Stage 1 Registered Report: Impulsivity and online sports betting behavior: Untangling the causal relationship

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Author note

We are presenting a Stage 1 Registered Report. In order to maximize transparency, we have written some aspects of the method section in the past tense, as two of three waves in the project have already been carried out. The analyses of the study can only be carried out after the final third wave, as the statistical models needed to test the hypotheses require at least three waves. In Stage 2, we will change the tense to past tense for all sections and add the discussion and conclusion sections.

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Stage 1 Registered Report: Impulsivity and online sports betting behavior: Untangling the causal relationship

The rapid expansion of online sports betting has raised concerns about its potential impact on individual health and public health. In order to further develop etiological models for gambling disorder (GD) in sports betting, it is essential to unravel the underlying causal processes. Recent studies have identified risky online gambling behavior as an early indicator of GD. The planned study focuses on impulsivity as a well-documented risk factor for GD and investigates whether increased impulsivity leads to risky online gambling behavior and subsequently contributes to GD. Impulsivity, risky gambling behavior, and GD symptoms will be assessed three times at three-month intervals using a longitudinal cross-lagged panel design. We aim to recruit a final sample of n = 370 regular sports bettors from the online gambling provider Tipico. Impulsivity and GD will be assessed using a combination of online experimental tasks and questionnaires. As a measure of risky gambling behavior, Tipico will provide player tracking data for the included participants. Random intercept cross‐lagged panel models will be used to test the evidence for our hypotheses. The results will improve our understanding of the causal pathways leading to risky gambling behavior and GD, and will inform the development of early prevention strategies.

Keywords: gambling disorder; player tracking data; longitudinal design; decision making; inhibitory control; cross-lagged panel design

Online sports betting is growing in popularity worldwide due to its legalization in a growing number of international jurisdictions and technological advances. For example, legalization took place in U.S. states after a Supreme Court ruling in 2018 (Winters & Derevensky, 2019) or in Germany according to the new State Treaty on Gambling in 2021 (GlüStV, 2021). As a result, more and more people are participating in online sports betting. For example, the number of online sports bettors in the US market is expected to reach 52 million by 2028, which would be an increase of 15.6% (*Online Sports Betting - US | Statista Market Forecast*, 2023). Profits for online sports betting in the US are also growing, with sports betting apps generating 0.3 billion $ in revenue in 2018, rising to 7.4 billion $ by 2022 (*Sports Betting App Revenue and Usage Statistics*, 2023).

Researchers and policymakers are concerned about the potential negative impact of such a large increase in the availability of online sports betting on individual health and public health, as increased availability leads to higher online sports betting participation and cross-sectional studies have linked online gambling participation to a significant rate of gambling problems (Allami et al., 2021). The general 12-month prevalence rates of GD are between 0.2 and 2.0 % (Kräplin & Goudriaan, 2018). To the best of our knowledge, there are no current international studies that specifically report the prevalence rates of GD among online sports bettors. A current study from Germany reported a 12-month prevalence rate of GD of 17.6% among those who report (also) participating in online sports betting (Meyer et al., 2023). It remains unclear why exactly there is a link between online sports betting and higher GD rates.

Established models of the etiology of GD (and other addictive behaviors) suggest that environmental, individual and gambling-related factors play a role in the development of GD (Blaszczynski & Nower, 2002; Brand et al., 2019; Bühringer et al., 2008). With an emphasis on psychological research, we will focus on impulsivity as one individual factor in our project. As impulsivity is a multifaceted construct, we will define it according to MacKillop et al. (2016) who proposed three independent facets of impulsivity:

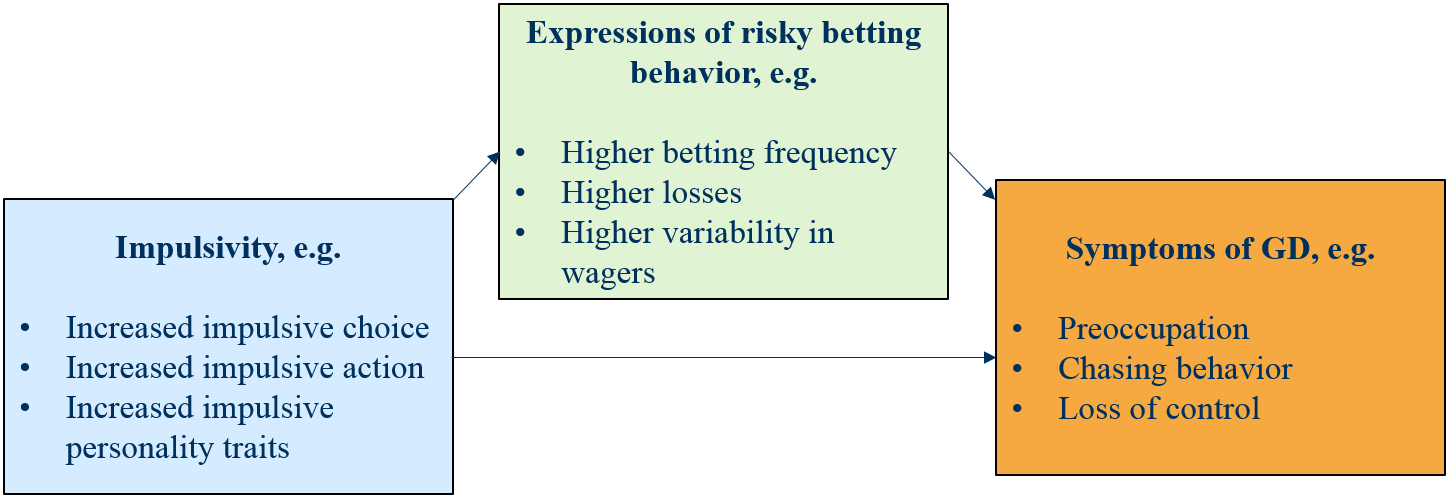
“impulsive choice, reflecting discounting of delayed rewards; impulsive action, reflecting ability to inhibit a prepotent motor response; and impulsive personality traits, reflecting self-reported attributions of self-regulatory capacity.” (p. 3361; MacKillop et al., 2016).

Increased impulsivity is a well-established risk factor for GD in general, with longitudinal research focusing on temperament and impulsive personality traits (Shenassa et al., 2012; Slutske et al., 2005, 2012). Cross-sectional case control studies have also provided evidence for increased impulsive choice (Amlung et al., 2017) and impulsive action (Chowdhury et al., 2017) in GD compared to healthy controls. To the best of our knowledge, there is so far only one study from our lab focusing particularly on impulsivity in *online* sports betting. We showed that impulsive personality traits are increased in online sports bettors with GD compared to those without GD and that increased impulsivity predicts GD one year later (Wirkus et al., under review).

