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RESEARCH ARTICLE

Does today's workload predict tomorrow's stress, fatigue, and other strain states? Exploring directionality in daily dynamics

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ABSTRACT

We examined whether whole day workload predicts strain (e.g. stress, fatigue, impaired cognition) experienced on the next day, and/or whether strain predicts next-day workload. Data were analysed (using dynamic structural equation models) from 196 adults with type 1 diabetes (T1D) who completed two weeks of 5 to 6 daily ecological momentary assessment (EMA) surveys. Workload was assessed with a version of the National Aeronautics and Space Administration Task Load Index (NASA-TLX) adapted for the whole day context. Higher overall workload during the day predicted a shorter sleep duration that night, as well as increased fatigue and slower perceptual speed the next day. In turn, increased stress, fatigue, and shorter sleep duration on one day predicted a higher perceived workload the following day. Among adults with T1D, strain and workload appear to reinforce each other across days, suggesting a potential feedback loop that may escalate if recovery is insufficient.

Practitioner Summary:: Measures of workload are widely used, and study results contribute to understanding and interpretation of workload. Specifically, results suggested that workload measures could also be affected by workload and strain on the days prior, and that both work and non-work workload are important to consider.

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Workload; stress; fatigue; sleep; cognitive performance

Introduction

Excessive levels of strain, the consequences of exposure to stressors or other demands (Sonnentag, Cheng, and Parker 2022), are problematic both for worker and non-worker populations. For instance, among workers, insufficient recovery and correspondingly high strain has been associated with burnout (Oerlemans and Bakker 2014; Werdecker and Esch 2021) and decreased job performance (Steed et al. 2021; Sonnentag, Cheng, and Parker 2022). In the U.S. alone, insufficient recovery and excessive strain among workers are estimated to cost the country $125 billion annually (Goh, Pfeffer, and Zenios 2016), with a majority of this cost attributable to productivity-related losses and the rest to healthcare and medical spending (Hassard et al. 2018). Several non-worker populations also often experience high levels of accumulated strain and associated issues. For instance, caregivers of frail older adults have lower self-reported mental and physical health compared to non-caregivers (Pinquart and Sörensen 2003). People with chronic conditions can have a large amount of patient work (i.e. activities aimed at maintaining and improving health) (Valdez et al. 2016). This considerable workload can lead to negative outcomes such as poorer health, decreased well-being, and non-adherence to treatment regimens (Sav et al. 2015).

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Exposure to workload from both work and non-work sources is a precursor to strain (Scott, Hwang, and Rogers 2006; Chari et al. 2018; Hernandez et al. 2022), but can typical levels of (work and non-work) workload exposure from just a single day lead to strain effects that last into the next day? In the Allostatic Load framework, environmental and internal demands trigger allostatic responses- the activation of physiological systems such as the HPA axis, autonomic nervous system, and immune processes—to help people contend with the demands (e.g. with increased arousal level) (Sterling and Eyer 1988; McEwen and Seeman 1999). When these allostatic responses are repeatedly activated or not followed by sufficient recovery, the body accumulates allostatic load (AL), the wear-and-tear that reflects chronic psychophysiological strain. Greater levels of this strain have been associated with symptoms typical of chronic stress such as fatigue (Rose et al. 2017), headaches (Borsook et al. 2012), and various sleep disturbances (Chen et al. 2014). Higher strain levels have also been associated with a greater frequency of long term health and functional issues (Seeman 1997; Seplaki et al. 2006). The model is vague, however, regarding the duration of high workload needed for strain effects to manifest. Prior research has often focused on examining strain after extended periods of insufficient recovery, such as a prior review finding a greater risk of coronary heart disease in employees working long hours (Virtanen et al. 2012) and another study finding that older adult caregivers with demanding caregiving duties were at greater risk for mortality compared to non-caregiving controls (Schulz and Beach 1999). Studies have also frequently investigated the associations between workload and strain on the same day (Keller and Meier 2024), with findings including greater fatigue and decreased cognitive performance on days with higher workload (Macdonald and Bendak 2000; Baulk et al. 2007; Hernandez et al. 2022). However, the question of whether workload can impact strain experienced on the next day has received less attention (Keller and Meier 2024).

Knowledge of the bidirectional lagged temporal dynamics between whole day workload and strain can improve understanding of the nature of workload, which can then help in interpretation of workload measures. For instance, if typical levels of workload exposure from just a single day can lead to next day strain effects, then even normal levels of workload could be interpreted as not only having strain implications for the same day but also potentially the following day. One prior study in the occupational health psychology literature found expected associations between workload and same-day fatigue, but no association between workload and next-day fatigue (Keller and Meier 2024). The authors interpreted this as evidence that workers in their sample typically achieved sufficient within-day recovery for the workload they experienced. However, their measure of workload – the Instrument for Stress Oriented Task Analysis (Semmer, Zapf, and Heiner 1995)- focused on psychological demands in the workplace. It is possible that different results might have emerged using a more general human factors oriented workload measure like the National Aeronautics and Space Administration Task Load Index (NASA-TLX) (Hart 2006) adapted for the whole day context which considers multiple dimensions of demands including physical, mental, and temporal (Hernandez et al. 2022). Furthermore, the authors did not examine whether strain could influence workload experienced on the following day. For instance, if a person is fatigued, this could increase her subsequent perception of workload (Inzlicht and Schmeichel 2012).

The objectives of this article were to examine whether whole day workload predicts strain experienced the next day, whether strain predicts whole day workload experienced the next day, and if strain and workload are concurrently associated with one another. We operationalised strain broadly in this study in that we examine its possible psychological and somatic manifestations (i.e. greater stress, fatigue, pain, and poorer sleep), its possible cognitive manifestations (i.e. poorer perceptual speed and/or sustained attention), and possible physiological consequences (i.e. less time in target blood glucose range). Prior research has suggested that, upon exposure to demands and the associated stress, blood glucose of individuals may increase as part of the acute stress response and the downstream effects of cortisol secretion (Goetsch et al. 1993; Chrousos 2009; Kusnanto et al. 2020; Sevil et al. 2021). At the daily level specifically, in individuals with type 1 diabetes a prior study found that greater daily stress was associated with greater blood glucose variability and time in hypoglycaemia for the same day (Gonder-Frederick et al. 2016). Concurrent and bidirectional single day lagged relationships are investigated between whole day workload and each of the aforementioned strain measures, allowing for a more comprehensive understanding of the temporal dynamics between workload and strain and how they might differ depending on the form of strain being considered.

