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RESEARCH ARTICLE

The impact of self-selected short sleep on monetary risk taking

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Summary

Risky choice has been widely studied in experimental settings, but there is a paucity of research examining the effects of self-selected sleep schedules on risky choices. The current study examined incentivised risky choices of 100 young, healthy adults whose self-selected (at-home) sleep schedules were tracked via actigraphy for 1 week prior to decision making. Average nightly sleep was 6.43 h/night. On each trial of the decision task, individuals chose between two monetary gambles, with separate blocks of trials presenting amounts to gain versus amounts to lose for each paired gamble choice. In general, participants were risk-averse when trying to maximise gains (GAINS) and risk-seeking when trying to minimise losses (LOSSES). These tendencies were amplified in trials where gambles differed more (vs less) in their riskiness. Response times were longer for real choices (vs. dummy trials of random choice), LOSS versus GAINS trials, and when gambles were more similar versus different in risk. Gamble choices were not impacted by actigraphy measured average sleep levels, which suggests self-selected moderate sleep deprivation does not affect risky monetary choices, as has been found in studies of experimentally induced sleep deprivation. However, our data showed that sleep variability increased risk-taking behaviour in the LOSS condition. Thus, risky decision-making may relate more to variability in sleep efficiency than to overall sleep duration or quality in naturalistic settings. The current study gives insight into how decision making in experimental sleep settings may or may not translate to more ecologically valid settings of self-directed sleep.

KEYWORD
decision-making, gains, insufficient sleep, loss, naturalistic sleep, sleep variability,

1 | INTRODUCTION

Insufficient sleep is a growing concern both in the USA and globally with survey data showing that roughly one-third of adults in many countries do not achieve the recommended 7 h of nightly sleep (Hafner et al., 2017). Studies have shown that insufficient sleep impacts various aspects of decision making (Harrison & Horne, 2000), at least in part due to the effect of sleep loss on prefrontal brain activation (Killgore, 2010). Most studies, however, involve experimentally manipulated sleep restriction or deprivation, and so understanding the extent to which these findings generalise to ecologically valid field settings requires complementary observational research. For example, we have shown the ability to integrate multiple pieces of information into a single decision is impaired both by experimental total sleep deprivation (Dickinson & Drummond, 2008) and by more ecologically valid self-selected short sleep duration (Dickinson et al., 2016). In both cases, individuals who are either sleep deprived or sleep restricted tended to focus on a single, relatively easy to understand piece of information to inform their decision, rather than also integrating a second, more complex piece of information. Similarly, total sleep deprivation (Anderson & Dickinson, 2010), chronic partial sleep restriction (Dickinson & McElroy, 2017), and observational short sleep levels (Holbein et al., 2019) all reduced prosocial behaviours during a common set of decision tasks.

The present paper aims to contribute to the literature by evaluating risky choice under self-selected sleep levels, using a risky choice paradigm previously utilised in the context of total sleep deprivation (McKenna et al., 2007). Risky choice, which we use to refer to the observed risk taking in a task, is a frequently studied topic in the literature on sleep and decision making. While some studies employing relatively mild sleep deprivation have reported no impact of experimental sleep deprivation on risky choices (Chaumet et al., 2009; Menz et al., 2012; Sundelin et al., 2019; Venkatraman et al., 2007), several others, of both short and long duration sleep loss, have reported an increase in risky choices during experimental sleep deprivation, though various factors can affect that general finding (e.g. Brunet et al., 2020; Castillo et al., 2017; Ferrara et al., 2015; Harrison & Horne, 2000; Killgore et al., 2006; McKenna et al., 2007; Womack et al., 2013). For example, Ferrara et al. (2015) reported that men were more likely than women to take increased monetary risk after sleep loss when trying to maximise gains after one night of total sleep deprivation. Task related factors can also influence the effects of sleep loss on risky choices. Sundelin et al. (2019) argued that decision tasks involving feedback, which necessarily include a learning component, may be more susceptible to sleep loss than those without feedback. Another factor moderating the effects of sleep loss on risky choices is whether the decision is framed in terms of maximising gains or minimising losses. McKenna et al. (2007) reported that 23 h of total sleep deprivation altered risky choices, but the effect varied depending on the type of decision. For decisions designed to maximise financial gain, sleep deprivation led to individuals taking more risk (McKenna et al., 2007). In contrast, for decisions designed to minimise loss, sleep deprivation was associated with less risky decisions. This study suggests decreased sensitivity to risk may be one mechanism underlying the sleep deprivation effect, since changes in risky choices over the separate domains of gains and losses both indicated a move towards risk neutrality in observed choices (McKenna et al., 2007). In contrast to McKenna et al., Sundelin et al. (2019) found no differential impacts of two nights sleep restriction (4 h in bed/night) on risky decisions related to gains vs losses.

The inconsistent findings related to the impact of sleep deprivation on observed risk taking, especially when sleep loss is relatively mild, underscore the need to examine the impact of real-world, self-selected insufficient sleep levels on risky choice. Very few studies have examined that question. Olson et al. (2016) reported acute reductions in sleep duration, relative to an individual's typical duration, did not increase risk taking on the Iowa Gambling Task, but reduced sleep did shorten the time horizon over which information was integrated into participants' decisions. In a large sample ($n > 2000$) of active duty military personnel, Mantua et al. (2021) reported that shorter habitual sleep duration was associated with an increased number of self-reported high risk behaviours.

