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Deep learning(s) in gaming disorder through the user-avatar bond: A longitudinal study using machine learning

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FULL-LENGTH REPORT

VASILEIOS STAVROPOULOS[1,3], DANIEL ZARATE[1*], MARIA PROKOFIEVA[2], NOIRIN VAN DE BERG[4], LEILA KARIMI[1], ANGELA GORMAN ALESI[5], MICHAELLA RICHARDS[6], SOULA BENNET[7] and MARK D. GRIFFITHS[8]

[1] Department of Psychology, Applied Health, School of Health and Biomedical Sciences, RMIT University, Australia

[2] Victoria University, Australia

[3] National and Kapodistrian University of Athens, Greece

[4] The Three Seas Psychology, Australia

[5] Catholic Care Victoria, Australia

[6] Mighty Serious, Australia

[7] Quantum Victoria, Australia

[8] International Gaming Research Unit, Psychology Department, Nottingham Trent University, UK

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ABSTRACT

Background and aims: Gaming disorder [GD] risk has been associated with the way gamers bond with their visual representation (i.e., avatar) in the game-world. More specifically, a gamer's relationship with their avatar has been shown to provide reliable mental health information about the user in their offline life, such as their current and prospective GD risk, if appropriately decoded. *Methods:* To contribute to the paucity of knowledge in this area, 565 gamers (M_{age} = 29.3 years; SD =10.6) were assessed twice, six months apart, using the User-Avatar-Bond Scale (UABS) and the Gaming Disorder Test. A series of tuned and untuned artificial intelligence [AI] classifiers analysed concurrently and prospectively their responses. *Results:* Findings showed that AI models learned to accurately and automatically identify GD risk cases, based on gamers' reported UABS score, age, and length of gaming involvement, both concurrently and longitudinally (i.e., six months later). Random forests outperformed all other AIs, while avatar immersion was shown to be the strongest training predictor. *Conclusion:* Study outcomes demonstrated that the user-avatar bond can be translated into accurate, concurrent and future GD risk predictions using trained AI classifiers. Assessment, prevention, and practice implications are discussed in the light of these findings.

KEYWORDS

gaming disorder, avatar, user-avatar bond, machine learning, artificial intelligence, online gaming

*Corresponding author.
E-mail: daniel.zarate.psychology@gmail.com

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INTRODUCTION

Since their commercial conception in the 1970s, videogames have become integrated into modern popular culture (Will, 2019). Alongside a boom in technological advancements and improved internet capabilities, the gaming industry has developed into a global community allowing millions around the world, and in Australia (where the present study was carried out), to enjoy gaming as a shared activity (Statista, 2023; Stavropoulos, Motti-Stefanidi, & Griffiths, 2022).

In the past two decades, gaming has greatly proliferated, with recent nationwide data suggesting that approximately 70% of all Australians (i.e., 17 million) play videogames in some form or frequency, while the vast majority of households (i.e., 8.6 million), including those with children, have access to digital game devices (Brand, Todhunter, & Jervis, 2017). Alongside the growth of gaming, gaming pathologies have begun to emerge (King et al., 2020). Literature highlights that while most gamers enjoy positive outcomes such as psychomotor/dexterity, cognitive, health, and educational benefits (Granic, Lobel, & Engels, 2014; Koulouris, Jeffery, Best, O'Neill, & Lutteroth, 2020; Nuyens, Kuss, Lopez-Fernandez, & Griffiths, 2017; Raith et al., 2021; Watson et al., 2019), a minority of gamers may experience harmful effects associated with excessive and/or disordered gaming (e.g., reduced educational/work performance, distress, loneliness; Burleigh, Griffiths, Sumich, Stavropoulos, & Kuss, 2019; Nuyens, Kuss, Lopez-Fernandez, & Griffiths, 2019; Şalvarlı & Griffiths, 2022; Stavropoulos et al., 2019; Colder Carras, Stavropoulos, Motti-Stefanidi, Labrique, & Griffiths, 2021; Van Looy, 2015; Šporčić & Glavak-Tkalić, 2018).

There is consensus that disordered gaming occurs as a consequence of the interplay between factors related to the individual players (e.g., personality, psychopathology), their immediate and more distant environmental surroundings (e.g., adverse family/peer interactions), as well as the game applications themselves (e.g., reinforcement schedules; King et al., 2019; Starcevic & Khazaal, 2020; Stavropoulos, Rennie, Morcos, Gomez, & Griffiths, 2021). For instance, in relation to individual factors, Király, Koncz, Griffiths, and Demetrovics (2023) highlighted disordered gaming risk factors including gender (being male), age (being younger), personality traits (higher neuroticism, higher impulsivity, low self-esteem), comorbidities (e.g., anxiety, autistic behaviours), motivation factors (e.g., escapism), and neurobiological predispositions (e.g., reduced grey-matter volume in the ventromedial and dorsolateral prefrontal brain areas). In relation to environmental factors, disordered gaming risk factors include poor quality of family relationships and parental monitoring, childhood maltreatment and easy access to gaming equipment, as well as pro-gaming peers and broader cultural influences (Király et al., 2023). Finally, in relation to specific structural characteristics of the game itself, disordered gaming risk factors include rewarding and reinforcing gaming experiences through operant conditioning processes, online game delivery, monetization aspects (e.g., buying/selling game winning equipment using offline currencies), and distinct game genres (e.g., Massively Multiplayer Online Role-Playing Games; MMORPGs; involving character development, socialization, competition and achievement elements; Király et al., 2023).

It should be noted that although higher gaming time has been related to higher disordered gaming risk, scholars have contended that it may not necessarily indicate disordered gaming, unless it compromises functionality in the gamer's everyday life (e.g., employment, education, and family life; Billieux, Flayelle, Rumpf, & Stein, 2019; Griffiths, 2010). Consequently, it is emphasized that high gaming involvement should be distinguished from disordered gaming (Billieux et al., 2019; Griffiths, 2010). Such literature has led to further calls for research examining the potentially harmful consequences of excessive gaming, as well as better identifying risk factors for developing problematic gaming patterns (Király, Potenza, & Demetrovics, 2022).

