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Development of gaming disorder: Underlying risk factors and complex temporal dynamics

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ABSTRACT

Empirical studies on gaming disorder (GD) predominantly employ cross-sectional designs, offering limited insights into the development of GD. The existing longitudinal studies on the risk factors of GD often yield contradictory results and typically rely solely on baseline data to predict future states. The present study was specifically designed to describe and link developmental changes in risk factors and symptoms of GD. We surveyed a sample of intensively playing digital game players ($N = 1301$) across three data collection waves over a span of six months. The survey incorporated four different GD operationalizations and considered 13 previously identified risk and protective factors. We found that (1) trends in individual levels of stress, internet addiction, ADHD, and aggression/hostility were associated with the development of GD. (2) Internet addiction, social media addiction, escape motive, and anxiety showed consistent baseline connections to GD trends. (3) Notably, no differences were observed among participants' latent classes with distinct GD trajectories in terms of gender, age, gaming time, or the proportion of multiplayer gameplay. (4) GD symptoms exhibited slight but consistent negative aggregate trends. Participants with higher baseline GD levels generally displayed smaller shifts over time, suggesting the temporal stability of high symptom levels.

1. Introduction

According to a recent meta-analysis conducted by Meng et al. (2022), the prevalence of (internet) gaming disorder (GD) has significantly increased in the years 2020–2021 compared to the years 2015–2019 (8.3% vs. 5.1%). The trend of the increased prevalence and symptom severity in the post-pandemic period was reported in a longitudinal study by Teng et al. (2021). This highlights the need for development of effective prevention programs, which are vital yet scarce (Bender et al., 2020; Xiang et al., 2020). Existing intervention programs focus on identifying high-risk populations (Bender et al., 2020; King, Delfabbro, Doh, et al., 2017), which presupposes adequate knowledge regarding risk factors for GD. However, a substantial heterogeneity is present in research on specific correlates of GD. A recent comprehensive meta-analysis of risk factors for gaming disorder (Ropovik et al., 2022) have found that 210 included papers studied altogether 414 distinct constructs. Only 29 constructs have been studied at least 10 times and only a negligible amount of research synthesized within the meta-analysis consisted of longitudinal studies. For testing causal claims, longitudinal designs are preferred over cross-sectional ones. The topic of risk factors inherently revolves around causal claims - that is, which variables lead to the development of gaming disorder over time? With a limited number of longitudinal studies available and research spread across a broad spectrum of risk factors, the current state of knowledge is insufficient to reliably determine which risk factors are essential for the development of GD.

The only currently available scoping review of longitudinal studies (57 papers included) focusing on gaming disorder (Richard et al., 2020) concluded a strong heterogeneity in temporal stability of gaming disorder, ranging from 20% to 84% (percentage of participants who fulfilled the criteria – played pathologically - in both periods of measurement). The stability differs between adolescents and adults

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(lower in adulthood) and also across various follow-up periods (a decrease in symptoms frequency/severity over time). However, none of the longitudinal studies reviewed modeled changes in GD symptoms (only GD as an aggregate score) even though it is the symptoms that form it. Such changes are interesting precisely because not all symptoms of GD appear to be of equal importance (Adamkovič et al., 2023; Castro-Calvo et al., 2021). Some are presented as core, while others are deemed peripheral (Billieux et al., 2019). The studies reviewed by Richard et al. (2020) differed in their choices of specific risk or protective factors. A limited number of variables, such as depression, ADHD, academic performance, anxiety, life satisfaction, and parent-child relationships, were investigated in at least five different studies. Furthermore, for several risk and protective factors, the available evidence is mixed (e.g., gaming time: Ferguson et al., 2022; Jeong et al., 2021; Liu et al., 2021, self-esteem: Teng et al., 2020; Wartberg et al., 2020, social support: Jeong et al., 2021; Teng et al., 2020), highlighting the importance of further replications.

2. Present study

The most comprehensive meta-analysis of risk and protective factors for GD to-date (Ropovik et al., 2022) found that the body of available evidence about the effects of various risk factors on GD was based almost exclusively on cross-sectional data, warranting caution when making causal inferences.

Building on the results of this meta-analysis while employing a longitudinal design stretching over a six-month period, we aimed to explore the developmental interplay between GD and various, potentially causally relevant, risk factors. We were interested in describing the development of GD, identifying and describing subgroups with distinct developmental trajectories of GD, and whether the trend in GD can be predicted by baseline level or rate of change of its risk factors. We also tried to examine the development of GD as a dynamic complex system and tried to disentangle the complex network of relationships on a within-subjects temporal and contemporaneous level as well as on a stationary between-subjects level. The ICD-11, describes GD as being evident over a period of at least 12 months, during which symptoms must be present. However, the manual also allows for a shorter duration in cases of severe symptoms, noting that 'the required duration may be shortened' (WHO, 2019). From a clinical perspective, information on disorder dynamics over a shorter period may be more relevant than over a longer timeframe. For instance, the typical duration of treatment for GD ranges from several weeks to six months (Hofstedt et al., 2023; King, Delfabbro, Wu, et al., 2017; Zajac et al., 2019), whereas for substance abuse, the average is eight months (Walker, 2008). This evidence supports the use of a six-month follow-up in a longitudinal study design.

Specifically, in the present study, we address three complementary research questions. RQ1. *What predictive power do the* 13 *strongest risk and protective factors of GD have for the development of GD symptomatology?* Here, we were interested in comprehensively modeling both, the relationship between baseline levels and developmental slopes of GD and risk factors (from the purposes of theory-building), and in predicting intercept and slope of GD using just baseline levels of risk factors (as a practitioner would). RQ2. *How do the GD symptom levels change over a six-month period?* How pronounced are these changes and in what direction? How variable is the rate of change across the population? How stable will the gaming disorder be over a six-month follow-up? Does temporal stability depend on the GD operationalization? How are the various levels of GD symptoms associated with the trend in GD going forward? RQ3. *What is the developmental pattern for risk factors over the same time period?* How variable is it? What is the link between the baseline and the future rate of change? RQ4. *How do symptoms of GD interact with each other over time within- and between-persons?* Which symptoms seem to be central to the development of GD, and which symptoms are more peripheral? How does the within-individual dynamic of GD symptoms differ from the between-individual dynamic?

3. Method

This study was approved by the Ethics committee at the Faculty of Arts, University of Presov.

4. Participants and data collection

Participants were recruited using Prolific services - a platform for online subject recruitment (for a detailed description see Palan & Schitter, 2018) that provides highly reliable data (Eyal et al., 2021). The sample is composed of digital game players older than 18 years (minimum at Prolific) who play digital games on any device for at least six hours per week. Participants were selected based on the internal Prolific screening question: "How many hours per week do you play video games on average?". The response categories were "0–3 h, 3–6 h, 6–9 h, 9–13 h, 13 h or more". Individuals who selected "0–3 h" and "3–6 h" were not recruited to avoid the inclusion of participants who do not play regularly or on average at least approximately one hour per day. The goal was to maximize the chances of obtaining a sample that is more likely to develop symptoms of GD. Because we assumed a gradual development of GD symptoms, potentially novice players (with no or small gaming time) were not included. Most of the participants (~92%) come from North America and Europe. Data collection took place in three waves in June, September, and December 2022. The attrition of participants at wave 2 was 19.6% and 17% at wave 3. At wave 1, out of the full sample, 42% were employed full-time, 14% part-time, 16% were unemployed, and 30% were students. Informed consent was obtained from all participants prior to data collection. More information about the sample is presented in Table 1.

