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Investigating the mechanisms of internet gaming disorder and developing intelligent monitoring models using artificial intelligence technologies: protocol of a prospective cohort

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Abstract

Background Internet gaming disorder (IGD), recognized by the World Health Organization (WHO), significantly impacts adolescent mental and physical health. With a global prevalence of 3.05%, rates are higher in Asia, especially among adolescents and males. The COVID-19 pandemic has exacerbated IGD due to increased gaming time from isolation and anxiety. Vulnerable groups include adolescents with poor academic performance, introverted personalities, and comorbid mental disorders. IGD mechanisms remain unclear, lacking prospective research. Based on Skinner's reinforcement theory, the purpose of this study is to explore the mechanisms of IGD from individual and environmental perspectives, incorporating age-related changes and game features, and to develop intelligent monitoring models for early intervention in high-risk adolescents.

Methods This prospective cohort study will investigate IGD mechanisms in middle and high school students in Shenzhen, China. Data will be collected via online surveys and Python-based web scraping, with a 3-year follow-up and assessments every 6 months. Unstructured data obtained through Python-based web scraping will be structured using natural language processing techniques. Collected data will include personal characteristics, gaming usage, academic experiences, and psycho-behavioral-social factors. Baseline data will train and test predictive models, while follow-up data will validate them. Data preprocessing, normalization, and analysis will be performed. Predictive models, including Cox proportional hazards and Weibull regression, will be evaluated through cross-validation, confusion matrix, receiver operating characteristic (ROC) curve, area under the curve (AUC), and root mean square error (RMSE).

Discussion The study aims to understand the interplay between individual and environmental factors in IGD, incorporating age-related changes and game features. Active monitoring and early intervention are critical for preventing IGD. Despite limitations in geographic scope and biological data collection, the study's innovative design and methodologies offer valuable contributions to public health, promoting effective interventions for high-risk individuals.

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Keywords Internet, Game, Mechanisms, Monitoring models, Artificial intelligence, Prospective cohort

Background

Internet gaming disorder (IGD) is a severe mental and physical health issue recognized by the World Health Organization (WHO), caused by persistent and repetitive use of internet games [1, 2]. IGD during adolescence can significantly impact physical and psychological well-being, influencing personality formation and mental health into adulthood [3–5]. The global prevalence of IGD is estimated at 3.05% [6], with higher rates in Asia, particularly among adolescents and males [5, 7, 8]. The Coronavirus Disease 2019 (COVID-19) pandemic has exacerbated IGD, with increased gaming time due to prolonged isolation and anxiety [9–11]. Adolescents with poor academic performance, introverted personalities, attention deficits, and comorbid mental disorders are particularly susceptible, leading to disrupted routines, declining academic performance, and compromised health [4, 12].

Adolescent IGD is influenced by both individual and environmental factors [5, 13, 14]. Key individual factors include high impulsivity, low self-control, poor emotional regulation, and stress coping difficulties [15, 16]. Impulsivity and lack of self-control are strongly linked to higher addiction risk [17, 18], while emotional regulation deficits and stress relief motivations exacerbate addiction [3, 19]. Environmental factors such as family dynamics, school environment, and peer influences are also critical [20, 21]. Positive family cohesion and parental monitoring reduce addiction risk, whereas neglect increases it [22]. Unmet psychological needs in school environments and peer influences, including peer gaming habits and victimization, significantly predict gaming addiction [23, 24].

Understanding the interplay between individual and environmental factors in constituting risk and protective factors for adolescent IGD remains a pressing issue. Based on Skinner's reinforcement theory [25], a model of adolescent gaming addiction suggests that immediate rewards from gaming positively reinforce behavior, while negative experiences, such as poor academic performance and criticism, have weaker negative reinforcement due to their delayed impact. Neuroscience research indicates that these reinforcement effects are tied to the reward and aversion circuits in the nervous system [26], with changes in the cortico-basal ganglia circuits forming the neural basis of compulsive addictive behaviors [27, 28]. However, previous studies have overlooked age-related changes and game characteristics. Since addiction involves continued behavior despite negative consequences, understanding of these consequences evolves with age, and adolescents and adults perceive them differently [29–31]. Studies show addicted players often form tight clusters online [32], but how this relates to age is unclear. Identifying and understanding these age-related clustering patterns may help prevent IGD. Additionally, game design, reward mechanisms, and social elements significantly influence player behavior and addiction risk. Investigating these aspects will help uncover new mechanisms of IGD.