While total sleep time has been shown to influence cognition generally, and decision making specifically (Dickinson et al., 2016), sleep efficiency has not been well examined in the context of cognition. One exception is Mantua et al. (2021), who reported that worse sleep quality, as reported on the Pittsburgh Sleep Quality Index (PSQI) and Insomnia Severity Index, was associated with increased engagement in high risk behaviours. In adolescents, poor sleep quality as assessed on the PSQI was associated with greater levels of both self-reported and experimental risk taking (Telzer et al., 2013). The current study utilises actigraphy-derived sleep efficiency in an effort to extend these findings with a prospectively assessed measure of sleep quality that was collected in the days immediately before the risky choice task session. To our knowledge, the influence of night-to-night (N2N) sleep variability on risk taking has never been examined, though N2N variability in total sleep time has been shown to influence cognition more generally (Bei et al., 2016). Moreover, increased night-to-night variability is common in populations more likely to show increased risk taking behaviours, such as individuals with psychiatric disorders and shift workers (Bernert et al., 2017; Buysse et al., 2010; Straus et al., 2015). Thus, examining the influence of both sleep quantity/quality and the associated night-to-night variability of those measures together may provide unique insights into the role of sleep in risky decisions.

The current study seeks to address some of the aforementioned gaps in the literature by examining the extent to which controlled laboratory sleep deprivation findings on risky decisions generalise to insufficient sleep levels obtained in the uncontrolled home environment. We studied young, healthy adults for a week with actigraphy and sleep diaries, with no constraints placed on their sleep schedules. At the end of the week, participants attended the laboratory for a decision experiment and were administered a risky choice task nearly identical to that administered in McKenna et al. (2007), where we could separately examine decisions related to maximising financial gain and those related to minimising financial loss. We also report response time data, which we conceptualise as providing insight into which task details lead to increased deliberation regarding one's choice. We hypothesised that self-selected shorter sleep levels (operationalised as average actigraphy measured total sleep time over the course of a full week), lower levels of objective sleep efficiency, and increased night-to-night variability in sleep would each be associated with reduced sensitivity to risk (i.e., more risky choices when maximising gain and less risky choices when minimising loss) and faster responding during risky decisions.

2 | METHODS

2.1 | Participants

We collected data from 102 young adults from a regional U.S. university and, due to two withdrawals mid-week, 100 participants completed the study (age: 22.98 ± 7.96 years; 50 females, 6 minority) and were included in the analysis. Inclusion criteria were: over 18 years of age, no self-reported gambling problems, intermediate diurnal preference type (assessed using the short-form morningness-eveningness questionnaire, *rMEQ*, of Adan and Almirall, 1991), subclinical risk levels of major depressive and anxiety disorder

(depression risk assessed using the PHQ-2, Kroenke et al., 2003, and anxiety risk assessed using the GAD-7, Spitzer et al., 2006). Most participants were students from the University (90 students, 9 staff, 1 faculty).

2.2 | Procedure

Participants were recruited to come to two laboratory sessions set 1 week apart. The recruitment invitation explained that during the first Session they would be assigned a sleep tracking device to wear for the full week between Sessions 1 and Session 2. During Session 1 the Need for Cognition questionnaire (NFC; Cacioppo & Petty, 1982), which measures one's preference for cognitively effortful endeavours, and Epworth Sleepiness Scale were administered (Johns, 1991). The weeklong study always commenced with Session 1 on a Tuesday ($n = 32$), Wednesday ($n = 63$), or Thursday ($n = 5$) to avoid weekend sleep effects. We did not include a factor for weekday vs free day in our analysis for two reasons. First, while weekend or "free day" sleep is often more variable than weekday or work/school day sleep, our mostly undergraduate student participants typically have greater variation in free days (both frequency and the exact day) due to varied class/work schedules than a non-student employed population. Second, when comparing Thursday–Sunday night-to-night data with weekday night-to-night data (2-tailed Z-tests) our participants were found to have no significant differences in night-to-night variability in sleep efficiency ($p > 0.10$) and only marginally higher variability in night-to-night total sleep time ($p = 0.067$) on the weekend (Thursday–Sunday) compared with weekdays.

Actigraph devices (AW-64 devices; Philips Respironics) were assigned to participants during Session 1 to be worn continuously until Session 2 a week later. Participants also kept simple sleep diaries over the course of weeklong study. The actigraphy data were scored using accepted protocols (e.g., Goldman et al., 2007) to identify the beginning and end points of each rest interval for each participant. Rest intervals were based on a combination of diary entries and both activity and light levels. Participants were told to maintain their usual routine regarding sleep, with no restrictions imposed by the researchers. At the end of the week, participants returned to the decision laboratory for Session 2 and were administered an incentivised risky choice task via computer.

