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OBJECTIVELY ASSESSING FATIGUE LEVELS AMONG CONSTRUCTION WORKERS

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ABSTRACT: The upsurge in commitment to safety from industry leaders and the implementation of better equipment and training have generated a 67% decline in recordable incident rates during the past two decades. Fatalities, however, have plateaued for the last decade and, in the past three years, have increased for the first time. Current research indicates that human factors like fatigue play a major role in accident causation and fatality occurrence. Under the effects of fatigue, the human body experiences a marked reduction in cognitive and physical abilities that inhibit normal thinking and motor processes. Early detection of fatigue could prevent high risk situations. Our hypothesis was that fatigue levels can be predicted based on activity variables. Activity variables are defined as the characteristics of the work environmental conditions, shift design, and personal habits (e.g., commute time). An activity variable questionnaire was created based on past literature and was delivered to a diverse sample of 160 US construction workers. Following this questionnaire, each worker completed a Psychomotor Vigilant Test (PVT) to objectively measure their actual levels of fatigue. The results indicate a correlation between the level of fatigue of an individual, the type of work that he/she performs and the amount of sleep obtained during the previous 24 hours. These findings inform the research community about specific ways that fatigue can be quickly and objectively measured without the intrusive and often expensive use of technology. Future research should focus on further revealing the effect that each specific trade has on fatigue.

1. INTRODUCTION

It is not news that the construction sector is one of the most hazardous and deadly of the industry (Sawacha et al. 1999). In 2015 the construction industry accounted for a fatality rate of 9.4 for every 100,000 full-time equivalent workers, nearly three-times greater than that of the overall working population. A revealing factor of its dangerous nature is that four of the ten most dangerous jobs in the U.S. belong to the construction industry (U.S. Bureau of Labor Statistics 2015).

In addition to the potential devastating effects of accidents and fatalities on the families of construction workers, these incidents come at a great economic cost for both the industry and society. Considering direct costs (medical cost), indirect costs (wages and household productivity), and the quality of life costs due to injury, the average construction fatality was estimated to cost $4 million (Waehrer et al. 2007). According to data from 2002, the construction industry accounted for 5.2% of all private industry employment but it was responsible for 15% of all private injury cost. All of this indicates that the construction industry is disproportionally costly in regards to accidents and fatalities. This translates to a yearly cost of approximately $11.5 billion (Waehrer et al. 2007).

Accidents have shown to be caused either by unsafe human acts and/or an unsafe design that generates a physical hazard (Kartam 1997). Furthermore, several decades of construction safety research have revealed that organizational and human factors, rather than technical failures, are the principal causes of accidents (Langford et al. 2000; Weick et al. 2008). The technological advances of the past two decades had allowed for the development of better equipment and training for construction workers, causing a remarkable decrease in recordable incidents. Nonetheless, fatalities have plateaued for the last decade and even increased in the past three years (U.S. Bureau of Labor Statistics 2015). This suggests that, in order to reduce the number of fatalities in the construction industry, it is imperative to focus on the human aspect of accident causation.

Fatigue is a human factor identified by some as the main risk factor in construction (Chan 2011). Fatigue is a leading cause of occupational injuries and fatalities, particularly in high-energy situations. Fatigue can be defined as a decreased ability to perform activities at the desired level due to lassitude or exhaustion of mental and/or physical strength (Gander et al. 2011; Hallowell 2010). When workers are fatigued they experience compromised alertness, judgement, reaction time (RT), mental acuity, physical strength, and the development of an uncooperative disposition ((Gillberg and Åkerstedt 1994; Kajtna et al. 2011; van der Linden et al. 2003; Lorist et al. 2005; Scott et al. 2006; Yaggie and Armstrong 2004). Such effects decrease a worker's ability to complete their work safely (Dembe et al. 2005).