Active monitoring plays a key role in preventing adolescent IGD. By monitoring gaming behavior, online time, and social interactions, excessive gaming and addiction risks can be identified early, allowing for timely intervention. Artificial intelligence (AI) technologies can process and analyzed large amounts of health data, enabling early disease prevention and identification [33, 34]. AI models can predict the risk of chronic diseases by analyzing physiological indicators, lifestyle habits, and genetic information [35, 36]. In IGD research, we plan to use online surveys and web scraping techniques with Python for data collection, combined with natural language processing to structure the data and develop a predictive model for early active monitoring of IGD behavior. These multi-layered data will provide new perspectives for developing intelligent monitoring models, and enabling early intervention for high-risk individuals.

Aims

This study, based on Skinner's reinforcement theory, aims to explore the mechanisms of IGD from individual, environmental, and game characteristics perspectives, incorporating age-related changes and game features. The study will focus on middle and high school students in Shenzhen, China, constructing a prospective cohort, combining online survey, web scraping techniques using Python, and natural language processing for data collection and structuring:

1) Investigate the multi-layered influences of individual, environmental, and game factors on the occurrence and development of IGD among students of different age groups (see Fig. 1. Study hypothesis).

2) Develop age-appropriate intelligent monitoring models for IGD.

Methods

Study design

This study employs a prospective cohort design (see Fig. 2). Participants will undergo a 3-year prospective follow-up, with data collected through online epidemiological questionnaires and Python-based web scraping techniques. Following the baseline survey, there will be a 36-month follow-up period, with follow-up assessments

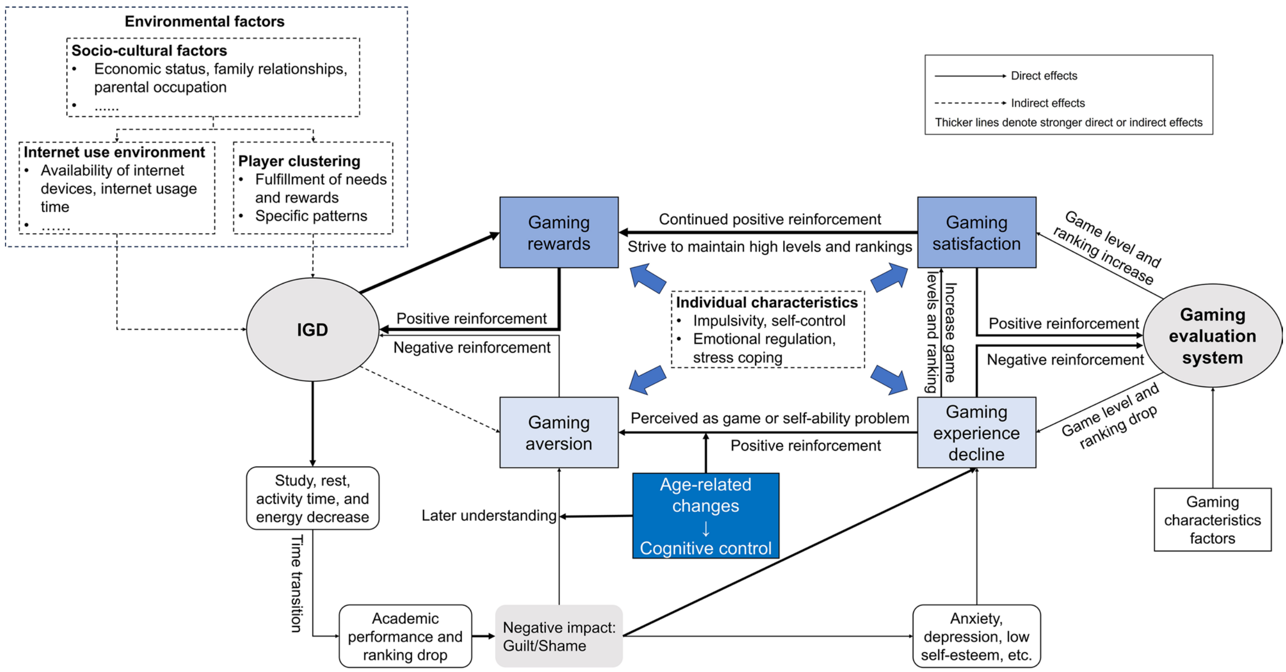

Fig. 1 Study hypothesis: A model of adolescent IGD based on Skinner's reinforcement theory. Abbreviation IGD, Internet gaming disorder. This hypothesis integrates individual and environmental factors. Environmental factors include socio-cultural aspects (economic status, family relationships), internet use (device availability, usage time), and player clustering. IGD is driven by gaming rewards that reinforce behavior through positive experiences from high levels and rankings, and aversion from negative experiences perceived as game or self-ability issues. Key individual factors impacting IGD are impulsivity, self-control, emotional regulation, and stress coping. The gaming evaluation system further reinforces behavior through level and ranking changes. IGD results in decreased study and activity time, academic decline, and negative psychological impacts like guilt, anxiety, and low self-esteem. Age-related changes influence cognitive control and understanding of gaming consequences. This model highlights the complex interactions contributing to IGD