The risky choice task paradigm we used extends from McKenna et al. (2007), which was adapted from Ellsberg (1961). The adapted version used here (and in the previous literature) has been shown, among other things, to replicate the well-known finding that individuals make less risky choices over gains but more risky choices over losses (Kahneman & Tversky, 2013). Over a set of 120 total trials, participants decided between two choices of gambles, one of which was riskier than the other (Figure 1). In other words, each gamble choice presented the participant with two options having the same expected payoff but different variance in payoffs. That is, each gamble presented some risk, but one gamble always presented a higher payoff variance to the participant compared with the other (safer) gamble. Because the difference in the variance between the gamble choices varied across trials, we can also use this gamble variance difference as a way to describe some gamble choices as being easier than others (i.e., higher variance differences present the participant with a more stark and therefore easier choice). Participants were not explicitly informed about risk levels, but rather they had to form their own judgements based on the gamble choice payoff information. Forty trials involved gambles where participants tried to maximise winning of money ("GAINS": Figure 1a), 40 trials involved gambles where participants tried to minimise losses of money ("LOSSES": Figure 1b), and 40 trials were control trials that involved no money ("dummy" trials: Figure 1c). As in McKenna et al. (2007), the task we administered did not provide any feedback to participants across trials. This is an important strength, as providing feedback during a decision task introduces a learning component on top of (in this case) the underlying risk preference component, which together will impact one's observed

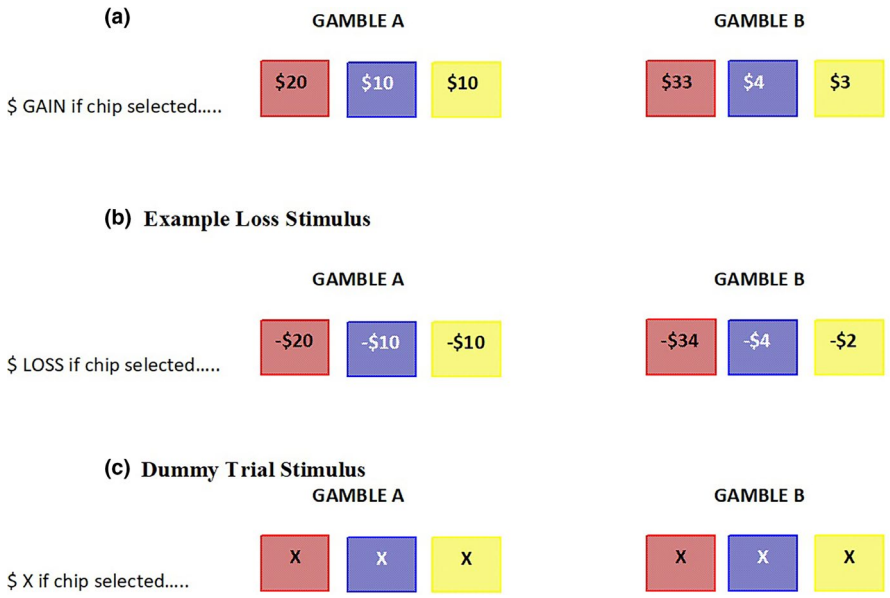

FIGURE 1 Examples of risky choice task stimuli. Participants made a series of choices between two possible gambles. (a): trials involving potential winning of money (GAINS); (b): trials involving potential losing of money (LOSS); (c): trials involving a random selection, with no implications for study payments (dummy trials)

risky choices. Indeed, Sundelin et al. have explicitly argued for the need to separately assess the impact of sleep loss on risky choices independent of any confounding influences of learning (Sundelin et al., 2019).

We refer to the trials involving real monetary gamble choices as "real" trials. The task informed subjects there was an equally likely chance of drawing a red, blue, or yellow chip from a container and one's payoff depended on the colour chip drawn. The participant was told to choose, for each trial, the preferred gamble. For "dummy" trials (Figure 1c), all payoffs were listed as X and participants were instructed to simply select Gamble A or Gamble B at random, and the decision had no payoff consequence. These dummy trials were included in the paradigm for use in a separate imaging experiment, but we nevertheless exploit them in our behavioral analysis to help interpret the response time (RT) data we generated.

Appendix S1 lists full instructions of the computerised task, along with the full set of risky choice stimuli used for both the GAINS and LOSS trials. At the conclusion of the experiment, one GAINS and one LOSS trial were selected at random, and the subject's chosen gamble for each was played out to add (GAINS) and subtract (LOSS) the appropriate payoff amount from their ultimate compensation from the study.

2.3 | Dependent variable measures

Regarding risky choice outcomes, we examined gamble choices in two ways. First, a subject-level analysis will pool the data for a given subject across all 40 real trials in a block to create a subject-specific outcome measure of risky choice, *Safe Choice Score*, following McKenna et al. (2007). Specifically, *Safe Choice Score* is defined as the proportion of the 40 trials where the less risky gamble was chosen (i.e., the gamble with the lower variance), minus the proportion of the 40 trials where the more risky gamble was chosen. Note that, as constructed, *Safe Choice Score* $\in [-1, +1]$ and operationalises one's underlying risk preference construct in this task. A *Safe Choice Score* $= 0$ indicates risk neutral preferences in the sense that an equal number of the more versus less risky gambles were chosen across the trials, a positive score suggests risk averse preference, negative score suggests risk seeking preferences. A *Safer Choice Score* is constructed separately for each individual for the GAINS and LOSS domain trials. In addition to analysis on subject-level *Safe Choice Score*, to compare with the previous literature, we also performed analysis using each (real) trial as the unit of observation by coding a dichotomous dependent variable (equal to 0 or 1) to indicate the selection of the *Safer Choice* for that trial (i.e., the gamble with the lower payoff variance in that trial). Such trial-level analysis will treat the data as a panel where the error term is clustered by participant to account for multiple observations per participant.