5. Measures

We have applied four different operationalizations of GD: (1) DSM-5-based IGD was measured using the IGDS9-SF (Pontes & Griffiths, 2015; $\omega_t = 0.92$). (2) ICD-11-based GD was measured using the Gaming Disorder Test (Pontes et al., 2019; $\omega_t = 0.91$). (3) Self-assessed gaming problems construct was modeled as a principal component score computed from two items: previously published single-item THL1 (Karhulahti & Koskimaa, 2019; Salonen & Raisamo, 2015): "How often have you felt that playing video, computer, or mobile games could be a problem for you in the past 12 months?" (never, sometimes, often, almost always) and a newly developed item: "Do you think that playing digital games over the last 12 months caused you such problems that would make you seek psychological or psychiatric help? (5-point Likert response scale). We treated GD as a continuous variable, ranging from non-pathological to extremely pathological gaming, rather than a above-threshold category (see Haslam et al., 2020).

Based on the meta-analysis by Ropovik et al. (2022), we have selected 13 risk and protective factors for gaming disorder that were backed by the most robust empirical evidence.

Table 1
Samples demographics.

	Age *M* (*SD*)	Gender			Daily gaming time *M* (SD)
		Males	Females	Non-binary	
Wave 1 T1 ($N_1 = 1301$)	30.72 (9.68)	968	299	29	3.98 (2.63)
Wave 2 T1 + 3 months ($N_2 = 1050$)	31.46 (9.92)	784	243	20	3.88 (2.65)
Wave 3 T1 + 6 months ($N_3 = 1077$)	31.74 (9.93)	811	241	23	3.60 (2.37)

5.1. Risk factors

1. Depression and anxiety were measured using the Patient Health Questionnaire, PHQ-4 (Kroenke et al., 2009).
2. Social anxiety was measured using the abbreviated version of the Social Phobia Inventory, Mini-SPIN (Connor et al., 2001).
3. ADHD was measured using the World Health Organization adult ADHD self-report scale, ASRS (Kessler et al., 2005; $\omega_t = 0.83$).
4. Internet addiction was measured using the short version of Young's Internet Addiction Test (Pawlikowski et al., 2013; $\omega_t = 0.84$).
5. Social media addiction was measured using the Bergen Social Media Addiction Scale, BSMAS (Andreassen et al., 2017; $\omega_t = 0.93$).
6. Impulsivity was measured using the short form of the Barratt Impulsiveness Scale (Spinella, 2007; $\omega_t = 0.87$).
7. Stress was measured using the Perceived Stress Scale (Cohen et al., 1983; $\omega_t = 0.91$).
8. Aggression and hostility were measured using the Physical Aggression and Hostility subscales of the Buss–Perry Aggression Questionnaire (Buss & Perry, 1992; $\omega_t = 0.84$).
9. Escape motivation was measured using the Motives for Online Gaming Questionnaire (Demetrovics et al., 2011; $\omega_t = 0.94$).

5.2. Protective factors

1. Self-esteem was measured using the single item reported in Robins et al. (2001).
2. Social support was measured using the Brief Perceived Social Support Questionnaire (Lin et al., 2019; $\omega_t = 0.91$).
3. The highest level of education was measured using the ISCED 2011 classification.

The order of measures was randomized. To counteract order effects, we also randomized the item order for all non-GD measures. Item ordering for GD measures was blocked to mimic the use of these measures in clinical practice.

6. Statistical analysis

6.1. Data wrangling

Prior to the analysis, we checked the data for missing data patterns and improbable responses. We dropped participants reporting gaming time of 0 hours. Participants' data were further screened for careless responding patterns. We removed participants who missed two out of two attention check items or missed at least one of the attention checks and were significant multivariate outliers (based on Mahalanobis distance), indicating possible randomness in responding. To reduce the dimensionality of the data, we computed factor scores for all constructs. For scales with four or more items, we estimated factor scores for a unitary factor using the Mean-and variance-adjusted weighted least squares method, accounting for the ordered categorical nature of the items. For scales having less than four items, we calculated principal component scores. The aim was that each of the constructs would be represented by a single score that would be psychometrically superior to an unweighted sum score. Lastly, we also estimated the reliability (internal consistency) of the scales of four or more items using the omega total coefficient based on the polychoric correlation matrix.

6.2. Models

To study the longitudinal interplay between gaming disorder and various predictors, we used latent growth curve modeling (LGCM). It is a statistical technique within the structural equation modeling framework, designed to analyze longitudinal data by capturing the trajectory of change over time at an individual level. It allows for the estimation of both fixed and random effects, providing insights into the average trajectory of change across a population and the individual variations from this average (Duncan et al., 2013). The model's intercept represents a variable's initial level and the slope shows its rate of change. LGCM enables researchers to investigate relationships between initial levels of different variables, how a variable's initial level affects its rate of change, and the association between the rates of change of different variables (Bollen & Curran, 2006).

For each combination of three GD operationalizations (IGDS9-SF, GDT, self-assessment) and 13 risk factors (ADHD, internet addiction, social media addiction, impulsivity, stress, aggression/hostility, escape motive, social support, anxiety, depression, social anxiety, self-esteem, social support, and education), we estimated a LGCModel, modeling latent intercepts and slopes for the respective GD operationalization and the given risk factor. Here, we examined whether the development of GD can be predicted by the initial level and by the rate of change of the given risk factor. Each model was estimated using the maximum likelihood with robust (Huber-White) standard errors and a Yuan-Bentler test statistic. For the imputation of missing data, we used the full-information maximum likelihood method. If the model had convergence issues, the estimation procedure automatically fell back to a different optimization method (nlminb instead of BFGS). Models were regarded as falsified as exactly fitting based on a significant value of the $\chi 2$ test statistics (see Ropovik et al., 2022). The approximate fit was assessed using the following fit indices: CFI, TLI, RMSEA, and SRMR. We used the *lavaan* R package (Rosseel, 2012).

Then, we used Growth mixture modeling to identify distinct subgroups (classes) of individual GD trajectories using the package *lcmm* (Proust-Lima et al., 2017). We modeled from one up to four latent classes and determined the optimal number of latent classes based on BIC (Bayesian Information Criterion). BIC is known to balance model fit and complexity well, and is widely recognized for its utility in penalizing more complex models, thus helping to avoid overfitting (Nylund et al., 2007). Each participant was assigned to the class with the highest posterior probability. Afterwards, we analyzed how groups of participants having different profiles of GD trajectories differed in various characteristics such as gender, age, gaming time, and the proportion of time spent on multiplayer games (using ANOVA and chi-square test).