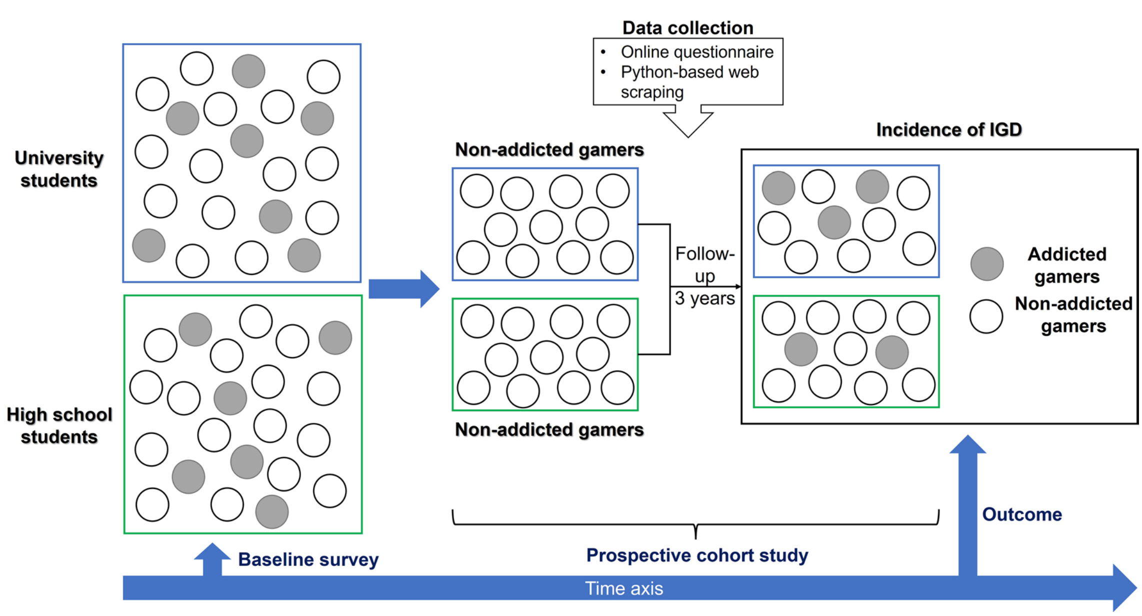

Fig. 2 Prospective cohort study design. Abbreviation IGD, Internet gaming disorder

conducted every 6 months. The project adheres strictly to ethical principles for observational studies, ensuring the rights and safety of participants throughout the study. The study protocol complies with the requirements of the Declaration of Helsinki and has been approved by the Ethics Committee of Southern University of Science and Technology (20230125).

Study sample and enrollment
The study sample consists of university and high school students in Shenzhen, China. University students (undergraduates only, excluding postgraduates) are recruited from a local public funded university, while high school students are recruited from a regular secondary school (including both junior and senior high school). Only currently enrolled students are included in the study, excluding those who are on leave, withdrawn, or dropped out. The specific inclusion and exclusion criteria are as follows:

Inclusion criteria:

1) High school students aged between 12 and 18 years, and university students aged between 17 and 25 years;
2) Currently enrolled students, with academic records managed by the respective schools at the time of the study;
3) Able to independently complete the study survey or complete it with assistance from the research staff;
4) Willing to participate in the study, with informed consent signed by themselves or their guardians.

Exclusion criteria:

1) Diagnosed with IGD at any point or showing significant signs of addiction at the baseline survey;
2) Currently receiving psychological or behavioral interventions (e.g., mindfulness therapy, cognitive behavioral therapy);
3) History of cognitive, speech, or other mental function disorders;
4) Transferring to another school during the study period, making follow-up impossible.

Exposure
This study investigates multiple potential exposure factors related to IGD. These factors include internet gaming usage (e.g., game type, duration and frequency of play, gaming partners), academic experiences (e.g., academic stress, academic burnout), and psycho-behavioral-social factors (e.g., impulsivity, mobile phone dependence, interpersonal relationships). The specific measurement methods for these exposure factors are detailed in the "Data acquisition" section.

Outcome
The primary outcome of this study is IGD, defined as a severe mental and physical health issue from persistent internet game use. IGD will be assessed using the Chinese version of Petry et al.'s criteria [37], based on the nine diagnostic criteria for gaming disorder outlined in the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) (Supplementary Table S1). These include preoccupation with gaming, withdrawal symptoms, increased tolerance, unsuccessful attempts to reduce gaming, loss of interest in other activities, jeopardized relationships, gaming to escape negative moods, continued gaming despite psychosocial problems, and deceiving others about gaming time. A diagnosis requires meeting five or more criteria within the past 12 months. This tool is widely validated and used in IGD research. Additionally, a self-developed internet gaming usage scale will be used to comprehensively assess participants for IGD behaviors (see "Data acquisition: Supplementary Table S2. Self-developed internet gaming usage scale".