Response times (RT) were also captured for each of the decision trials. In the context of our study, we conceptualise RTs as providing an indicator of more deliberation in this particular paradigm (i.e., trials requiring greater deliberation produce longer RTs). We assessed the validity of this assumption with two RT comparisons: (1) real trials compared with dummy trials; and (2) trials where the difference in variance between Gamble A and B is smaller. To examine the extent to which RT is influenced by the amount of deliberation required on a given trial, we hypothesised that real trials would have longer RTs than dummy trials, and trials where the risk level of the choices was more similar would have longer RTs than trials where the risk choice contrast was greater.

2.4 | Data processing

Actigraphy data were processed with manufacturer software (Actiware, version 6.0.9). The sleep opportunity window was unconstrained in order to measure self-selected sleep in the most naturalistic way possible. We obtained total sleep time and sleep efficiency data from the actigraph, and we constructed the N2N variability measures following the approach used in recent research (Straus et al., 2015; Walters et al., 2020). The N2N variability measure for sleep outcome measure, X, across N days/nights was calculated as:

$$\text{N2N variability of } X = \sqrt{\frac{(X_2 - X_1)^2 + (X_3 - X_2)^2 + \ldots + (X_n - X_{(n-1)})^2}{(n-1)}}$$

3 | RESULTS

Figure 2 shows the histogram of average nightly sleep levels over the 1-week data recording period. Average actigraphy-measured nightly sleep was 385.84 (±57.51) minutes per night in our sample. Figure S1 in Appendix S1 shows the distributions of bed and wake times extracted from the actigraphy records of our present data, which represent the typical self-selected bed and wake times in our observational sample of 100 participants.

3.1 | Gamble choices

We next evaluated the actual risky choices of the participant as reflected in the choices of riskier versus safer gambles. We note our data replicate the general domain-effect that subject choices were consistent with risk averse preferences in the GAINS domain (average *Safer Choice Score* of 0.368; one-sample *Z*-test $p < 0.001$) but risk seeking preferences in the LOSS domain (average *Safer Choice Score* of −0.080: $p < 0.05$) (McKenna et al., 2007; Sundelin et al., 2019). Tables 1 and 2 present the results from both subject-level and trial-level analysis of risky choices, separated by GAINS versus LOSS domain trials. The difference across Tables 1 and 2 is whether the key independent variable sleep measures are actigraphy measured average nightly total sleep time and its N2N variability or average nightly sleep efficiency and its N2N. We estimated models separated by choice of sleep measure and its variability due to the high correlation between total sleep time and sleep efficiency in the actigraphy data (simple correlation of $\rho = 0.5099$).

The results in Tables 1 and 2 on the subject-level data (far left columns of each table) showed no significant predictive capacity of our individual specific demographic controls (*Age*, *Female*, *rMEQ score*, *NFC score*, *Epworth*). The trial-level analysis did reveal a significant impact of *Variance Dif between Gambles* in predicting the likelihood of choosing the safer (lower variance) gamble. In both Tables 1 and 2, our results showed that participants were more likely to choose the safer gamble in the GAINS domain but the riskier gamble in the LOSS domain as the variance difference between gambles increased (i.e., the riskier gamble of the pair was much more risky in such instances).

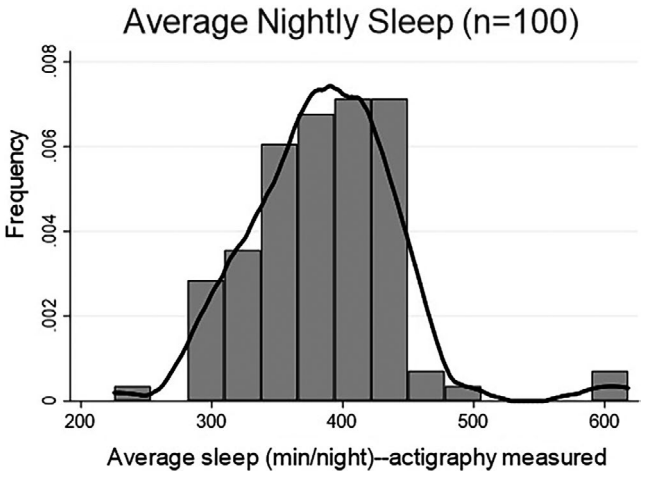

FIGURE 2 Voluntary nightly objective sleep levels. Sleep was measured via actigraphy over 7 consecutive nights. Line shows the smoothed kernel density estimate of the distribution

Regarding actigraphically derived mean sleep measures and sleep variability, neither average nightly total sleep time nor sleep efficiency was a significant predictor of risky choice in our task (Tables 1 and 2). Sleep variability, as measured by *N2N total sleep time variability*, did not predict risky choices (Table 1). However, greater *N2N sleep efficiency variability*, was associated with a reduced likelihood of making a safer choice (i.e., a greater likelihood of making riskier choices) on LOSS trials (Table 2). N2N variability in sleep efficiency did not influence risk taking on the GAINS trials.