The development of individual GD symptoms and the risk factors were analyzed using linear mixed-effects models (restricted maximum-likelihood estimation), employing the package *lme4* (Bates et al., 2015). For each symptom within each GD operationalization, we tested whether the symptom level exhibited a significant change while accounting for individual variations in initial response and rate of change over time for each participant. This was tested using a likelihood ratio test, comparing the full model (wave as a fixed factor, by-subject random intercept, and by-subject random slope for wave) and a null model in which GD was predicted only by an intercept (while having the same random-effects structure). We estimated the average change in symptoms (wave coefficient), the variability of that change across participants (SD of the random intercepts and slopes), and the extent to which baseline symptom levels are associated with the rate of change.

For exploratory purposes, we also fitted a series of graphical vector-autoregression network models for panel data using the *psychonetrics* package (Epskamp, 2021). Compared to the approach using unitary factor scores or sum scores, network modeling requires a shift in the notion about the ontology of GD. In the network approach, symptoms are assumed to act as independent causal agents, directly affecting each other. Under this approach, psychopathology is modeled as a complex system, emerging from self-sustaining recurrent interactions of causally linked symptoms. Network analysis then allows one to explore complex patterns of symptom relationships and identify which symptoms are central and which are peripheral to the given disorder (see Borsboom et al., 2021). On top of that, the longitudinal design utilized in the present study allowed us to explore the within-subject dynamics of the GD network by modeling three distinct symptom networks: temporal, contemporaneous, and between-subjects. Edges in a temporal network

represent directed lag-1 partial relationships, that is, showing how a node at time-point t predicts another node or itself at time t+1, while accounting for all other nodes at time t (equivalent to Granger causality). The contemporaneous network, estimated on the residuals of the temporal model, renders "pure" contemporaneous effects by eliminating prior influences at time t−1 and other contemporaneous relationships. A between-subject network model reveals relationships between stationary means of variables across individuals while adjusting for the average levels of all other nodes. Essentially, an edge in this network signifies an association between the longer-term average levels of two nodes across participants, controlling for the typical level of the other nodes (Epskamp, 2020). First, we employed maximum likelihood estimation and assessed model fit using the same criteria as for the LGCModels. Then, we pruned edges that were non-significant at alpha = .01 and used a recursive step-up model search that minimized BIC as the criterion.

Data (in both long and wide format), R code, and full analytic outputs are freely available at https://osf.io/5h7r9/.

7. Results

Baseline means, *SD*s, and correlations for the sum scores of scales used in this study are displayed in Table 2. The diagonal values represent the reliability estimates (Omega total coefficient). Descriptives and correlations for waves two and three can be found in Appendix A. In the present sample, 2.79%, 1.35%, and 1.27% of participants in waves 1, 2, and 3, respectively, were above the cut-off for disordered gaming in GDT. Of all participants, 4.15% were above cut-off in at least one of the waves, while 0.25% were above cut-off in all three waves. Gaming time of 0 hours per week was indicated by five participants (0.38%) in T1, five participants (0.48%) in T2, and ten participants (0.97%) in T3. Due to failing both attention checks, 80 participants (6.17%) were excluded in T1, 74 participants (7.08%) in T2, and 66 participants (6.19%) in T3. Due to failing one attention check and having an above-cut-off Mahalanobis distance, 44 participants (3.40%) were excluded in T1, 49 participants (4.69%) in T2, and 39 participants (3.66%) in T3.

Across the three time points, the employed scales generally failed the chi-square model test as the unitary factor models did not explain all systematic variance shared by the items. Even the approximate fit for some of the scales was poor, most notably in cases of aggression/hostility, impulsivity, social support, and stress. Detailed results are reported in Table 3.

7.1. Longitudinal interplay between gaming disorder and various risk factors

First, we aimed to examine whether the baseline level or the rate of change in 13 individual risk factors predicted the individual's development of GD. The results for IGDS9-SF and GDT operationalizations are shown in Tables 4 and 5 (results for self-assessment can be found in Appendix A). What are the key insights that generalize across GD operationalizations? Most latent growth curve models fitted the data well. That said, some of the models had various convergence issues and there were a few Heywood case (out of bounds) parameters in some of the models that converged without an error or warning. We disregarded such parameter results and deemed these models as unreliable. Cross-sectionally-wise, the initial level of GD is relatively well predicted by the risk factors at baseline. These same baseline levels of risk factors have, however, no predictive link to the trajectory of GD development after accounting for the trend in the risk factors. It turns out that predicting the rate of change in GD based on observing the trend in risk factors is difficult, too. Among the 13 risk factors trends, only stress was a consistent predictor of GD development across all three operationalizations, albeit the associated *p*-values were not convincing and would all be > .05 if adjusted for multiple testing (Holm's correction). Other good GD slope predictors that were significant for two out of three GD operationalizations were the following: internet addiction (with very tightly associated trends, highly significant even after the adjustment for multiple testing), ADHD (tightly associated but with large slope *SE*s, non-significant after Holm's correction), and aggression/hostility (small-to-medium associations, non-significant for GDT and GD self-assessment after Holm's correction).

To examine the diagnostic utility of risk factors for predicting the development of GD, we also tested a set of LGCModels, where the intercept (baseline) and slope (trend) of GD are predicted solely by the risk factors at baseline, not accounting for the longitudinal trend in the risk factors. Here, all the models converged without any issues and provided an exact fit to the data (these were $df = 2$ models, though). None of the risk factors could predict the trend in self-assessed GD. However, there were four risk factors with consistent links to the trend in GD for both GD operationalizations, IGDS9-SF and GDT: internet addiction, social media addiction, escape motive, and anxiety. Detailed results can be found in Appendix A.

7.2. Characteristics of participant groups differing in GD trajectories

Second, we used Growth mixture modeling to examine whether there

Table 2
Descriptives.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	Mean	SD
[1] IGDS9-SF	.92																1.97	.72
[2] GDT	.81	.92															1.96	.90
[3] self-assessment	.61	.62	NA														1.45	.60
[4] ADHD	.47	.44	.36	.82													1.58	.79
[5] internet addiction	.69	.65	.52	.56	.84												1.52	.85
[6] social media addiction	.48	.40	.36	.38	.51	.93											1.74	.89
[7] impulsivity	.31	.31	.28	.45	.35	.21	.87										2.02	.54
[8] stress	.44	.40	.30	.53	.48	.36	.31	.91									1.83	.78
[9] aggression/ hostility	.41	.37	.29	.34	.39	.29	.25	.52	.84								2.63	1.20
[10] escape	.55	.43	.31	.29	.41	.35	.18	.47	.40	.94							2.79	1.19
[11] social support	−.23	−.20	−.18	−.20	−.19	−.09	−.21	−.42	−.28	−.24	.91						3.49	1.02
[12] anxiety	.41	.34	.28	.45	.41	.38	.24	.73	.46	.42	−.32	NA					1.12	.95
[13] depression	.42	.37	.30	.47	.44	.33	.29	.74	.47	.43	−.42	.73	NA				1.07	.91
[14] social anxiety	.36	.32	.23	.37	.37	.26	.13	.51	.32	.38	−.29	.49	.47	NA			2.00	1.16
[15] self-esteem	−.21	−.19	−.11	−.28	−.22	−.13	−.25	−.52	−.28	−.30	.38	−.43	−.49	−.52	NA		2.65	1.24
[16] education	−.03	−.02	−.03	−.03	−.01	.02	−.14	−.11	−.10	−.06	.10	−.11	−.11	−.09	.16	NA	5.79	1.56

Note: Omega reliability coefficients on the diagonal.

