1213/ANE.0000000000003511

Schwab-Reese, L. M., Drury, I., Allan, H., & Matz, K. (2020). "Oh, this is actually okay": Understanding how one state child welfare training system adapted to the COVID-19 pandemic. *Child Abuse & Neglect*, *110*, 12. doi:10.1016/j.chiabu.2020.104697

Seay, K. D., & McRell, A. S. (2021). Child welfare services response to COVID-19: Addressing face-to-face contact. *Journal of Child and Family Studies*, *30*(8), 2055–2067. doi:10.1007/s10826-021-02000-7

Shaffer, F., & Ginsberg, J. P. (2017). An overview of heart rate variability metrics and norms. *Frontiers of Public Health*, *5*, 258. doi:10.3389/fpubh.2017.00258

Shaffer, F., McCraty, R., & Zerr, C. L. (2014). A healthy heart is not a metronome: An integrative review of the heart's anatomy and heart rate variability. *Frontiers in Psychology*, *5*, 1040. doi:10.3389/fpsyg.2014.01040

Soteriades, E. S., Psalta, L., Leka, S., & Spanoudis, G. (2019). Occupational stress and musculoskeletal symptoms in firefighters. *International Journal of Occupational Medicine and Environmental Health*, *32*(3), 341–352. doi:10.13075/ijomeh.1896.01268

Stahlschmidt, M. J., He, A. S., & Lizano, E. L. (2021). A dynamic theory of moral distress in child welfare workers. *British Journal of Social Work, 19*. doi:10.1093/bjsw/bcab247

Stults-Kolehmainen, M. A., Tuit, K., & Sinha, R. (2014). Lower cumulative stress is associated with better health for physically active adults in the community. *Stress*, *17*(2), 157–168. doi:10.3109/10253890.2013.878329

Tselebis, A., Lekka, D., Sikaras, C., Tsomaka, E., Tassopoulos, A., Ilias, I., Pachi, A. (2020). Insomnia, perceived stress, and family support among nursing staff during the pandemic crisis. *Healthcare (Basel)*, *8*, 4. doi:10.3390/healthcare8040434

Umair, M., Chalabianloo, N., Sas, C., & Ersoy, C. (2021). HRV and stress: A mixed methods approach for comparison of wearable heart rate sensors for biofeedback. *IEEE Access*, *9*, 14005–14024. doi:10.1109/ACCESS.2021.3052131

U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2022). *Child maltreatment 2020*. Retrieved from https://www.acf.hhs.gov/cb/report/child-maltreatment-2020

Van Amelsvoort, L., Schouten, E., Maan, A., Swenne, C. A., & Kok, F. J. (2000). Occupational determinants of heart rate variability. *International Archives of Occupational and Environmental Health*, *73*(4), 255–262. doi:10.1007/s004200050425

Verkuil, B., Brosschot, J. F., Tollenaar, M. S., Lane, R. D., & Thayer, J. F. (2016). Prolonged non-metabolic heart rate variability reduction as a physiological marker of psychological stress in daily life. *Annals of Behavioral Medicine*, *50*(5), 704–714. doi:10.1007/s12160-016-9795-7

Wettstein, A., Kühne, F., Tschacher, W., & La Marca, R. (2020). Ambulatory assessment of psychological and physiological stress on workdays and free days among teachers. A preliminary study. *Frontiers in Neuroscience*, *14*, 112. doi:10.3389/fnins.2020.00112

Wong, C. A., Ming, D., Maslow, G., & Gifford, E. J. (2020). Mitigating the impacts of the COVID-19 pandemic response on at-risk children. *Pediatrics*, *146*(1), 6. doi:10.1542/peds.2020-0973

Zeitlin, W., Chakravarty, S., Lawrence, C., & DeCristofano, A. (2019). Direct practice contact: Predicting frontline child welfare workers' time with clients. *Children and Youth Services Review*, *100*, 9–15. doi:10.1016/j.childyouth.2019.02.020