Follow-up
Participants will undergo a 3-year follow-up with assessments every 6 months, totaling six follow-ups to evaluate the incidence of IGD. To ensure quality, a follow-up manual and standardized training for personnel will be implemented. A specialized follow-up report form will cover exposure factors, outcome variables, and psychological, behavioral, and social impacts. A cohort follow-up system and regular reminders will enhance compliance and reduce loss to follow-up. Participants will be reminded via WeChat, phone, and email, with reasons for missed follow-ups recorded. Quality control will involve reviewing follow-up data and contacting participants to correct or update information, ensuring an accurate and complete cohort follow-up database for assessing IGD incidence.

Sample size
Based on a 2-year longitudinal study by Jeong et al. on the severity, incidence, and persistence of IGD in children and adolescents [14], playing internet games for ≥240 min per day was identified as an independent predictor of IGD. The incidence rate of IGD in the control group (p_0) was 4.8%, and in the exposed group (p_1) was 14.9%. Using the formula $\bar{p}=(p_0+p_1)/2$, $\bar{q}=1-\bar{p}$, $q_1=1-p_1$, with a two-sided test level of α=0.05 and β=0.10, the sample size calculation formula for cohort studies (1) was applied. Assuming a 1:1 ratio between the exposed and control groups, 181 participants are required for each group. Considering a 20.0% loss to

follow-up rate, each group needs 227 participants, resulting in a total sample size of 454 participants.

$$n = \frac{\left(u_{1-\frac{\alpha}{2}}\sqrt{2\,\overline{p}\,\overline{q}} + u_{1-\beta}\sqrt{p_0q_0 + p_1q_1}\right)^2}{(p_1 - p_0)^2} \tag{1}$$

Data acquisition

Online epidemiological questionnaire survey

An online questionnaire will collect participants' demographic data, internet gaming usage, and psycho-behavioral-social factors. The questionnaire will be promoted through campus posters, social media, official emails, and WeChat groups for broad dissemination. Respondents will be initially screened for quality assurance. The questionnaire content is detailed in Table 1.

Data acquisition via Python-based web scraping

In this study, we will use Python-based web scraping techniques combined with ChatGPT-4.0's "Scraper" plugin to obtain unstructured data, and ChatGPT-4.0's "Make A Sheet" plugin to save unstructured data. This approach will actively gather information related to gaming behavior published by participants on platforms such as gaming forums, Baidu Tieba, and public social media. The detailed acquisition process is as follows (illustrated using League of Legends, a popular online game among adolescents, see Fig. 3):

1) Identify target websites: Select the target gaming forums and other websites to scrape, understanding their data structures, page layouts, and request parameters.
2) Send HyperText Transfer Protocol (HTTP) requests: Use Python's "Requests" library to send HTTP requests and retrieve the HyperText Markup Language (HTML) code of the gaming forum web pages.
3) Parse HTML code: Use Python's "BeautifulSoup" library to parse the HTML code and extract the necessary unstructured gaming-related data, including information on post authors, titles, publication dates, content, and replies (comments). During the data acquisition process, we will strictly adhere to the website's robots.txt protocol to ensure the legality and stability of data acquisition. Additionally, we will use proxy servers to prevent IP blocking, ensuring stable data acquisition.

Natural language processing (NLP)

After acquiring unstructured data from players using Python-based web scraping, we will use Alibaba Cloud's NLP technology to structure the data (see Fig. 4). The specific step include: registering an Alibaba Cloud account, creating an NLP instance, installing the Alibaba Cloud Python Software Development Kit (SDK), configuring access credentials, creating a sentiment analysis request object, sending the request, and obtaining the response.

Data management

A dedicated data management team will oversee data collection, entry, and quality control. Trained in Good Clinical Practice (GCP) and Standard Operating Procedures (SOPs), they will ensure standardized data handling. Quality control will include logical, range, time window, consistency, data integrity, and terminology checks. Discrepancies will be recorded in a "Data Query Form" and resolved promptly. Raw data will be cleaned, integrated, or transformed for analysis, while web-scraped data will be processed by removing HTML tags, converting data types, and storing it locally. Both data management and statistical analysis personnel will supervise the data, locking the database if necessary, and performing regular backups to maintain data traceability and integrity.