As described by (Dawson et al. 2012), in order to properly manage fatigue it is essential to be able to detect early signs of fatigue among workers. This would allow for a correcting intervention before a worker reaches unsafe levels of fatigue. Several subjective questionnaires and technologies have been developed to assess fatigue. Nevertheless, none of these resources are suited for the construction industry. The developed questionnaires are subjective and most are very time consuming. On the other hand, most technologies that claim to assess fatigue have not been submitted to a rigorous validation process and their implementation in a construction site would be costly and troublesome (Techera et al. 2016a). Consequently, we offer the following research question: *what objective variables can be measured at the beginning of a shift that can determine the level of fatigue of an individual?* We hypothesize that a construction worker's level of fatigue can be assessed by measuring simple activity variables at the beginning of the shift. Based on previous research a set of activity variables, potential predictors of fatigue, were defined. An objective tool to assess fatigue was chosen and a protocol was designed to test the aforementioned hypothesis. By means of regression analysis some activity variables were identified as predictors of fatigue.

2. LITERATURE REVIEW

2.1 Construction Work and Fatigue

There are several characteristics of construction work that contribute to its hazardous nature. Construction is constantly changing across the different stages of a project and sites are diverse and complex work environments. These factors jeopardize the process of familiarization with the environment to the point where most possible hazards are recognized (Buchholz et al. 1996). Furthermore, construction work commonly requires working in awkward postures, in confined or dangerous spaces, lifting heavy equipment or performing forceful exertions (Schneider and Susi 1994). Given these challenges, it is essential that workers are fit for duty, vigilant, and mindful, which can be compromised by fatigue.

There are two main reasons why fatigue compromises safety in an occupational environment (Spurgeon et al. 1997). First, fatigue diminishes the ability of an individual to perceive and react to new information. (Grandjean 1979; Johnston et al. 1998; Lorist et al. 2000; Reiner and Krupinski 2011). Second, fatigue diminishes the ability of an individual to perceive risk (Tixier et al. 2014). Consequently, under the effects of fatigue a construction worker becomes more vulnerable to the construction site's hazardous environment.

Several industries such as aviation, transportation, and mining have recognized and measured the impact of fatigue on safety and productivity and have developed approaches to mitigate its effects (Arnaldo et al. 2016; Marcus and Rosekind 2016; Rosekind et al. 1995). Specifically, in construction, (Chan 2011) developed a seminal study that underlines the importance of addressing fatigue in this sector. In that study, a group of 254 construction workers, 44 safety supervisors, and 23 managers were asked to identify the principal safety risk factors that affected their daily work. From a pool of 219 risk factors, fatigue was identified as the principal and most compromising risk factor for safety by 78% of the participants. Such evidence makes the development of effective ways to manage fatigue a priority in the construction industry.

2.2 Fatigue Management

Some researchers have developed theoretical models to manage fatigue. Such models receive the name of Fatigue Risk Management Systems (FRMS). A FRMS is "a scientifically based and flexible layered system of defenses to minimize the adverse effects of fatigue on workforce alertness, performance, and safety" (Gander et al. 2011). However, these FRMS can't be properly implemented in the industry due to the lack of an easy, economic, and reliable way of assessing fatigue.

2.2.1 Objective Assessment of Fatigue

Fatigue has shown to provoke changes in several human physiological variables. Consequently, some disciplines have developed ways to objectively assess fatigue based on the change of such variables. First, researchers have measured Neuro-behavioral performance. This strategy evaluates changes in cognitive ability, mood, and physical capability due to a decay in the central or peripheral nervous system (Balkin et al. 2004). Second, Electroencephalography has been used to detect changes in amplitude, frequency or location of brain waves. Brain waves have shown to have a different behavior among fatigued and non-fatigued individuals; especially theta (3.5-7Hz), alpha (8-13Hz) and beta (14-30Hz) (Lal et al. 2003; Okogbaa et al. 1994). Third, Pupilometry has been used to measure visually-guided saccadic velocity (SV), initial pupil diameter (PD), pupillary constriction latency (CL), and amplitude of pupil constriction (CA) (Goldich et al. 2010). Finally, Oculometry has been used to measure the amplitude and frequency of eyelid movement that have also been correlated to fatigue levels (Wierwille et al. 1994). Based on these findings several products have been created to assess fatigue objectively. Some of these products include: the FIT-2500, the Smart Cap, and the Optalert.

Despite these technological and physiological advancements, the Psychomotor Vigilant Test (PVT) is the most reliable and properly validated tool to objectively assess fatigue. The PVT is based on the neuro-behavioral decay that takes place under the effects of fatigue. The RT of an individual is a direct measure of his/her neuro-behavioral performance. Consequently, it offers an objective indirect measure of fatigue (Dinges and Powell 1985; Dorrian et al. 2005; Loh et al. 2004). Additionally, PVT is portable and easy to use while other physiological technologies are cumbersome and very expensive, making them infeasible for site evaluations. For this reason, we used the PVT to objectively assess fatigue among construction workers in our study.

