# Modeling urgency in the lab: Exploring the associations between self-reported urgency and behavioral responses to negative outcomes in laboratory gambling

Charlotte Eben[1], Loïs Fournier[2], Frederick Verbruggen[1], and Joël Billieux[2-3]

[1]Department of Experimental Psychology, Ghent University

[2]Institute of Psychology, University of Lausanne, Lausanne, Switzerland

[3]Centre for Excessive Gambling, Addiction Medicine, Lausanne University Hospitals (CHUV), Lausanne, Switzerland

## Author Note

**Author contributions:** Conceptualization: CE, FV and JB; Data curation: CE and LF; Formal analysis: CE and LF; Funding acquisition: FV; Methodology CE, FV, and JB; Software: CE and LF; Supervision: JB; Roles/Writing - original draft: CE and JB; Writing - review & editing: CE, LF, FV, and JB. Note that LF acted as 'co-pilots' for the whole project (see https://cobe.ugent.be/openScience.html for more information.

**Correspondence:** Correspondence concerning this article should be addressed to **Joël Billieux**, Institute of Psychology, University of Lausanne, Switzerland, Quartier UNIL-Mouline – Bâtiment Géopolis; CH-1015 Lausanne; and **Charlotte Eben**, Department of Experimental Psychology, Ghent University, Henri Dunantlaan 2, B-9000 Gent, Belgium. Email: charlotte.eben@ugent.be

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**Abstract**

Impulsivity is a multifaceted construct that relates to different behaviors in everyday life and has been associated with many psychopathological disorders and behavioral problems, such as problematic gambling behavior. One questionnaire to measure these several facets on a trait level is the UPPS-P Impulsive Behavior Scale. Specifically, the UPPS-P investigates five distinct facets: (a) negative urgency, (b) lack of premeditation, (c) lack of perseverance, (d) sensation seeking, and (e) positive urgency. Negative urgency at a trait level in particular seems to be associated with the development of psychopathological disorders. To date, there are no established state measures of negative urgency. However, it was recently proposed that speeding after losses might be a suitable measure. Thus, in this study, we explored the possible relationship between a state measure and a trait measure of negative urgency through the UPPS-P questionnaire. We used correlational and network analyses in an aggregated database of eight samples (total N = 1216) to explore the potential relationships between post-loss speeding and UPPS-P scores (by combining trait vs. item-based analyses). We found that the degree of speeding after losses (post-loss speeding) did not correlate with the trait measure of impulsivity in general and negative urgency specifically, either at the trait or on an item-based level. This null finding indicates that our state measure of post-loss speeding and negative urgency on a trait level does not seem to capture the same underlying constructs. Implications for personality research are discussed.

*Keywords:* UPPS-P, impulsivity, urgency, gambling

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## Introduction

Impulsivity is a multifaceted construct that relates to many different behaviors in everyday life and is incorporated in most influential personality models. In its extreme manifestation, it is frequently used as a feature of mental conditions in nosography manuals (Enticott & Ogloff, 2006; Moeller et al., 2001; Whiteside & Lynam, 2001). Its multidimensional nature has led to inconsistent use of the term impulsivity in the literature (Cyders et al., 2014). Typically, impulsivity is assumed to be a stable personality trait and therefore assessed with self-report questionnaires. However, some researchers have developed state measures for impulsivity as well, which are typically investigated in laboratory tasks. The results of investigations into the relationship between trait and state measures are mixed, but typically point in the direction of low correlations between trait and state impulsivity (Allen et al., 2021; Gay et al., 2008; Roxburgh et al., 2022; Wilbertz et al., 2014). In the present study, we explored whether negative urgency as a measure of impulsivity relates to a potential behavioral measure of urgency ("state" measure).

In recent years, one of the most popular frameworks and corresponding questionnaire used to assess impulsivity is the UPPS-P model (Cyders et al., 2014; Cyders & Smith, 2007, 2008; Whiteside & Lynam, 2001). The UPPS-P was based on a factor analytical approach that aimed to further clarify the various dimensions underlying the broad and multifaceted impulsivity construct on a trait level. To this end, Whiteside and Lynam (2001) selected the most commonly used and influential impulsivity questionnaires (e.g., Barratt Impulsiveness Scale; Patton et al., 1995) and a widely used personality questionnaire (NEO Big Five questionnaire; Costa & McCrae, 1992) to assess various aspects of impulsivity (through specific items related to, e.g., neuroticism, extraversion, or conscientiousness) and administered them to a sample of college students. The original exploratory factor analyses identified four moderately related but distinct factors: (a)

*negative urgency*, the tendency to act rashly when experiencing intense negative emotions; (b) *lack of premeditation*, the lack of consideration of the consequences of one's actions; (c) *lack of perseverance*, difficulty in completing demanding or boring tasks; and (d) *sensation seeking*, the constant seeking of excitement, including openness to novel experiences, despite potential risks. Cyders and Smith (2007) later suggested a fifth factor, namely, *positive urgency*, the tendency to act rashly when experiencing intense positive emotions. Since the development of the scale, the structural validity of these factors has been confirmed multiple times through confirmatory factor analyses (Billieux et al., 2021; Goh et al., 2020). This factorial structure has also been reproduced in clinical samples characterized by psychiatric disorders (Dugré et al., 2019). Furthermore, UPPS-P based scales have been developed for specific populations such as children (Geurten et al., 2021) or people who have experienced traumatic brain injuries (Rochat et al., 2010); short-form questionnaires have also been developed (Billieux, Rochat, et al., 2012; Cyders et al., 2014).

A crucial specificity of the UPPS-P framework is that – contrary to other dominant impulsivity models – it considers emotion-laden impulsivity (through its positive and negative urgency dimensions). This is especially interesting because urgency has been shown to be the impulsivity component that contributes to most (i.e., a wide range of) psychiatric symptoms, thus constituting a transdiagnostic factor of psychopathology (Berg et al., 2015; Smith & Cyders, 2016). In particular, existing evidence suggests that negative emotional experiences might trigger impulsive actions, which can lead to the development of several problematic and unregulated behaviors, such as substance use or problematic gambling (Berg et al., 2015; Billieux et al., 2010; Halcomb et al., 2019; Selby et al., 2008).