Handling of missing data

Before statistical analysis, we will assess data completeness to determine the extent and causes of missing data. Objectively missing data (e.g., non-exposure to a study

Table 1 Content of the online epidemiological questionnaire

Data type	Variables
Demographic characteristics	Gender, age, school name, grade, major (for university students), family economic status, parents' occupations, current residence and duration, height, weight, vision status, smoking (including tobacco or e-cigarettes), and alcohol use.
Internet gaming usage	Custom items will measure the time spent on internet gaming and the types of games played. Internet gaming refers to multiplayer games requiring an internet connection, typically involving multiple players in a virtual environment. Internet gaming usage will be assessed using items in Supplementary Table S2. Additional data will be collected via Python-based web scraping, detailed in section "*Data acquisition via Python-based web scraping*".
Academic experiences	Academic stress (ESSA), academic burnout (MBI-SS).
Psycho-behavioral-social factors	• Psychological factors: impulsivity (BIS-11), self-control (BSCS), emotional regulation (DERS), stress coping (CISS), generalized anxiety disorder (GAD-7). • Behavioral factors: mobile phone dependence (MPPUS), social media dependence (BSMAS). • Social factors: social support (MSPSS), parenting styles (PAQ), interpersonal relationships (IPRI).

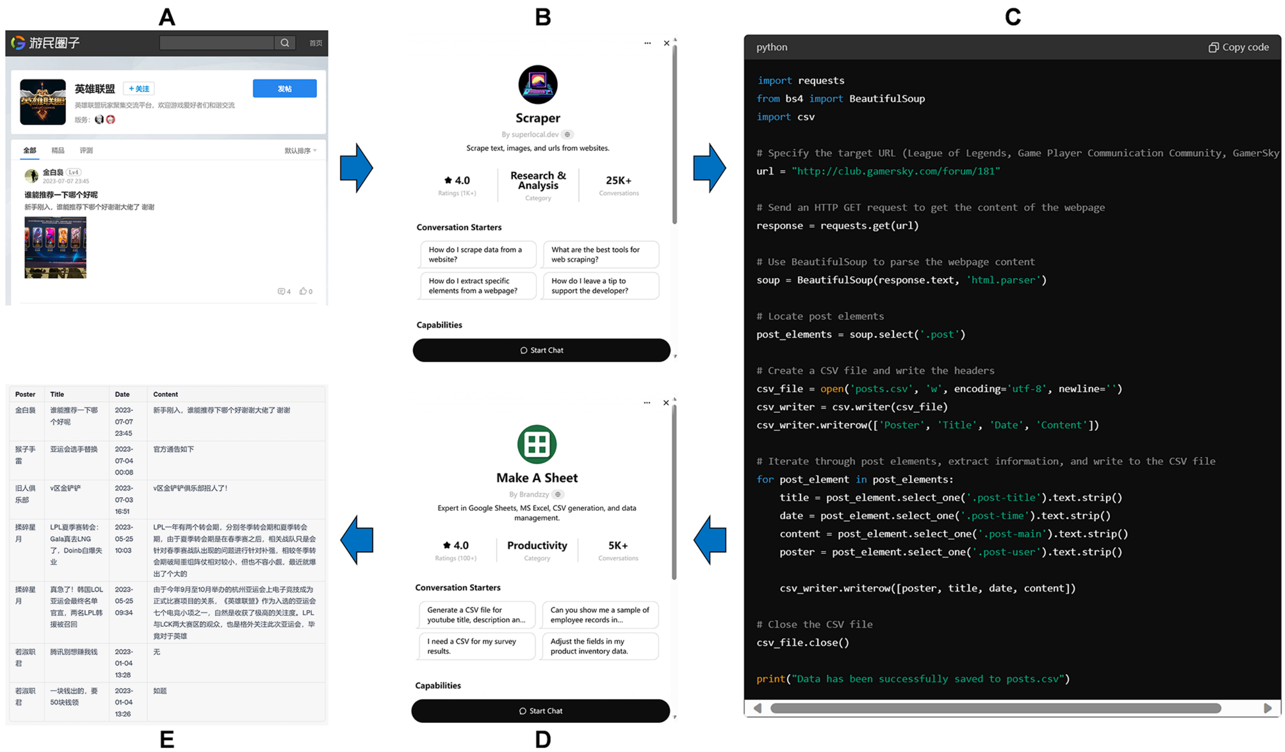

Fig. 3 Acquiring participant gaming behavior information using Python-based web scraping combined with ChatGPT plugins. Panel A: posts made by players on gaming forums; Panel B: ChatGPT-4.0's "Scraper" plugin; Panel C: Python-based web scraping combined with the "Scraper" plugin to acquire gaming forum post information (unstructured data); Panel D: ChatGPT-4.0's "Make A Sheet" plugin outputting unstructured data; Panel E: Acquired unstructured data on participant gaming behavior