Disordered gaming

The World Health Organization (WHO) officially included gaming disorder (GD) in the 11th revision of the International Classification of Diseases (ICD-11; WHO, 2019). The ICD-11 defines GD as a pattern of gaming behaviour characterized by impaired control over gaming, increasing priority given to gaming over other activities to the extent that it takes precedence in daily life, and continuation/escalation of gaming despite the occurrence of negative consequences. The ICD-11 further states that a diagnosis of GD must have a significant impairment to an individual's personal, family, social, educational, occupational and/or other important areas of functioning (typically evident over a period of at least 12 months). Given the increased recognition of disordered gaming as a legitimate psychiatric condition, research into more specific risk factors and potential influencers of addictive gaming has greatly increased (Bäcklund, Elbe, Gavelin, Sörman, & Ljungberg, 2022; Liao, Chen, Huang, & Shen, 2022).

The WHO's (2019) diagnostic classification of GD followed the inclusion of the provisional diagnosis of internet gaming disorder (IGD) in the fifth edition of the Diagnostic and Statistical Manual for Mental Disorders (DSM-5; American Psychiatric Association, 2013). According to the DSM-5 (2013), and similar to WHO (2019) the criteria for diagnosing IGD includes: preoccupation with gaming, withdrawal symptoms when gaming is not possible, tolerance (i.e., needing to spend increasing amounts of time gaming), unsuccessful attempts to control or reduce gaming, loss of interest in other activities, continued excessive gaming despite negative consequences, and significant impairment in personal, social, educational, or occupational areas of functioning (with at least five of these criteria being met for more than a year to be considered as having a gaming disorder).

In the present study, the ICD-11 criteria for GD (WHO, 2019) were employed for three compelling reasons: (i) it is the only official (and not provisional) disordered gaming diagnosis currently employed worldwide; (ii) it has been supported that the ICD-11 diagnostic framework emphasizes more serious/pivotal (and a succinct number of) GD symptoms, without compromising diagnostic validity (Jo et al., 2019); and (iii) it provides consistency and comparability in relation to empirical evidence internationally (Pontes & Griffiths, 2019).

User-avatar bond

A number of scholars in the gaming studies field have reiterated that greater emphasis should be given to game-related features. This includes the user-avatar bond (UAB), as a potential GD risk factor in role-playing games (RPGs; Green, Delfabbro, & King, 2021; Lemenager, Neissner, Sabo, Mann, & Kiefer, 2020). RPGs have been consistently demonstrated to be a genre of videogames that have a higher risk of GD among individuals (Stavropoulos, Gomez, Mueller, Yucel, & Griffiths, 2020; Stavropoulos, Pontes, Gomez, Schivinski, & Griffiths, 2020; Szolin, Kuss, Nuyens, & Griffiths, 2022). An avatar is a visual in-game representation of the player, with the term originating from the Sanskrit word 'avatāra', referring to the embodiment of a deity in a human form (Lochtefeld et al., 2002; Szolin et al., 2022).

Within the gaming context, the avatar facilitates a process whereby the gamer may, to an extent, experience embodiment with their gaming persona/figure, while they are able to portray themselves in ways that align more with their desired self-expressions (Šporčić & Glavak-Tkalić, 2018; Stavropoulos, Gomez et al., 2020; Stavropoulos, Pontes et al., 2020). Consequently, a complex psychological attachment is facilitated between gamers and their avatars. This increases game engagement and can also influence some gamers' online and offline behaviours through subconscious processes (e.g., altered perceptions, automatic thoughts, and non-deliberate actions corresponding with their avatar features; Burleigh, Stavropoulos, Liew, Adams, & Griffiths, 2018; Liew, Stavropoulos, Adams, Burleigh, & Griffiths, 2018; Ortiz de Gortari, Pontes, & Griffiths, 2015; Ratan, Beyea, Li, & Graciano, 2020). Considering the UAB's particular strength/intensity, empirical research indicates that factors such as age, and the duration of engagement with the game world, may play a critical role in the how an individual connects with their avatar (e.g., younger gamers, with lengthier game involvement, could be more UAB receptive/susceptible, due to more dynamic/fluid personality features and time/emotional game investment; Stavropoulos, Gomez et al., 2020; Stavropoulos, Pontes et al., 2020; Stavropoulos, Ratan, & Lee, 2022; Rehbein, 2016).

Moreover, Blinka et al. (2008) noted that the UAB encompasses critical aspects and subdimensions. These entail identification (e.g., the gamer becomes more like their avatar, and they feel the same or alike), immersion (e.g., the avatar's needs in the world of the game [such as participating in a competition/task] are experienced as offline needs by the gamer, and can even be prioritised to their needs outside of the game [such as sleeping and/or eating] in the case of disordered gaming), and compensation/idealization (e.g., the avatar is who/how the gamer would like to have been in their offline life, but they may not be in a position to; the avatar may express an individual's ideal self).

Additionally, it has been argued that the need of some gamers, who might be experiencing low-self-esteem and/or may be dissatisfied by their offline self, could lead them to escape their discomfort through their idealized avatars within the game world (Stavropoulos, Gomez et al., 2020; Stavropoulos, Pontes et al., 2020; Stavropoulos, Ratan et al., 2022). Such avatar-mediated mood modification tendencies may cause some gamers to immerse/over-engage with (and emotionally depend on) their in-game character, fuelling their GD risk (Stavropoulos, Gomez et al., 2020; Stavropoulos, Pontes et al., 2020; Stavropoulos, Ratan et al., 2022). These findings are reinforced by other notable studies (e.g., those examining wishful avatar identification; Burleigh et al., 2018; Green et al., 2021; Liew et al., 2018; Yee, Bailenson, & Ducheneaut, 2009).

It has also been proposed that the UAB could operate as a form of 'digital phenotype', meaning a digital/gamified footprint of an individual's mental health, that, if analysed, can be translated into information not only concerning the gamer's risk of GD, but also for other psychopathological conditions (e.g., depression, anxiety [Loi, 2019; Stavropoulos et al., 2021; Zarate, Stavropoulos, Ball, de Sena Collier, & Jacobson, 2022]). Despite the consistent associations between GD and the UAB in the extant literature, the translation of the UAB into GD risk has never to date, to the best of the authors' knowledge, been investigated (Burleigh et al., 2018; Liew et al., 2018; Ortiz de Gortari et al., 2015; Ratan et al., 2020).