## Relationship between state and trait measures of impulsivity measured with the UPPS-P

Recently, efforts have been made to identify a state measure of urgency as one facet of impulsivity and how trait and state measures might be related. Earlier studies suggested

a potential relationship between negative urgency as a specific dimension of the UPPS-P and difficulty in inhibiting prepotent responses (which is typically seen as "impulsive action" in the literature; e.g., Bari & Robbins, 2013) in lab-based tests (Allen et al., 2021; Billieux, Lagrange, et al., 2012; Johnson et al., 2016; Wilbertz et al., 2014). For example, Wilbertz et al. (2014) found a positive correlation between stop-signal reaction time (SSRT) and urgency in a functional magnetic resonance imaging study showing that individuals who scored higher on the urgency scale had longer SSRTs (i.e., poorer response inhibition). Similarly, Gay et al. (2008) found a positive correlation between the number of commission errors in a go/no-go task (again, indicating poorer inhibition) and negative urgency. More recently, Allen et al. (2021) also found a relationship between negative urgency and negative emotional response inhibition measured in an emotional stop-signal task: participants who scored high on the factor negative urgency in the UPPS-P also had more difficulty in inhibiting their responses to negative emotional stimuli. In this study, no correlation was found for inhibition of responses toward positive emotional stimuli and positive urgency. Another recent study by Roxburgh et al. (2022) found that negative urgency was associated with impaired response inhibition (again, indexed by longer SSRTs) in a threatening condition (induced by threat of shock), but not in a non-threatening condition. Taken together, these studies suggest that there is a relationship between high scores on the (negative) urgency scale and difficulties in inhibiting prepotent responses, but this relationship might be context dependent (as indicated by the results of studies by Allen et al., 2021, and Roxburgh et al., 2022).

By contrast, other studies observed only weak or no relationships between performance in behavioral tasks measuring response inhibition and self-report measures such as the UPPS-P (Creswell et al., 2019; Cyders & Coskunpinar, 2011, 2012; Reynolds et al., 2006; Schluter et al., 2018; Sharma et al., 2014). There is also evidence that there may not be a correlation with state measures that capture other aspects of impulsivity such as "response caution". In a perceptual decision-making task, response caution reflects

how much evidence that the individual samples before making a decision. If individuals sample more evidence, they emphasize accuracy (at the cost of speed); by contrast, if they sample less evidence, speed is emphasized (but with an increased chance of making a mistake). A lack of response caution is considered to be "reflection impulsivity" (Robbins & Dalley, 2017) and is a process that cannot be equated with "impulsive action" as assessed with tasks measuring inhibitory control. Recent work suggests no relationship between any of the UPPS-P factors and response caution estimated with evidence accumulation models (Hedge et al., 2020). Thus, the literature is mixed on the relationship between trait and state measures of impulsivity.

In addition, some researchers have argued that response inhibition tasks are not only unable to capture the emotional component of impulsivity, but they may also lack external validity because they usually use an external stop signal (Halcomb et al., 2019; Nigg, 2017). Therefore, in a recent overview, Halcomb et al. (2019) suggested the development of a translational model of urgency and argued that animal or other preclinical models could help increase the external validity of such a translational model. For example, they proposed that unexpected reward omission might create (negative) urgency in animals (Amsel, 1958; Vindas et al., 2012; Zentall, 2011) and humans. In consistency with this proposal, Gipson et al. (2012) showed that participants who scored high in negative urgency also showed increased operant responding to unexpected reward omission compared with participants who scored lower in negative urgency. This finding suggests that reward omission might be a good candidate for studying negative urgency in the lab.

In human research, it is possible to investigate reward omission with gambling-like tasks. For example, in a self-paced gambling task, Verbruggen et al. (2017) measured how fast participants started the next game by pressing a response key as a function of the outcome of the previous game. These researchers found that, across experiments, participants started the next trial faster after losses compared with non-gambles or gambled wins. Subjective ratings in this study revealed that losses were rated as negative

emotional events. This post-loss speeding effect has now been replicated many times(Chen et al., 2020; Eben et al., 2022; Eben et al., 2020). Interestingly, speeding can also be observed in real-life online gambling. For example, a recent study found that players started the next game of an online commercial game called "Mystery Arena" faster after a loss than after a win (Chen et al., 2022). The authors assumed that this speeding after losses reflects an "urge to continue gambling." From such findings, we assumed that there might be a relationship between the urge to act in response to negative outcomes in gambling-like tasks (i.e., negative urgency at a "state" level in the lab) and the urge to act in response to general negative events in everyday-life (i.e., negative urgency at a "trait" level). Thus, in the present study, we explored whether post-loss speeding as a behavioral measure of impulsivity relates to individual differences in impulsivity traits based on the UPPS-P model (Cyders et al., 2014; Whiteside & Lynam, 2001).

## Aim of our study

Apart from a few notable exceptions (cited in the previous section), most previous research that tried to link the self-reported urgency trait to behavioral performances in laboratory tasks assessing impulsivity did not take into account the affective component of rash actions, even though this is part of the very definition of urgency (Whiteside & Lynam, 2001). Therefore, our aim in the present study was to investigate the relationship between a task postulated to capture a state measure of negative urgency (speeding after the omission of reward in a gambling task) and a self-reported urgency measure (based on the UPPS-P model) in a large and heterogeneous online sample (in terms of gender, age, and nationality). To ensure that we had sufficient power, we collapsed available data from eight experiments. In each of these experiments, we used the self-reported scores on a UPPS-P questionnaire (in order to have a measure of trait negative urgency) and a measure of post-loss speeding (in order to have a state measure of negative urgency).

## Method

All processed data and code reported in this study can be found on the Open Science Framework (OSF; https://osf.io/rck6a/). We also report all data exclusions and all measures in the study. Four data sets were taken from Eben et al. (2020), two from Eben et al. (2022); the two unpublished data sets are on OSF: https://osf.io/6h9wv/, and https://osf.io/qm2a8/ ('Cards Array Task'). None of our analyses were preregistered and therefore all were done from an exploratory approach.

### Participants

To test our predictions, we further analyzed published and unpublished data sets. In total, 1216 participants (recruited via Prolific.co or in the lab) completed eight experiments and were included in the analyses (554 females, 642 males, 10 who indicated that they were non-binary, and 10 who preferred not to indicate their gender; age $M$ = 27.9 years, $SD$ = 9.6 years; *range* = 18-75 years; for detailed participant information per sample, see Table 1). Only participants who were able to speak English were allowed to participate. Settings in Prolific made it possible to ensure that participants could not participate in two or more of the experiments considered for the present study.