2.2.2 Potential Predictors of Fatigue

In order to define the independent variables in our study, we reviewed literature for potential predictors of fatigue. Further, it is important to determine the variables that can be practically measured at the beginning of a shift that could influence the level of fatigue of an individual later in the shift. We started with the work of (Techera et al. 2016b) who meta-analyzed the causes and consequences of occupational fatigue. This study revealed nine main variables that influence the onset of fatigue: Sleep Deprivation, Incomplete Recovery, Workload, Overtime and Long Working Hours, Work Environment, Mental Exertion, Muscular Exertion, Social Environment, and Emotional Predisposition. We used these dimensions as potential activity variables (predictors) given that they were studied and validated broadly in laboratory settings.

3. METHODOLOGY

The protocol for this study consisted of: (1) choosing a valid and reliable tool to perform a PVT; (2) Choosing a group of activity variables easily measurable at the beginning of a shift, which according to past research, could be predictors of fatigue; (3) Measuring the variables and conducting tests with PVT on site to deliver a sufficient sample of construction workers, and (4) Testing the alternative hypothesis that the level of fatigue of a construction worker can be assessed by measuring simple activity variables at the beginning of the shift. This protocol was approved by the Institutional Review Board of the University of Colorado at Boulder.

3.1 Fatigue Objective Assessment Tool

The PVT-192 (Ambulatory Monitoring, Inc., Ardsley, et al., 1985), is the current "gold standard" to measure simple reaction time (RT). The principal challenge with using this technology is its extremely high cost, which makes it impractical for application in research or the industry.

Recently, a new software "PC-PVT" was developed to perform simple RT measures among individuals. The principal objective of the developers of this software was to develop a PVT with the same reliability and functionality as the PVT-192 (Khitrov et al. 2013). The mentioned software has achieved these objectives offering a reliable, valid, more familiar and economic way of measuring simple RT.

The functionality of the PC-PVT is analogous to that of the PVT-192. In order to participate in a PC-PVT a participant sits in front of a laptop computer with his/her dominant hand on the mouse. Before starting, the screen shows an instructional message and when the participant clicks the mouse, the test starts. The participant will observe a black screen and suddenly a stimulus will appear in the form of a red four-digit millisecond counter that stops the count once the participant clicks the mouse. The counter will display the RT of the individual for 500ms and then disappear. This sequence repeats at random intervals, between 2 and 10 seconds. This test has been validated in a 5 min and a 10 min modality and we decided to implement the 5 min modality (Khitrov et al. 2013). The PC-PVT stores the following relevant data: (1) time of the assessment; (2) number of minor lapses (RT> 500ms); (3) number of major lapses (RT>1000ms); (4) number of stimulus displayed; (4) minim RT; (5) maxim RT; (6) mean RT; and (7) median RT. In this study we have selected the median RT as the dependent variable and most accurate objective measure of fatigue. The mean can more easily be affected by lapses in RT which are usually observed with the first stimulus due to the inexperience of the construction worker with the PC-PVT protocol. For more information regarding the PC-PVT please refer to (Khitrov et al. 2013).

3.2 Construction Work and Fatigue

Based on the variables presented by (Techera et al. 2016b) as principal contributors to occupational fatigue, we developed a sub set of activity variables that could be easily measured at the beginning of a shift. Accordingly, each variable is accompanied by a question that inquires about the specific value of such a variable. These questions were assembled in the so-called 'Activity Questionnaire' for its implementation in the data collecting proses. Table 1 summarizes the principal variables, the subset of activity variables and the questions.

Table 1: Potential predictors of fatigue

Causes of fatigue	Activity Variables	Activity Questionnaire
Sleep Deprivation	Sleep in 24h	How many hours did you sleep during the past 24hs?
Incomplete Recovery	Rest in 24h	Besides sleeping, how many restful hours have you had in the past 24hs?
	Time off	How many hours have you had off since your last shift?
Workload	Consecutive shifts	How many previous consecutive shifts have you worked?
Overtime and LWH	Previous shift	How long was your last shift?
Work Environment	Repetitive	Are you performing repetitive tasks at work?
	Vibration	Are you exposed to vibration while working?
	Noise	Are you exposed to loud noises at work?
	Light	Is the work environment well lit?