While increased impulsivity seems to be a valid risk factor for GD, it is unclear exactly how increased impulsivity contributes to the development of GD in general and in online sports betting in particular. As a very valuable basis for explaining the possible mechanisms, some studies have shown that increased impulsive personality traits are related to riskier betting behavior (Hing et al., 2018; Russell et al., 2019; Valenciano-Mendoza et al., 2023). According to established multifactorial etiological models of behavioral addictions (Blaszczynski & Nower, 2002; Brand et al., 2019), increased impulsivity may lead to specific risky gambling patterns (e.g., betting on riskier odds, higher variability in stakes). These patterns may in turn lead to GD in sports betting, in interaction with other variables such as dysfunctional emotion regulation and the lack of external control in online environments. One promising approach to support this assumption is studies of player tracking data, which have shown that risky gambling behavior is an early marker of GD (Braverman et al., 2013; Di Censo et al., 2023; Gray et al., 2012).

The planned study will be the first to explicitly test these causal assumptions. The main assumption to be tested is that increased impulsivity causes risky online betting behavior, which in turn leads to GD (Figure 1).

**Figure 1**

*******Heuristic mediation model to explain the development of gambling disorder in sports betting (figure taken from the preregistration;* [*https://doi.org/10.23668/psycharchives.13483*](https://doi.org/10.23668/psycharchives.13483)*)*

We propose three directional hypotheses to test our main assumption:

* H1. Increased impulsivity among online sports bettors leads to higher GD severity.
* H2. Increased impulsivity among online sports bettors leads to riskier betting behavior in online sports betting, e.g. higher betting frequency.
* H3. Risky betting behavior is a mediator between impulsivity and GD severity.

As we regard impulsivity as multifaceted construct, we assume in detail that the predictor impulsivity will consist of (a) impulsive choice, (b) impulsive action, and (c) impulsive personality traits. Accordingly, hypothesis testing will take all 3 facets into account (see subsection ‘Hypothesis testing’). The results of this study will improve the causal understanding of problematic developments in gambling behavior and provide targets for early prevention measures.

# Method

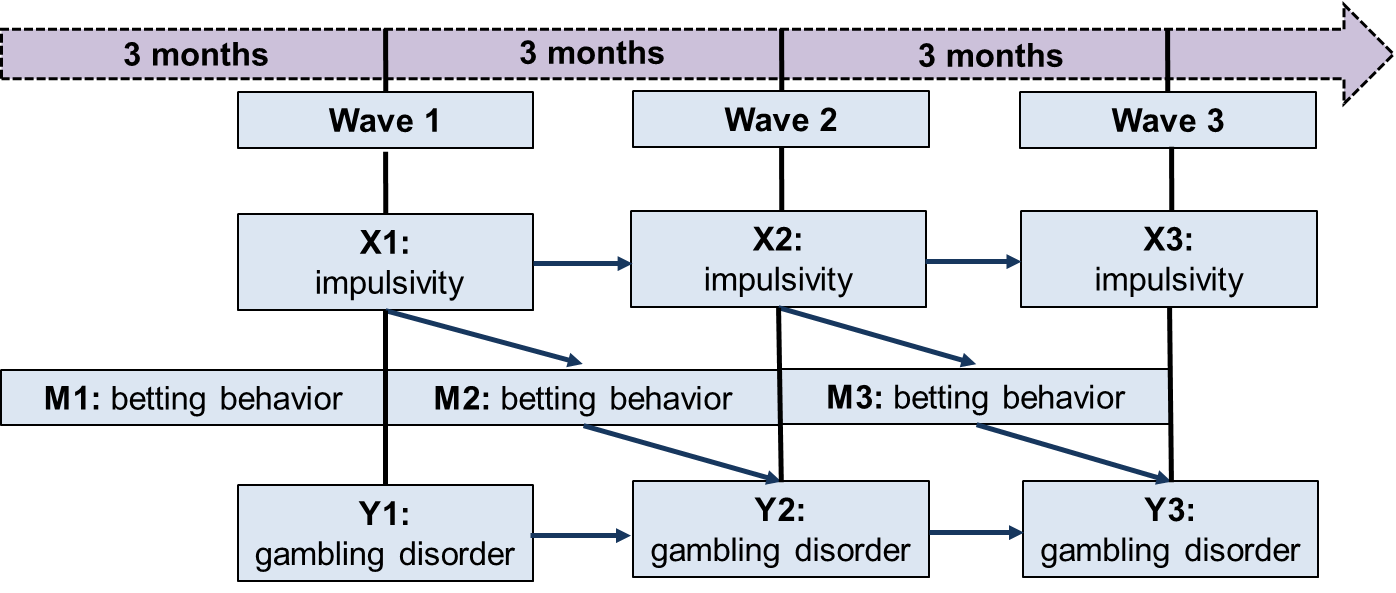
## Statement on transparency and ethics

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study. We fulfil Level 3 of the PCI RR bias control (<https://rr.peercommunityin.org/help/guide_for_authors>). Due to time constraints imposed by the project schedule, data collection had already started on October 202023 and the first wave was successfully completed on November 24 2023 with n = 954. By March 2024, we had already contacted all 954 participants and 709 have so far participated in wave 2. These data are accessible to the authors for quality checks (see section ‘Missing values, data quality, and data exclusion’). The study including hypotheses had been preregistered at PsychArchives of the Leibniz Institute of Psychology (ZPID) on October 162023 at <https://psycharchives.org/en/item/e31cfc4c-153d-463e-ab8c-f3bee6883604> before data collection started. The study design is presented according to the PCI RR format in Table 1. The study data (with access restricted to researchers), materials, analysis script, and preregistration of the accepted Stage 1 manuscript are and will be publicly available at PsychArchives. The study was ethically approved by the Institutional Review Board (IRB) of the TU Dresden (IRB00001473; reference number: SR-EK-260062023).

## Design

In a prospective cross-lagged panel design, we will assess sports bettors’ impulsivity and GD online three times at three-month intervals. The data on impulsivity and GD collected at all three survey dates will be combined with the data on tracked online betting behavior aggregated over the three months prior to each of the three online assessments. This design allows causal analysis in a non-experimental setting. For Hypothesis 1, the reciprocal predictive relationship between impulsivity (X) and GD symptoms (Y) is of interest. For Hypothesis 2, the reciprocal predictive relationship between impulsivity and betting behavior (M) is of interest. For Hypothesis 3, betting behavior will be examined as a potential mediating variable in the relationship between impulsivity and GD symptoms (Figure 2).