Additionally, we examined working versus not, working full time versus not, being age 50 and above or not, and being 65 and above or not as potential moderators of the temporal dynamics between whole day workload and the different strain measures. The rationale was that workers, especially full-time workers, could experience more workload on average than others and that this could influence the results. For instance, whole day workload may predict strain experienced on the next day only for workers and/or full-time workers and not other individuals in the sample because only workers may experience an amount of whole day workload that results in strain that carries more strongly over into the next day. Part-time workers may not experience the same amount of carry-over in strain if their work hours are minimal, so the full-time worker versus not distinction was tested. Also, due to various declines in bodily systems with age (Shephard 1999; Harada, Natelson Love, and Triebel 2013), older individuals may be more affected compared to younger individuals when exposed to workload and different forms of strain. Thus, age 50 or 65 and above were examined as a potential moderators, with the former serving as a common cut-off for midlife and older versus not (Wilson, Lee, and Shook 2021; Van der Heijden, Veld, and Heres 2022; Kuerbis, Behrendt, and Morgenstern 2023) while the latter is common for distinguishing between older adults and younger ones (Lohne-Seiler et al. 2014; Javed et al. 2020).

Methods

Study overview

We analysed data from a sample of adults with type 1 diabetes (T1D), inclusive of workers and non-workers. Whole day workload and strain may be of particular relevance for adults with T1D because, aside from typical sources of workload they can experience like work and caregiving duties, they must also often engage in a large amount of patient work. According to prior work, engaging in the recommended self-management activities for diabetes, including checking blood glucose, taking insulin, and meal planning, can require two to four hours daily (Russell, Suh, and Safford 2005; Shubrook et al. 2018).

Participants were recruited from three clinical sites and study procedures are described in greater detail in the study's protocol paper (Pyatak et al. 2021). In brief participants completed the following: baseline training call and surveys, two weeks of 5 to 6 smartphone based ecological momentary assessment (EMA) surveys and cognitive assessments daily while wearing a continuous blood glucose monitor and accelerometer, and follow-up surveys. EMA surveys and cognitive tests were administered at fixed three-hour intervals, with a start time that was selected by participants and instructed to be as close as possible to their wake time. Participants were given the option to select different wake times for different days, and were informed what the corresponding time for the last survey per day would be. If they expressed concern that the last survey time conflicted with their sleep schedule or was not feasible for other reasons, then five surveys daily were scheduled instead of six. An average of 12.6 days (SD = 3.1) of EMA surveys and cognitive tests were completed by participants. The Mobile EMA application (mEMA: ilumivu.com) was used to administer EMA surveys and cognitive assessments. A measure of whole day workload was completed at the end of each day during the ambulatory assessment phase of the study. All the strain relevant measures were assessed at each EMA instance, and measurements collected on the same study day were averaged for each measure to create day-specific strain measures. This research complied with the tenets of the Declaration of Helsinki and was approved by the Institutional Review Board at the University of Southern California (Proposal #HS-18-01014). Written informed consent was obtained from each participant.

Measures

Whole day workload

Whole day workload (i.e. whole day TLX) was measured with a version of the NASA-TLX (Hart and Staveland 1988) adapted for the whole day context by changing its reference period from a particular task to a whole day (Hernandez et al. 2022). For instance, the item for mental demands was originally 'How mentally demanding was the task?' and was changed to 'How much mental activity was required for your whole day?' Alterations were performed in a consensus effort by the investigative team to alter the reference period of the items but maintain readability and simplify phrasing as appropriate for the study sample. Like with the original scale, participants were asked six items covering different aspects of workload: mental demand, physical demand, temporal demand, performance, effort, and frustration level. The response options were slider scale based and ranged from 0 (e.g. low mental demand) to 100 (e.g. high mental demand). Overall workload was computed for each day by averaging the ratings from the six whole day TLX items. Please refer to the Supplementary Text S1 for the actual wordings of the items in the measure.

The reliability and validity of the whole day TLX has been examined in prior research (Hernandez et al.

2022). The six items of the whole day TLX measure were not reflective of (i.e. caused by) a unidimensional whole day workload factor, but instead were formative in that the items appeared to capture factors that caused the perception of workload (consistent with theory) (Hart and Staveland 1988; Hernandez et al. 2022). Common psychometric tests such as confirmatory factor analysis are typically relevant for reflective items, while important psychometric checks for formative items include a conceptual check that they comprehensively cover factors impacting the construct of interest, examining collinearity between items, and testing for expected associations with other constructs (Diamantopoulos and Winklhofer 2001). In the development of the original TLX, after several studies the six dimensions represented by the TLX items were found to parsimoniously and comprehensively capture factors impacting workload (Hart and Staveland 1988). The within-person centred values for responses to the six whole day TLX items were found in this study to have variance inflation factors ranging from 1.1 to 1.5, suggesting low collinearity (O'brien 2007). In prior work, the sum of the items (i.e. workload composite) had expected within-person associations with engagement in strenuous and restful activities over the day, fatigue, negative affect, stress, and pain (Hernandez et al. 2022). Because the measure is formative, internal consistency metrics based on factor loading assumptions (like Alpha or McDonald's Omega) are not appropriate indicators of quality. As noted by Bollen (1989), formative indicators are not expected to correlate; in fact, high collinearity can be problematic (Diamantopoulos and Winklhofer 2001).