**Table 1**

*Information on the task used and detailed participant information for every sample in this study.*

| Study | Experiment | Task | Lab or online? | N | Mean age | SD age | Min age | Max age | Female | Male | Non-binary | No gender indication | Gambling habit |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Eben et al., (2020) | Experiment 1 A | Gambling task with non-gambles (Figure 1, Panel A) | Lab | 18 | 20.4 | 1.42 | 18 | 24 | 15 | 3 | - | - | - |
| Eben et al., (2020) | Experiment 1 B | Gambling task with non-gambles (Figure 1, Panel A) | Online | 84 | 29.9 | 10.74 | 18 | 67 | 38 | 46 | - | - | - |
| Eben et al., (2020) | Experiment 2 | Doors task with non-gambles (Figure 1, Panel B) | Lab | 24 | 21.8 | 2.84 | 18 | 29 | 17 | 5 | - | 2 | - |
| Eben et al., (2020) | Experiment 3 | Cards task with non-gambles (Figure 1, Panel C) | Online | 96 | 35.4 | 12.94 | 18 | 67 | 54 | 40 | - | 2 | - |
| Eben et al., (2022) | Experiment 2 | Coin tossing task from Langer & Roth (1975) (Figure 1, Panel D) Only the random group | Online | 199 | 25.6 | 7.92 | 18 | 59 | 77 | 118 | 2 | 2 | 26 |
| Eben et al., (2022) | Experiment 3 | Coin tossing task from Langer & Roth (1975) (Figure 1, Panel D) Only the additional 24 random trials | Online | 596 | 27.4 | 8.85 | 18 | 75 | 273 | 314 | 6 | 3 | 145 |
| Unpublished | - | Cards guessing task without non-gambles (Figure 1, Panel E) | Online | 96 | 30.7 | 10.15 | 18 | 67 | 39 | 56 | - | 1 | 31 |
| Unpublished | - | Card array task without non-gambles (Figure 1, Panel F) | Online | 103 | 26.6 | 8.54 | 18 | 58 | 41 | 60 | 2 | - | 33 |

**Apparatus, stimuli, and procedure**

In this study, we collapsed data (a) from all experiments of Eben et al. (2020), (b) from Experiments 2 and 3 of Eben et al. (2022), and (c) from two unpublished experiments that investigated the illusion of control (for further information, see the OSF repositories: https://osf.io/nx85m/ and https://osf.io/6h9wv/). For an overview of the stimuli and trial procedures, see Figure 1 and Table 1 in the online supplementary material (https://osf.io/yexth). Detailed information (including all materials and software used) can be found on OSF (see above). All experiments were self-paced, which means that participants had to press a key to start the next trial. The time to start the next trial (start response time [start RT]) was our measure of response vigor.

In short, Eben et al. (2020) used three different tasks. Two experiments had a gambling task in which participants could choose between a non-gambling option with a certain amount of points to win and a gambling option with a higher amount of points but also a lower probability of winning. After choosing their option, participants were presented with the outcome. In Experiments 2 and 3, participants were presented with gambling trials, and non-gambling trials. In the non-gambling trials participants simply had to press a key to continue, whereas in the gambling trials, they had to guess whether the reward was hidden behind the left or right door or card. In the last two experiments, Eben et al. (2020) presented participants with an equal amount of trials per condition.

For the Eben et al. (2022) study, participants were told (as a cover story) that the purpose of the study was to investigate subtle social cues in avatars. They were presented with a video of an avatar asking them to guess the outcome of a coin toss. They had to press the left (heads) or the right arrow key (tails) to indicate their choice, after which they were presented with the outcome. Crucially, sequences of wins and losses were predetermined (as in Langer & Roth, 1975), which created three different groups: one group was presented with a lot of wins at the beginning, one group was presented with a lot of losses at the beginning, and one group had randomly distributed wins and losses. In

order to account for sequence effects, here we decided to include only the group with the randomly distributed trials (random group) and the 24 additional randomly distributed trials of Experiment 3.

In the two unpublished data sets, participants were presented with a card or chose a card to play and had to decide whether this card would be higher or lower than six. After their choice, they were presented with the outcome.

**The short version of the UPPS-P**

In all experiments, participants completed the short UPPS-P (SUPPS-P; Cyders et al., 2014). The SUPPS-P was derived from the original 59-item scale (Whiteside & Lynam, 2001), and consists of 20 items measuring five dimensions: negative and positive urgency (e.g., "When I am upset, I often act without thinking" and "I tend to act without thinking when I am really excited", respectively), (lack of) premeditation (e.g., "My thinking is usually careful and purposeful", reversed), (lack of) perseverance (e.g., "I finish what I start", reversed), and sensation seeking (e.g., "I quite enjoy taking risks"). Participants have to indicate how much they agree from "Agree strongly" to "Disagree strongly" on a four-point Likert scale (Cyders et al., 2014; Whiteside & Lynam, 2001). For our sample, we obtained the following values for internal consistency (Cronbach's alpha): negative urgency $\alpha = 0.73$, positive urgency $\alpha = 0.76$, (lack of) premeditation $\alpha = 0.77$, (lack of) perseverance $\alpha = 0.68$, and sensation seeking $\alpha = 0.64$. Although these values seem relatively low (Tavakol & Dennick, 2011), they remain acceptable, especially since each impulsivity trait is obtained with only four items.