	Temperature	What is the approximate temperature in your work environment now?
Mental Exertion	Mental demand 1 Mental demand 2	Are you performing mentally demanding tasks at work? How mentally demanding is your job? From 0 to 9
Muscular Exertion	Physical demand 1 Physical demand 2	Are you performing physically demanding tasks at work? How physically demanding is your job? From 0 to 9
Social Environment	Coworker Supervisor	Do you have a good relationship with your coworkers? Do you have a good relationship with your supervisor?
Self-Predisposition	Start time Condition	What is the start time of your shift today? Do you have a condition that doesn't allow you to rest well?

Additionally, demographic variables such as age, years of experience, position, and gender were included in the Activity Questionnaire accounting for a total of 22 variables.

3.3 Data Collection Process

Keeping in mind the practical application of the potential findings of this study, in the development of a fatigue assessment tool that will determine if a worker is fit for duty, the data collection process took place at to the beginning of the worker's shift. In general, the researchers met with a group of 4 to 12 construction workers and after sharing a brief introduction to the purpose of the project, the data collection procedure was explained. Consecutively, the workers first filed out the Activity Questionnaire and then took part in the PC-PVT on a laptop that met all the requirements of the software. Participation was anonymous.

3.4 Sample

The research sample consisted of 160 men between the ages of 19 and 65 (age: μ_x= 37.0 y/o, S = 10.5 yrs) with an average experience of 9.6 years (μ_x = 9.6 yrs.; S = 8.4 yrs.). A total of 40 worked in traditional commercial and civil construction and the other 120 worked in power transmission and distribution operations in the U.S. These two main types were characterized as Type 1 (traditional construction) and Type 2 (Linemen).

3.5 Statistical Procedure

The data obtained were either continuous (i.e. reaction time) or dichotomous (i.e. yes/no). Given the characteristics of our data, in order to test our hypothesis, a Multiple Linear Regression Analysis (MLRA) was performed. This method is generally used either to describe or to predict a relationship (Pedhazur 1997). According to (Miller and Kunce 1973) a minimum of 10 data points per variable of interest may be sufficient to evaluate the predictive character of an independent variable. Other authors suggest a minimum of 30 data points per each variable of interest (Pedhazur and Schmelkin 2013). However, there is no hard rule regarding this number because it depends entirely on the characteristics of the data and the real correlation between the independent variables and the criterion measured.

In our case, the following variables were not included in the regression given their null or nearly null variability: Gender, Coworkers, Light, Supervisor, and Condition. Additionally, the variable "experience" was excluded from the analysis given the lack of previous evidence of its influence on fatigue, and the dichotomous variable "Type" was included in the analysis. Consequently, the MLR analysis was performed on 16 activity variables with the Median RT of each participant as the dependent variable.

The statistical analysis followed the following order: (1) study of collinearity, (2) Stepwise MLR, (3) Forward MLR, and (4) Backward MLR. With the results obtained from these procedures, a predictive model was designed. After obtaining a predictive model all the underlying assumptions of MLR were validated. All statistical analyses were performed in SPSS Version 24.

4. RESULTS

4.1 Study of Collinearity

No collinearity was found among the variables included in the model.

4.2 Stepwise MLR and Forward MLR

All 3 models (Stepwise, Forward, and Backward) of MLR were designed to admit a new variable as a predictor if the difference in explained variability was significant with a 95% significance level. Additionally, each variable that does not present a significant explained variability at a 90% significance level can be removed from the model. Table 2 shows a summary of the Stepwise model where the variables “Type” and “Sleep 24h” were found as significant predictors of changes in reaction time as measured by the PC-PVT. This model is able to predict 18.5% of the variability as measured by the adjusted R^2.

Table 2: Stepwise Model Summary

Predictive Variables	R^2	Adjusted R^2	Std. Error of the Estimate	df	F Statistic Change	p-value
Type	0.155	0.150	39.378	158	29.039	0.000
Type + Sleep 24h	0.197	0.187	38.507	157	8.229	0.005

4.3 Backward MLR

The Backward MLR analysis selected one more variable as a predictor: “Physical 1”, however, this variable won’t be considered in the overall model because it doesn’t contribute significantly to a change in predictability (coefficient change t-test, p-value: 0.095).