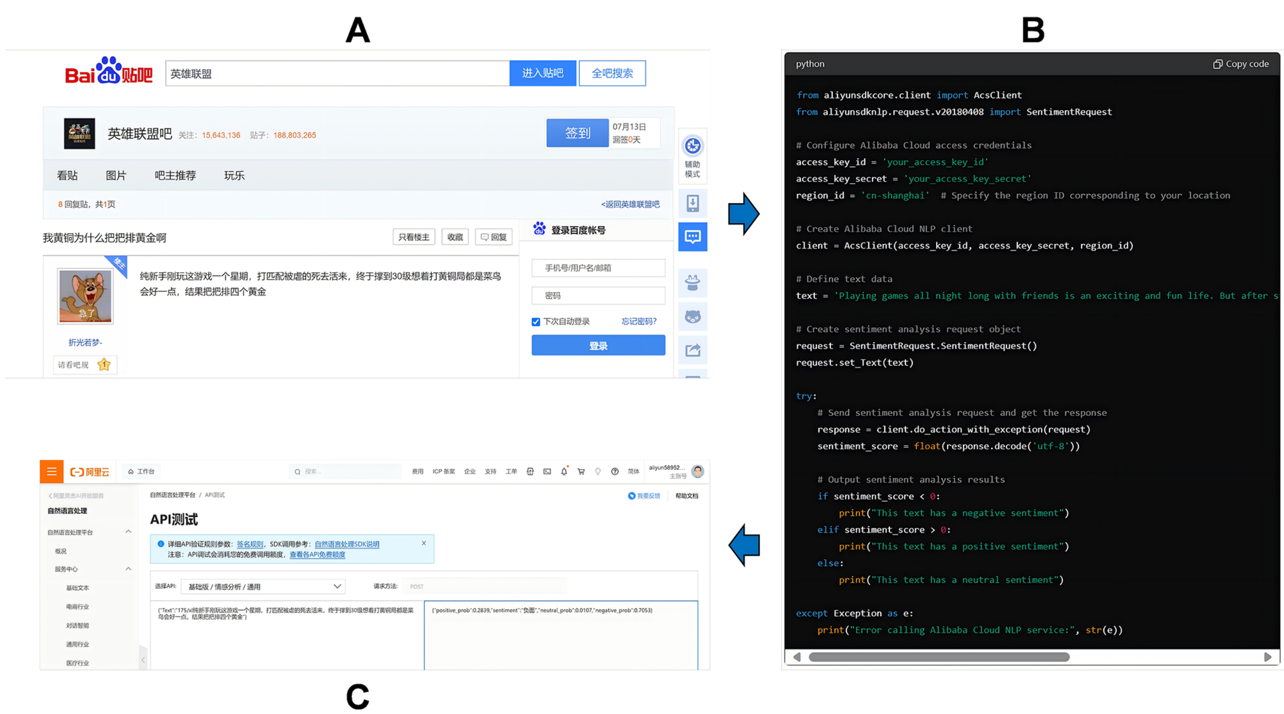

Fig. 4 Structuring participants' unstructured information using Alibaba Cloud's NLP technology. Panel A: posts made by players (unstructured text); Panel B: Application Programming Interface (API) call to Alibaba Cloud's NLP functions; Panel C: Sentiment analysis results of participants' natural language (indicating the player's sentiment as "negative")

factor) will not be treated as missing. For genuinely missing data, we will choose imputation or analysis methods based on the missing data mechanism and its relevance to the study's primary scientific questions. We will consider three scenarios: (1) Missing Completely at Random (MCAR): Impute using sample means, medians, or generalized estimating equations; if MCAR data is below 15.0%, analyze only complete cases. (2) Missing at Random (MAR): Use regression models, Markov Chain Monte Carlo (MCMC), or fully conditional specification (FCS) for multiple imputation. (3) Missing Not at Random (MNAR): Apply pattern mixture models for comparative analysis of missing and non-missing data.

Statistical analysis

Data analysis will be conducted using Statistical Analysis System (SAS) version 9.4 (SAS Institute, Inc., Cary, NC, USA), IBM Statistical Package for the Social Sciences (SPSS) version 26.0 (IBM Corp., Armonk, NY, USA) with the PROCESS macro, and Mplus version 8.4 (Muthén & Muthén, Los Angeles, CA, USA). A significance level of $\alpha = 0.05$ will be used for all hypothesis tests, with $P < 0.05$ considered statistically significant.