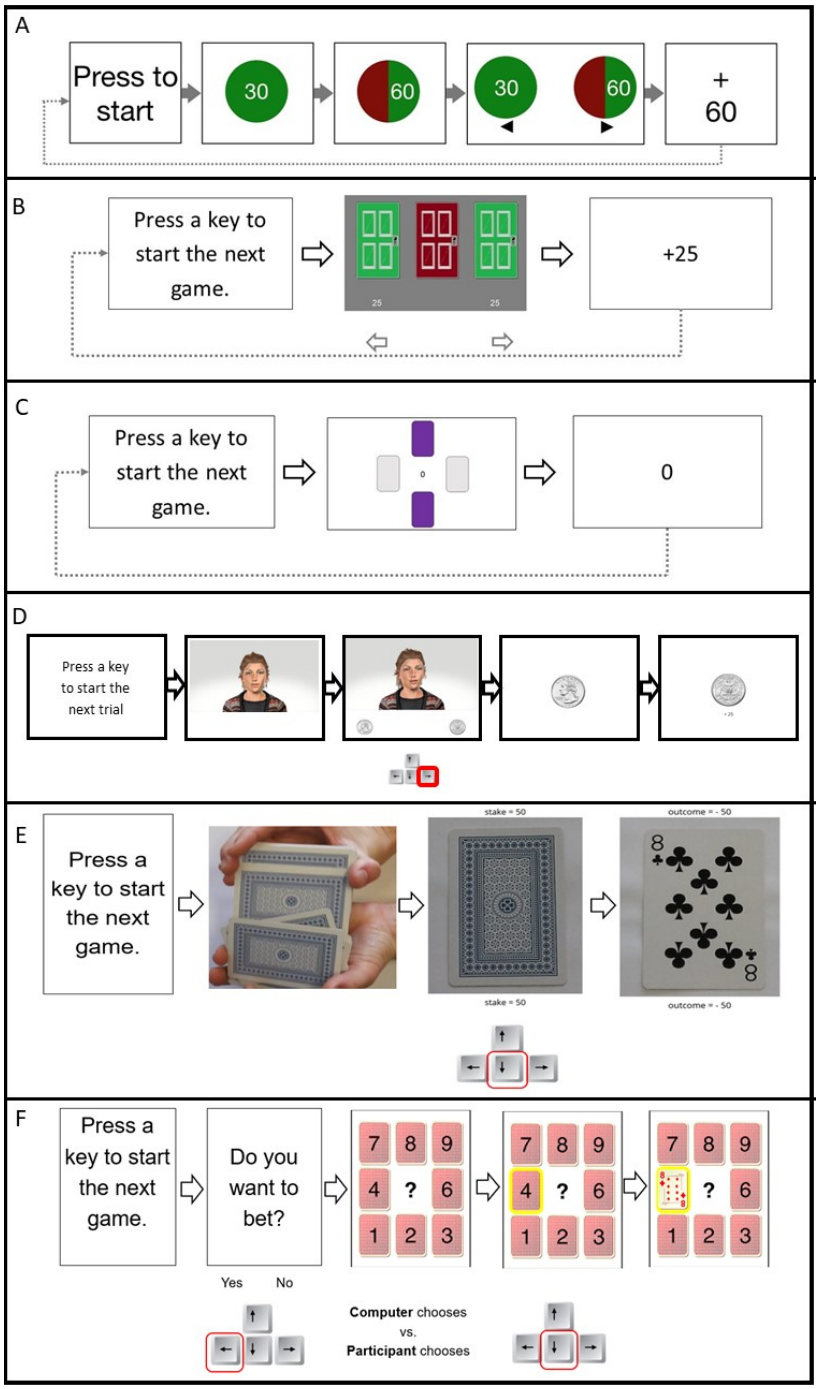


**Figure 1**

*Trial procedures of all studies used. Panels A, B, and C: Eben et al. (2020); panel D: Eben et al. (2022); panels E and F: unpublished data. See the original studies or the OSF repositories (cited in the main text) for detailed information about each procedure.*

***Analyses***

All data processing and analyses were completed with R (R Core Team, 2018, version 4.0.2) by using the packages reshape (Wickham, 2018, version 0.8.8), reshape2 (Wickham, 2020, version 1.4.4), er (Lawrence, 2016, version 4.4-0), Hmisc (Harrell, 2021, version 4.6-0), doBy (Højsgaard & Halekoh, 2021, version 4.6.11), bootnet (Epskamp, 2021, version 1.5), glasso (Friedman et al., 2019, version 1.11), huge (Jiang et al., 2021, version 1.3.5), igraph (file., 2021, version 1.2.9), knitr (Xie, 2021, version 1.37), mice (van Buuren & Groothuis-Oudshoorn, 2021, version 3.14.0), networktools (Jones, 2021, version 1.4.0), qgraph (Epskamp et al., 2021, version 1.9), and tidyverse (Wickham, 2021, version 1.3.0).

We conducted correlational analyses by using both latent construct and network analyses. The network approach differs from the latent construct approach, as single items do not reflect latent constructs but rather constitute the construct, therefore allowing us to investigate interrelationships between single items; the advantage is that relationships that might be masked when using a latent construct approach can be identified (Borsboom & Cramer, 2013; Guyon et al., 2017). Combining these two different approaches allowed us to endorse a robust data analytic strategy toward a multiverse approach.

First, we performed correlational analyses by using the latent construct approach (i.e., Pearson correlation) in order to explore the relationships between the impulsivity traits assessed by the SUPPS-P and our behavioral (or state) measure of impulsivity (post-loss speeding, i.e., the difference score between wins and losses). For this analysis, we calculated the post-loss speeding effect for every experiment by subtracting the mean start RT of trials following losses from the mean start RT of trials following wins. For all experiments that included non-gambling trials (i.e., those using the procedures of Eben et al., 2020), we also calculated the difference between trials following losses and trials following non-gambling trials. For the SUPPS-P, we calculated the sum score for every SUPPS-P factor. We then examined the Pearson correlation between our win-loss difference score and the SUPPS-P factors (see Figure 2). Where possible, we also examined

the Pearson correlation between these factors and the mean difference scores between wins and non-gambling trials and losses and non-gambling trials (see Figure 3).

We then performed network analyses in order to explore the relationships between the items of the SUPPS-P and our behavioral (or state) measure of impulsivity (post-loss speeding, i.e., the difference score between wins and losses). Gaussian graphical models are network models that are composed of nodes representing variables of interest (each item on the SUPPS-P and our difference score as a behavioral measure) and edges describing the relationships between these variables with partial correlations (Epskamp et al., 2018). Before estimating network models, we checked whether variables were colinear by using the Hittner method (Hittner et al., 2003). In order to relax the assumption of normality, we applied a non-paranormal transformation of the variables, as they were non-normally distributed (Liu et al., 2009). Using the ggmModSelect algorithm, we stepwise generated unregularized Gaussian graphical models and selected the optimal model on the basis of Bayesian information criterion (Foygel & Drton, 2010; Isvoranu & Epskamp, 2021). Furthermore, we used both the spinglass community detection algorithm (Eaton & Mansbach, 2012; Reichardt & Bornholdt, 2006) and the walktrap community detection algorithm (Golino & Epskamp, 2017; Pons & Latapy, 2005) to retrieve the internal structure of the data. To establish the robustness of the findings, we also checked the accuracy and stability of the model's parameter estimates, which can be found on OSF (https://osf.io/3jgdy).