The present study

Analytical advancements in the field of machine learning (ML) can support artificial intelligence (AI) applications, which allow the automatic prediction/translation of one form of information/data into another (e.g., a gamer's UAB into GD risk; Horton & Kleinman, 2015; Kuhn & Wickham, 2020). To achieve such predictions, ML/AI procedures require training on related data, where predictors (e.g., UAB sub-dimensions) and outcomes (e.g., GD risk) are known, such that they can learn how to interpret/use the first variable to identify the latter (in the form of supervised algorithms; Horton & Kleinman, 2015; Kuhn & Silge, 2022; Kuhn & Wickham, 2020). After this stage is completed, a new set of data is examined by the trained AI/ML, where the accuracy of its predictions is validated (i.e., while in the first stage of the process AI learns to detect GD risk based on the UAB, in the second stage it makes predictions to demonstrate their learning quality; Kuhn & Silge, 2022).

Indeed, recent research examples have aimed to use ML/AI to diagnose GD via Resting Brain State, MRI, PET and EEG data with encouraging findings (Han et al., 2021; Song et al., 2021). Taking these into consideration, the present study innovatively examined a recently collected longitudinal dataset using AI/ML classifiers, aiming to translate gamers reported UAB identification, immersion, and compensation/idealization into their present and prospective (i.e., six months later) GD risk, while also taking into consideration their age and years of videogame engagement. In particular the choice of a longitudinal design was chosen over cross-sectional data collection because it allows the examination of the direction of causality between the behaviours examined, while additionally enabling the potential translation of the user-avatar bond into prospective GD risk (Zarate, Dorman, Prokofieva, Morda, &

Stavropoulos, 2023). Consequently, the following research questions (RQs) were formulated:

- RQ1: How can, if at all, ML/AI applications be trained to identify whether a gamer presents with current GD risk, based on their UAB reported identification, immersion, compensation, age, and length of gaming involvement (i.e., concurrent GD phenotype)?
- RQ2: How can, if at all, ML/AI applications be trained to identify whether a gamer presents with future GD risk (i.e., six months later), based on their UAB reported identification, immersion, compensation, age, and length of gaming involvement (i.e., prospective GD phenotype)?

METHODS

Participants

A sample of 627 gamers were initially recruited. Of these, seven were excluded as preview-only responses, 19 as spam, one as a bot, 12 due to lack of consent, eight for failing validity questions (e.g., claimed they played non-existing games; e.g., *Risk of Phantom*), and 15 for insufficient responses. Therefore, the final sample comprised 565 role-playing-gamers (M_{age} = 29.3 years SD = 10.6, Min_{age} = 12, Max_{age} = 68; $Males_{cisgender}$ = 283, 50.1%), who were longitudinally assessed in the community, six months apart (two time-points, T1 and T2). With regards to demographics at T1, 271 (55.3%) reported being full-time employed, 176 (36%) had an undergraduate degree, 359 (73.6%) stated heterosexual orientation, 410 (72.5%) identified as of Australian/English ancestry, 142 (25.1%) resided with their family of origin, and 148 (30.2%) were single.

With regards to gaming patterns at T1, they reported having been a gamer for on average for 5.62 years (Min=<1 year, Max = 30 years; SD = 4.49), for an average of 2.23 h daily during weekdays ($Min_{=}$<1 h, Max = 15 h; SD = 1.82) and 3.39 h during the weekend ($Min_{=}$<1 h, Max = 18; SD = 2.40). Considering social media use patterns at T1, they reported having been a social media user for an average of 7.06 years (Min=<1 year, Max=17; SD = 7.06), spending an average time of 2.55 h during weekdays (Min=<1 h, Max = 15 h; SD = 2.16), and 3.01 h during the weekend (Min=<1 h, Max = 16 h; SD = 2.48) with 145 (26%) reporting *Facebook* as their preferred platform. The maximum random sampling error for a sample of 565 at the 95% confidence interval (z = 1.96) equalled ± 4.12% satisfying Hill's (1998) recommendations. Missing values of the analysed variables at T1 ranged between 3 (0.5% not stating their age) to 16 (2.83% not answering Item 9 on the User-Avatar Bond Scale), and were missing completely at random in the broader dataset ($MCAR_{test}$ = 38.4, p = 0.14 $_{[9\ missing\ patterns]}$; Little (1988).

Attrition between waves was 276 participants (48.8%). Therefore, retention/attrition were studied in relation to participants' sociodemographic information considering statistical significance and effect size (Cohen's d, very small~0.01, small~0.20, medium~0.50, large, 0.80, very large~1.20; Sawilowsky, 2009); Cramer's V > 0.25 = very strong, >0.15 = strong, >0.10 = moderate, >0.05 = weak, >0 no or very weak). Low to moderate effect-sizes were found regarding the associations between attrition and gender (χ^2 = 4.26, df = 6, p = 0.642, Cramer's V = 0.087), sexual orientation (χ^2 = 7.75, df = 4, p = 0.101, Cramer's V = 0.126), ancestry (χ^2 = 8.94, df = 4, p = 0.063, Cramer's V = 0.126), romantic relationship engagement (χ^2 = 3.76, df = 4, p = 0.440, Cramer's V = 0.088), educational status (χ^2 = 11.2, df = 7, p = 0.129, Cramer's V = 0.152), employment status (χ^2 = 7.58, df = 6, p = 0.271, Cramer's V = 0.124), number of years spent gaming ($t_{Welch's}$ = 3.509, df = 526, p < 0.001, Cohen's d = 0.296), average daily gaming time during the week ($t_{Student}$ = 0.873, df = 555, p = 0.383, Cohen's d = −0.0741), average daily gaming time during the weekend ($t_{Student}$ = 0.159, df = 553, p = 0.874, Cohen's d = 0.0135), number of years spent using social media ($t_{Student}$ = 2.501, df = 556, p = 0.013, Cohen's d = 0.2118), average daily social media use time during the week ($t_{Student}$ = −2.313, df = 543, p = 0.021, Cohen's d = −0.1983), average daily social media use time during the weekend (t_{Welch} = −2.447, df = 501, p = 0.015, Cohen's d = −0.2111), and age ($t_{Student}$ = 4.967, df = 560, p < 0.001, Cohen's d = 0.4192). Tables 1 and 2 provide detailed description of the sample at T1.