3.2 | Response times

Summary data on RT are presented in Figure 3 (panels a–c), and Table 3 presents the supporting statistical results. Specifically, we found longer RTs related to the following trial characteristics: real (vs dummy) choices; choices in LOSS (vs GAINS) trials; choices where the gamble options are more similar (defined as lower differences in the payoff variance of each choice). These three variables account for 30% of the total variance in RT in our data (Table 3).

Additionally, Table 4 shows decisions across both GAINS and LOSS domains became faster across trials (i.e., as the task progressed, RT decreased). The only other significant predictor of RT was the dichotomous indicator variable, *Safer Choice*, where our results indicated choosing the *Safer Choice* gamble resulted in a quicker decision in the GAINS trials but not in LOSS trials. Regarding the other independent variables, neither the individual-specific control measures nor the objective actigraphy-measured 1-week sleep metrics significantly predicted RT ($p > 0.05$).

TABLE 1 Predictors of safer gamble choices (*TST and N2N-TST variability* covariates)

	Subject-level analysis (OLS regressions) Dependent variable = *Safe choice score* ∈[−1, +1]		Trial-level analysis (random effects GLS regression, errors clustered by subject) Dependent variable = *Safer choice (=1)*	
Variable	**GAINS**	**LOSSES**	**GAINS**	**LOSSES**
Constant	−0.2106 (0.4391)	−0.5226 (0.4552)	0.1421 (0.2189)	0.4439 (0.2041)*
Trial	–	–	0.0009 (0.0005)	−0.0006 (0.0006)
Variance Dif between gambles	–	–	0.0013 (0.0001)**	−0.0012 (0.0001)**
Avg nightly total sleep time	0.0004 (0.0007)	0.0011 (0.0007)	0.0002 (0.0002)	0.0006 (0.0003)
N2N total sleep time variability	0.0004 (0.0007)	−0.0008 (0.0008)	0.0002 (0.0003)	−0.0004 (0.0003)
Epworth	0.0147 (0.0108)	0.0167 (0112)	0.0076 (0.0062)	0.0088 (0.0055)
rMEQ score	0.0400 (0.0218)	0.0208 (0.0226)	0.0205 (0.0110)	0.0106 (0.0113)
Age	−0.0074 (0.0047)	−0.0078 (0.0049)	−0.0038 (0.0028)	−0.0039 (0.0023)
Female (=1)	0.0118 (0.0776)	−0.0893 (0.0805)	0.0049 (0.0335)	−0.0473 (0.0383)
NFC score	−0.0022 (0.0012)	−0.0017 (0.0013)	−0.0011 (0.0006)	−0.0009 (0.0006)
R-squared (overall)	0.1154	0.1110	0.1221	0.0867
Observations	100	100	3967	3903

Coefficients (standard errors) shown. *0.05, **0.01 for the 2-tailed test. Trial-level analysis restricted to Real Trials. Trial-level analysis results similar using nonlinear random effects probit estimation.

Avg, average; N2N, night-to-night; NFC, need for cognition; rMEQ, reduced morningness-eveningness questionnaire; Variance Dif, variance difference.

TABLE 2 Predictors of safer gamble choices (*Sleep Efficiency and N2N-Sleep Efficiency variability* covariates)

	Subject-level analysis (OLS regressions) Dependent variable = *Safe Choice Score* ∈[−1, +1]		Trial-level analysis (random effects GLS regression, errors clustered by subject) Dependent variable = *Safer Choice (=1)*	
Variable	**GAINS**	**LOSSES**	**GAINS**	**LOSSES**
Constant	0.0266 (0.7140)	0.1909 (0.7282)	0.2723 (0.2783)	0.8228 (0.3333)*
Trial	–	–	0.0009 (0.0005)	−0.0006 (0.0006)
Variance Dif between gambles	–	–	0.0013 (0.0001)**	−0.0012 (0.0001)**
Avg nightly sleep efficiency	0.0002 (0.0072)	−0.0008 (0.0073)	0.00002 (0.0028)	−0.0006 (0.0038)
N2N sleep efficiency variability	−0.0019 (0.0101)	−0.0224 (0.0103)*	−0.0010 (0.0052)	−0.0116 (0.0056)*
Epworth	0.0129 (0.0110)	0.0079 (0.0113)	0.0067 (0.0060)	0.0043 (0.0052)
rMEQ score	0.0393 (0.0221)	0.0147 (0.0226)	0.0201 (0.0107)	0.0074 (0.0112)
Age	−0.0084 (0.0045)	−0.0065 (0.0046)	−0.0043 (0.0027)	−0.0032 (0.0020)
Female (=1)	0.0289 (0.0758)	−0.0780 (0.0773)	0.0141 (0.0325)	−0.0412 (0.0353)
NFC score	−0.0023 (0.0013)	−0.0021 (0.0013)	−0.0011 (0.0006)	−0.0011 (0.0006)
R-squared (overall)	0.1101	0.1349	0.1212	0.0903
Observations	100	100	3967	3903

Coefficients (standard errors) shown. *0.05, **0.01 for the 2-tailed test. Trial-level analysis restricted to Real Trials. Trial-level analysis results similar using nonlinear random effects probit estimation.

Avg, average; N2N, night-to-night; NFC, need for cognition; rMEQ, reduced morningness-eveningness questionnaire; Variance Dif, variance difference.