1) Baseline characteristics: Descriptive analysis of demographics, internet gaming usage, academic experiences, and psycho-behavioral-social factors will be performed. Continuous data will be presented as mean ± standard deviation (SD) or median (Interquartile Range [IQR]), and categorical data as frequency (percentage). Differences between groups will be compared using t-tests or Mann-Whitney U tests.
2) Survival analysis: Time to first IGD occurrence during follow-up will be analyzed using Kaplan-Meier estimates and Log-rank tests. Cox proportional hazards models will calculate hazard ratios (HR) and 95% confidence intervals (CI).
3) Correlation and interaction analysis: Spearman rank correlation and interaction analyses will be conducted on IGD, demographics, gaming usage, academic experiences, and psycho-behavioral-social factors. Correlation coefficients and interaction term statistics (e.g., F values) will be reported.
4) IGD mechanism models: Mediation, moderation, and mixed effects models will be constructed using path analysis, logistic regression, and Structural Equation Modeling (SEM) based on correlation and interaction results. Robust Maximum Likelihood Estimation (MLE) will be used, with standardized regression coefficients (β) and indirect effects reported. Bootstrap resampling (1,000 iterations) will calculate 95% CI. Model fit indices will guide SEM modifications.
5) Propensity Score Matching (PSM): PSM will balance confounding factors between exposure and control groups. Logistic regression will calculate propensity scores, with nearest neighbor matching (caliper = 0.02) performed at a 1:1 ratio. Standardized differences ($d < 0.1$) will confirm covariate balance.
6) Sensitivity analysis: Various imputation strategies will assess the impact on effect estimates (e.g., HR, β). Stratified analysis will explore demographic effect modifications on gaming behavior and IGD association pre- and post-PSM. Forest plots will report sensitivity analysis results.

Predictive model

The construction of the predictive model involves key steps: data collection, preprocessing, feature extraction, model training, and evaluation:

1) Data collection: We will gather data on personal characteristics, internet gaming usage, academic experiences, and psycho-behavioral-social factors of gaming addicts through online surveys and Python-based web scraping. Baseline data will be used for training and testing, while prospective cohort data will validate the model.
2) Data preprocessing: This includes cleaning, normalization, feature selection, and data splitting. Cleaning removes incomplete or erroneous data; normalization scales the data; feature selection identifies important features via correlation and principal component analysis data splitting divides the sample into training, validation, and test sets in a 6:2:2 ratio.
3) Feature extraction: Relevant features will be extracted from the dataset based on research hypotheses and analysis results.
4) Model training:

- Model and software: We will use Cox proportional hazards and Weibull regression models to predict IGD. The Cox model predicts IGD risk over time, while the Weibull model predicts the exact time of IGD occurrence. These models will be implemented using Python 3.12.4 with the "lifelines" library ("CoxPHFitter" and "WeibullAFTFitter").
- Predictor determination: Significant predictors will be identified through statistical analysis, normalized using the Min-Max method, and selected based on a significance level of $P < 0.01$.

5) Model evaluation: Performance will be assessed using 10-fold cross-validation, confusion matrix, receiver operator characteristic (ROC) curve, area under the curve (AUC), and root mean square error (RMSE):

- Confusion matrix: We will calculate sensitivity (Se), false negative rate (β), specificity (Sp), false positive rate (α), Youden's index, positive predictive value (PPV), negative predictive value (NPV), overall accuracy (π), and F1 score.
- ROC curve and AUC: ROC curves will be plotted and AUC values calculated to determine feature cut-off values and compare model performance.
- RMSE: RMSE will be calculated to compare regression performance using the formula (2):

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n}(T_j - Y_j)^2}{n}} \quad (2)$$

Where T_j is the actual value and Y_j is the predicted value.

6) Model selection: The optimal model will be chosen based on evaluation results and cost-effectiveness analysis of IGD prevention.
7) Risk stratification: The model will stratify gamers into risk levels to provide targeted interventions:

- Risk prediction and assessment: Predict each player's IGD risk using the model.
- Set risk thresholds: Establish thresholds for low, medium, and high risk based on study data.
- Risk stratification: Classify players based on predicted scores and thresholds.
- Develop targeted interventions (see Table 2): Create intervention strategies based on risk levels. Low-risk players receive health tips; medium-risk players get targeted support and gaming restrictions; high-risk players need strict measures like time limits and professional counseling.
- Feedback and optimization: Collect and analyze the effectiveness of interventions, and adjust the predictive model and strategies based on feedback to better manage adolescent gaming behavior.

Strengths

This study has three main strengths: Firstly, it focuses on the mechanisms of IGD among adolescents, especially in the post-COVID-19 era, addressing an urgent public health issue. Secondly, it utilizes advanced data collection techniques, such as online surveys and Python-based web scraping, tailored to the highly active internet user group of university and high school students. These methods ensure real-time, accurate, and objective data collection while reducing participants' reluctance. Additionally, NLP is employed to structure data, uncovering multi-layered information beyond traditional surveys. Lastly, the study adopts an interdisciplinary approach, integrating gaming psychology theories with AI technologies and utilizing prospective cohort studies and SEM. This combination provides new perspectives and methodologies for addressing adolescent mental health issues by merging insights from psychology, computer science, and public health.