Strain

The psychological and somatic strain measures considered in this study were stress, fatigue, pain, and sleep duration. For stress, the item was 'How stressed are you right now?' and the questions for fatigue and pain followed the same format. Response options were slider scale based and ranged from 0 (not at all) to 100 (extremely). Such single item questions are common in EMA studies as they reduce the burden from repeated assessments while also providing meaningful information (King et al. 2019; Tung et al. 2022). For every study day, a daily average was computed for each variable and utilised in analyses. Note that single item EMA measures are often utilised to minimise participant burden, but their validity and reliability are often not formally investigated (Trull and Ebner-Priemer 2020) in part because most validation frameworks require multiple items. Instead, single item EMA measures often have their use justified by being derived from validated global measures and/or by being used in prior EMA studies. The single items here for stress, fatigue, and pain were all used in prior work (Broderick et al. 2009; Dunton et al. 2019). Assuming completion of five assessments in a day, daily average stress, fatigue, and pain were computed here and found to have within person reliabilities of 0.64, 0.44, and 0.72, respectively. These were computed using the variance decomposition approach (Raykov and Marcoulides 2006). Associations have been observed in prior work using measures with within-person reliabilities as low as .18, but lower reliability decreases statistical power for detecting effects (Sliwinski et al. 2018). This attenuation can be partially offset with more observations from each person in the sample (Sliwinski et al. 2018).

Sleep duration was computed in hours for the night of the whole day workload reports using a combination of self-reported sleep/wake times and accelerometer computed sleep/wake times. Specifically, an algorithm by Thurman et al. (2018) was applied that computed the weighted average of self-reported and accelerometry-derived sleep data for each individual, giving more weight to the empirically more likely value for each day.

Cognitive tests were administered at the end of each EMA survey, allowing assessment of the potential performance consequences of cognitive strain. One test, the Go/No-Go, measured sustained attention ability (Fortenbaugh et al. 2015). In this task, participants were shown a series of 75 images, either a mountain or city, and asked to tap an onscreen button when presented with a city but withhold tapping for images of mountains. Each test was approximately 1 minute in duration (Pyatak et al. 2021). Four primary outcome measures were described for the Go/No-Go task: variability of reaction time, d' (d-prime), mean reaction time, and criterion (Fortenbaugh et al. 2015). In a factor analysis, the first two measures loaded onto a sustained attention ability factor while the latter two loaded on sustained attention strategy. We were more interested in the potential performance consequences of strain rather than changes in response strategy. The two sustained attention ability performance measures, d' and response time variability, were highly correlated ($r = -76$), but d' was used as the primary outcome variable here because it was explicitly computed based on performance metrics (i.e. correct and incorrect button presses) while response time variability was not. Response time variability was more likely to be impacted by factors other than sustained attention performance such as distractions. d' was calculated with a signal detection approach based on the difference in the number of targets (mountains) a participant correctly withheld a response to, and the number of non-targets (cities) the participant incorrectly withheld a response to. For every study day, a daily average was computed for sustained attention ability.

The second cognitive test was the Symbol Search task, an assessment of visual-spatial attention and perceptual speed (Sliwinski et al. 2018). It involved asking participants to press one of two cards at the bottom of the screen that had symbols matching one of two cards at the top as quickly as possible, for 20 trials. Each test was approximately 45 seconds in duration (Pyatak et al. 2021). The faster the median reaction time for correct trials (measured in milliseconds), the greater the perceptual speed (Sliwinski et al. 2018). In this article, Symbol Search scores were recoded (i.e. multiplied by negative one) so that higher values indicated greater perceptual speed. For every study day, a daily average was computed for perceptual speed.

To capture physiological strain, blood glucose (BG) was measured with a continuous glucose monitor (CGM), the Abbott FreeStyle Libre Pro Flash Glucose Monitoring System. The device records interstitial glucose every 15 minutes, to which an algorithm is applied to estimate BG. The recorded BG data were reprocessed with an algorithm equivalent to the FreeStyle Libre 2 system by the Abbott Diabetes Clinical Research group. We computed commonly considered BG metrics from the CGM data including % time in range (i.e. proportion of time spent with glucose in the 70–180 mg/dL range), % time high (181–250 mg/dL), % time very high (>250 mg/dL), % time low (<70 mg/dL), and glycemic variability (i.e. coefficient of variation) (Battelino et al. 2023). Of these metrics, prior work found associations between daily stress and same day time low and glycemic variability (Gonder-Frederick et al. 2016). Metrics were computed for each day based on CGM data collected only when participants were awake (based on accelerometer and self-report derived sleep times), so it would match the time period that participants completed the EMA surveys.

Statistical analyses

To analyse our primary research questions, multilevel dynamic structural equation modelling (DSEM) was used. The DSEM aspect of this approach allows for considering changes across time in several variables simultaneously (e.g. workload and stress) (Asparouhov, Hamaker, and Muthén 2018), while the multilevel aspect takes into account non-independence in observations stemming from the multiple datapoints collected for each individual (Dash 2022). Note that in two level models with multiple observations per person, as was used here, associations can be divided into within and between person effects (Morselli 2021). The former captures how within person changes in variables covary with one another, and was the primary level of interest in this article, while the latter captures how a person's study average level of one variable covaries with the study average of another between people. Altogether, multilevel DSEM makes it possible to simultaneously model multivariate time series data obtained from multiple individuals.

To examine how workload and strain influence each other over time, the multilevel DSEM approach was used to examine the cross-lagged panel model shown in Figure 1 (Zyphur et al. 2020), which is focused on the within-person level of the multilevel model. The autoregressive (AR1 and AR2) paths modelled the possibility that each variable was influenced by its value on the prior day. The estimate for the cross-lagged path from whole day workload to strain on the next