**Figure 2**

*******Planned cross-lagged panel design, with three waves in which impulsivity, gambling disorder severity, and (aggregated) online sports betting behavior are assessed. The crossed arrows represent the main assumption that increased impulsivity causes risky online betting behavior, which in turn leads to GD*

## Participants

### Sample size and power calculations

We calculated the required sample size for the study based on Hypothesis 3, as it was expected that the mediation hypothesis would require the largest sample size. In order to determine the appropriate sample size, we relied on a simulation study that specifically explored the sample size requirements for testing within-person indirect effects in longitudinal data (Pan et al., 2018). In this simulation study, a small effect size is defined as 0.14, ‘halfway’ as 0.26, medium as 0.39, and large as 0.59. We assumed an intra-class correlation of GD during 9 months of 0.6 (Currie et al., 2013), small associations (0.14) between impulsivity and risky gambling behavior during 9 months (based on a study of multiple addictive behaviors; Kräplin et al., 2020), and a small to medium association (0.26) between risky gambling behavior and GD during 9 months (Xuan & Shaffer, 2009). The required sample size for our study was calculated to be n = 370 using the bootstrap method and given the planned three waves, a planned power of 80%, and an alpha level of 5% (see Table 4; Pan et al., 2018). Since Hypotheses 1 and 2 require a smaller sample size than Hypothesis 3, the sample size determined for Hypothesis 3 provides sufficient statistical power to adequately test Hypotheses 1 and 2.

After this theoretical consideration regarding sample size, we took into account the response, retention, and exclusion rates. In another study of online sports bettors from our lab, where online surveys were also conducted (RIGAB study; https://osf.io/k6c23/; Czernecka et al., 2023), the response rate was 13% of which a further 30% had to be excluded due to incomplete or implausible questionnaire data. Based on the experience from the RIGAB 12 month follow-up, a retention rate of 60% is expected between the first online survey and the third survey wave 9 months later. In addition, the exclusion of further data due to data quality checks was estimated at 25 %. Based on these response rates, the retention estimates, and the data exclusion estimates, 925 participants need to participate in the first wave to achieve a sample of 370 participants in the third and final wave (60% retention rate, 25% data quality exclusion, 10% buffer). Assuming a linear decline in the retention rate, we estimated that 555 participants have to participate in the second wave (80 % retention rate and 25% data quality exclusion). Therefore, we estimated that we would have to invite 10,153 Tipico account holders in the first wave, of whom about 1,320 would be assumed to respond (response rate 13%) and n = 925 (30% data quality exclusion) could be included in the final sample of the first wave.

### Recruitment and retention

The target sample of n = 370 regular sports bettors will be recruited from the online gambling provider Tipico. Tipico is a globally active and leading sports betting provider in Germany and holds a license for online sports betting in Germany. By contract with TU Dresden, Tipico has not had and will not have an influence on the study planning, funding or the study results and publication. In order to ensure a high level of data protection, the contract also includes specific recruitment and assessment procedures.

Participants were recruited via an email from Tipico. Please see the subsection ‘Procedure’ for further details. The sample includes Tipico account holders who live in (partly) German-speaking countries (Germany, Austria, and Switzerland) and have German language skills at a native level to understand the questionnaires and task instructions. We included online sports bettors between 18 and 55 years of age (based on evidence for age effects on neurocognitive characteristics; Denburg et al., 2005; Fein et al., 2007; Murman, 2015). Further inclusion criteria are that the account holders have used their Tipico account for sports betting within the previous three months (i.e. have placed at least one bet during this period) and have provided online informed consent. No further inclusion or exclusion criteria were applied to maximize the generalizability of the results to the overall population of sports bettors.

By November 2023 we had successfully recruited the required number of participants for wave 1. Tipico sent study invitations to 27,000 account holders between October 20, 2023 and November 22, 2023. Of those invited, 1,553 participated in our study (response rate = 5,8%). Of these, 38,6% had to be excluded for data quality reasons so we received usable data sets from n = 954 participants in the first wave. By March 2024, we have already contacted all 954 participants again and 709 participated in wave 2, which translates to a retention rate of 74% (80% retention rate at wave 2 was planned). Due to low data quality, 11% of the participants were excluded (25% data quality exclusion was expected), leaving usable data from 629 participants. We have exceeded our target sample size of n = 555 for wave 2 and are confident to reach the target sample size of n = 370 for wave 3. We have integrated several strategies into the study to minimize the dropout rate. First, participants receive an increasing amount of recompensation over time for their participation (15€ for wave 1, 20€ for wave 2, and 30€ for wave 3). We regularly communicate with participants by email, e.g. if bank details for the bank transfer are incorrect. Furthermore, we send three reminders every two weeks for waves 2 and 3 (with the option to opt out), giving participants a total of eight weeks to complete the study.

## Measures

### Operationalization and study materials

The study data is collected using Labvanced, which is hosted on a server at the University of Osnabrück (more information at https://www.labvanced.com/privacy.html). Labvanced is a web-based platform that allows researchers to create and run customized experiments for cognitive psychology and to also integrate online surveys. The study material (in German) can be found at PsychArchives (<https://doi.org/10.23668/psycharchives.14178>). Our main variables are and will be assessed and operationalized as follows:

#### (1) Gambling disorder (GD) severity

We will use GD severity as an outcome for testing hypotheses 1 and 3. We operationalize GD severity as the number of criteria fulfilled according to the Diagnostic and Statistical Manual of Mental Disorders (5th ed.; DSM-5; American Psychiatric Association, 2013). To assess GD severity, an internal German translation of the DSM-5 version of the DSM-5 Stinchfield questionnaire using dichotomous items is used (adapted according to DSM-5 criteria from Buchner et al., 2009; Stinchfield et al., 2016).

#### (2) Impulsivity

Impulsivity is the predictor in all three hypotheses. Three facets of impulsivity are assessed: impulsive choice, impulsive action and impulsive personality traits (MacKillop et al., 2016).

*(a) Impulsive choice*

We operationalize impulsive choice via delay discounting in the 27-item Monetary Choice Questionnaire (MCQ) by Kirby et al. (1999). Participants are presented with two choices on a computer screen: a smaller monetary reward that is available sooner, or a larger monetary reward that is available later. In the MCQ (as in other delay discounting paradigms), the subjective values of the delayed rewards decline hyperbolically according to the discounting rate *k* (Mazur, 1987). Individuals with increased impulsive choice are expected to have higher *k* values in the MCQ. The MCQ showed good to excellent test–retest reliability on repeated assessments over 2 years (mean r=0.83; Strickland et al., 2023). We calculate the *k* values in the MCQ according to the procedure described in detail by Kaplan et al. (2016).