Table 3
Confirmatory factor analyses.

Variable/Scale	Wave	*Chi-square*	*df*	*p*-value	*CFI*	*TLI*	*RMSEA*	*RMSEA CI* LB	*RMSEA CI* UB	*SRMR*
ADHD/ASRS	1	56.1	9	0	.97	.94	.07	.05	.08	.03
	2	87.3	9	0	.94	.90	.10	.08	.11	.04
	3	103.1	9	0	.93	.88	.10	.09	.12	.04
aggression/hostility /BPAQ	1	403.3	9	0	.66	.44	.19	.18	.21	.11
	2	325.1	9	0	.67	.45	.19	.18	.21	.11
	3	401.9	9	0	.60	.33	.21	.19	.23	.11
escape/MOGQ	1	8.4	2	.02	1.00	.99	.05	.02	.09	.01
	2	12.8	2	.00	.99	.98	.08	.04	.12	.01
	3	24.6	2	0	.99	.96	.11	.07	.15	.01
GD/GDT	1	10.7	2	.01	.99	.97	.06	.03	.10	.01
	2	4.9	2	.09	1.00	.99	.04	.00	.08	.01
	3	16.0	2	0	.98	.93	.08	.05	.13	.02
GD/IGDS9-SF	1	164.5	27	0	.94	.91	.07	.06	.08	.04
	2	146.1	27	0	.93	.90	.07	.06	.08	.05
	3	146.8	27	0	.93	.91	.07	.06	.08	.04
impulsivity/BIS	1	1154.6	35	0	.56	.43	.17	.16	.17	.11
	2	979.7	35	0	.49	.34	.17	.16	.18	.11
	3	1044.7	35	0	.54	.41	.17	.16	.18	.10
internet addiction/YIAT	1	58.2	9	0	.96	.94	.07	.05	.09	.03
	2	66.9	9	0	.94	.89	.08	.06	.10	.04
	3	70.5	9	0	.94	.90	.08	.07	.10	.04
social media addiction/BSMAS	1	41.9	9	0	.97	.95	.06	.04	.07	.02
	2	30.2	9	0	.97	.96	.05	.03	.07	.02
	3	35.2	9	0	.97	.95	.05	.04	.07	.02
social support/BPSSQ	1	147.7	9	0	.95	.91	.11	.10	.13	.04
	2	113.9	9	0	.95	.91	.11	.09	.13	.04
	3	104.7	9	0	.95	.92	.10	.09	.12	.03
stress/PSS	1	512.8	35	0	.87	.84	.11	.10	.12	.08
	2	436.9	35	0	.87	.83	.11	.10	.12	.08
	3	470.5	35	0	.86	.82	.11	.11	.12	.07

Table 4
Results of latent growth curve modeling for IGDS9-SF.

Variable	Chi-square	*df*	*p*-value	*CFI*	*TLI*	*RMSEA*	*SRMR*	iGD ~ iP	sGD ~ iP	sGD ~ sP	iGD ~ iP p-val	sGD ~ iP p-val	sGD ~ sP p-val	iGD ~ iP Holm *p*-val	sGD ~ iP Holm *p*-val	sGD ~ sP Holm *p*-val
ADHD	57.4	8	0	.98	.96	.07	.02	.56	−.05	.72	.00	.62	.04	0	1	.41
social media addiction	45.4	8	0	.98	.96	.06	.02	.58	−.02	NA	.00	.82	.01	0	1	.09
impulsivity	23.7	8	.00	.99	.99	.04	.01	.37	.07	−.02	.00	.44	.95	0	1	1
stress	24.1	8	.00	.99	.99	.04	.01	.49	−.02	.58	.00	.83	.03	0	1	.36
aggression/ hostility	25.7	8	.00	.99	.99	.04	.01	.45	.06	.43	.00	.42	.00	0	1	.01
social support	5.0	8	.76	1.00	1.00	.00	.01	−.27	.04	−.35	.00	.70	.46	0	1	1
anxiety	26.4	8	.00	.99	.99	.04	.01	.49	−.08	.66	.00	.43	.13	0	1	1
depression	21.4	8	.01	.99	.99	.04	.01	.46	−.08	.50	.00	.46	.26	0	1	1
social anxiety	21.1	8	.01	.99	.99	.04	.01	.42	.03	.78	.00	.79	.11	0	1	1
self-esteem	6.4	8	.61	1	1	0	0.01	−.22	−.05	NA	.00	.66	.66	0	1	1
education	1.5	8	.99	1	1	0	0.01	−.02	−.00	−.14	.58	.99	.21	1	1	1

Notes: i prefix represents the intercept, s prefix represents the slope (or rate of change). GD states for the gaming disorder, P states for the predictor, iGD ~ iP: regression of the intercept of GD (the initial level of GD) on the intercept of the predictor. Models for self-esteem and education did not converge properly, so their results are likely spurious.

are distinct patterns of GD development in the population. If so, we aimed to examine the differences (in terms of their characteristics) between the subgroups of participants with a common trend in GD. A model with three latent classes got chosen based on the lowest BIC value. The development of GD for the three different subgroups can be seen in Fig. 1. The upper two plots show the trend in GD measured by the IGDS9-SF instrument, when the subject grouping into latent classes was based on IGDS9-SF and GDT, respectively. The lower two plots show the trend in GD if measured by the GDT instrument. First, it can be seen that GD did not undergo pronounced changes during the course of the study, on aggregate (note that the factor scores were standardized and the scale on the plot ranges only from −0.5 to 0.5 *SD*s). Second, trends for GD when measured using different instruments were quite similar. What mattered more was the instrument that was used to identify latent classes, in the first place.

We subsequently examined whether the participants falling into the identified latent classes systematically differed in some of their characteristics. In Appendix A, we report descriptive statistics and tests of mean (or proportion) differences for when the latent class formation was based on IGDS9-SF and GDT, respectively. In essence, regardless of the latent class operationalization, we did not detect significant differences between the classes of participants in terms of gender, age, gaming time, or and the proportion of time spent on multiplayer games, while the means/proportions for the groups were fairly similar.

7.3. Development of GD symptoms and risk factors over time

Third, we examined whether the levels of individual symptoms significantly changed, accounting for individual participants' variation at baseline and rate of change over time. We report the results of the

Table 5
Results of latent growth curve modeling for GDT.