4.4 Model

The MLR analysis has given place to the model presented in Table 3 as the best predictor of RT changes as measured by the PC-PVT. Table 3 represents the coefficients of the regression equation (Eq. 1) together with the corresponding standard error.

Table 3: Model Coefficients

Predictive Variables	Unstandardized B_i	Standard Error	Standardized B_i	t	Significance p-value
Constant	199.645	16.163		12.352	0.000
Type	38.854	7.030	0.395	5.527	0.000
Sleep24h	5.395	1.881	0.205	2.869	0.005

4.4.1 Regression equation (Eq. 1):

$\mathbf{[1]}\ \boldsymbol{y = 199.6 + 38.9x1 + 5.4x2 + E}\quad \text{Were x1} = \text{Type (1 or 2); x2} = \text{Sleep 24h; E} = \text{error}$

4.4.2 Residual Statistics:

Table 4 shows some descriptive statistics of the residuals together with Mahalanobi’s distance, Cook’s distance and centered Leverage Values that will be useful to assess outliers, high leverage, and influence.

Table 4: Residual Statistics

	Minimum	Maximum	Mean	Std. Deviation	N
Residual	-97.512	125.342	0.000	38.264	160
Std. Residual	-2.532	3.255	0.000	0.994	160
Stud. Deleted Residual	-2.615	3.379	0.001	1.013	160
Mahal. Distance	0.331	18.871	1.988	2.531	160
Cook's Distance	0.000	0.241	0.007	0.022	160
Centered Leverage Value	0.002	0.119	0.013	0.016	160

4.5 Model Validation

4.5.1 Linearity, Homoscedasticity, Normality, and Independence

Multiple Linear Regression relies on four assumptions over the residuals which must be tested for validation. The first assumption is "Linearity of the relationship". The second assumption is "Homoscedasticity" which evaluates if the spread of the residuals is equal along the predicted variables. The third assumption is normality of the residuals, and the last assumption is the independence of errors.

A good way to assess linearity is by looking at a scatterplot of the residuals along the predicted values. The assessment consists in plotting the regression line together with another line that is sensitive to the local nature of the data. This latter type of line receives the name of "lowess" line which stands for <u>lo</u>cally, <u>we</u>ighted <u>s</u>catterplot <u>s</u>moother. If the lowess line follows the fitted line closely then the assumption of linearity is met. This is the case with our model and it can be observed in Figure 1