### *Exclusion criteria*

For the start RT difference scores, we used the same exclusion criteria as in the previous studies with these data: we excluded trials with choice RT > 2500 ms, start RT > 5000 ms, the first trial of each block, and trials in which the previous outcome was not known. All exclusion criteria were entirely in line with previous work. For all analyses, we excluded participants that had missing items on the SUPPS-P.

In addition, for the network analyses, we excluded three participants from Experiment 2 of Eben et al. (2022), as the raw data (scores on each items) for the SUPPS-P were not recorded. Therefore, we used the data of 1213 participants for the network analyses.

## Results

### Correlations

None of the correlations between the win-loss difference score and any of the factors of the SUPPS-P were significant (for further details, see Figure 2). Similarly, no correlation between the start RT difference scores including non-gambling trials and the factors of the SUPPS-P, was significant. Generally, all correlation coefficients were between -.03 and .04 (for further details, see Figure 3). Note that we performed the same analyses with within-participant z-scored RT data (to control for general differences in response speed). The results were the same as for the raw RT and can be found on OSF (https://osf.io/gneus).

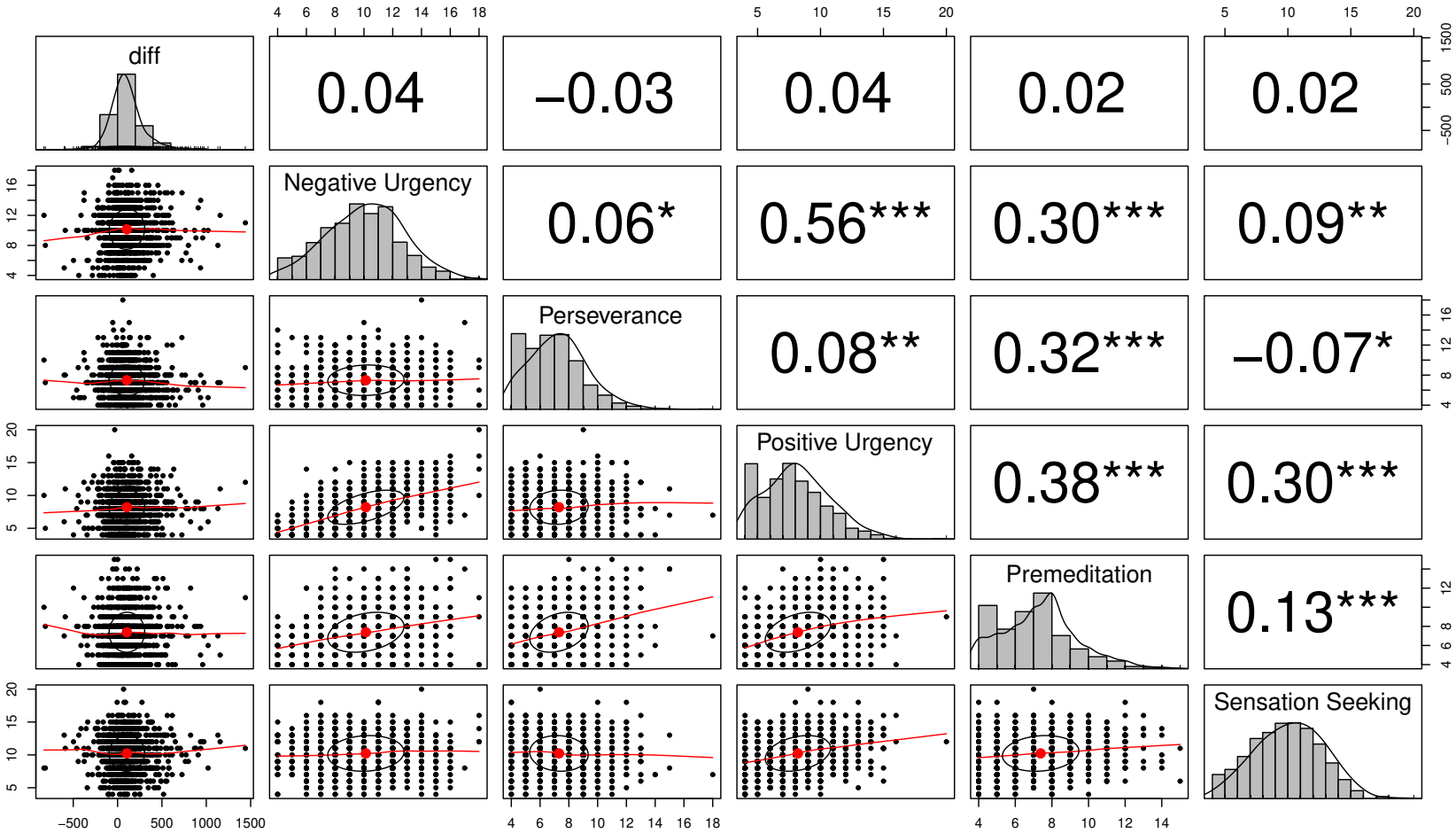


**Figure 2**

*Correlation matrix between the win-loss difference score and the factors of the SUPPS-P. Starting from the first row: win-loss start RT difference score, negative urgency, perseverance, positive urgency, premeditation, and sensation seeking. Here we display the distribution of the measure, the scatter plot between two measures, and the Pearson correlation coefficient of two measures.*

N = 1216. Uncorrected $p$-values with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$