*(b) Impulsive action*

We assess impulsive action with a Go/Nogo task from our lab (Wolff et al., 2020). The task consists of 140 Go trials and 20 Nogo trials. Concerning the online assessment, a study within our faculty found no differences in known effects (e.g., task-switching effects) or reliability between a laboratory setting and home performance (Miller et al., 2018). A pilot study revealed that our smartphone-based task was more difficult than the original keyboard-based task, so we were concerned about the risk of ceiling effects for Nogo errors. In a second pilot study, we tested some modifications to make the task easier (i.e., a longer presentation of the target and the inclusion of a blank screen after the target). Finally, in order to achieve similar Nogo error rates to the original keyboard-based task, we decided to prolong the presentation time by inserting a blank screen after each target. In the final task, each trial consists of a fixation cross (750 ms) followed by two either vertically or horizontally arranged dots (500 ms) and a blank screen (250 ms). The participants are instructed to tap a button on their smartphone screen if the orientation of the dots is vertical (Go, predominant trial type) and to withhold the response if the orientation of the dots is horizontal (Nogo). In one of our studies, in which the original version of this Go/Nogo task was developed, the retest reliability was moderate (r=0.55; unpublished calculation from the study ‘Volitional Dysfunction in Self-control Failures and Addictive Behaviors’; see <https://osf.io/rhjb4>). We operationalize impulsive action with the balanced integration score (BIS; Liesefeld & Janczyk, 2018), which gives equal weighting to reaction time and accuracy to account for individual differences in the balance of the speed-accuracy trade-off (Bogacz, 2015). The BIS is calculated by first standardizing the reaction times (correct Go trials) and the percentage of correct rejections (correct Nogo trials) to bring them to the same scale. Then the standardized reaction times are subtracted from the standardized percentage of correct values. A higher BIS is an indicator of increased impulsive action.

*(c) Impulsive personality traits*

We operationalize impulsive personality traits according to the UPPS-P model and assess it with the German version of the SUPPS-P Impulsive Behavior Scale (Wüllhorst et al., submitted). This is a short questionnaire with 20 items in the form of statements. Participants answer the items on a four-point Likert scale, indicating the extent to which the statements apply to them. The scale ranges from ‘very true’ to ‘very false’. The scale consists of five sub-dimensions of impulsivity: (1) and (2) positive and negative urgency (the tendency to act rashly under conditions of positive or negative affect), (3) premeditation (the tendency to reflect on the consequences of an action before performing the action), (4) perseverance (an individual’s ability to remain focused on a task), and (5) sensation seeking (the tendency to enjoy and pursue activities that are exciting and openness to new experiences that may be dangerous). Reliability in terms of internal consistency (Wüllhorst et al., submitted) ranges from .76 (sensation seeking) to .85 (positive urgency). The test-retest-reliability of the questionnaire is unclear and can be examined in our study. Previous studies with the long version of the UPPS have shown good to excellent test–retest reliability (Weafer et al., 2013). As recommended by the authors of the German validation study of the SUPPS-P, we will base the three outcomes on the three factors solution that best fitted the data (Wüllhorst et al., submitted). We will use the sum scores to calculate each of the three factors of the impulsive personality traits, i.e. the sum scores of the positive urgency subscale and the negative urgency subscale will be added to the factor ‘urgency’, the sum scores of premeditation and perseverance will be added to the factor ‘lack of conscientiousness’, and the sum score of sensation seeking is a separate factor. Higher values in urgency, in lack of conscientiousness and in sensation-seeking indicate higher impulsive personality traits.

#### *(3) Risky betting behavior*

We will use risky betting behavior as the outcome in hypothesis 2 and the mediator in hypothesis 3. We will base the operationalization of risky betting behavior on already aggregated player tracking data, which we will receive from the sports betting provider Tipico. For reasons of data protection, this only involves data from the last9 months prior to the final online survey. We will then divide the data into three-month sections, each containing the three months prior to each wave of the survey.

Based on previous research (Currie et al., 2012; Czernecka et al., 2023; Dragicevic et al., 2011), risky betting behavior will be operationalized as presented in Table 2.

Table 2. Operationalization of risky betting behavior based on player tracking data.

|  |  |  |
| --- | --- | --- |
| **Received player tracking data** | **Operationalization of risky betting behavior** | **Calculation** |
| **Active days:** total number per month | Higher number of active days per month | Sum of active days over 3 months |
| **Bets:** number of bets per month; maximum number of bets on a single day within each month | Higher number of bets | Total sum of bets (prematch and live action) over 3 months |
|  | Higher maximum number of prematch bets | Sum of maximum number of prematch bets on a single day within each month over 3 months |
|  | Higher maximum number of live action bets | Sum of maximum number of live action bets on a single day within each month over 3 months |
| **Stakes:** total stakes per month; variance | Higher amount of total Stakes | Total sum of stakes (prematch and live action) over 3 months |
|  | Larger standard deviation of total stakes | Standard deviation of stakes for prematch and live action bets over 3 months |
| **Winnings and losses:** total winnings per month | Higher sum of total losses (stakes minus wins) | Difference of sum of total stakes minus sum of total winnings over 3 months |
| **Odds:** monthly average; variance | Higher mean weighted odds | Mean weighted odds for live action bets and prematch bets over 3 months (weighted by the number of live action and prematch bets respectively for each month and divided by the total of bets over 3 months) |
|  | Higher standard deviation of odds | Standard deviation of odds for prematch and live action bets over 3 months |
| **Deposits:** amount deposited per month, variance of amount deposited, number of deposits per month, maximum number of deposits on a single day within each month | Higher number of deposits | Sum of number of deposits over 3 months |
|  | Higher amount of deposits | Sum of amount deposited over 3 months |
|  | Larger standard deviation of amount deposited | Standard deviation of amount deposited over 3 months |
|  | Higher maximum number of deposits | Sum of maximum number of deposits on a single day within each month over 3 months |
| **Withdrawals**: amount withdrawn per month, variance of amount withdrawn, number of withdrawals per month, maximum number of withdrawals on a single day within each month | Higher number of withdrawals | Sum number of withdrawals over 3 months |
|  | Higher amount of withdrawals | Sum of amount withdrawn over 3 months |
|  | Larger standard deviation of amount withdrawn | Standard deviation of amount withdrawn over 3 months |
|  | Higher maximum number of withdrawals | Sum of maximum number of withdrawals on a single day within each month over 6 months |
| **Connection of survey data with player tracking data** | | |
| Gambling types played (survey) | More often multiplayer | Sum of the different kinds of gambling played reported in the last 12 (wave 1) or 3 (wave 2 and 3) months |
| Total stakes per month,  Net income (survey) | Proportion of stakes to net income | Sum of total stakes over 3 months divided by 3 and then divided by the declared monthly mean net income over the last 12 months (online survey) |

*Note.* Data concerning bets, stakes, winnings and odds were each received separately for prematch and live action bets. For the calculation of the pooled standard deviations, a minimum number of at least one bet / deposit / withdrawal per considered month (i.e. a total of 3) is required.