4 | DISCUSSION

Choices over monetary risk often present a pattern consistent with risk aversion when gambles relate to monetary gains but more risk seeking preferences when gambles relate to monetary losses (Barberis et al., 2001; Kahneman & Tversky, 2013; Wakker, 2010). Our results are consistent with this pattern and, in that sense, replicate the payoff domain specific result from McKenna et al. (2007) using a largely similar task. We also found this "risk averse for gains, risk seeking for losses" pattern was amplified when the difference between gambles was more stark. Additionally, McKenna et al. (2007) found that 23 h of total sleep deprivation produced choices consistent with a decreased sensitivity to risk (i.e., domain specific differences in risky choices were diminished). Here, we did not find similar alterations to risky choice patterns in those who self-selected shorter sleep duration over the course of the study week. However, relatively few participants were fully sleep restricted (e.g., mean sleep durations <6 h) prior to the experimental session. This suggests more modest levels of sleep loss, even when relatively chronic, may not lead to changes in risky choice. This is consistent with the findings of Sundelin et al. (2019), who found two nights of 4-h sleep restriction did not influence participants risky choices on either gain or loss trials, where each trial contrasted a guaranteed outcome to a risky outcome. The discrepancy between the findings of experimental laboratory-based total sleep deprivation in McKenna et al. (2007) and those reported here with home-based self-selected sleep schedules (only some of which involved sleep restriction) also highlights the importance of studying the impact of sleep loss in real-world settings. While total sleep deprivation does indeed occur outside the laboratory, usually in operational settings, chronic sleep restriction is considerably more common. Indeed, a recent survey reported 50.6% of Australian adults reported sleeping an insufficient amount (i.e., <7 h/night) on a regular basis and 12% routinely sleep <5.5 h/night (Adams et al., 2017). The results of this study suggest chronic sleep restriction, as manifested in self-selected short sleep, may not negatively affect risk-based decisions, at least those related to monetary risk. Rather, it may be total sleep deprivation or more chronic and/or severe sleep restriction is needed before risky choice patterns change.

On the other hand, some aspects of sleep variability did impact risky monetary choices. Specifically, greater night-to-night variability in sleep efficiency was associated with taking more risk when trying to minimise potential losses. Given that subjects were, overall, risk seeking in the LOSS domain, this result indicates those individuals having more variability in sleep efficiency across our 1 week sleep data collection period made even riskier choices. Venkatraman and co-authors have twice reported blunted responses within the anterior insula component of limbic system in response to losses during experimental sleep deprivation (Venkatraman et al., 2007, 2011). If night-to-night variability in sleep quality has a similar effect on the limbic system, it would suggest individuals may be willing to take more risk when faced with monetary losses, because they experience less negative affect should they lose the gamble. This limbic system mechanism hypothesis has implications for gambling or investing behaviours, which often present gambles over loss amounts. Another potential mechanism to explain increased risky choices during loss trials in those with more irregular sleep efficiency is that such irregularity increases impulsivity. However, to