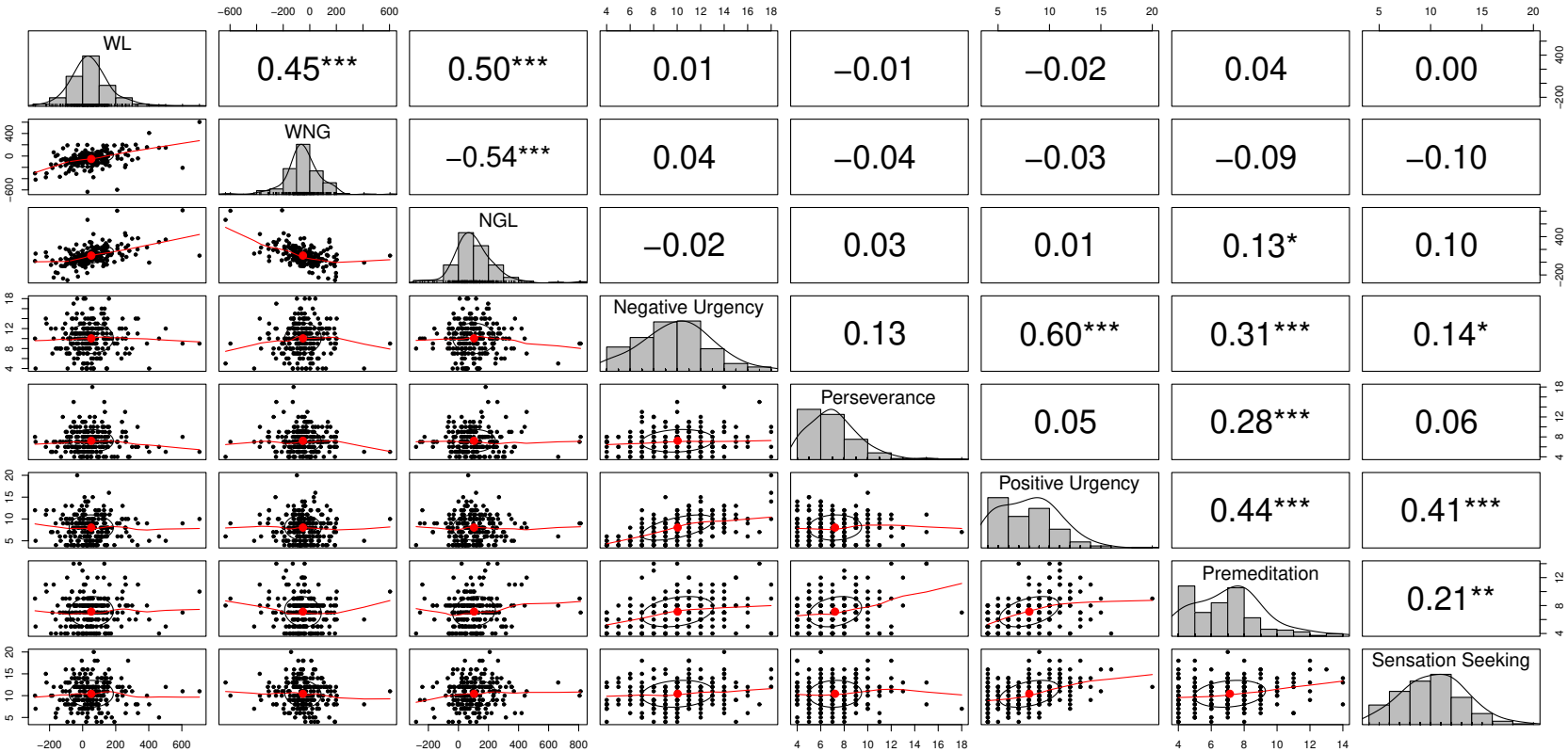


**Figure 3**

*Correlation matrix between the win-loss, non-gambling-win, and non-gambling-loss difference scores and the factors of the SUPPS-P. Starting from the first row: win minus loss start RT difference score (WL), win minus non-gamble start RT difference score (WNG), non-gamble minus loss start RT difference score (NGL), negative urgency, perseverance, positive urgency, premeditation, and sensation seeking. Here we display the distribution of the measure, the scatter plot between two measures, and the Pearson correlation coefficient of two measures.*

N = 222. Uncorrected $p$-values with * for $p < .05$, ** for $p < .01$, and *** for $p < .001$

***Network analyses***

Figure 4 depicts the resulting network when using the spinglass community detection algorithm. Here, we identified the same five clusters of items as in the literature (i.e., negative and positive urgency, lack of premeditation, lack of perseverance, and sensation seeking; Cyders & Smith, 2007; Whiteside & Lynam, 2001). Most importantly, the network analyses did not identify any relationship between the items on the SUPPS-P and our post-loss speeding difference score. For further information on the network accuracy and the network stability, see OSF (https://osf.io/3jgdy). Note that we also ran the network on z-scored RT difference scores as in the correlational analyses, but the resulting network looked exactly the same as the network reported here. The z-scored data used in that network can be found on OSF (https://osf.io/safp4).

Figure 5 depicts the resulting network when using the walktrap community detection algorithm. Here we identified the same four clusters of items as found in recent studies, using the same algorithm (Billieux et al., 2021), combining positive and negative urgency into one cluster. Again, the network analyses did not identify any relationship between the items on the SUPPS-P and our post-loss speeding difference score.