Measures

In addition to data concerning demographics, gaming use, and social media use, the following data were collected.

Gaming Disorder Test (GDT-4; Pontes et al., 2021). The GDT-4 assesses the diagnostic features/severity of disordered gaming with a design directly modelled on the WHO (2019) conceptualisation. There are four items each addressing a

Table 1. Participant's age, gaming/social media use years and daily week and weekend consumed time at T1

	Age	Number of years spent gaming	Mean daily gaming time in the week	Mean daily gaming time at the weekend	Number of years spent using social media	Mean daily social media use time in the week	Mean daily social media use time at the weekend
N	562	556	557	555	558	545	543
Mean	29.3	5.62	2.23	3.39	7.06	2.55	3.01
SD	10.6	4.49	1.82	2.40	4.41	2.16	2.48
Min	12.0	0.00	0.00	0.00	0.00	0.00	0.00
Max	68.0	30.0	15.0	18.0	17.0	15.0	16.0

Table 2. Participants' sociodemographic, gaming and social media use information at T1

		N	Total N	Proportion	p
Gender	Man (cisgender)	283	565	0.501	1.000
	Woman (cisgender)	259	565	0.458	0.053
	Man (transgender)	4	565	0.007	<0.001
	Woman (transgender)	1	565	0.002	<0.001
	Nonbinary	12	565	0.021	<0.001
	Not Listed	3	565	0.005	<0.001
	Prefer not to say	3	565	0.005	<0.001
Sexual Orientation	Heterosexual-Straight	359	488	0.736	<0.001
	Homosexual	36	488	0.074	<0.001
	Bisexual	75	488	0.154	<0.001
	Asexual	5	488	0.010	<0.001
	Other	13	488	0.027	<0.001
Ancestry	Aus./Engl.	412	565	0.552	0.015
	Chinese	20	565	0.035	<0.001
	German	7	565	0.012	<0.001
	Indian	10	565	0.018	<0.001
	Other	118	565	0.209	<0.001
Occupational Status	Full-time employed	271	490	0.553	0.021
	Part-time employed	77	490	0.157	<0.001
	Student	64	490	0.131	<0.001
	Trainee	2	490	0.004	<0.001
	Not currently working	32	490	0.065	<0.001
	On temporary leave (education leave, public service leave, training, maternity leave)	5	490	0.010	<0.001
	Other	39	490	0.080	<0.001
Educational Status	Professional degree (i.e., MD, JD, etc. completed)	10	489	0.020	<0.001
	PhD degree (completed)	17	489	0.035	<0.001
	Postgraduate studies (MSc completed)	67	489	0.137	<0.001
	Undergraduate university course (completed)	176	489	0.360	<0.001
	Intermediate between secondary level and university (e.g., technical training)	97	489	0.198	<0.001
	Senior secondary school (Years 11–12)	101	489	0.207	<0.001
	Secondary school (Years 7–10)	9	489	0.018	<0.001
	Other	12	489	0.025	<0.001
Livingwith_w1	Family of origin (two parents/partners, only child)	34	564	0.060	<0.001
	Family of origin (two parents/partners and siblings)	108	564	0.191	<0.001
	Mother (only child, parent divorced-separated-widowed)	19	564	0.034	<0.001
	Mother and sibling(s) (parent divorced-separated-widowed)	17	564	0.030	<0.001
	Father (only child, parent divorced-separated-widowed)	6	564	0.011	<0.001
	Father and sibling(s) (parent divorced-separated-widowed)	5	564	0.009	<0.001
	With partner	149	564	0.264	<0.001
	Alone	61	564	0.108	<0.001
	With friend(s)	28	564	0.050	<0.001
	Temporary accommodation	4	564	0.007	<0.001
	Other	18	564	0.032	<0.001
	With partner and children	115	564	0.204	<0.001
Relationship status	Single	148	490	0.302	<0.001
	In a romantic relationship (A romantic relationship is defined as a romantic commitment of particular intensity between two individuals of the same or the opposite sex (When you like a guy [girl] and he [she] likes you back).	157	490	0.320	<0.001
	Engaged	24	490	0.049	<0.001
	Married	145	490	0.296	<0.001
	De facto	16	490	0.033	<0.001
Partner games together	Yes	99	344	0.288	<0.001
	No	245	344	0.712	<0.001
Partner uses social media together	Yes	227	340	0.677	<0.001
	No	113	340	0.333	<0.001

(continued)

Table 2. Continued

		N	Total N	Proportion	p
Social media users	Yes	550	565	0.973	<0.001
	No	15	565	0.027	<0.001
Facebook users	No	168	565	0.297	<0.001
	Facebook	397	565	0.703	<0.001
Twitter users	No	320	565	0.566	0.002
	Twitter	245	565	0.434	0.002
Instagram users	No	195	565	0.345	<0.001
	Instagram	370	565	0.655	<0.001
Pinterest users	No	469	565	0.830	<0.001
	Pinterest	96	565	0.170	<0.001
TikTok users	No	368	565	0.651	<0.001
	Tik Tok	197	565	0.349	<0.001
Most preferred social media	Facebook	145	557	0.260	<0.001
	Twitter	66	557	0.118	<0.001
	Instagram	135	557	0.242	<0.001
	Pinterest	5	557	0.009	<0.001
	Tik Tok	99	557	0.178	<0.001
	Other, please define which	107	557	0.192	<0.001
Gaming with best friend	No	336	565	0.595	<0.001
	Yes	229	565	0.405	<0.001
Using social media with best friend	No	189	565	0.335	<0.001
	Yes	376	565	0.665	<0.001
Gaming with other friends	No	312	565	0.552	0.015
	Yes	253	565	0.448	0.015
Using social media with offline friends	No	154	565	0.273	<0.001
	Yes	411	565	0.727	<0.001
Gaming with family members	No	406	565	0.719	<0.001
	Yes	159	565	0.281	<0.001
Using social media with family members	Yes	472	564	0.837	<0.001
	No	92	564	0.163	<0.001