In order to operationalize risky betting behavior with a meaningful number of variables, we will perform a principal axis factor analysis that includes all the aggregated betting data (Table 2) and use each participant’s factor scores. To handle missing data, we will use the expectation-maximization (EM) algorithm to estimate the covariance matrix (Truxillo, 2005; Weaver & Maxwell, 2014). Factor selection will be conducted using the eigenvalue, scree plot, parallel analysis, and the interpretability of the factors. Factors with eigenvalues greater than one are considered according to the Kaiser Guttman rule. However, this rule often leads to a large number of factors. Therefore, we will further consider the factors before the ‘elbow’ in the screeplot, i.e. the point where the curve bends. Finally, we will use parallel analysis, a Monte-Carlo based simulation method that compares the observed eigenvalues with those obtained from a random data set (Horn, 1965). A factor is retained if the eigenvalue is higher than the eigenvalue of the corresponding factor from random variables. We will use parallel analysis and the interpretability of the resulting factors will be given the greatest weight when deciding on the number of factors. Higher factor score(s) of the participants will indicate riskier betting behavior.

#### (4) Sociodemographic variables

We assess sociodemographic variables using self-developed items based on previous studies (Czernecka et al., 2023; Kotter et al., 2018). We assess the variables age, gender, native language, education, income, and preferred gambling types to describe the sample.

### Procedure

We recruited participants via an email from Tipico. If an account holder was interested in participating in the study, they could follow the individualized link in the email. After reading the study information, interested persons could confirm whether they want to voluntarily participate in the study. After giving informed consent, participants were assessed using questionnaires and behavioral tasks (duration: approx. 20 minutes for the first wave, second and third wave 15 minutes each). All participants answer the questionnaires and conduct the tasks in the same order at all three waves: (a) sociodemographic variables (shortened at waves 2 and 3), (b) impulsive decision-making, (c) impulsive action, (d) gambling disorder severity, (e) impulsive personality traits. After the survey, participants were redirected to the secure, web-based software platform Research Electronic Data Capture (REDCap; Harris et al., 2009, 2019) hosted at TUD Dresden University of Technology to provide their e-mail address, other contact details, and bank details for participant compensation. For waves 2 and 3, participants were contacted again via e-mail if they were included in the study (for exclusion due to poor data quality, see subsection ‘Missing values, data quality, and data exclusion’). After wave 3, we will receive the player tracking data from the lastnine months prior to the final online survey.

## Statistical analysis

### Missing values, data quality, and data exclusion

We use and will use Stata 15.1 for Windows to check the data quality and aggregate the data according to our operationalizations. As outlined in the ‘Statement on transparency and ethics’ section, the first wave of our data collection has already been completed. We have already performed some data quality checks to exclude participants with poor data quality. This was necessary so that we could continuously monitor the correct number of participants (i.e., without exclusions) in order to invite additional account holders if necessary (see ‘Sample size and power calculation’). Overall, we expect three different kinds of missing and excluded data, which we will handle differently:

1. Exclusion due to poor data quality

Regarding the questionnaire data, missing values are not expected after the questionnaire is completed, as the answers required to test our hypotheses are mandatory. It is not possible to continue the survey without completing all parts. However, the questionnaires (sociodemographic variables, impulsive personality traits) will contain ‘bogus items’ (attention-check questions such as ‘Please select option 4 for this item.’) to control attention and seriousness when completing the questionnaire. Participants who have not answered these control items correctly were and will be completely excluded from the study. A plausibility check was and will also be performed on the time it takes participants to complete all study items (i.e., at least 10 minutes for the first wave survey and at least 7.5 minutes for the second and third wave). Participants who are below the plausible time limit were and will be completely excluded from the study.

1. Exclusion due to accuracy check

Regarding impulsive choice, we do not expect any missing values for the MCQ, as the responses are mandatory to progress in the study. We followed and will follow the recommendation by Kaplan et al. (2019) and exclude participants’ values from the data set with a consistency score below 75%, as this may indicate a lack of attention. In addition, we excluded and will exclude participants’ values who did and do not switch in the MCQ, i.e. always choosing the smaller or later option, as this may also indicate inattention.

Regarding impulsive action, we followed and will follow the standard procedure in our lab to ensure data quality in the Go/Nogo task (Wolff et al., 2016, 2020). To ensure that observations are only used for further analyses if participants understood and actually followed the task instructions, participants’ values were and will be excluded from further analyses if accuracy in the critical condition of the task (i.e., Go trials) is below chance (i.e., if the binomial probability of a participant achieving higher accuracy than observed by chance is >.05; following Friedman et al., 2008). Error rates for further analyses included and will include only no-go trials. Reaction times for further analyses included and will include only correct go trials. Reaction times below 100 milliseconds (ms) and reaction times deviating from the median by more than 3.32 median absolute deviations were and will also be excluded (Wilcox & Keselman, 2003). If participants have a missing value in the MCQ and/ or the Go/Nogo task due to our exclusion criteria, we will handle the missing values with full information maximum likelihood (FIML) within the models to test our hypotheses (see ‘Hypothesis testing’).

c) Missing values in the player tracking data

For the transaction data, we do not expect any implausible outliers, based on our experience in a previous study with aggregated player tracking data from our lab (Czernecka et al., 2023). For the summarized variance indices computed from the original transaction data, we expect some individuals with too few data points to compute a reliable aggregated variance (i.e. variance of stakes, variance of number of bets, variance of odds). A minimum number of at least one bet / deposit / withdrawal per month (i.e. a total of 3) is required for the calculation of the pooled standard deviations (Table 2). For individuals with less than three bets/ deposits/ withdrawal, there will be missing variance sum values. There will also be missing values for the variable ‘proportion of stakes to net income’ if participants choose to not report their net income. To handle missing data, we will use the expectation-maximization (EM) algorithm to estimate the covariance matrix in the factor analysis of the player tracking data (Truxillo, 2005; Weaver & Maxwell, 2014).