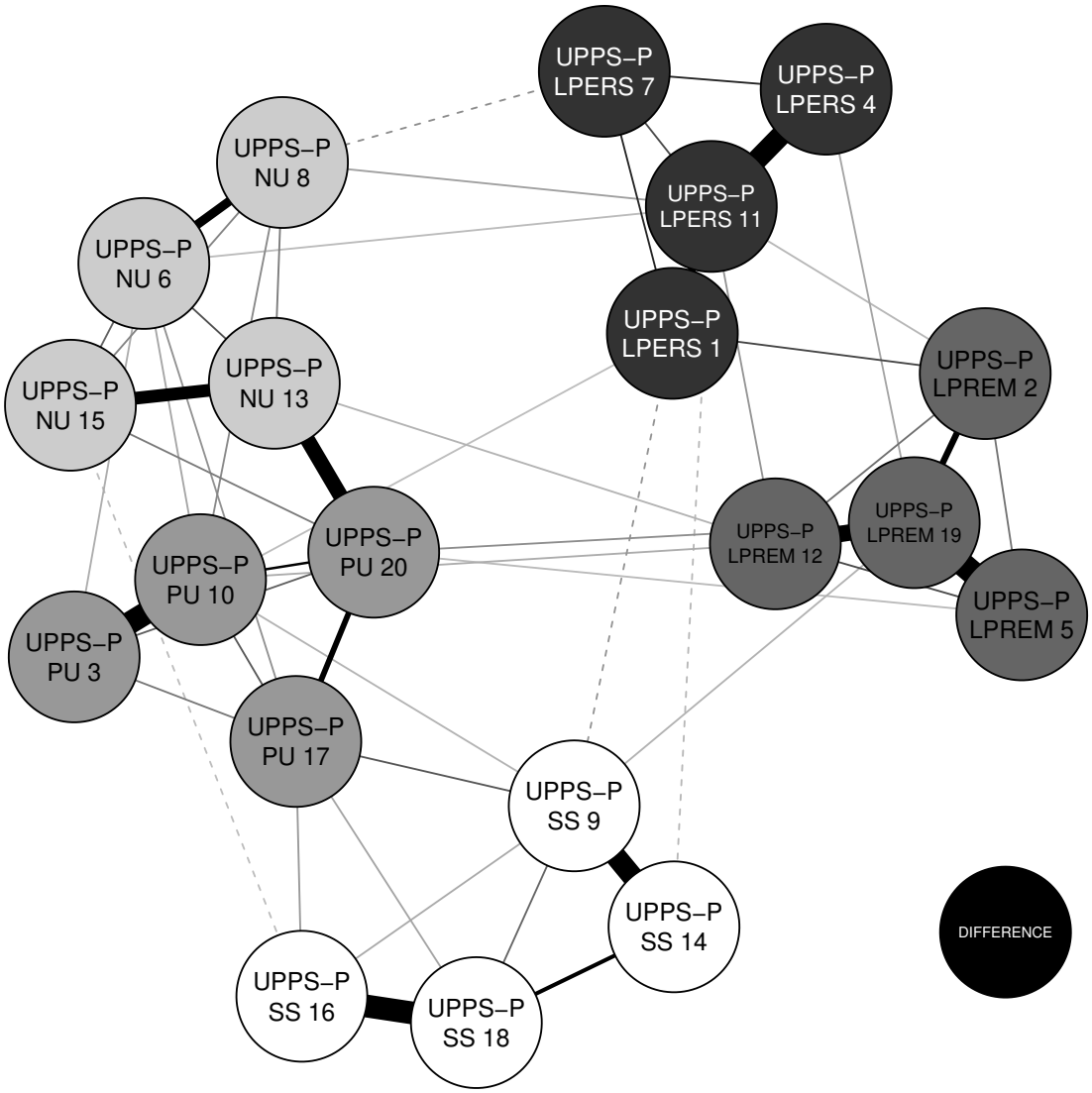


**Figure 4**

*Network of the SUPPS-P items and the start RT difference score between wins and losses. Node colors are defined according to the* ***spinglass community detection algorithm****. LPERS = lack of perseverance, LPREM = lack of premeditation, PU = positive urgency, NU = negative urgency, and SS = sensation seeking.*

Thicker edges indicate a stronger relationship between nodes. Dashed edges indicate a negative relationship between nodes.

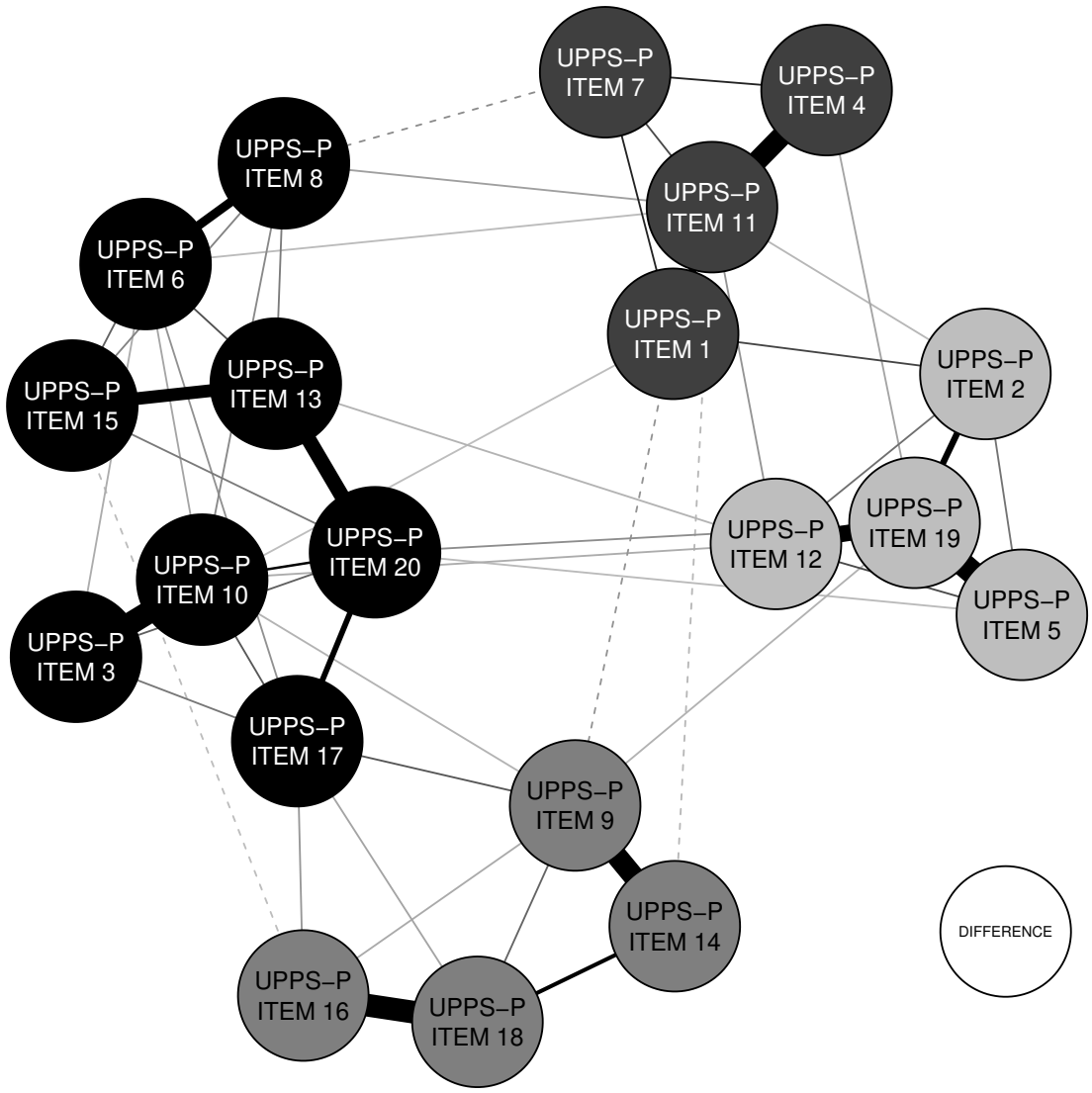


**Figure 5**

*Network of the SUPPS-P items and the start RT difference score between wins and losses. Node colors are defined according to the* ***walktrap community detection algorithm****. From black to bright gray: (positive and negative) urgency, lack of perseverance, sensation seeking and lack of premeditation. Thicker edges indicate a stronger relationship between nodes. Dashed edges indicate a negative relationship between nodes.*

## Discussion

In the present study, we investigated the relationship between a self-report (trait) measure of (negative) urgency (based on the UPPS-P model) and a purported behavioral (state) measure of negative urgency (modeled through a gambling task). To accomplish this, we collapsed the data of eight experiments across two published and two unpublished studies. We then calculated latency difference scores (a) between trials following wins and losses and, where applicable, (b) between non-gambles and wins and (c) between losses and non-gambles. We then examined the relationship between these difference scores and the scores of the SUPPS-P. First, we simply used correlations to investigate the relationship with the five latent factors of the SUPPS-P, and then we used network analyses to further investigate the relationships between single items and our behavioral difference scores.