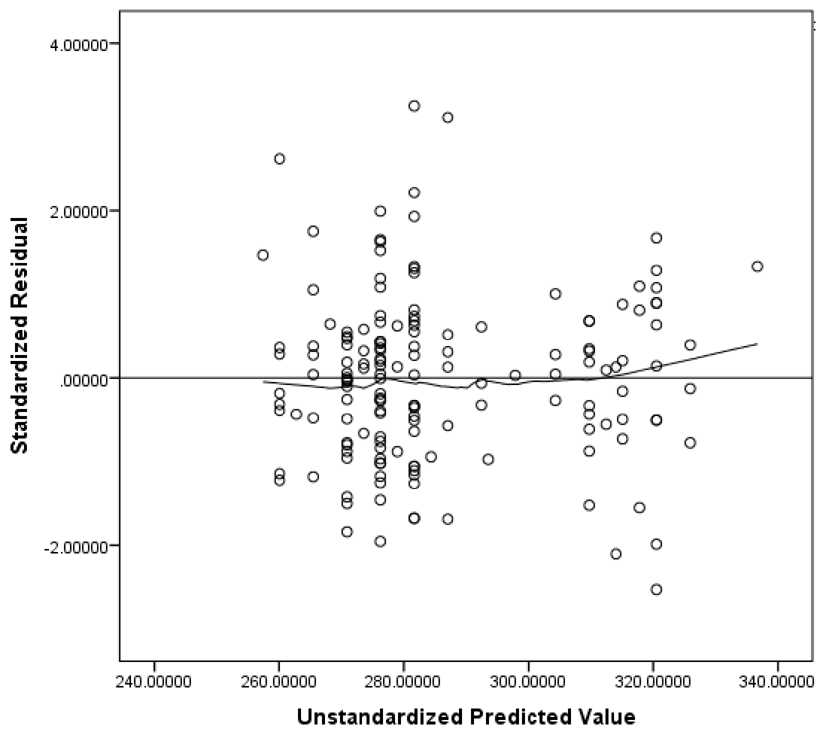

Figure 1 Test for Linearity

The Homoscedasticity of conditional residual distributions assumption states that the variance of the residuals is equal along the predictors. Consequently, we can also use Figure 1 to test this assumption. Figure 1 shows mainly two groups of points (type 1 and type 2 workers) equally vertically-distributed along the horizontal axis. Therefore, the amount of variability is equal along the predicted values.

The normality of the residuals can be easily assessed from looking at the histograms of the residuals and it can also be tested by looking at the skewness and kurtosis of the residuals. These observations were made and the residuals showed to be normal.

Regarding Independence, the participants didn't follow a specific time sequence and therefore the residuals are independent from one another and of the values of the predictor variables.

4.5.2 Outliers, Leverage, and Influence

Outliers are extreme values in the vertical direction. To assess the existence of outliers in the residuals we can look at the studentized deleted residual in Table 4. Given the degrees of freedom of our model and after applying Bonferroni correction, we conclude that no value should be greater than 3.68. Given that the maximum studentized deleted residual is 3.38 there are no outliers in the data.

Leverage refers to outliers in the horizontal axis. The presence of these outliers can be detected by looking at the Mahalanobi's distance in Table 4. We can observe that the maximum value is outside of the range divided by 3 standard deviations from the mean. Consequently, there is at least one outlier in the horizontal axis. However, Cook's distance is lower than 1, indicating that such outliers don't jeopardize the predictability of the model.

5. Discussion

This study constitutes the first effort to test the hypothesis that activity variables can predict changes in the level of fatigue of a construction worker. The alternative hypothesis has shown to be significant and an individual's level of fatigue, as measured by the PC-PVT, has shown to be correlated to at least 2 variables: (1) the type of worker (traditional construction or electrical worker) and the amount of sleep obtained in the previous 24 hours. These results agree with those obtained by (Dawson and McCulloch 2005) who stated that "managing fatigue is about sleeping".

The model created in this study shouldn't be applied to predict the level of fatigue of construction workers given the low explained variability of the model. However, these findings underline two important factors: (1) even within construction, the type of work performed strongly correlated to the level of fatigue experienced by individuals; (2) in fatigue prediction, the amount of sleep obtained during the past 24h is the main predictive activity variable.

Given the limited sample size, additional variables such as trade could not be selected as potential predictors. However, given the results obtained in this study, in which the type of worker was found to be the principal predictor of fatigue, the influence of trade in fatigue should be promptly addressed. Future research with a larger sample size could reveal new predictors, thus explaining more of the variability in the data. This could potentially give place to a fatigue predictive model.

REFERENCES

Arnaldo, R. M., Comendador, F. G., Sanz, L. P., and Sanz, A. R. (2016). "Friendly Fatigue Alert Mobile Apps to Help Aviation Workers Prevent, Identify and Manage Alertness and Fatigue." *Advances in Safety Management and Human Factors*, Advances in Intelligent Systems and Computing, P. Arezes, ed., Springer International Publishing, 421–432.

Balkin, T. J., Bliese, P. D., Belenky, G., Sing, H., Thorne, D. R., Thomas, M., Redmond, D. P., Russo, M., and Wesensten, N. J. (2004). "Comparative utility of instruments for monitoring sleepiness-related performance decrements in the operational environment." *Journal of Sleep Research*, 13(3), 219–227.

Buchholz, B., Paquet, V., Punnett, L., Lee, D., and Moir, S. (1996). "PATH: A work sampling-based approach to ergonomic job analysis for construction and other non-repetitive work." *Applied Ergonomics*, 27(3), 177–187.

Chan, M. (2011). "Fatigue: the most critical accident risk in oil and gas construction." *Construction Management and Economics*, 29(4), 341–353.

Dawson, D., Chapman, J., and Thomas, M. J. W. (2012). “Fatigue-proofing: A new approach to reducing fatigue-related risk using the principles of error management.” *Sleep Medicine Reviews*, 16(2), 167–175.