### Selection bias

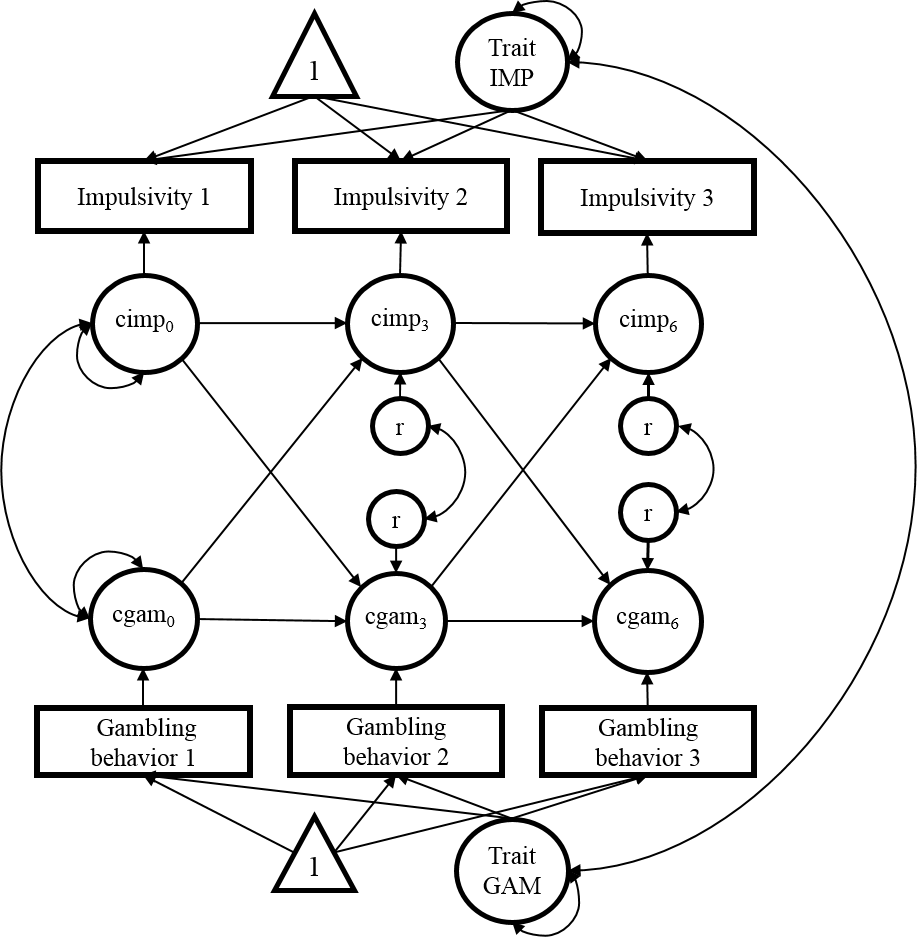
We will estimate a possible selection bias concerning the sample twofold. First, we will request double the number of player tracking records so that Tipico will not know who participated in our study. In our first wave we reached n = 954, so we will randomly select another n = 954 account holders and request the player tracking data of these n = 1908 account holders. We will compare the player tracking data (Table 2) of the participants in our study with the randomly selected account holders to check for selection bias. Second, with a nonresponder questionnaire asking about selected sociodemographic characteristics and the reasons for not participating in the study.

### Hypothesis testing

To analyze the evidence for hypotheses 1 and 2, that increased impulsivity predicts more GD symptoms and riskier gambling behavior in online sports betting, respectively, we will conduct random intercept cross‐lagged panel models (RI-CLPM; Hamaker et al., 2015) within a structural equation modelling (SEM) framework. A key strength of this model is that it can account for stable trait factors that capture stable individual differences, allowing researchers to infer within-person associations between variables. To test hypothesis 1, we will run five separate models for each predictor. The five models will all include GD severity as the outcome. To test Hypothesis 1a, the predictor is impulsive choice (k value), to test Hypothesis 1b, the predictor is impulsive action (BIS), and to test Hypothesis 1c, the predictors are impulsive personality traits (urgency, lack of conscientiousness, and sensation seeking). See Figure 3 for an overview of the proposed model. Hypothesis 1c will be confirmed if two of the three personality factors significantly predict GD. Overall, Hypothesis 1 will be fully supported if all sub-hypotheses are confirmed, and partially supported if at least one sub-hypothesis is confirmed.

To test hypothesis 2, the number of separate models we will run is dependent on the number of predictors (5 as for hypothesis 1) and dependent on the number of dimensions that best fit our outcome variable risky gambling behavior. Regarding the outcome variable risky gambling behavior, we will perform a factor analysis that will determine the number of dimensions included in our models. The method for factor extraction is described in the section ‘operationalization and study materials: (3) Risky betting behavior’. If the factor selection indicates several factors, we will run five separate models (5 predictors) for each of the factors. We set the upper limit for the number of factors for risky gambling behavior at three in order to have a reasonable number of factors for our modelling. Depending on the result of the factor analysis, the sub-hypotheses for risky gambling behavior will be considered supported if impulsivity correlates with at least one (factor solution with one or two factors) or two (factor solution with three factors) factors of risky betting behavior. For Hypothesis 2a (impulsive choice), Hypothesis 2b (impulsive action), and Hypothesis 2c (impulsive personality traits), we will consider each hypothesis to be confirmed if one of the models to test each hypothesis (or > 1 model) show significant predictive associations with risky betting behavior. Similar to Hypothesis 1c, Hypothesis 2c will be confirmed if two of the three personality factors significantly predict risky betting behaviour. Overall, Hypothesis 2 will be fully supported if all sub-hypotheses are confirmed, and partially supported if at least one sub-hypothesis is confirmed.

**Figure 3**

*******Proposed Random Intercept Cross-Lagged Panel Model (RI-CLPM; Hamaker et al., 2015) for the causal relationship between impulsivity and gambling behavior over three time points.*

*Note.*

Triangles represent constants (for the mean structure), squares represent observed variables, and circles represent latent variables.

imp = impulsivity

gam = gambling behavior (i.e. risky gambling behavior or gambling disorder severity)

cimp/ cgam = within-person centered variables

r = residual variance of the within-person centered variables

time points are indicated by the numbers: 1=first three months, 2=second three months, 3=third three months

To test hypothesis H3, i.e., that risky sports betting behavior is a mediator in the relationship between increased impulsivity and GD severity, we will run a three-variable RI-CLPM and compute indirect effects at the within-person level (similar procedure as in Joshanloo, 2023). We will treat this hypothesis test as independent from the results of Hypotheses 1 and 2. Per Hayes (2022; p. 122), our inference about the indirect effect (ab) will be based on the bootstrap results for the indirect effect itself, rather than the results for the constituent paths (a and b). Bootstrapping will be used to test the statistical significance of the indirect effects. Depending on the number of factors representing risky gambling behavior, we will run at least five models with the five impulsivity variables as predictors and GD severity as outcome. For Hypothesis 3a (impulsive choice), Hypothesis 3b (impulsive action), and Hypothesis 3c (impulsive personality traits), we will consider the hypotheses to be confirmed if at least one of the models (or >1 models) shows a significant mediation effect. Hypothesis 3c will be confirmed if risky gambling behavior significantly mediates the association between at least two of the three personality factors and GD severity. Overall, Hypothesis 3 will be fully supported if all sub-hypotheses are confirmed, and partially supported if at least one sub-hypothesis is confirmed.