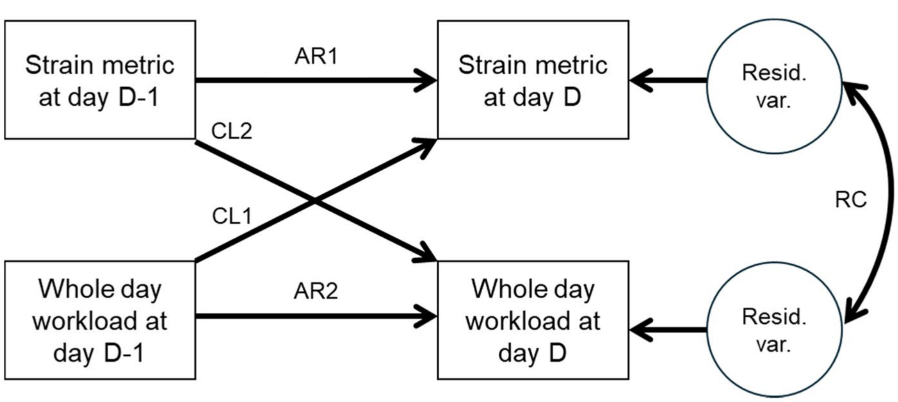

Figure 1. Dynamic structural equation models for within-person relationships between strain relevant variables and whole day workload, as measured by the whole day NASA-TLX.
Note: AR: autoregressive; CL: cross lagged; RC: residual correlation; Resid. var.: residual variance.

day (i.e. CL1) addressed the primary research question of whether whole day workload predicted strain experienced on the next day. The estimate of the other cross-lagged path from strain to whole day workload on the next day (i.e. CL2) addressed the other primary question of whether strain predicts whole day workload experienced on the next day. Finally, the residual correlation (RC), or the correlation after adjustment for prior day values, addressed the secondary question of whether strain and workload are concurrently associated with one another on the same day. A total of eleven different multilevel DSEMs were examined, one for each pairing of the whole day workload measure and the eleven strain measures described prior. To facilitate model convergence, in each model, only participants with >0 variance in the strain measures were included. Thus, the eleven DSEMs can have varying sample sizes depending on the number of participants that reported a particular strain measure without any variation.

To aid with interpretation, in addition to unstandardised estimates for the cross lagged paths, standardised estimates were also computed based on the 'STDYX' output in M*plus*, which standardises estimates at the within-person level based on the within-person variances of the predictor and outcome variables. For standardised cross lagged paths, an estimate with a magnitude of 0.03 can be interpreted as a small effect, 0.07 as a medium effect, and 0.12 as a large effect (Orth et al. 2024). For residual correlations, the traditional guidelines for correlation effect size interpretation can be used: .10, .30, and .50 as small, medium, and large effects, respectively (Cohen 1988). Estimates for the cross lagged paths and residual correlations are presented with their 95% confidence intervals, which can be interpreted as indicating statistical significance at an alpha of 0.05 if they do not contain 0.

We examined if working status (i.e. working or not), working full time or not, age 50 and older or not, and age 65 and above or not were moderators of any of the pathways of interest (i.e. either cross lagged relationship, or the residual correlation). The presence of moderation was determined based on the confidence interval for the cross-level interaction of a within-person path estimate (e.g. CL1) with binary variables indicating whether a participant was a worker or not, full-time worker or not, age 50+ or younger, and age 65+ or younger.

While the focus of this article was on the within-person temporal dynamics between whole day workload and strain (i.e. Figure 1), covariances between person averages of these variables were specified at the between-person level. The standardised version of these covariances capture the correlations between individuals' average whole day workload and the average for each strain measure, and were reported for comprehensiveness.

All primary analyses were completed using M*plus* version 8.11 (Muthén and Muthén 1998) via the R package MplusAutomation (Hallquist and Wiley 2018) in the statistical software R (R Core Team, 2020). Models were estimated in Mplus using Bayesian estimation with default (noninformative) priors, implemented via Markov chain Monte Carlo (MCMC) sampling. For continuous outcomes, Mplus uses a Gibbs sampling algorithm (with Metropolis–Hastings steps where required). Missing data were handled using a full-information Bayesian approach based on the joint likelihood of the observed data, under the assumption that data were missing at random (MAR). For continuous variables, this approach is mathematically equivalent to full information maximum likelihood estimation (Asparouhov and Muthén 2010).

Results

Sample characteristics

A total of 196 participants were in the study sample with a mean age of 39.6 years (SD = 14.3) and 35% (n = 69) of whom identified as full-time workers. Table 1 lists the sample characteristics. Figure 2 shows the distributions of study average workload for workers (n = 92, 47%) and non-workers (n = 104, 53%), where the median for workers as indicated by the vertical line (47.5) was slightly greater than the median for non-workers (43.3). Only a small portion of the sample reported caregiving on ≥10% of beeps (n = 18, 9.2%), and an even smaller portion reported both caregiving on ≥10% of beeps and working full or part-time (n = 5, 2.6%). Across all participants, ≥4 EMA surveys were completed on 86% of all data collection days. The median EMA completion rate was 92%.

Multilevel DSEM results

Results of the multilevel DSEMs are shown in Tables 2 and 3. They are described in greater detail below.

Does whole day workload predict next day strain (CL1 path)?

Experiencing greater whole day workload compared to one's average was associated with greater fatigue (B = 0.119 [95% CI: 0.034 to 0.208], standardised estimate= 0.084) on the following day, which is

Table 1. Participant characteristics (n = 196).

Participant characteristics	Full sample N = 196
Gender, N(%)	
Female	107 (54.6)
Male	89 (45.4)
Age, years, M (SD)	39.6 (14.3)
Diabetes Duration (years)	20.7 (12.6)
% blood glucose time in range (70–180 mg/dL)	52.5 (22.4)
% low glucose (<70 mg/dL)	5 (5.7)
% high glucose (181–250 mg/dL)	21.6 (9.8)
% very high glucose (>250mg/dL)	20.9 (21.3)
Technology	
CGM as part of usual care, n (%)	115 (58.7)
Including AID, n (%)	45 (23)
No technology, n (%)	81 (41.3)
Race/Ethnicity, N(%)	
Hispanic	80 (40.8)
Non-Hispanic White	56 (28.6)
Non-Hispanic Black	29 (14.8)
Asian	7 (3.6)
Other/Multi	20 (10.2)
Not provided	4 (2)
Level of education, N(%)	
High school or lower	50 (25.5)
Some College	66 (33.7)
Bachelor's degree	55 (28.1)
Graduate degree	22 (11.2)
Not provided	3 (1.5)
Annual household income, N(%)	
Less than $25,000	47 (24)
$25,000 to less than $50,000	43 (21.9)
$50,000 to less than $75,000	15 (7.7)
$75,000 or more	40 (20.4)
Not provided	51 (26)
Health insurance, N(%)	
Government sponsored	78 (39.8)
Private	75 (38.3)
Both government & private	11 (5.6)
No health insurance	4 (2)
Not provided	28 (14.3)
Employment status, N(%)	
Working full-time	69 (35.2)
Working part-time	23 (11.7)
Not working	104 (53.1)
Caregiving, N(%)	
Caregiving reported on ≥10% of beeps	18 (9.2)
Caregiving on <10% of beeps	178 (90.8)
Caregiving on ≥10% of beeps and working	5 (2.6)