Variable	Chi-square	*df*	*p*-value	*CFI*	*TLI*	*RMSEA*	*SRMR*	iGD ~ iP	sGD ~ iP	sGD ~ sP	iGD ~ iP p-val	sGD ~ iP p-val	sGD ~ sP p-val	iGD ~ iP Holm *p*-val	sGD ~ iP Holm *p*-val	sGD ~ sP Holm *p*-val
ADHD	51.5	8	0	.98	.97	.07	.01	.57	−.08	.52	0	.42	.15	0	1	1
social media addiction	54.1	8	0	.98	.97	.07	.02	.83	−.09	.81	0	.23	.00	0	1	0
impulsivity	25.1	8	.00	.99	.98	.04	.01	.53	−.09	.77	0	.45	.15	0	1	1
stress	18.6	8	.02	1.00	.99	.03	.01	.41	.07	−.12	0	.48	.73	0	1	1
aggression/ hostility	18.2	8	.02	1.00	.99	.03	.01	.50	−.04	.32	0	.51	.05	0	1	.52
social support	18.2	8	.02	1.00	.99	.03	.01	.45	−.04	.16	0	.55	.07	0	1	.74
anxiety	32.1	8	0	.99	.98	.05	.01	.56	−.08	.72	0	.43	.33	0	1	1
depression	3.4	8	.90	1.00	1.00	.00	.01	−.27	−.03	−.28	0	.74	.51	0	1	1
social anxiety	35.4	8	0	.99	.98	.05	.01	.46	−.07	.59	0	.44	.12	0	1	1
ADHD	16.2	8	.04	1.00	.99	.03	.01	.47	−.11	.50	0	.21	.15	0	1	1
social media addiction	12.1	8	.15	1.00	1.00	.02	.01	.42	−.10	.33	0	.20	.14	0	1	1
self-esteem	3.4	8	.90	1	1	0	0.01	−.26	.10	NA	.00	.12	.58	0	1	1
education	7.6	8	.48	1	1	0	0.01	−.03	.07	−.05	.38	.25	.57	1	1	1

Notes: i prefix represents the intercept, s prefix represents the slope (or rate of change). GD states for the gaming disorder, P states for the predictor, iGD ~ iP: regression of the intercept of GD (the initial level of GD) on the intercept of the predictor. Models for self-esteem and education did not converge properly, so their results are likely spurious.

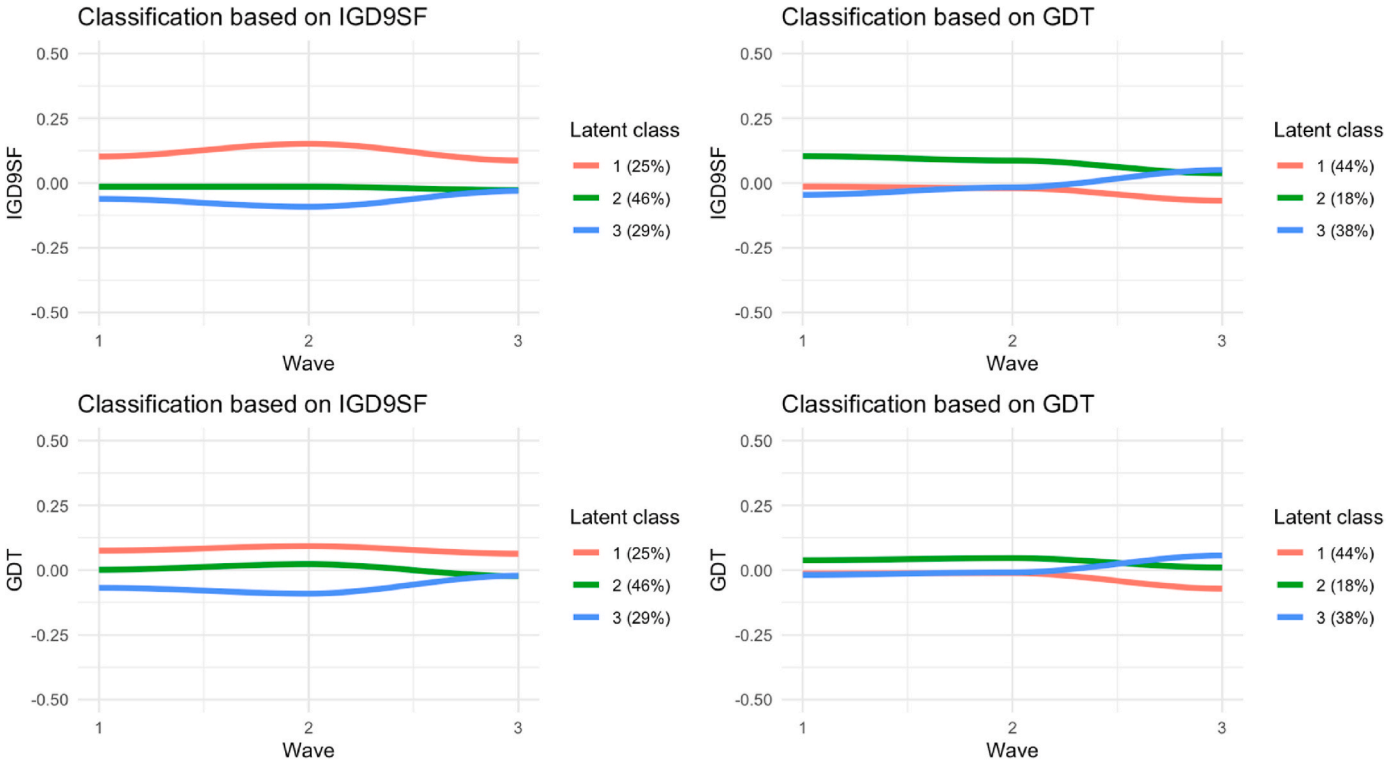

Fig. 1. GD trajectories for distinct subgroups (latent classes) of participants.

linear mixed effects models in Table 6.

For both IGDS9-SF and GDT symptoms, aggregate trends were slightly, but consistently negative. First, the raw decrease in IGDS9-SF symptoms level was $Mdn = -.06$ per wave, on average. Except for items 7 and 9 with a flat trend, the slight decrease in all other IGDS9-SF symptoms was significant. Second, intercept *SD* larger than wave *SD* roughly by a factor of $Mdn = 5$ clearly shows that participants differed in their baseline GD levels much more than in their individual slopes. Third, consistently negative correlations between the random intercepts and slopes show that participants with higher baseline symptom levels tended to show smaller wave effects (decrease, on average). That is, participants high on GD symptoms tended to show smaller change, indicating temporal stability of high symptom levels. On the flipside, participants with low baseline GD symptom levels exhibited larger mean change in symptoms. Basically the same pattern was found for GDT symptoms. The aggregate time trends for GD symptoms can be seen in Fig. 2.

We also examined the development of risk factors. Generally, the raw wave coefficients were smaller than for GD symptoms. Apart from social support (in fact, a protective factor, which significantly increased), half of the risk factors levels significantly decreased and half trended sideways. Between-participant variance in baseline was also significantly larger than the variance in slopes. Time trends for risk factors are shown in Fig. 3, detailed results can be found in Appendix A.

Table 6
Results of linear mixed-effects models.