The models will be estimated with observed variables and robust maximum likelihood (MLR) using Mplus 8.1 (Muthén & Muthén, 1998–2022). When testing the indirect effects using bootstrapping (for hypothesis 3), MLR cannot be used and ML will be used instead. Estimation will be conducted under missing data theory, using all available data. Data will be analyzed using FIML to handle missing data. FIML estimation produces largely unbiased parameter estimates and accurate standard errors in the presence of missing data. Model fit of the RI-CLPM will be evaluated using three indices: the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR). For CFI, values larger than .95 indicate good fit, while values between .90 and .95 indicate adequate fit. For RMSEA and SRMR, values below .05 indicate good fit, while values below .08 indicate adequate fit (Gunzler et al., 2021; Kline, 2015; West et al., 2023). Model results will only be interpreted if all fit indices demonstrate good fit, or if the indices show a combination of good and adequate fit.

For hypotheses 1 and 2, we will use 95% confidence intervals and the standard p < .05 criteria to determine whether our coefficients differ significantly from zero. Hypothesis 3 will be tested using bootstrapped mediation analysis. The mediation hypotheses will be tested at the within-person level. The significance of the indirect effects will be assessed with 95% asymmetrical confidence intervals based on 10,000 bootstrap iterations (Hayes, 2022).

# Results & Discussion

[Please note that the results and discussion will be completed in Stage 2 after data collection.]

# Strength and limitations

The advantage of focusing on a specific mechanism in the etiology of GD is that the measures and hypotheses are concise and coherent. A limitation is that we will not be able to test other important variables and pathways of the multifactorial models of GD etiology.

A strength is that, for the first time, we combine objective player tracking data from a provider with survey data and behavioral tasks. By using a smartphone survey, we see the advantage of a low threshold for participation, as most Tipico account holders use a smartphone app to place bets. Two limitations of this approach are the sample selection and the uncontrollable environment of data collection. Regarding the sample selection, we may have certain account holders who will be more likely to participate in the study, such as those with smartphones, those who only participate to receive monetary compensation, and younger ones. We will estimate the selection bias by comparing player tracking data of responders and non-responders and by analyzing the non-responders’ questionnaires. With regard to the data collection environment, smartphone surveys always have the disadvantage of less control over environmental influences and subsequently the participants’ attentional status. We try to address this issue by applying several exclusion criteria related to inattention, such as attention control questions.

A final limitation is the relatively short interval of three months between the 3 consecutive surveys. The advantage is an estimated lower dropout rate compared to longer intervals between the surveys. The disadvantage is that we do not expect many changes within certain variables, especially in impulsive personality traits. However, in the RI-CLPM the stable trait variance is considered separately, so that we do not expectproblems in interpreting the data.

# Conclusions

[Please note that the conclusions will be completed in Stage 2 after data collection.]