Note. H_a is proportion $\neq 0.5$.

particular symptom (e.g., *"I have had difficulties controlling my gaming activity"*) using a five-point Likert-type scale from 1 (*Never*) to 5 (*Very often*). Total scores range from 4 to 20 with higher scores indicating greater GD severity. Participants at GD risk were classified those with more than 3/5 (*Often*) in ¾ of the GDT-4 items (Pontes et al., 2021). The internal consistency coefficients were sufficient across both study waves (Cronbach's $\alpha_{\text{GDT wave 1}} = 0.808$, McDonald's $\omega_{\text{GDT wave 1}} = 0.812$, Cronbach's $\alpha_{\text{GDT wave 2}} = 0.854$, McDonald's $\omega_{\text{GDT wave 2}} = 0.862$).

User-Avatar-Bond Questionnaire (UAB-Q; Blinka, 2008)

The UAB-Q was used to assess different gamer-avatar bond dimensions. The 12 UAB-Q items are answered on a 5-point Likert scale from 1 (*strongly disagree*) to 5 (*strongly agree*) comprising three factors: identification (four items; *"Both me and my character are the same"*), immersion (five items: *"Sometimes I think just about my character while not gaming"*), and compensation (three items: *"I would rather be like my character"*). The scores range from 12 to 60 with higher scores indicating stronger UAB experiences both overall and on the respective subscales. The internal consistency coefficients were sufficient across both study waves (Cronbach's $\alpha_{\text{UAB-Q wave 1}} = 0.804$; McDonald's $\omega_{\text{UAB-Q wave 1}} = 0.813$, Cronbach's $\alpha_{\text{UAB-Q wave 2}} = 0.849$; McDonald's $\omega_{\text{UAB-Q wave 2}} = 0.867$, Cronbach's $\alpha_{\text{Ident. wave 1}} = 0.701$; McDonald's $\omega_{\text{Ident. wave 1}} = 0.729$, Cronbach's $\alpha_{\text{Ident. wave 2}} = 0.770$; McDonald's $\omega_{\text{Ident. wave 2}} = 0.789$ Cronbach's $\alpha_{\text{Immers. wave 1}} = 0.717$; McDonald's $\omega_{\text{Immers. wave 1}} = 0.727$, Cronbach's $\alpha_{\text{Immers. wave 2}} = 0.764$; McDonald's $\omega_{\text{Immers. wave 2}} = 0.775$, Cronbach's $\alpha_{\text{Comp. wave 1}} = 0.604$; McDonald's $\omega_{\text{Comp. wave 1}} = 0.656$, Cronbach's $\alpha_{\text{Comp. wave 2}} = 0.660$; McDonald's $\omega_{\text{Comp. wave 2}} = 0.709$).

Procedure

Approvals were granted by the Victorian University Human Research Ethics Committee [HRE21-044], the Department of Education and Training of The Victorian State Government, Australia [2022_004542], and the Melbourne Archdiocese of Catholic Schools [1179]. Participants were sampled from the community (e.g., RMIT, Victoria, Melbourne and Deakin Universities), Victorian public and catholic schools, Australian gamers' groups (e.g., Aus Gaymers Network), venues (e.g., Fortress Melbourne), and online forums (e.g., AusGamers), as well as advertising via *YouTube* videos. Gamers older than 12 years were eligible to voluntarily/anonymously participate and were provided with the plain language information statement describing the study aims, risks and their participation rights (e.g., withdrawal without any penalties and/or repercussions at any point) and provided their informed consent. For adolescents (i.e., 12–18 years), these were firstly addressed by their responsible parent/guardian and secondly by the adolescents themselves. Data collection involved three data-streams, paired via a non-identifiable code, unique for each participant: (i) a battery of demographic, internet/gaming/social media use questions, and psychometric questionnaires/scales available via an online *Qualtrics* link; (ii) wearing an actigraphy tracker (*Fitbit*) for seven days to monitor physical activity/sleep (e.g., daily steps and sleep duration), that was electronically paired with the other data-streams via a unique code (i.e., records were automatically collected via the *Fitbit* portal based on the participant's code and those not owning a *Fitbit* were provided with a device during a mutually arranged/agreed meeting with the research team) and; (iii) carrying a mobile monitoring application, called *Aware Light* (Van Berkel, D'Alfonso, Susanto, Ferreira, & Kostakos, 2023) recording screen on/off time, number and length of calls (i.e., duration) and texts (i.e., length in characters) for seven days (i.e., *Light Aware* data were also matched with the other data-streams through the unique participant code). The procedure was repeated four times, once every six months, with the present study being based on the first two completed collection waves (for detailed information see Supplementary Materials 1.

Data analysis

To address RQ1 (i.e., concurrent GD digital phenotype; identifying present GD risk based on an individual's age, number of years spent gaming, and reported avatar identification, immersion and compensation/idealization) machine learning (ML) procedures using the Tidymodels package were conducted in R-Studio (Horton & Kleinman, 2015; Kuhn & Wickham, 2020). Firstly, data were balanced considering Yes/No GD risk cases to improve learning/ML-prediction using the synthetic minority oversampling technique (SMOTE; DMwR package; Torgo & Torgo, 2013). This algorithm introduces additional cases of the minority group by taking into consideration a potential number (k) of their nearest neighbours based on Euclidean distance (Chawla, Bowyer, Hall, & Kegelmeyer, 2002).

Practically, k-NN operates by identifying the distance between a suggested case and all other data cases considered. Firstly, it chooses a number (k) of cases nearest to the point of interest. Then, it attaches the most frequent class to that point (e.g., Yes/No GD risk; Chawla et al., 2002). Secondly, data were split into 4/5 training and 1/5 testing, stratifying Yes/No GD risk proportions to be equal across the splits, while adopting a conservative bell-shaped Bayesian prior distribution. It should be noted that when adopting a Bayesian perspective, a potential distribution/variability is required for every model parameter before proceeding to data analysis. The range of these values was carefully/modestly/conservatively suggested here to follow a Cauchy shape (i.e., t-shape with seven degrees of freedom; Muth, Oravecz, & Gabry, 2018).