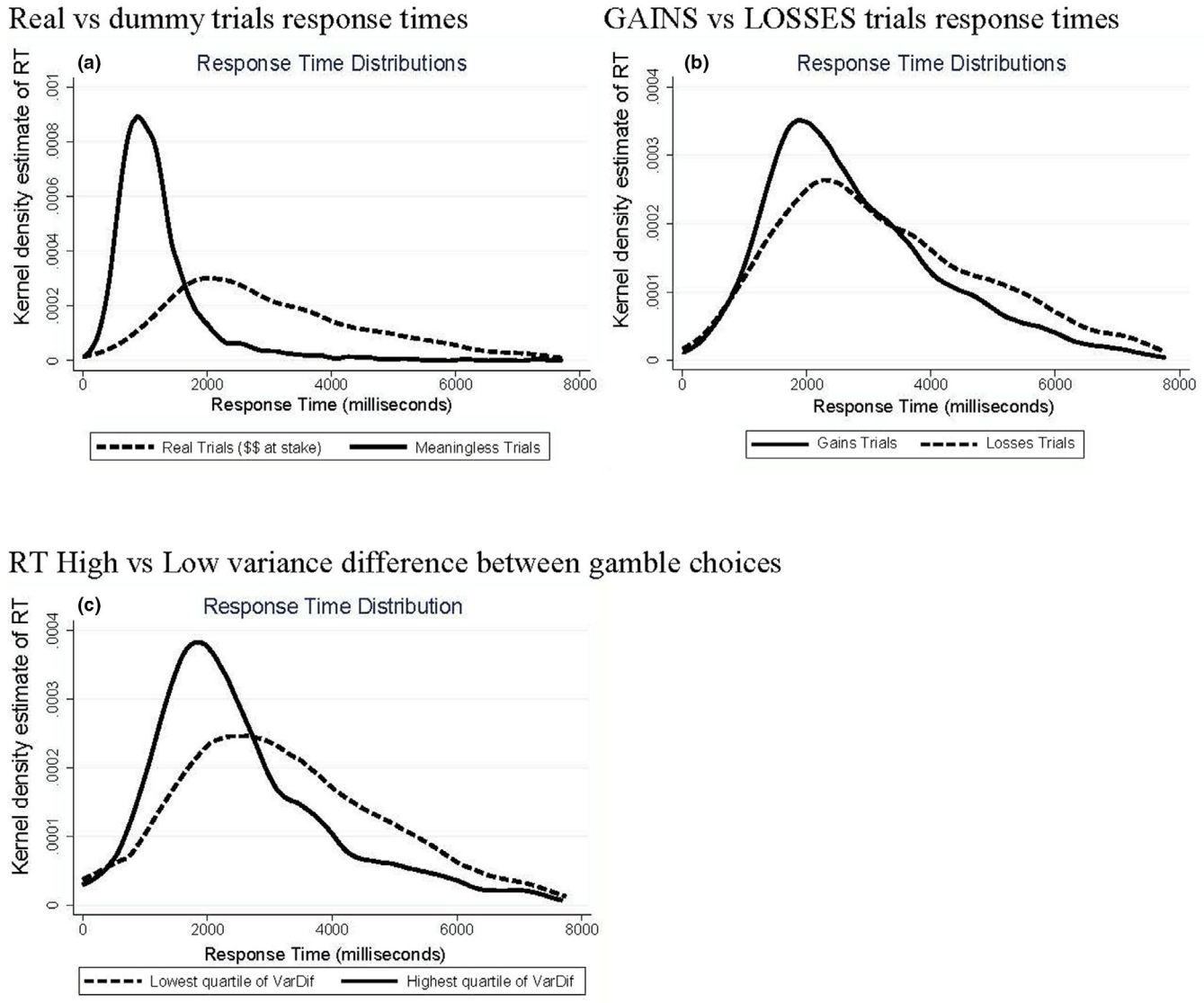

FIGURE 3 Response times on risky choice task. (a) $N = 3878$ total trial level observations of Dummy Trials, $N = 7870$ trial level observations of Real Trials. (Total $N = 12{,}000$ trials administered with 252 total trials (2.1%) and 130 Real Trials (1.7%) discarded from analysis due to recorded response time (RT) = 0). (b): Distributions generated from consequential *real* trials with monetary incentives: $N = 3967$ Gains and 3903 Losses trials. Data pooled across subjects and trials for display shown. (c): $N = 2000$ trial level observations in each quartile shown above. Only Real Trials with RT > 0 ($n = 7870$) considered in establishing the quartiles, and all Real Trial gamble choices had the same expected gain or loss (quartiles established prior to discarding trials with RT = 0). While summary distributions pool Gains and Losses Trial data, the results are similar with separate plots for Gains and Losses data (available on request). The lower quartile represents gamble choices for which the difference between the riskiness of the two gambles is smallest, which implies a more difficult risky choice for the participant because the two options become more similar. Summary graph combines all trials, Gains and Loss treatment, and across all participants and so is not constructed with all independent observations (multiple observations per subject per treatment). Panels a–c: A random-effects regression with errors clustered at the individual subject level documents longer response times are associated with: (a) Real Choice trials, compared with dummy trials; (b) LOSS trials, compared with GAINS trials; and (c) lower variance difference between gamble options. See Table 3 for these results ($p < 0.001$ in each instance)

the extent RT on this task reflects deliberation in one's decisions (a hypothesis supported by findings in Figure 3a and Table 3), our finding that night-to-night sleep efficiency variability does not significantly affect RT (Table 4) suggests that impulsivity did not vary with sleep efficiency variability and, thus, is likely not the mechanism influencing risky choice on loss trials. Our data are therefore more consistent with the hypothesis that night-to-night variability in sleep efficiency increased risk tolerance in LOSS trials via the *affect* mechanism. Interestingly, night-to-night variability in sleep efficiency did not impact risk taking related to gains, and night-to-night variability in total sleep time did not affect either type of risk taking.

A few limitations of the study should be considered when interpreting results. First, our primary interest here was to examine if laboratory-based sleep deprivation findings would translate to

observational, unmanipulated sleep levels observed in a university community sample. Thus, we did not design the study to test a particular theoretical mechanism underlying the impact of sleep loss on risky choice. Indeed, despite some very good studies examining the neural correlates of risk during sleep loss, there is no well accepted theory regarding how or why sleep loss affects risky choice. Thus, future research should seek to better develop theories related to mechanisms explaining how sleep or sleep loss impacts specific components of risk taking. Second, the models tested here only accounted for a modest amount of variance (about 9–13%) in the risky choices made by participants. One potential explanation for this may be the task we administered is not a sufficiently sensitive measure of risky choices (e.g., we did not see the typical gender effect on risk preference in this study, as noted in Charness & Gneezy, 2012). However, the fact that the models in our prior total sleep deprivation study with this task explained as much as 29.7% of the variance in risky choices argues against task insensitivity being the likely issue. We should note, though, the gambles used in the current study had a smaller range in variance difference between the higher risk and lower risk gambles compared with the previous TSD study using this risky choice paradigm (McKenna et al., 2007). Future research could vary this attribute of the gamble choices or even provide a certain payment safe-option to determine the contribution that relative risk level plays in moderating the sleep effect. Another difference with McKenna et al. is that our between-subject design may have had less power to detect sleep effects than the within-subject designed utilised by McKenna et al. (2007). Mitigating that limitation, though, is the fact our sample size here was considerably larger than that of McKenna et al. (100 vs 26, respectively). The cross-sectional nature of this study also does not allow us to assess the causal influence of interindividual differences in sleep quantity or quality on risky decisions in a way one can with a within-subjects design. The field would benefit from future studies taking a longer-term longitudinal approach to capture naturally occurring large differences in sleep quantity or quality (e.g., during the school term vs during vacation). An additional limitation is we ran eight primary models related to risk

TABLE 3 Documenting the significance of trends in distribution graphs

Key task determinants of response times (RT) **Dependent variable = RT (milliseconds)**	
Variable	**Coefficient (Robust standard error)**
Real choice trial (=1)	2137.125 (87.617)**
Gains trial (=1)	−318.421 (56.3325)**
Variance difference between gambles	−2.02141 (0.168)**
R-squared (overall)	0.3022

N = 11,748 observations. **0.01 for the 2-tailed test. Random effects generalised least squares. Errors clustered at the subject-level.