AID: Automated Insulin Delivery system; CGM: Continuous glucose monitor.

considered a medium cross lagged effect. Greater whole day workload was also associated with lower perceptual speed (B= −0.001 [95% CI: −0.002 to −0.00007], standardised estimate= 0.053) on the following day, a small cross lagged effect.

Does strain predict next day whole day workload (CL2 path)?

Experiencing greater stress compared to one's average was associated with greater reported whole day workload (B = 0.078 [95% CI: 0.026 to 0.133], standardised estimate= 0.111) on the following day, a medium to large cross lagged effect. Greater fatigue was also associated with higher reported whole day workload

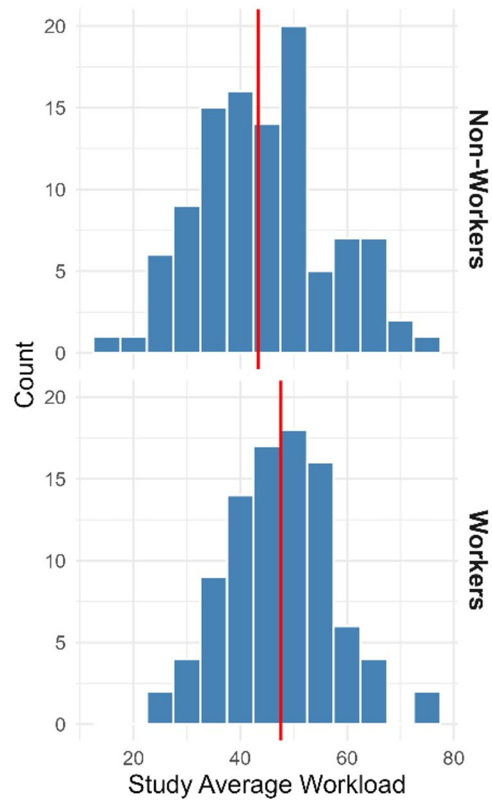

Figure 2. Distribution of study average workload for workers and non-workers in the sample, with vertical lines at the median.

(B = 0.054 [95% CI: 0.006 to 0.104], standardised estimate= 0.068) on the following day, a medium cross lagged effect. Finally, a lower sleep duration was associated with higher reported whole day workload (B= −0.872 [95% CI: −1.356 to −0.462], standardised estimate= −0.127) on the day of waking, a large cross lagged effect.

This pattern of results suggested a possible mediation pathway where fatigue and stress may impact next day workload through sleep duration. Thus, we tested for mediation through sleep duration in exploratory analyses using the model shown in Figure 3, which added sleep duration paths to the Figure 1 model. The indirect effect was computed as the product of the 'a' and 'b' paths shown in Figure 3. Mediation by sleep duration was significant for fatigue (indirect effect B= −0.004 [95% CI: −0.009 to −0.0004]) but not stress (indirect effect B = 0.000 [95% CI: −0.004 to 0.004]). Specifically, inconsistent mediation (i.e. a suppression effect) was observed, whereby the indirect path was one where greater fatigue predicted a longer sleep duration which in turn predicted a lower workload rating the following day (B= −0.004 [95% CI: −0.009 to −0.0004]), while in the direct path fatigue predicted a greater workload the following day

Table 2. Unstandardised Coefficients and 95% confidence intervals for parameters for dynamic structural equation models, one for each strain relevant variable. The strain variables here are possible psychological, somatic, and cognitive manifestations of strain.

	Stress n = 195	Fatigue n = 196	Pain n = 192	Sleep duration n = 192	Perceptual Speed n = 194	Sustained Attention n = 194
Within-person estimates						
Whole Day TLX Predicting Strain Variable (CL1)	0.067 (−0.019, 0.158) Std.=0.07	0.119 (0.034, 0.208)* Std.=0.084	0.062 (−0.006, 0.13) Std.=0.07	−0.011 (−0.025, 0.002) Std.=-0.066	−0.001 (−0.002, −0.00007)* Std.=-0.053	0 (−0.002, 0.001) Std.=-0.016
Strain Variable Predicting Whole Day TLX (CL2)	0.078 (0.026, 0.133)* Std.=0.111	0.054 (0.006, 0.104)* Std.=0.068	0.006 (−0.079, 0.076) Std.=0.015	−0.872 (−1.356, −0.462)* Std.=-0.127	−0.512 (−3.581, 2.103) Std.=-0.008	0.909 (−0.75, 2.842) Std.=0.036
Residual Correlation between Whole Day TLX and Strain Variable (RC)	0.4 (0.341, 0.462)*	0.281 (0.186, 0.363)*	0.134 (0.047, 0.217)*	−0.18 (−0.271, −0.08)*	0.012 (−0.045, 0.074)	−0.03 (−0.088, 0.033)
Between-person estimate						
Correlation between Person Mean Whole Day TLX and Mean Strain Variable	0.64 (0.517, 0.738)*	0.372 (0.192, 0.531)*	0.25 (0.032, 0.436)*	0.195 (−0.031, 0.4)	−0.051 (−0.255, 0.165)	−0.185 (−0.362, 0.008)

Note: Std.=standardised estimate; not provided for the residual correlations since they can already be interpreted on a 0 to 1 scale.
*Confidence interval does not contain 0 indicating statistical significance at alpha = 0.05.