Symptom	Wave	*SE*	Intercept *SD*	Wave *SD*	Residual *SD*	I–S correlation	LR test *p*-value
IGDS9-SF 1	−.12	.02	.92	.16	.69	−.53	.00
IGDS9-SF 2	−.04	.01	.76	.11	.59	−.35	.00
IGDS9-SF 3	−.09	.02	.91	.21	.66	−.54	.00
IGDS9-SF 4	−.06	.01	.89	.17	.59	−.58	.00
IGDS9-SF 5	−.08	.02	.98	.17	.71	−.62	.00
IGDS9-SF 6	−.05	.01	.90	.13	.62	−.55	.00
IGDS9-SF 7	−.01	.01	.69	.17	.49	−.58	.49
IGDS9-SF 8	−.08	.02	.91	.02	.79	NA	.00
IGDS9-SF 9	.01	.01	.70	.16	.47	−.38	.49
GDT 1	−.08	.02	.94	.24	.57	−.56	.00
GDT 2	−.12	.02	1.01	.21	.67	−.56	.00
GDT 3	−.09	.02	.94	.04	.68	NA	.00
GDT 4	−.04	.01	.85	.20	.50	−.65	.00

Notes: Wave coefficient: the estimated fixed effect of wave on the symptom, indicating the average change in the symptom per unit increase in wave. LR Test *p*-value: the *p*-value from the likelihood ratio test comparing the full model (including wave as a fixed effect and random slope) to the null model (excluding wave).

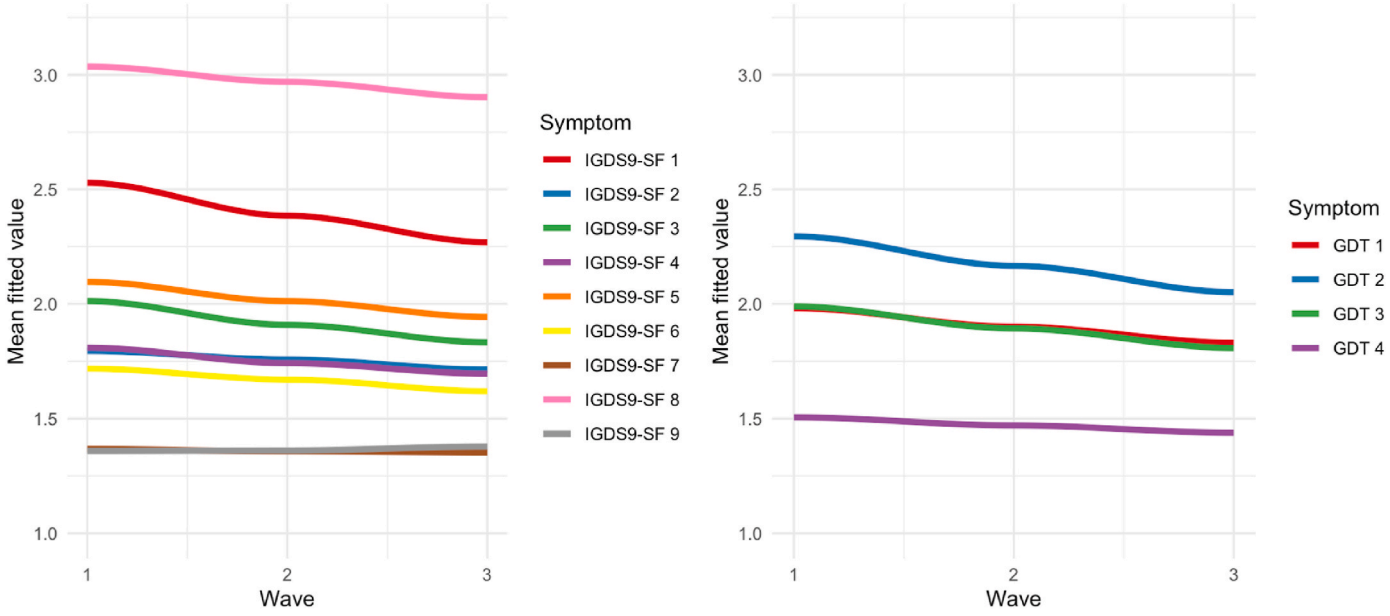

Fig. 2. Aggregate time trends for IGDS9-SF and GDT symptoms.

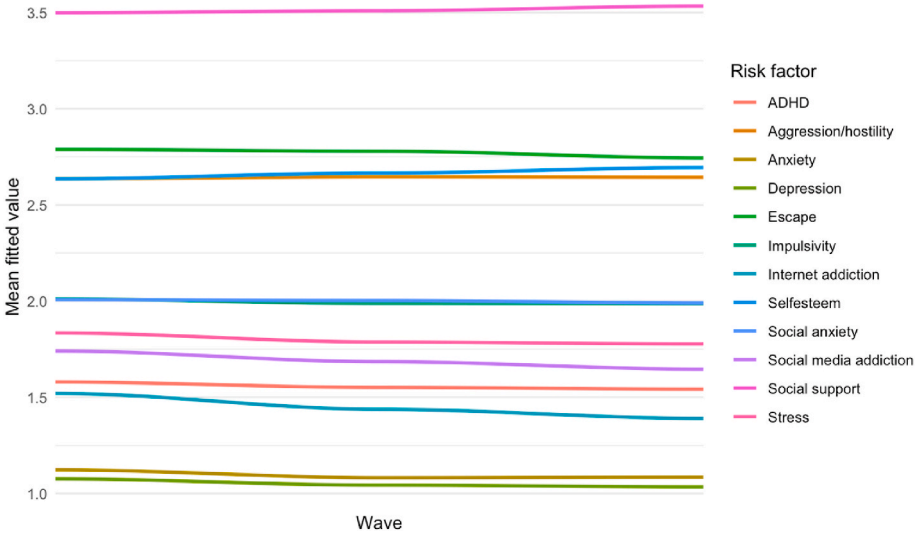

Fig. 3. Aggregate time trends for GD risk factors.

7.4. Dynamics in the network structure of GD

Lastly, we carried out an exploratory dive into the development of gaming disorder's network structure. Figs. 4 and 5 show the temporal, contemporaneous, and between-subjects network for the IGDS9-SF and GDT operationalizations, respectively. Let's look at the DSM-5 GD symptomatology first.

The temporal network was moderately connected (estimates mostly ranged in the .1 to .3 range). The most prominent temporal role in the network was played by the node Loss of control (symptom #4) which turned out to be predictive of the future state of several other nodes. This node emitted the most links. Apart from Tolerance (#3) or Problems (#9), Loss of control (#4) also counted among the most temporally stable given the relatively strong self-loops. These symptoms might then also possibly be more resistant to intervention. Another temporally more connected and stable symptom was Continued use. On the flip side, there were some symptoms that seemed to play a less central role in the development of GD, as they did not emit significant temporal predictive effects, like Preoccupation (#1), Withdrawal (#2), Deception (#7), or Escape (#8). The pattern of contemporaneous relationships (the second network) between the GD symptoms was similar, even after partialling out the temporal effects. The enduring nature of these relationships underscores the resilience of these connections, irrespective of temporal dynamics. Switching to the between-subjects level (third network), there seem to be links between the longer-term average levels of symptoms Loss of Interests (#5), Deception (#7), and Problems (#9).

The temporal network for the GDT operationalization did not contain any temporal edges stronger than .1 used to visually prune the networks. There was only one significant autocorrelation indicating relatively higher temporal stability of Loss of control (#1). Otherwise, the past value of one GDT symptom turned out not to provide any useful information for predicting the present values of any other symptom. This would suggest that each GDT symptom evolved rather independently over the given time frame. When also considering the two other networks, it is obvious that the relationships among symptoms are not as strong not only within individuals over time (temporal) but also within individuals at a given moment in time (contemporaneous), as they are across individuals (between-subjects). Most notably, Loss of control (#1) and Continued use (#3) seemed to play a more central role than the other two GDT symptoms. Stronger between-subjects than within-subjects relationships might then indicate that the observed associations between symptoms at the between-subject level are not solely due to direct contemporaneous interactions between symptoms. It could be the case that other factors not represented in the contemporaneous network, such as individual differences in biological or environmental factors, are contributing to these between-subject associations. Alternatively, this finding could suggest that while two symptoms often co-occur across individuals, they do not necessarily influence each other within an individual.