We did not find any correlation between the factors of the SUPPS-P and our behavioral difference scores. In addition, we failed to find evidence of relationships between any of the SUPPS-P items and our behavioral measures, which were used to model urgency-like behavior through a laboratory task in our network analyses. Lastly, depending on the community detection algorithm, the network analyses suggested either that positive and negative urgency are two distinct clusters, as proposed earlier in the literature (Cyders & Smith, 2007; Whiteside & Lynam, 2001), or that positive and negative urgency cohere as a single cluster (as reported by Billieux et al., 2021).

Previous research suggested that reward omission (here losses) might be suitable to model urgency behaviorally in animals and in humans and thus can contribute to the development of a translational model of urgency (Halcomb et al., 2019). However, our findings show that speeding after losses does not seem to be related to self-reported urgency traits (or to other impulsivity traits, as assessed by the UPPS-P). These findings are not in line with those of Gipson et al. (2012), who showed that reward omission led to invigorated behavior, which, in turn, was related to negative urgency in their study.Of note, Gipson and colleagues (2012) used an operant conditioning paradigm in which reward

omission was unexpected. Thus, expectations might have modulated the effect of reward omission in this case (see also Chen et al., 2020). Nevertheless, our findings are consistent with other research showing no associations or only weak associations between behavioral tasks and self-reported impulsivity facets (Creswell et al., 2019; Cyders & Coskunpinar, 2011, 2012; Reynolds et al., 2006; Schluter et al., 2018; Sharma et al., 2014).

Thus, it seems that post-loss speeding in gambling tasks and negative urgency (or other factors), as measured with the SUPPS-P, do not measure overlapping underlying constructs. Yet, experimental procedures are very specific and measure maximal performance in millisecond ranges, in contrast to the perceived average performance real life, as measured by self-reports (Dang et al., 2020; Halcomb et al., 2019). In addition, according to Cyders and Coskunpinar (2012), behaviors in lab experiments reflect a mere "snap shot" of behavior that might not capture the same overall construct as self-report questionnaires do. This mismatch in measurements contributes to the "jingle" fallacy in impulsivity research (Sharma et al., 2013), which refers to giving different constructs the same name. This is a well-known problem in personality research, especially in impulsivity research. Because of this fallacy, some researchers have even recommended dropping the construct of impulsivity completely and focusing on single factors instead (Strickland & Johnson, 2021). In our study, we specifically focused on negative urgency as one factor but, even then, we were not able to find a relationship between a suggested behavioral measure of negative urgency and a self-reported urgency trait. Nevertheless, it should be considered that these two measures still complement each other by assessing different aspects of rash emotional actions (Halcomb et al., 2019). Thus, as we seem to measure different potentially complementary aspects of behavior with behavioral tasks and self-report measures, it is possible that there is no need for a relationship between these two, as the different mechanisms might be contributing to the same (problematic) behavior.

The fact that trait and state measures do not necessarily need to be related is supported by the fact that behavioral task and personality questionnaires are generally

designed with different goals in mind (Dang et al., 2020; Enkavi et al., 2019; Hedge et al., 2018). For example, Hedge et al. (2018) emphasized that most experimental tasks were designed to keep between-subject variability low to allow within-subject condition comparison. However, this in turn leads to low reliability in individual differences (see also Enkavi et al., 2019). Therefore, some researchers have argued that RT measures, especially RT difference scores, might not suitable for detecting individual differences (Draheim et al., 2019). Moreover, others have argued that only one measure is not a good predictor for behavior (Benjamin et al., 2020; Eisenberg et al., 2019; Rushton et al., 1983). For this reason, questionnaires consist of more than one item to increase their predictive validity. By contrast, we used only one RT difference score per participant, which has arguably a similar (predictive) validity as one single item of a questionnaire.

One limitation of our study worth noting is that the majority of previous work that found links between UPPS-P impulsivity facets and behavioral tasks (e.g., stop-signal tasks) used the original 59-item scale. In contrast, we used the short version of the UPPS-P to keep our experiments short enough to increase the engagement of the participants. Applying the long version of the UPPS-P would not have been feasible. It is known, however, that the content validity of the short-version questionnaire tends to be lower (i.e., short-versions measure narrower constructs; see Smith et al., 2000). Thus, this might have contributed to the absence of relationships shown in the present study. Another limitation of the present study is that six different gambling tasks were used to model our behavioral measure of negative urgency. These tasks have very different visual appearances, and we cannot determine whether they correlate, as we have only one task per participant. However, all tasks share two important features, which in our opinion made them a good measure of urgency: first, all tasks were gambling tasks in which participants could win and lose points, and second, all tasks were self-paced, meaning that participants had to press a key to start the next game. In all tasks, we measured the time it took participants to initiate the next trial. Thus, all tasks allowed a similar comparison

between the time taken to start a trial after a win and the time taken to start a trial after a loss (resulting in our post-loss speeding difference score). In addition, some of the studies presented participants with non-gambling trials. For these studies, we also compared the time taken to start the non-gambling trials with the other two types of trials. Notably, all tasks independently showed that participants sped up after losses compared with wins and non-gambling trials. Therefore, all tasks have something in common: a blocked reward leads to more invigorated behavior. Unfortunately, because of low sample sizes in the single samples, we were not able to compute the networks for the single samples; however, the correlational analyses for each single sample can be found on OSF (https://osf.io/yexth).

In summary, we could show that the degree of speeding after a loss compared with non-gambles and wins (post-loss speeding) was not related to higher self-reported measures of impulsivity in everyday life. Given the fact that we had a big sample size because we collapsed data across studies, we assume that our behavioral measure of post-loss speeding and negative urgency as defined in the UPPS-P framework might not capture exactly the same underlying mechanisms. This is consistent with other work suggesting that single RT difference scores might not be suitable to investigate individual differences in behavioral tasks. Therefore, future research should invest in examining which constructs are being measured and which other measures contribute to a better understanding of these constructs.

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