Table 3. Unstandardised Coefficients and 95% confidence intervals for parameters for the dynamic structural equation models with blood glucose (BG), one for each BG measure.

	% Time in Range (BG) n = 179	% Time High (BG) n = 179	% Time Very High (BG) n = 169	% Time Low (BG) n = 153	Glycemic Variability n = 180
Within-person estimates					
Whole day TLX predicting strain variable (CL1)	0.049 (−0.053, 0.137) Std.=0.023	−0.044 (−0.123, 0.032) Std.=-0.028	0.014 (−0.094, 0.130) Std.=0.019	−0.038 (−0.087, 0.011) Std.=-0.052	0.002 (−0.044, 0.051) Std.=0.001
Strain variable predicting whole day TLX (CL2)	−0.009 (−0.044, 0.028) Std.=-0.014	−0.009 (−0.059, 0.040) Std.=-0.015	0.012 (−0.038, 0.063) Std.=0.027	−0.059 (−0.213, 0.092) Std.=-0.030	−0.008 (−0.084, 0.066) Std.=-.01
Residual correlation between whole day TLX and strain variable (RC)	−0.002 (−0.057, 0.054)	−0.012 (−0.068, 0.056)	−0.087 (−0.17, −0.012)*	−0.048 (−0.174, 0.07)	0.027 (−0.038, 0.077)
Between-person estimate					
Correlation between person mean whole day TLX and mean strain variable	−0.107 (−0.296, 0.082)	−0.003 (−0.213, 0.196)	0.048 (−0.165, 0.257)	0.186 (−0.111, 0.447)	0.123 (−0.072, 0.293)

Note: Std.=standardised estimate; not provided for the residual correlations since they can already be interpreted on a 0 to 1 scale.
*Confidence interval does not contain 0 indicating statistical significance at alpha = 0.05.

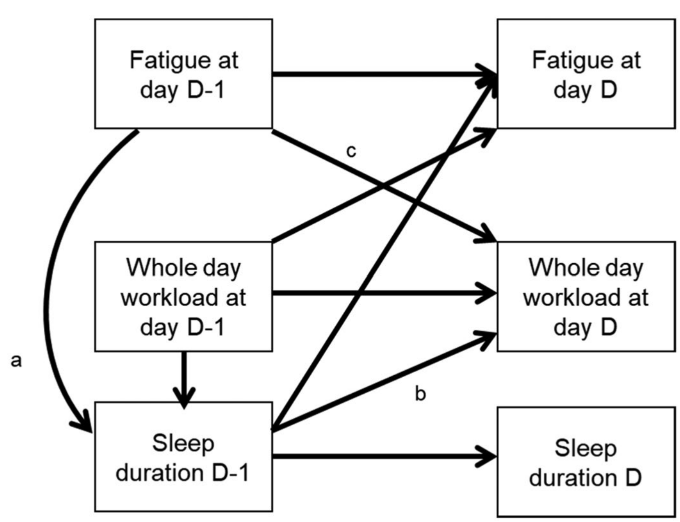

Figure 3. Dynamic structural equation model examining whether sleep duration acted as a mediator between fatigue and next day workload. The mediation model for stress substituted out fatigue for stress.

(B = 0.052 [95% CI: −0.003 to 0.106]). Thus, if not for the inconsistent mediation through sleep duration, the magnitude of the relationship between fatigue and next day workload would have been greater.

Are whole day workload and strain concurrently related (RC path)?

Greater whole day workload was concurrently associated with greater stress (r = 0.40, [95% CI: 0.341 to 0.462]), fatigue (r = 0.281, [95% CI: 0.186 to 0.363]), pain (r = 0.134, [95% CI: 0.047 to 0.217]), a lower percentage of time with very high blood glucose (r = −0.087, [95% CI: −0.170 to −0.012]), and lower sleep duration at the end of the day (r = −0.180, [95% CI: −0.271 to −0.080]). The magnitudes of these associations are moderate, moderate, small, small, and small respectively.

Do working status or age act as moderators?

Being a worker versus a non-worker moderated the path from pain to next day whole day workload (B= −0.188 [95% CI: −0.312 to −0.061]), such that the association was positive for non-workers (B = 0.134 [95% CI: 0.039 to 0.238]) and trending towards being negative for workers (B= −0.053 [95% CI: −0.148 to 0.041]). It also moderated the path from glycemic variability to next day whole day workload (B=-0.158 [95% CI: −0.300 to −0.006]), such that the association was trending towards being positive for non- workers (B = 0.045 [95% CI: −0.042 to 0.131]) and trending towards being negative for full-time workers (B= −0.102 [95% CI: −0.209 to 0.008]).

Working full-time moderated the path from pain to next day whole day workload (B=-0.137 [95% CI: −0.275 to −0.001]), such that the association was trending towards being positive for non-full-timeworkers (B = 0.075 [95% CI: −0.008 to 0.159]) and trending towards being negative for full-time workers (B= −0.072 [95% CI: −0.195 to 0.051]). It also moderated the residual correlation between % time in range and same day whole day workload (B = 0.129 [95% CI: 0.011 to 0.269]) such that the correlation was trending towards being negative for non-full-timeworkers (r= −0.045 [95% CI: −0.116 to 0.054]) and trending towards being positive for full-time workers (r = 0.086 [95% CI: −0.01 to 0.169]). Finally, working full-time moderated the path from glycemic variability to next day whole day workload (B=-0.159 [95% CI: −0.311 to −0.019]), such that the association was not significant for non-full-timeworkers (B = 0.045 [95% CI: −0.042 to 0.131]) and negative for full-time workers (B= −0.128 [95% CI: −0.256 to −0.0002]).

Being age 50 and older or not (n = 51) did not moderate any of the relationships between whole day workload and the strain variables.