**Table 1**

*The PCI RR study design template*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Question** | **Hypothesis** | **Sampling plan** | **Analysis Plan** | **Rationale for deciding the sensitivity of the test for confirming or disconfirming the hypothesis** | **Interpretation given different outcomes** | **Theory that could be shown wrong by the outcomes** |
| 1. What is the longitudinal relationship between impulsivity and gambling disorder (GD) severity in online sports bettors? | Increased impulsivity (consisting of (a) impulsive choice, (b) impulsive action, and (c) impulsive personality traits) among online sports bettors leads to higher GD severity. | Our target sample size for the third and final wave is 370 (see column ‘Rationale for deciding the sensitivity of the test for confirming or disconfirming the hypothesis’).  After this theoretical consideration regarding sample size, we took into account the response, retention, and exclusion rates. In another study of online sports bettors from our lab, where online surveys were also conducted (RIGAB study; https://osf.io/k6c23/; Czernecka et al., 2023), the response rate was 13% of which a further 30% had to be excluded due to incomplete or implausible questionnaire data. Based on the experience from the RIGAB 12 month follow-up, a retention rate of 60% is expected between the first online survey and the third survey wave 9 months later. In addition, the exclusion of further data due to data quality checks was estimated at 25 %. Based on these response rates, the retention estimates, and the data exclusion estimates, 925 participants need to participate in the first wave to achieve a sample of 370 participants in the third and final wave (60% retention rate, 25% data quality exclusion, 10% buffer). Assuming a linear decline in the retention rate, we estimated that 555 participants have to participate in the second wave (80 % retention rate and 25% data quality exclusion). Therefore, we estimated that we would have to invite 10,153 Tipico account holders in the first wave, of whom about 1,320 would be assumed to respond (response rate 13%) and n = 925 (30% data quality exclusion) could be included in the final sample of the first wave. | To analyze the evidence for hypotheses 1 and 2, that increased impulsivity predicts more GD symptoms and riskier gambling behavior in online sports betting, respectively, we will conduct random intercept cross‐lagged panel models (RI-CLPM; Hamaker et al., 2015) within a structural equation modelling (SEM) framework. A key strength of this model is that it can account for stable trait factors that capture stable individual differences, allowing researchers to infer within-person associations between variables. To test hypothesis 1, we will run five separate models for each predictor. The five models will all include GD severity as the outcome. To test Hypothesis 1a, the predictor is impulsive choice (k value), to test Hypothesis 1b, the predictor is impulsive action (BIS), and to test Hypothesis 1c, the predictors are impulsive personality traits (urgency, lack of conscientiousness, and sensation seeking). Hypothesis 1c will be confirmed if two of the three personality factors significantly predict GD. Overall, Hypothesis 1 will be fully supported if all sub-hypotheses are confirmed, and partially supported if at least one sub-hypothesis is confirmed. | We calculated the required sample size for the study based on Hypothesis 3, as it was expected that the mediation hypothesis would require the largest sample size. In order to determine the appropriate sample size, we relied on a simulation study that specifically explored the sample size requirements for testing within-person indirect effects in longitudinal data (Pan et al., 2018). In this simulation study, a small effect size is defined as 0.14, ‘halfway’ as 0.26, medium as 0.39, and large as 0.59. We assumed an intra-class correlation of GD during 9 months of 0.6 (Currie et al., 2013), small associations (0.14) between impulsivity and risky gambling behavior during 9 months (based on a study of multiple addictive behaviors; Kräplin et al., 2020), and a small to medium association (0.26) between risky gambling behavior and GD during 9 months (Xuan & Shaffer, 2009). The required sample size for our study was calculated to be n = 370 using the bootstrap method and given the planned three waves, a planned power of 80%, and an alpha level of 5% (see Table 4; Pan et al., 2018). Since Hypotheses 1 and 2 require a smaller sample size than Hypothesis 3, the sample size determined for Hypothesis 3 provides sufficient statistical power to adequately test Hypotheses 1 and 2. | If we find evidence for hypothesis 1 and 2, this would support the theory that impulsivity is a risk factor for risky gambling behavior and GD (for a review, see e.g. Kräplin & Goudriaan, 2018).  There may also be evidence for an inverse relationship, i.e. that GD/ risky gambling behavior predicts later increased impulsivity. This would support assumptions from research on substance-related disorders (De Wit, 2009) that behavioral addictions and related behaviors (in the online environment) are associated with  dysfunctional alterations in reward-based learning,  leading to a general overvaluation of immediate rewards  (Everitt & Robbins, 2016) and/or a blunted valuation of anticipated long-term rewards (Krönke et al., 2020).  If we would not find evidence for the hypothesized associations, this could mean that there are other significant factors influencing the development of GD that have a greater impact than impulsivity. | The sub-theory to be tested was developed by us. However, this theory is embedded in larger multifactorial models on the etiology of addictive behaviors (Blaszczynski & Nower, 2002; Brand et al., 2019; Bühringer et al., 2008). If we find evidence for our hypotheses 1 and 2, this would call into question parts of these models in which impulsivity does not play a role. One example is the Behaviorally Conditioned (BC) pathway of the Pathways Model of Problem and Pathological gambling by Blaszczynski & Nower (2001). |
| 2. What is the longitudinal relationship between impulsivity and risky gambling behavior in online sports bettors? | Increased impulsivity (consisting of (a) impulsive choice, (b) impulsive action, and (c) impulsive personality traits) leads to riskier betting behavior among online sports bettors, e.g. higher betting frequency. | To test hypothesis 2, the number of separate models we will run is dependent on the number of predictors (5 as for hypothesis 1) and dependent on the number of dimensions that best fit our outcome variable risky gambling behavior. Regarding the outcome variable risky gambling behavior, we will perform a factor analysis that will determine the number of dimensions included in our models. Factor selection will be conducted using the eigenvalue, scree plot, parallel analysis, and the interpretability of the factors. Factors with eigenvalues greater than one are considered according to the Kaiser Guttman rule. We will further consider the factors before the ‘elbow’ in the screeplot, i.e. the point where the curve bends. Finally, we will use parallel analysis, a Monte-Carlo based simulation method that compares the observed eigenvalues with those obtained from a random data set (Horn, 1965). A factor is retained if the eigenvalue is higher than the eigenvalue of the corresponding factor from random variables. The interpretability of the resulting factors will be given the greatest weight when deciding on the number of factors. If the factor selection indicates several factors, we will run five separate models (5 predictors) for each of the factors. We set the upper limit for the number of factors for risky gambling behavior at three in order to have a reasonable number of factors for our modelling. Depending on the result of the factor analysis, the sub-hypotheses for risky gambling behavior will be considered supported if impulsivity correlates with at least one (factor solution with one or two factors) or two (factor solution with three factors) factors of risky betting behavior. For Hypothesis 2a (impulsive choice), Hypothesis 2b (impulisive action), and Hypothesis 2c (impulsive personality traits), we will consider each hypothesis to be confirmed if one of the models to test each hypothesis (or >1 model) show significant predictive associations with risky betting behavior. Similar to Hyopthesis 1c, Hypothesis 2c will be confirmed if two of the three personality factors significantly predict risky betting behaviour. Overall, Hypothesis 2 will be fully supported if all sub-hypotheses are confirmed, and partially supported if at least one sub-hypothesis is confirmed. |
| 3. What is the longitudinal relationship between impulsivity, risky gambling behavior, and GD severity in online sports bettors? | Risky betting behavior is a mediator between impulsivity (consisting of (a) impulsive choice, (b) impulsive action, and (c) impulsive personality traits) and GD severity. | To test hypothesis H3, i.e., that risky sports betting behavior is a mediator in the relationship between increased impulsivity and GD severity, we will run a three-variable RI-CLPM and compute indirect effects at the within-person level (similar procedure as in Joshanloo, 2023). We will treat this hypothesis test as independent from the results of Hypotheses 1 and 2. Per Hayes (2022; p. 122), our inference about the indirect effect (ab) will be based on the bootstrap results for the indirect effect itself, rather than the results for the constituent paths (a and b). Bootstrapping will be used to test the statistical significance of the indirect effects. Depending on the number of factors representing risky gambling behavior, we will run at least five models with the five impulsivity variables as predictors and GD severity as outcome. For Hypothesis 3a (impulsive choice), Hypothesis 3b (impulisive action), and Hypothesis 3c (impulsive personality traits), we will consider the hypotheses to be confirmed if at least one of the models (or >1 models) shows a significant mediation effect. Hypothesis 3c will be confirmed if risky gambling behavior significantly mediates the association between at least two of the three personality factors and GD severity. Overall, Hypothesis 3 will be fully supported if all sub-hypotheses are confirmed, and partially supported if at least one sub-hypothesis is confirmed. | If we find evidence for the mediating effect, this would suggest that risky gambling behavior is indeed able to (at least partly) explain the relationship between impulsivity and GD.  Alternatively, if there is no evidence for the mediation effect, this could suggest a moderation effect or that the relationship between impulsivity and GD is much more complex, with significant variables moderating and mediating the relationship that were not captured in our study. | If we find evidence in favor of hypothesis 3, this would not disprove the multifactorial models, but it would provide a meaningful specification of how exactly impulsivity contributes to the development of GD. Specification is often lacking in these types of models, which tend to heuristically include all factors. |

# Disclosure statement

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# Author credit statement

AJ – Data curation, investigation, project administration, software, supervision, validation, visualization, writing – original draft,

MJ – Methodology, writing – review & editing,

RC – Methodology, project administration, writing – review & editing,

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