Finalized training and testing datasets were similar regarding Yes/No GD risk proportions ($\chi^2 = 0$, df $= 1$, $p = 1$). For cross-validation and ML hyperparameters' tuning, training data were additionally divided 10 times (i.e., folds) and training data bootstrapped versions were also created. Thirdly, the ML recipe (i.e., predictive equation) was introduced, such that: (i) the binary Yes/No GD risk at T1 was the outcome and age, number of years spent gaming, avatar-identification, avatar-immersion and avatar-identification were the independent predictors; (ii) a minimum ratio of 50% GD risk cases was maintained across all samples tested, including the cross-validation and bootstrapped training data versions; and (iii) zero variance, strongly sparse/skewed, and potentially highly inter-correlated predictors were excluded, to solidify findings. It should also be highlighted that the latter did not effectively exclude any predictor in the current recipe.

Predictors were also scaled and centred prior to the recipe to accommodate classification (i.e., 0 = mean and 1 = Standard Deviation [SD]; Kuhn & Wickham, 2020). Fourthly, a series of supervised ML models (i.e., models where the outcome is known in the training step/stage) recommended for binary classification (see Table 3) were introduced, alongside the null model (i.e., no ML prediction) in their tuned and their untuned versions, where hyperparameters were appropriately adjusted (Kuhn & Wickham, 2020). A hyper-parameter constitutes an ML parameter, the value of which needs to have been specified prior to the learning ML being trained, in contrast to simple parameters which are "learned" during the training of the model. Therefore, hyperparameters pose external model configurations (i.e., not based on the data) employed for the estimation of model parameters. Fine-tuned hyperparameters increase the capacity of a learning model to perform with higher accuracy, and are achieved through a "grid" process in tidymodels (Kuhn & Wickham, 2020).

Fifthly, model and recipes were combined to create different workflows, which were: (i) trained in the default versions on the training data; (ii) tuned considering their hyperparameters via the bootstrapped versions the training data, and; (iii) tested across their default/tuned versions on the testing data. To address RQ2 (i.e., prospective GD digital phenotype in six months), the same procedure was repeated with GD T2 being the outcome/dependent variable. Findings were compared based on their confusion matrices, accuracy, precision, the area under the curve,

Table 3. ML models trained, tuned and tested

Type	Operation	Hyperparameters tuned	R-package/engine employed
Least Absolute Shrinkage Selection Operator (LASSO)	LASSO constitutes a regression analysis based, supervised ML classifier, that applies variable selection and regularization to increase prediction accuracy. It achieves that via reducing noises and selecting certain features to regularize the model. From a calculation perspective lasso considers the magnitude rate of the coefficient, as a penalty to the loss function. Therefore, the loss function is amended to reduce model complexity via restraining the sum of predictors' coefficients [Loss function = OLS + A (penalty) X summation (addition of s size[s] of coefficients)].	*penalty* = To perform regularization (i.e., L1), LASSO considers/adds a penalty to the size of regression coefficients (i.e., predictor effects), aiming to minimize them. The optimum penalty value is obtained via the tuning process.	*glmnet*
K Nearest Neighbours (k-NN)	Th k-NN algorithm entails a supervised, non-parametric classification/prediction, that relies on estimating proximity/relevance/distance of one case with "*k*" others, as per their Euclidean distance. Alternatively, k-NN classifies/categorizes a case taking into consideration its neighbouring cases (i.e., similarity of a case with previously identified cases).	*neighbors* = The number (k) of neighbouring points to be considered in order to optimize the learning/prediction performance of the algorithm, as defined via the tuning process.	*knn*
Support Vector Machine Kernel (SVM-K)	Kernel ML is based on pattern examination/analysis and is mostly known via its popular support-vector machine (SVM) version. The kernel function refers to a mathematic procedure, which enables SVM to pursue deep learning via conducting bidimensional classifications of uni-dimensional data through the projection of a lower-dimension to a higher one. Subsequently, a kernelized SVM employs a linear computation to address non-linear/classification problems.	*cost* = In SVM, cost resembles/postulates the logistic function via a piecewise linear. In practice, the cost hyperparameter programs/guides the algorithm's optimization regarding the rate/size of misclassification allowed in the training sample. Higher cost values indicate tighter margins and the opposite. *degree* = The degree hyperparameter dictates the flexibility/boundaries of prediction(s), such that higher values allow higher flexibility. *scale_factor* = The scaling hyper-parameter of categorical/classification kernel(s) reflects the optimum normalization patterns/process (i.e., kernel width) required to avoid any data modification.	*kernlab*
X Gradient Boosting (XGB)	XGBoost is recommended for structured/tabular data. It implements gradient boosted decision trees to optimize prediction. XGBoost does so via providing a parallel tree boosting that integrates/considers weak prediction/learner models/decision trees. However, and in contrast to random forest bagging	*mtry* = The number of independent variables to be randomly assessed at each decision tree split. *min_n* = An integer/value/number for the least data points in a node (i.e., tree branch) that enables further split. *tree_depth* = The value defining the highest tree depth (i.e., subsequent	*xgboost*

(continued)