Being age 65 and older or not (n = 14) was a significant moderator of the concurrent associations between whole day workload and same day stress (B = 0.45 [95% CI: 0.175 to 0.707]), % time in blood glucose range (B= −0.44 [95% CI: −0.656 to −0.102]), % time high (B = 0.46 [95% CI: 0.202 to 0.696]), % time very high (B= −0.50 [95% CI: −0.746 to −0.17]), and sleep duration (B= −0.54 [95% CI: −0.851 to −0.181]). For individuals below 65, the concurrent associations with workload were r = 0.381 [95% CI: 0.316 to 0.442] for stress, r = 0.021 [95% CI: −0.054 to 0.099] for time in range, r= −0.032 [95% CI: −0.102 to 0.037] for time high, r= −0.075 [95% CI: −0.14 to 0.005] for time very high, and r= −0.137 [95% CI: −0.235 to −0.035] for sleep duration. For individuals 65 and above, the magnitudes of correlations were generally higher, with values of r = 0.706 [95% CI: 0.565 to 0.808], r= −0.393 [95% CI: −0.58 to −0.174], r = 0.432 [95% CI: 0.224 to 0.6], r= −0.521 [95% CI: −0.668 to −0.306], and r= −0.606 [95% CI: −0.76 to −0.383], respectively.

Are average whole day workload and average strain associated? (between-person relationships)

Greater person-level average whole day workload was correlated with greater average stress (r = 0.64, [95% CI: 0.517 to 0.738]), fatigue (r = 0.372, [95% CI: 0.192 to 0.531]), and pain (r = 0.25, [95% CI: 0.032 to 0.436]). These were large, moderate, and moderate correlations, respectively.

Sensitivity analysis

We examined if use of the daily medians of stress, fatigue, pain, perceptual speed, and sustained attention, instead of their daily means, would affect results from dynamic structural equation models (Supplementary Table S1). The computed estimates were nearly identical to those in Table 2. Other strain measures did not utilise daily means.

Discussion

A comprehensive picture of the temporal dynamics between whole day workload, inclusive of work and non-work sources, and strain measures emerged from the present analyses. Greater whole day workload was associated with greater same day stress, fatigue, pain, less time with very high blood glucose, and a lower sleep duration at the end of the day, as consistent with prior literature (Macdonald and Bendak 2000; Åkerstedt et al., 2002; Baulk et al. 2007; Jansen et al. 2020; Hernandez et al. 2022). Note however that previous studies rarely controlled for lagged effects, as was done here, which allows for examination of if workload has associations with same day strain relevant measures with less confounding by possible carryover effects from the day prior (e.g. fatigue or workload from yesterday). Another novel contribution of this article was the examination of the bidirectional lagged associations between whole day workload and strain. In contrast to one prior study finding no association between whole day workload and next day fatigue (Keller and Meier 2024), we did find that greater whole day workload predicted greater fatigue and slower perceptual speed on the next day (medium and small effects respectively). This could signify that same day recovery from workload was often insufficient, leading to strain effects that carried into the next day. Also, greater stress, fatigue, and lower sleep duration on one day predicted a greater reported level of whole day workload on the following day (large, medium, and large effects, respectively). This is consistent with the theory that people's perception of workload takes into account the resources available to them (Wickens et al. 2021), so greater stress/fatigue on one day (i.e. less resources) may lead to a perception of less energetical resources on the next day, thereby increasing workload perception (Muraven and Baumeister 2000; Inzlicht and Schmeichel 2012). Another possibility is that fatigue may lead to less efficient performance on the next day (e.g. worse planning), contributing to an actual increase in workload (Hockey 2013).

Overall, there was evidence for the possibility of a positive feedback loop where perceived whole day workload and strain could continually increase one another across days if a person is continually exposed to greater workload than their average level. Such a feedback loop sounds intuitive, but this is to our knowledge the first time it has been empirically supported with data from a longitudinal EMA study. Workload measures are widely used in human factors work (Matthews, De Winter, and Hancock 2020), and knowledge of the potential feedback loop could inform how workload measures are interpreted. For instance, the loop could imply that workload measures may not only be impacted by workload exposure on the current day but could also be affected by workload and strain on the days prior.

Five of the 33 DSEM paths were significantly moderated by being age 65 and older versus not such that, compared to younger adults, older adults had associations of greater magnitude between workload and same day stress, blood glucose, and sleep duration. Results seemed to support the assertion that older adults may be more susceptible to negative same day effects of workload, possibly because of declines in bodily systems with age (Shephard 1999; Harada, Natelson Love, and Triebel 2013). Note, however, that the number of individuals aged 65 and older was small (n = 14), meaning results need to be interpreted cautiously and require replication with a larger 65 and older sample.

Unanticipated findings

Greater whole day workload was not associated with decrements in next day sustained attention or with less time in target blood glucose (BG) range. It is unclear why perceptual speed decreased after higher workload days but not sustained attention. Perhaps, the simple explanation is that perceptual speed and sustained attention are distinct domains of cognitive functioning (Harvey 2019), so it may not be reasonable to expect all cognitive domains to be affected by workload exposure in the same way. In terms of BG, one may expect that greater workload exposure should have led to an increase in the physiological stress response resulting in increased BG levels and a corresponding lower proportion of time in target BG range (Marik and Bellomo 2013). Instead, however, we observed that greater whole day workload was concurrently associated with less time with very high BG. A possible explanation is that workload ratings may not only reflect efforts in tasks like work and caregiving, but efforts in diabetes specific patient work like checking blood glucose and taking insulin. On days when higher whole day workload was reported, the corresponding diabetes patient work may also have been high, leading to a concurrent reduction in percent time with very high BG. Another possible explanation is that on days when people had very high BG they may not have been capable of working as intensely, due to the possible acute symptoms of high BG such as fatigue, nausea, and dizziness (Institute for Quality and Efficiency in Health Care 2020). This argument is supported by a prior finding that more time with very high overnight BG predicted more sedentary behaviour the next day (Pyatak et al. 2023).

Only 3 of the 33 DSEM paths were significantly moderated by full-time worker status, suggesting that most of the workload-strain pathways were similar across full-time workers and non-full-time workers. Perhaps because this was a sample with T1D, even non-workers experienced an amount of whole day workload from their patient work and other responsibilities (e.g. caregiving, housework, etc.) that would often carry over into (i.e. predict) next day fatigue.