Limitations

Firstly, due to resource constraints, this study is conducted exclusively in Shenzhen, China, which may limit the generalizability of the findings. We hope that the initial results will raise awareness among government, educational, and health authorities about the severity of IGD, leading to more resources being allocated to this field in the future. Secondly, as an observational study relying primarily on online questionnaires and AI technology, it is challenging to obtain biological samples and neurobiological information from the participants. This may limit our exploration of the biological mechanisms underlying IGD. However, this design allows real-time acquisition of gaming behavior data, filling gaps in previous research. We also consider the dynamic effects of age changes and game types on the development of IGD, aspects that have been overlooked in prior studies.

Discussion

The COVID-19 pandemic has led to prolonged online education and improved internet access in many households, potentially increasing the risk of IGD among

Table 2 Risk stratification and intervention strategies for IGD

Risk level	Intervention strategies
Low risk	Periodically send tips and suggestions for healthy gaming habits and advice on balancing gaming with other life activities.
Moderate risk	Provide targeted support and counseling, and set limits on gaming time, such as restricting daily gaming hours or enforcing breaks after continuous gaming.
High risk	Implement stricter measures, such as further limiting gaming time, issuing strong warnings within the game, temporarily banning gaming, and guiding players to seek professional psychological counseling.

adolescents [9, 10, 38]. Our study aims to explore the current state of IGD, its possible mechanisms, and whether these mechanisms differ across age groups. Traditional studies have relied on passive monitoring, detecting IGD only when addiction is imminent, making interventions challenging and less effective. Proactive identification of high-risk individuals early on could prove more preventive than traditional measures like limiting gaming time. To address these issues, our prospective cohort study will combine online surveys and AI technology to collect real-time gaming behavior data from adolescents. Using Skinner's reinforcement theory, we will consider age and game type variations to deeply investigate IGD's development mechanisms, tackling this significant adolescent public health concern.

Abbreviations

IGD	Internet gaming disorder
WHO	World Health Organization
COVID-19	Coronavirus Disease 2019
AI	Artificial intelligence
DSM-5	The fifth edition of the Diagnostic and Statistical Manual of Mental Disorders
ESSA	Educational Stress Scale for Adolescents
MBI-SS	Maslach Burnout Inventory-Student Survey
BIS-11	Barratt Impulsiveness Scale
BSCS	Brief Self-Control Scale
DERS	Difficulties in Emotion Regulation Scale
CISS	Coping Inventory for Stressful Situations
GAD-7	Generalized Anxiety Disorder 7-item scale
MPPUS	Mobile Phone Problem Use Scale
BSMAS	Bergen Social Media Addiction Scale
MSPSS	Multidimensional Scale of Perceived Social Support
PAQ	Parental Authority Questionnaire
IPRI	Interpersonal Relationship Inventory
PS5	PlayStation 5
WOW	World of Warcraft
PUBG	PlayerUnknown's Battlegrounds
LOL	League of Legends
ChatGPT	Chat Generative Pre-trained Transformer
NLP	Natural Language Processing
SDK	Software Development Kit
API	Application Programming Interface
HTTP	HyperText Transfer Protocol
HTML	HyperText Markup Language
MCAR	Missing Completely at Random
MAR	Missing at Random
MCMC	Markov Chain Monte Carlo
FCS	Fully Conditional Specification
MNAR	Missing Not at Random
SAS	Statistical Analysis System
SPSS	Statistical Package for the Social Sciences
SD	Standard Deviation
IQR	Interquartile Range
HR	Hazard Ratios
CI	Confidence Intervals
SEM	Structural Equation Modeling
MLE	Maximum Likelihood Estimation
PSM	Propensity Score Matching
ROC	Receiver Operator Characteristic
AUC	Area Under the Curve
RMSE	Root Mean Square Error
Se	Sensitivity
Sp	Specificity
PPV	Positive Predictive Value
NPV	Negative Predictive Value

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12889-024-20028-4.

Supplementary Material 1

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Author contributions
YEH and RPW conceived the study. YEH designed the study, generated hypotheses, and interpreted the data in the study. RPW, YYH, YPX, and WZ collaborated in the design of the study. YEH and RPW prepared the initial draft protocol and YYH, YPX, and WZ revised the manuscript. YYH and YPX conducted the literature search. The corresponding author, YEH, attests that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted. All authors read, critically reviewed, and approved the final manuscript.

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Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
The protocol for this study has been approved by the Southern University of Science and Technology Institutional Review Board, which have accepted responsibility for supervising all aspects of the study (approval NO: 20230125). All participants and/or their guardians who agree to participate in the study will sign informed consent.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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