TABLE 4 Predictors of response times—Trial level analysis

	(random effects GLS regression, errors clustered by subject) **GAINS TRIALS** **Dependent variable = *Trial response time (milliseconds)***		**(random effects GLS regression, errors clustered by subject)** **LOSSES TRIALS** **Dependent variable = *Trial response time (milliseconds)***	
Variable	**(1)**	**(2)**	**(3)**	**(4)**
Constant	2571.022 (1238.656)**	3573.623 (1249.991)**	4245.227 (1608.575)**	5095.915 (1913.05)**
Trial	−8.656 (1.721)**	−8.654 (1.722)**	−13.516 (1.570)**	−13.514 (1.570)**
Variance Dif between gambles	−1.689 (0.236)**	−1.688 (0.236)**	−2.209 (.247)**	−2.210 (0.247)**
Avg nightly total sleep time	−0.319 (1.676)	−0.523 (1.677)	1.243 (2.009)	1.085 (1.973)
Sleep efficiency	1.895 (10.144)	−8.469 (12.191)	−14.478 (15.748)	−24.070 (18.962)
N2N total sleep time variability	−2.027 (1.328)	—	−2.340 (1.626)	—
N2N sleep efficiency variability	—	−31.801 (21.552)	—	−30.324 (32.152)
Epworth	22.853 (22.070)	15.334 (21.808)	33.429 (30.433)	26.555 (29.402)
rMEQ score	75.668 (47.400)	68.800 (46.076)	8.570 (65.717)	2.535 (65.656)
Age	5.233 (10.577)	9.621 (10.327)	11.045 (15.860)	16.063 (13.595)
Female (=1)	−98.626 (146.717)	−112.347 (144.072)	49.154 (199.059)	29.342 (193.597)
NFC score	−0.760 (2.571)	−0.997 (2.525)	1.595 (3.212)	1.317 (3.201)
Safer choice (=1)	−386.558 (67.237)**	−387.266 (66.902)**	68.491 (54.184)	67.916 (54.324)
R-squared (overall)	0.0917	0.0931	0.0589	0.0582
Observations	3967	3967	3903	3903

Coefficients (standard errors) shown. *0.05, **0.01 for the 2-tailed test. Analysis restricted to Real Trials (*N* = 8000 total: 4000 per treatment. Trials with recorded response time = 0 were discarded from all analysis).

Avg, average; GLS, generalised least squares; N2N, night-to-night; NFC, need for cognition; rMEQ, reduced morningness-eveningness questionnaire; Variance Dif, variance difference.

preference and four related to RT, and we did not control for multiple comparisons. Thus, our significant results may represent Type I error, arguing for the need to replicate our findings using real-world sleep schedules.

Related to our focus on external validity, it is important to note the sleep levels of our participants were not manipulated in any way, and we explicitly put no limitation on compensatory behaviours (e.g., caffeine consumption). While this presents a limitation in the sense that variables known to influence performance or alertness are not controlled in our study, it is also a strength in that our findings may better reflect what would be observed in a general community sample of U.S. young adults than would findings from a tightly controlled study. However, our exclusion criteria imply our results may not apply beyond the population of healthy young adults. The focus on external validity, rather than internal control, may also help to explain why our models generally only accounted for 9–12% of the variance in our outcome variables. Additional uncontrolled factors likely influenced the results, as well. Finally, as in McKenna et al. (2007), our design did not allow for feedback learning. Thus, to the extent such learning may also decline in the presence of low sleep levels or variability in sleep level or quality, our results may not generalise to risky decisions that include feedback on each decision.

In summary, our data indicate that how sleep impacts risky choice in more naturalistic settings with self-selected sleep schedules may be related to variability in sleep quality, as opposed to mean levels of sleep duration or quality. They also suggest that results of experimental sleep deprivation studies may not translate cleanly to real-world settings. While these results require replication and generalisation, the fact that night-to-night variability in sleep efficiency from a naturalistic setting was found to significantly increase one's tendency to make risky choices in certain settings (i.e., LOSS gamble scenarios) is noteworthy. This argues for more research to understanding the robustness of this finding with respect to night-to-night variability in sleep quality, because such variations are not uncommon in the real world and yet are rarely studied experimentally or observationally.

CONFLICT OF INTEREST

All authors report no conflict of interest.

AUTHOR CONTRIBUTIONS

Study design, DLD SPAD; data collection, DLD SPAD; analysis, DLD CF JB SPAD; writing, DLD CF JB SPAD.

DATA AVAILABILITY STATEMENT

Data available on request from the authors.

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