Table 3. Continued

Type	Operation	Hyperparameters tuned	R-package/engine employed
	of generated trees, XG-Boosting operates in a sequential manner, with any subsequent tree being influenced by the previous/last tree outcome.	splits) suggested to optimize prediction. *Learn rate (i.e., shrinkage)* = The value/rate required for the boosting adaptation to occur over successive iterations. *loss_reduction* = The reduction rate of the loss function suggested to progress with tree splits. *sample_size* = The amount/ proportion of data required to be utilized in the algorithm's fitting process over each iteration.	
Random Forests	Random Forest is a flexible and broadly employed supervised, ensemble (i.e., composite) ML model, that integrates/considers the results of numerous decision trees (i.e., bagging), while being trained/ learning to address a prediction/ classification task. Practically, random forests conduct a meta-estimation that averages/considers the outcomes of multiple decision tree classifiers, implemented on different data sub-samples, to improve accuracy and deter over-fitting.	*mtry* = The number of independent variables to be randomly assessed at each decision tree split. *min_n* = An integer/value/number for the least data points in a node (i.e., tree branch) that enables further split.	*ranger*
Naïve Bayes	Naïve Bayes operates as a probabilistic, supervised, ML classifier, which functions generatively. This suggests that it aims to model the data class distribution, while assuming conditional independence probability (i.e., data characteristics/ measures are independent) to predict the way a specific class would generate input data.	*smoothness* = This refers to the Kernel component Smoothness, which defines the density value required for the algorithm to converge quicker, to the real density of random numeric predictors. *Laplace* = Laplace transformation/ smoothing refers to a technique/ strategy/method that addresses the problem/risk of zero probability in the algorithm.	*naivebayes*
Logistic Regression	Logistic Regression is also considered a supervised ML classifier that employs a logistic function to predict/model binary/dichotomous dependent outcomes.	*penalty* = In logistic regression, as with LASSO, the regularization penalty hyperparameter aims to address generalization error and therefore reduce overfitting risks. As such, it enhances the probability of simpler concluded models. *mixture* = A regularization parameter value ranging between 0 and 1 to enhance model accuracy [mixture 1 corresponds with LASSO; 0 with ridge regression and in the interim with elastic modelling in between LASSO and ridge].	*glm*

Note: Glmnet is derived from "Friedman et al. (2010). Package 'glmnet'. *CRAN R Repositary*."; Ranger is derived from "Wright and Ziegler (2017). Package 'ranger'." Kernlab is derived from "Karatzoglou, Smola, and Hornik (2023). Package 'kernlab'. *CRAN R Project*". Xgboost is derived from "Chen et al. (2023). Package 'xgboost'. *R version*, *90*, 1–66.". All other engines ae derived from " Kuhn, M., & Silge, J. (2022). *Tidy Modeling with R*. " O'Reilly Media, Inc.".

recall, and f-measures (see yardstick r package; Kuhn, Vaughan, & Vaughan, 2020).[1]

Preceding the analysis, estimation for the sample size was also considered from the overfitting perspective of the developed models. In machine learning, overfitting refers to the modelling error occurring, when a function used in a model is too closely aligned to a limited set of data points. This indicates insufficiency of the data and results in a model generating accurate predictions for training data but not for new/testing data (Chawla et al., 2002). The present study addressed overfitting by considering the imbalance in the dataset, and using the Synthetic Minority Over-Sampling TEchnique (SMOTE; Chawla et al., 2002; Torgo & Torgo, 2013), applying early stopping in Random Forest application, as well as use of regularization technique LASSO. Further measures included cross-validation and hyperparameter tuning of the developed models (see Table 3).

Ethics

All procedures performed in the study involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. The paper does not contain any studies with animals performed by any of the authors. Informed consent was obtained from all individual participants included in the study.

[1]Accuracy reflects the ratio of correctly predicted cases, across the total number of cases. It is produced through the accumulation of the true positive and the true negative cases divided by the sum of all true positive, true negative, false positive and false negative cases. Accuracy values closer to 1 are considered desirable. Accuracy >0.90 = Excellent; 70%<Accuracy<90% = Very good; 60%<Accuracy<70% = Good; Accuracy<60% is poor (Allwright, 2022).
Area under the curve (AUC) refers to the area under the receiver operating characteristic (ROC) curve, as the latter is visualized in an orthogonal axis system/graph, where the horizontal line captures the false positive rate (FPR; 1 – specificity) and the vertical axis the sensitivity (True positive rate [TPR]; values closer to 1 are considered better/improved). AUC <0.5 = No discrimination; 0.5<AUC<0.7 = Poor discrimination; 0.7<AUC<0.8 = Acceptable discrimination; 0.8<AUC<0.9 = Excellent discrimination; AUC>0.9 = Outstanding discrimination (Statology, 2021).
Positive Predictive Value [PPV] or Precision is irrespective of the prevalence of a condition, and reflects the proportion/ratio of all the true positive classified cases divided by the addition of the true positive and the false positive cases (i.e., how many of those classified as positive were actually positive? Values closer to 1 are considered better/improved).
Recall or sensitivity is associated to the prevalence of a condition and reflects the proportion/ratio of all the true positive classified cases divided by the sum of all the true positive and the false negative classified cases (i.e., how many of the true positive cases have been recalled? Values closer to 1 are considered better/improved).
Specificity reflects the proportion/ratio of all the true negative classified cases divided by the sum of all the true negative and the false positive classified cases (i.e., how many of the true negative cases have been correctly classified? Values closer to 1 are considered better/improved).
F-Measure or F1-score/F-Score reflects the ratio of the multiplication of recall and precision, multiplied by two and then divided by the accumulation of recall and precision, such that the balance between precision and recall achieved by the model is captured. Higher values are considered better/improved (Jiao & Du, 2016).

RESULTS

Before addressing RQ1 and RQ2, Yes/No GD risk$_{wave_1}$ participants were identified with $N_{no\_GD\_Risk}$ = 430 (80.22%) and $N_{Yes\_GD\_Risk}$ = 106 (19.78%). For RQ1, to accommodate ML learning, oversampling of the minority class was conducted using k-NN SMOTE (Chawla et al., 2002; Torgo & Torgo, 2013) resulting in a balanced dataset (i.e., $N_{Yes\_GD\_Risk}$ = 530; 50%). Data were then split into 80% training and 20% testing and the proportions of Yes/No GD risk were compared across the two parts showing non-significant differences ($\chi^2 = 0$, df = 1, $p = 1$; Cramer's V = 0.00; 50% Yes GD risk across both training and testing). The prediction recipe was introduced, scaling of predictors was conducted, descriptives of the training, testing and whole dataset were estimated (see *bake recipe* section; Supplementary Material 2), while 10 sub-divisions and bootstrapped versions of the training data were produced for cross-validation and hyperparameter tuning (see *folds & train_boot* section, Supplementary Material 2). Models and workflows of the Null, LASSO, SVM-Kernel, Random Forests, Naïve Bayes, and Logistic Regression (see Table 3) in their default hyperparameter versions (i.e., untuned) were then introduced, trained on the training data, and tested on the testing data. Table 4 summarizes their performance suggesting that, while all classifiers performed/learned acceptably and better than the null model, except LASSO, Random Forests learning outperformed other classifiers with excellent indicators across all criteria (see Fig. 1). Immersion was the most significant predictor for Random Forests (i.e., >25 points) with all other predictors exceeding 10 points (see VIP section, Supplementary Material 2).