Dawson, D., and McCulloch, K. (2005). “Managing fatigue: It’s about sleep.” *Sleep Medicine Reviews*, 9(5), 365–380.

Dembe, A. E., Erickson, J. B., Delbos, R. G., and Banks, S. M. (2005). “The impact of overtime and long work hours on occupational injuries and illnesses: new evidence from the United States.” *Occupational and Environmental Medicine*, 62(9), 588–597.

Dinges, D. F., and Powell, J. W. (1985). “Microcomputer analyses of performance on a portable, simple visual RT task during sustained operations.” *Behavior Research Methods, Instruments, & Computers*, 17(6), 652–655.

Dorrian, J., Rogers, N. L., Dinges, D. F., and others. (2005). “Psychomotor vigilance performance: Neurocognitive assay sensitive to sleep loss.” Marcel Dekker New York.

Gander, P., Hartley, L., Powell, D., Cabon, P., Hitchcock, E., Mills, A., and Popkin, S. (2011). “Fatigue risk management: Organizational factors at the regulatory and industry/company level.” *Accident Analysis & Prevention*, Advancing Fatigue and Safety Research, 43(2), 573–590.

Gillberg, M., and Åkerstedt, T. (1994). “Sleep restriction and SWS-suppression: effects on daytime alertness and night-time recovery.” *Journal of Sleep Research*, 3(3), 144–151.

Goldich, Y., Barkana, Y., Pras, E., Zadok, D., Hartstein, M., and Morad, Y. (2010). “The Effects of Sleep Deprivation on Oculomotor Responses.” *Current Eye Research*, 35(12), 1135–1141.

Grandjean, E. (1979). “Fatigue in industry.” *British Journal of Industrial Medicine*, 36(3), 175–186.

Hallowell, M. R. (2010). “Worker fatigue: managing concerns in rapid renewal highway construction projects.” *Professional Safety*, 55(12), 18–26.

Johnston, R., Howard, M., Cawley, P., and Posse, G. (1998). “Effect of lower extremity muscular fatigue on motor control performance.” *Medicine & Science in Sports & Exercise®*, 30(12), 1703–1707.

Kajtna, T., Štukovnik, V., and Grošelj, L. D. (2011). “Effect of acute sleep deprivation on concentration and mood states with a controlled effect of experienced stress.” *Zdravniški Vestnik*, 80(5).

Kartam, N. A. (1997). “Integrating Safety and Health Performance into Construction CPM.” *Journal of Construction Engineering and Management*, 123(2), 121–126.

Khitrov, M. Y., Laxminarayan, S., Thorsley, D., Ramakrishnan, S., Rajaraman, S., Wesensten, N. J., and Reifman, J. (2013). “PC-PVT: A platform for psychomotor vigilance task testing, analysis, and prediction.” *Behavior Research Methods*, 46(1), 140–147.

Lal, S. K. L., Craig, A., Boord, P., Kirkup, L., and Nguyen, H. (2003). “Development of an algorithm for an EEG-based driver fatigue countermeasure.” *Journal of Safety Research*, 34(3), 321–328.

Langford, D., Rowlinson, S., and Sawacha, E. (2000). “Safety behaviour and safety management: its influence on the attitudes of workers in the UK construction industry.” *Engineering Construction and Architectural Management*, 7(2), 133–140.

Lerman, S. E., Eskin, E., Flower, D. J., George, E. C., Gerson, B., Hartenbaum, N., Hursh, S. R., and Moore-Ede, M. (2012). “Fatigue Risk Management in the Workplace:” *Journal of Occupational and Environmental Medicine*, 54(2), 231–258.

van der Linden, D., Frese, M., and Meijman, T. F. (2003). “Mental fatigue and the control of cognitive processes: effects on perseveration and planning.” *Acta Psychologica*, 113(1), 45–65.

Loh, S., Lamond, N., Dorrian, J., Roach, G., and Dawson, D. (2004). “The validity of psychomotor vigilance tasks of less than 10-minute duration.” *Behavior Research Methods, Instruments, & Computers*, 36(2), 339–346.

Lorist, M. M., Boksem, M. A., and Ridderinkhof, K. R. (2005). “Impaired cognitive control and reduced cingulate activity during mental fatigue.” *Cognitive Brain Research*, 24(2), 199–205.