Results of mediation analyses suggested that sleep duration suppressed the magnitude of the positive association between fatigue and next day workload, since fatigue also predicted longer sleep duration which in turn was associated with lower whole day workload. Sleep in large part serves a general restorative function (Zisapel 2007), so perhaps sleep duration was longer when fatigue was greater to facilitate restoration, leading to a greater perception of energetical resources and lower workload ratings on the next day. Overall, the results imply that the longer that individuals sleep after a high fatigue day, the less of an impact fatigue has on the perception of workload the following day.

Limitations

The study sample was comprised of adults with T1D recruited during various stages of the COVID-19 pandemic, which could limit generalisability of study findings. Nevertheless, the design of this study (e.g. measures used and statistical methods applied) could potentially provide guidance for future efforts to examine the temporal dynamics of whole day workload and strain in other populations. It may be the case that bidirectional day lagged associations between whole day workload and strain may only be present for specific populations, and not others.

The study focused on the totality of workload people experienced over the whole day, not on determining the sources of workload, so our workload measures were correspondingly constrained. We did not additionally ask about source specific workload (e.g. workload from caregiving or work) to avoid excessive participant burden. The disadvantage of the whole day workload measure was that it did not allow for identification of specific sources of workload, but the advantage, which was most important for this study, was the measurement of people's total workload exposure. Thus, while for study results there is ambiguity regarding whether different types of workload impacted observed relationships, we reduced the issue of only capturing a portion of people's workload exposure.

The study was not adequately powered to examine the within-person dynamic relationships between workload and strain variables with p-value corrections for multiplicity of testing, so none were applied to avoid type II error, meaning that results could have be susceptible to type 1 error and require replication. It has been argued that the need for multiple-comparison adjustments is best judged case by case rather than applied universally (Althouse 2016). Such adjustments reduce type I error but increase type II error, so the decision should reflect which error is more costly for the research question (Rothman 2014). In confirmatory studies with clinical or treatment implications, avoiding type I error is typically paramount, making adjustment appropriate (Althouse 2016). In contrast, for post-hoc or theory-building analyses without direct clinical consequences, the greater risk may be missing potentially meaningful effects (Rothman 1990). Here, the study was originally powered to detect momentary dynamic relationships between blood glucose and strain variables; shifting the analytic focus to the daily level in the present analyses substantially reduced statistical power, as day-level analyses rely on far fewer observations per person. We assert that the non-*p*-value adjusted results should be interpreted cautiously and require replication in future work (Althouse 2016).

BG is merely one of several potential indices of physiological strain stemming from allostasis and allostatic load from workload exposure (Juster et al. 2011; Bizik et al. 2013), and many factors aside from workload can also impact BG including food consumed, exercise, and hydration (American Diabetes Association 2018). Other possible indices of psychological strain from workload include cortisol, blood pressure, and heart rate, though each are also affected by several non-workload factors. Note though that, in the allostatic load framework, overall physiological strain from any source (i.e. physiological 'wear and tear') is often computed as a composite score of several biomarkers (Juster et al. 2011), and researchers often examine associations between this overall score and their construct of interest. For instance, occupational health researchers have often computed overall physiological strain and investigated their associations with constructs of interest including job demands, work related stress, and burnout (Mauss et al. 2015). Only BG was measured here, but future work could also measure other biomarkers to enable computation of a more comprehensive physiological strain score as consistent with the allostatic load framework.

While the temporal sequencing of study measures (e.g. whole day workload one day and strain on the next) suggests the possibility of causality between variables, this alone does not provide conclusive evidence of causality. The strongest evidence may come from randomised controlled trials. For instance, if individuals are randomised to experience low or high whole day workload days and then have strain assessed on the following day, then this could provide more definitive evidence of if the effect of whole day workload on next day strain is causal or not.

Conclusion

While prior studies have often examined concurrent associations between workload and strain, to our knowledge none have used longitudinal data to examine bidirectional day lagged associations. Upon examining these associations in a sample of adults with type 1 diabetes, we found that more whole day workload predicted greater fatigue and slower perceptual speed on the next day, and lower sleep duration the same night. Also, greater stress, fatigue, and lower sleep duration on one day predicted a greater reported level of whole day workload on the following day. Thus, there was evidence for the possibility of a positive feedback loop where perceived whole day workload and strain could continually increase one another across days if a person is continually exposed to greater workload than their average level, as could be the case if a worker is tasked with a demanding project spanning multiple days or if a patient has complications with their treatment regimen requiring several days of problem solving. Workload measures are often administered in human factors work, and a more comprehensive understanding of the temporal dynamics of the experience of whole day workload and strain can contribute to understanding and interpretation of workload measures.

Author contributions

CRediT: **Raymond Hernandez**: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Writing – original draft; **Stefan Schneider**: Formal analysis, Methodology, Supervision, Writing – review & editing; **Raeanne C. Moore**: Supervision, Writing – review & editing; **Jeffrey S. Gonzalez**: Writing – review & editing; **Claire Hoogendoorn**: Project administration, Writing – review & editing; **Shawn C. Roll**: Supervision, Writing – review & editing; **Haomiao Jin**: Methodology, Supervision, Writing – review & editing; **Jason Fanning**: Methodology, Supervision, Writing – review & editing; Jack **P. Ginsberg**: Supervision, Writing – review & editing; **Elizabeth A. Pyatak**: Conceptualization, Funding acquisition, Supervision, Writing – review & editing.

Disclosure statement

RCM is a co-founder, has equity interest, is a consultant and receives compensation from NeuroUX, a company that develops mobile cognitive tests. The terms of this arrangement have been reviewed and approved by UC San Diego in accordance with its conflict of interest policies. NeuroUX cognitive tests were not used for this study. The other authors have no conflicts of interest to report.

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Data availability statement

The data that support the findings of this study are available from the corresponding author, R.H., upon reasonable request. Code for the primary study analyses and example *Mplus* analyses outputs are available at https://osf.io/mcu78/files/osfstorage

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