8. Discussion

In the present study, we focused on outlining the trajectory of GD development (including the symptom-level changes and their mutual connections) over half a year and the role of potential risk/protective factors in this process.

8.1. Prediction of the development of gaming disorder using the known risk factors

Evidence-based insights into the within-person dynamics of GD development could greatly benefit clinical practitioners and therapists. For instance, is it possible to make accurate predictions about the medium-term GD development based on the current level of GD and its main risk factors? From a clinical perspective, knowing that elevated levels of internet addiction, social media addiction, escape motive, or anxiety at the initial screening can lead to a significant deterioration of GD in the next six months may inform the treatment. For example, interventions can target improvement in control over the general digital technology usage, anxiety reduction, or other personalized needs. Gaming disorder, social media addiction, and internet addiction as constructs under the same umbrella of technology-mediated addictive behaviors (Baggio et al., 2018) often overlap or are tightly linked (Li et al., 2023; Ropovik et al., 2022). The model of compensatory internet use (Kardefelt-Winther, 2014) explains how people with impaired psychological health (e.g., high anxiety) might resort to ineffective coping strategies (including excessive use of digital technologies) promoted by escape motivation, as digital technologies offer instant gratification (Adams et al., 2018).

When taking into account the developmental trends in risk factors,

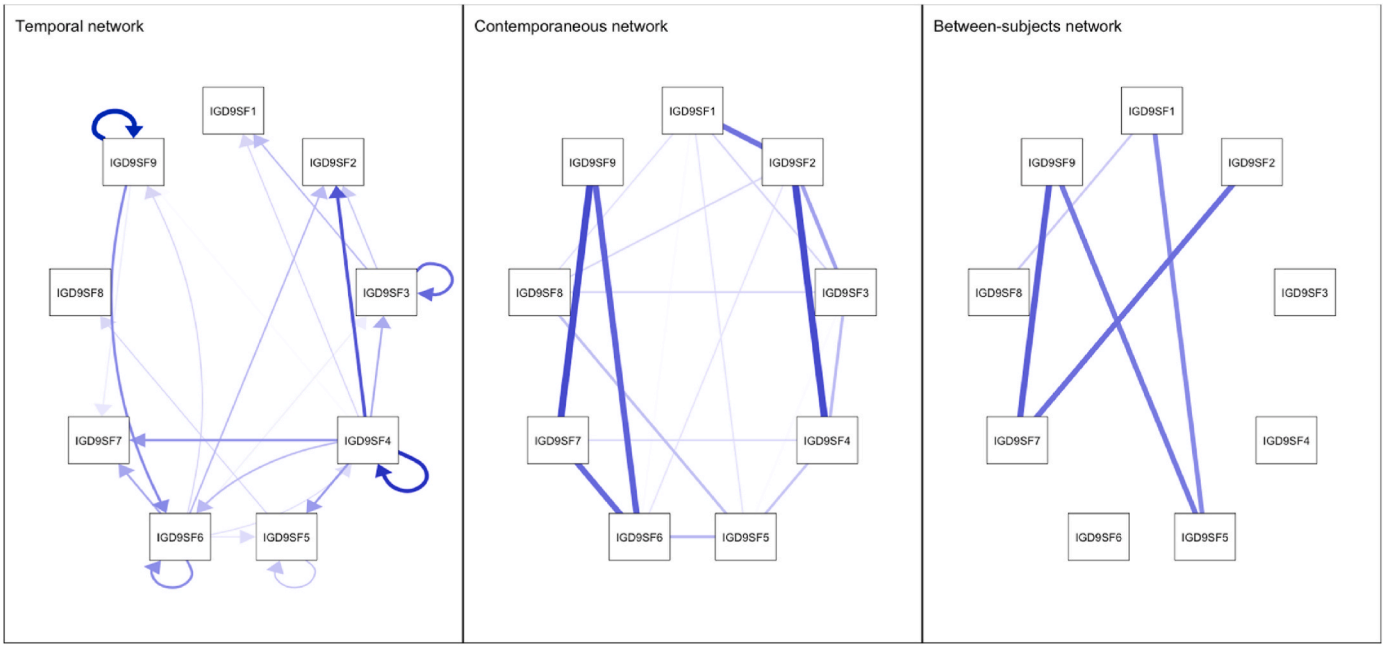

Fig. 4. Within- and between-subjects networks of IGDS9-SF symptoms.

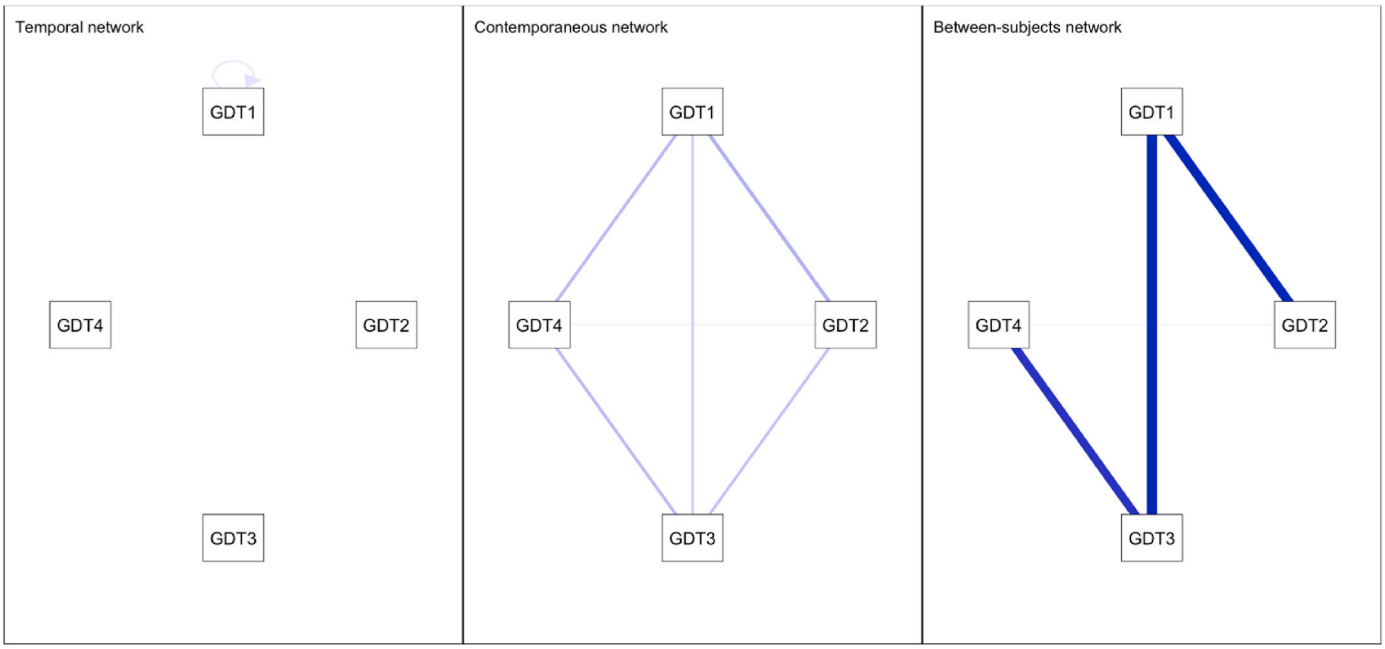

Fig. 5. Within- and between-subjects networks of IGDS9-SF symptoms.