Lorist, M. M., Klein, M., Nieuwenhuis, S., de Jong, R., Mulder, G., and Meijman, T. F. (2000). “Mental fatigue and task control: Planning and preparation.” *Psychophysiology*, 37(5), 614–625.

Marcus, J. H., and Rosekind, M. R. (2016). “Fatigue in transportation: NTSB investigations and safety recommendations.” *Injury Prevention*, injuryprev-2015-041791.

Miller, D. E., and Kunce, J. T. (1973). “Prediction and Statistical Overkill Revisited.” *Measurement and Evaluation in Guidance*.

Okogbaa, O. G., Shell, R. L., and Filipusic, D. (1994). “On the investigation of the neurophysiological correlates of knowledge worker mental fatigue using the EEG signal.” *Applied Ergonomics*, 25(6), 355–365.

Pedhazur, E. (1997). *Multiple Regression in Behavioral Research: Explanation and Prediction*. Holt, Rinehart and Winston.

Pedhazur, E. J., and Schmelkin, L. P. (2013). *Measurement, Design, and Analysis: An Integrated Approach*. Psychology Press.

Reiner, B. I., and Krupinski, E. (2011). “Demystifying Occupational Stress and Fatigue Through the Creation of an Adaptive End-User Profiling System.” *Journal of Digital Imaging*, 25(2), 201–205.

Rosekind, M. R., Smith, R. M., Miller, D. L., Co, E. L., Gregory, K. B., Webbon, L. L., Gander, P. H., and Lebacqz, J. V. (1995). “Alertness management: strategic naps in operational settings.” *Journal of Sleep Research*, 4(s2), 62–66.

Sawacha, E., Naoum, S., and Fong, D. (1999). “Factors affecting safety performance on construction sites.” *International Journal of Project Management*, 17(5), 309–315.

Schneider, S., and Susi, P. (1994). “Ergonomics and Construction: A Review of Potential Hazards in New Construction.” *American Industrial Hygiene Association Journal*, 55(7), 635–649.

Scott, J. P., McNaughton, L. R., and Polman, R. C. (2006). “Effects of sleep deprivation and exercise on cognitive, motor performance and mood.” *Physiology & behavior*, 87(2), 396–408.

Spurgeon, A., Harrington, J. M., and Cooper, C. L. (1997). “Health and safety problems associated with long working hours: a review of the current position.” *Occupational and Environmental Medicine*, 54(6), 367–375.

Techera, U., Hallowell, M. R., Marks, E., and Stambaugh, N. (2016a). “Measuring Occupational Fatigue: A Comprehensive Review and Comparison of Subjective and Objective Methods.” *ASCE Construction Research Congress 2016*, American Society of Civil Engineers, San Juan, Puerto Rico, 1546–1555.

Techera, U., Hallowell, M., Stambaugh, N., and Littlejohn, R. (2016b). “Causes and consequences of occupational fatigue: Meta-analysis and systems model.” *Journal of Occupational and Environmental Medicine*, 58(10), 961–973.

Tixier, A. J.-P., Hallowell, M. R., Albert, A., van Boven, L., and Kleiner, B. M. (2014). “Psychological antecedents of risk-taking behavior in construction.” *Journal of Construction Engineering and Management*, ASCE(04014052), 1–10.

U.S. Bureau of Labor Statistics. (2015). “Census of Fatal Occupational Injuries Summary, 2014.” <http://stats.bls.gov/news.release/cfoi.nr0.htm>.

Waehrer, G. M., Dong, X. S., Miller, T., Haile, E., and Men, Y. (2007). “Costs of occupational injuries in construction in the United States.” *Accident Analysis & Prevention*, 39(6), 1258–1266.

Weick, K. E., Sutcliffe, K. M., and Obstfeld, D. (2008). “Organizing for high reliability: Processes of collective mindfulness.” *Crisis management*, 3(1), 81–123.

Wierwille, W. W., Wreggit, S. S., Kirn, C. L., Ellsworth, L. A., and Fairbanks, R. J. (1994). “Research on vehicle-based driver status/performance monitoring; development, validation, and refinement of algorithms for detection of driver drowsiness. final report.”

Yaggie, J., and Armstrong, W. J. (2004). “Effects of lower extremity fatigue on indices of balance.” *Balance*, 312(322), 2004.