gaming disorder development was predicted only by the rate of change in stress, internet addiction and aggression/hostility. Stress and hostility, as predisposing factors, would fit with the two types proposed in the GD typology by Lee et al. (2016) adapted from the typology of gamblers. Within the Emotionally vulnerable type, stress functions as a driving force leading emotionally vulnerable people to use ineffective coping mechanisms, that is, excessively playing digital games (see also Kaess et al., 2017 who corroborated stress vulnerability in IGD youth from a neurobiological perspective). Moreover, the cognitive-behavioral model of IGD (Dong & Potenza, 2014) highlights the role of stress reduction as one of the three main motivational forces leading to excessive gaming. Aggression/hostility on the other hand would fit with the Impulsive/aggressive type (Lee et al., 2016) for which expression of aggression by engaging in extensive gaming is typical. The evidence accumulated from the longitudinal studies (for a systematic review see Zhuang et al., 2023) is however, ambiguous with regard to potential risk factors of GD, e.g., the predictive effect of anxiety was found for 6 and 12 months follow-up (Adams et al., 2018; Teng et al., 2021) but not for 9 months follow up (Chang et al., 2022; Marrero et al., 2021). More primary studies with both shorter and longer follow-ups are needed for future synthesis.

8.2. Description of gaming disorder development over a period of 6 months

To what extent have the individual symptoms of GD changed over the six months? Our results suggest that not much. While we observed statistically significant changes in almost all symptoms, the practical impact of these changes seems negligible. The biggest average change was observed for preoccupation (DSM-5) and prioritization (ICD-11), both potentially linked to the initial rapid onset of excessive gaming that precedes GD. A similar but more pronounced downward trend was observed over 18 months (King et al., 2013) and an almost complete diminishment of formerly severe symptoms in the 5-year longitudinal study by Konkolÿ Thege et al. (2015). The negative intercept-wave correlations in the linear mixed-effects models for almost every GD symptom (except escape) suggest that participants with higher baseline symptom levels tend to experience smaller symptom change over time and vice versa. In other words, the development of GD progresses slowly in people who already exhibit high levels of symptoms, but the initial development of symptoms can be more rapid, as also inferred from case studies by Benarous et al. (2019). When various biological, cognitive, psychological, and environmental vulnerabilities converge over time, the initial increase in time spent gaming, which precedes the development of GD, happens very fast.

The initial uptick in gaming time may be rapid, but the actual increase or decrease in the symptoms toward the full development of GD is more gradual. Our results align with three developmental models of GD. The model proposed by Paulus et al. (2018) describes this process in three stages: starting with gaming for fun, progressing to gaming with a loss of control, and culminating obsession. Similarly, the I-PACE model (Brand et al., 2016, 2019) emphasizes a gradual and prolonged course of development of GD. The authors highlight the initial role of increased gratification from gaming (akin to the fun stage in the Paulus et al., 2018 model), which gradually diminishes and is replaced by compensating effects – habitual behaviors (corresponding to the loss of control and obsession stages present in Paulus et al., 2018 model). These patterns subsequently intensify and sustain the disorder in the long run. In a similar vein, the cognitive-behavioral model (Dong & Potenza, 2014) assumes effects on brain functions. Over time, alterations in these functions might lead to a weakening of self-control and promote craving. This longer-lasting and gradual development of GD is further supported by a qualitative study by Sun et al. (2023), which frames the development in three stages: early exposure, continuous and progressive engagement, and pathological use accompanied by the emergence of the symptoms. The middle stage, continuous and progressive engagement with digital games, is considered as a critical factor for the subsequent development of GD, emphasizing its longer-term character.

Other explanations to consider when assessing the general decreasing trend of GD symptoms could be a phenomenon known as regression to the mean (Barnett, 2004). Critical to the appropriateness of using this phenomenon as an explanation is the fact that we have not sampled the entire population of gamers, but only those who already play intensively. Therefore, extreme levels of gaming time, due to the sample selection, could have resulted in lower scores in subsequent measurements ($M_1 = 3.99 -> M_3 = 3.59$). Since gaming time is naturally connected to GD symptoms, this may potentially explain a decrease in their intensity/severity.

9. Limitations and future directions

First, for the purposes of this study, we aimed to sample a population of intensively playing gamers, that is people who may have a potential for developing GD. However, our sample selection criteria depended on the capabilities of the recruitment agency (Prolific). The sample was selected using the available prescreening criteria - we recruited only those participants who answered the question "How many hours per week do you play video games on average?" with responses "6–9 h", "9–13 h", or "13 h or more". Despite its drawbacks, we opted for this approach due the considerable savings in time and resources. Second, while the construct of self-assessed gaming problems has not been validated before, we included it in the analyses because it closely simulates the reasoning of individuals seeking professional help. That is, thinking about the overall impact of excessive gaming on their lives, rather than thinking about individual symptoms and their severity. Third, some of the established scales used to measure the risk factor appeared to have issues with internal validity. Specifically, several of them violated the assumption of local independence, i.e., the items on the scale should be independent, conditional upon the modeled univariate latent factor. This introduces an additional layer of uncertainty into the analyses where factor or sum scores derived from these scales were utilized.

For GD, from the clinical viewpoint, predictions for long intervals, such as 2–3 years, seem to be less useful than predictions for shorter periods. For instance, knowing how a patient will feel in upcoming months may be more pertinent than projecting years into the future. However, if we posit that GD typically dissipates after a few years, it is still needed to study its dynamics within a longer time interval. Clinicians could further benefit from information whether people with varying developmental trends (decrease or increase of symptoms) possess specific demographic characteristics. Although we have identified three distinct groups based on the developmental trend in GD, we did not find meaningful links with mean age, gender, gaming time, or a preference for playing multiplayer games of these groups. Thorough understanding of the long-term dynamics and biological and psychological differences driving various developmental trends in GD is a task for future longitudinal studies.

10. Data sharing

All data, R scripts, and materials related to this study are available on the OSF repository: https://osf.io/5h7r9/

Authors' contributions

MM: Conceptualization, Methodology, Investigation, Data curation, Writing - Original Draft, Writing - Review & Editing. **IR**: Conceptualization, Methodology, Formal analysis, Data curation, Writing - Original Draft, Writing - Review & Editing. **MA**: Conceptualization, Methodology, Formal analysis, Data curation, Writing - Original Draft, Writing - Review & Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All data, R scripts, and materials related to this study are available on the OSF repository: https://osf.io/5h7r9/.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2023.108112.

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