To optimize learning and modelling capacity, the versions of LASSO, SVM-Kernel, Random Forests, Naïve Bayes and Logistic Regression, as well as XGB and k-NN were later tuned (see Table 3 regarding their respective hyperparameters' functions), trained on the training data and tested on the testing data. Table 5 summarizes the tuned hyperparameters' values per classifier and Table 6 their performance. Results suggest that, while all classifiers performed/learned acceptably and better than the null model, including LASSO, Random Forests learning outperformed other classifiers comparatively with excellent indicators across all criteria, followed by XGB, SVM-Kernel, and k NN (see Fig. 2).

The same process was repeated for RQ2 with Random Forests again outperforming other classifiers in both their tuned and untuned versions. Tables 7–9 summarize the performance of the untuned versions, the tuned hyperparameters' values, and the performance of the tuned classifiers respectively. Figures 3 and 4 visualize the performance of the tuned and untuned models (see Supplementary Material 3 and 4).

DISCUSSION

The present longitudinal study employed a relatively large, normative sample of gamers to train AI/ML automated

Table 4. Null model and untuned algorithms performance on testing data (GD Wave 1)

	Null model	Random forests	Logistic regression	LASSO	Naïve Bayes	SVM Kernel
ROC_AUC	0.5	0.975	0.701	0.5	0.788	0.741
PPV	0.5	0.942	0.641	0.5	0.8	0.664
F_meas	0.667	0.933	0.673	0.667	0.712	0.685
Recall	1	0.925	0.708	1	0.642	0.708
Accuracy	0.5	0.934	0.656	0.5	0.741	0.675

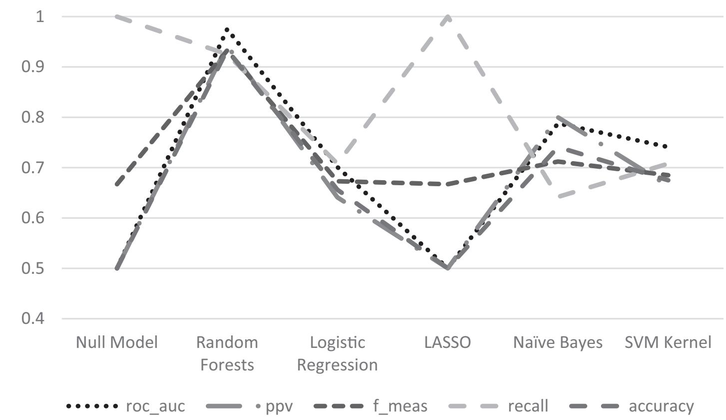

Fig. 1. Untuned classifiers performance across the criteria (GD Wave 1)

Table 5. Hyperparameter tuning summary across classifiers (GD Wave 1)

Type	Hyperparameters tuned	Tuning results
Least Absolute Shrinkage Selection Operator (LASSO)	*penalty*	0.00139
K Nearest Neighbours (k-NN)	*neighbors*	10
Support Vector Machine Kernel (SVM-K)	*cost*	32
	scale_factor	1
X Gradient Boosting (XGB)	*mtry*	1
	min_n	6
	tree_depth	15
	Learn rate (i.e., shrinkage)	11
	loss_reduction	0.0425
	sample_size	0.171
Random Forests	*mtry*	1
	min_n	6
Naïve Bayes	*smoothness*	0.5
	Laplace	0
Logistic Regression	*penalty*	0.00234
	mixture	0.55

See Table 3 for detailed information regarding the classifiers applied.

procedures to identify an individual's concurrent and prospective (i.e., six months later) GD risk, based on their age, number of years spent gaming, and reported avatar identification, immersion, and compensation/idealization. Five untuned (i.e., in their default versions) and seven tuned (i.e., ML/AI hyper-parameters/calculation features specifically adjusted to improve learning) recommended, and widely employed ML classifiers, were comparatively examined twice (i.e., current and prospective GD risk; Blinka, 2008; Kuhn & Silge, 2022).

The data were split into training and testing parts for the AIs to be trained and assessed respectively, while a prediction recipe was introduced. The models were trained, tuned, and tested, such that their capacity to learn whether an individual presents or not to be at GD risk at present and six months later, could be confirmed. Findings demonstrated that while all AI classifiers tested in the present study, were able to learn and performed better than the null model (i.e., random prediction), Random Forests had the strongest learning potential. Of the UAB aspects identified, immersion was the most important predictor of GD risk.

Gaming disorder and user-avatar bond

The present study's findings align with previous studies suggesting that stronger/higher UAB experiences are more likely to associate with excessive/disordered/problematic gaming, when/if there is a tendency for the individual to 'escape from reality', as a result of identity-related issues including poor self-concept, psychological vulnerability, and 'wishful identification' (i.e., compensation for negative self-perceptions; Green et al., 2021; Lemenager et al., 2020; Šporčić & Glavak-Tkalić, 2018; Stavropoulos, Gomez et al., 2020; Stavropoulos, Pontes et al., 2020; Van Looy, 2015). Moreover, scholars have supported that one of the most important indicators of GD is the process of transporting the

Table 6. Tuned algorithms performance on testing data (GD Wave 1)

	Null model	Random forests	Logistic regression	LASSO	Naïve Bayes	SVM Kernel	XGB	k-NN
ROC_AUC	0.5	0.981	0.704	0.704	0.811	0.96	0.955	0.939
PPV	0.5	0.951	0.647	0.647	0.755	0.959	0.873	0.966
F_meas	0.667	0.938	0.676	0.676	0.725	0.916	0.889	0.876
Recall	1	0.925	0.708	0.708	0.698	0.877	0.906	0.802
Accuracy	0.5	0.939	0.66	0.66	0.736	0.92	0.887	0.887

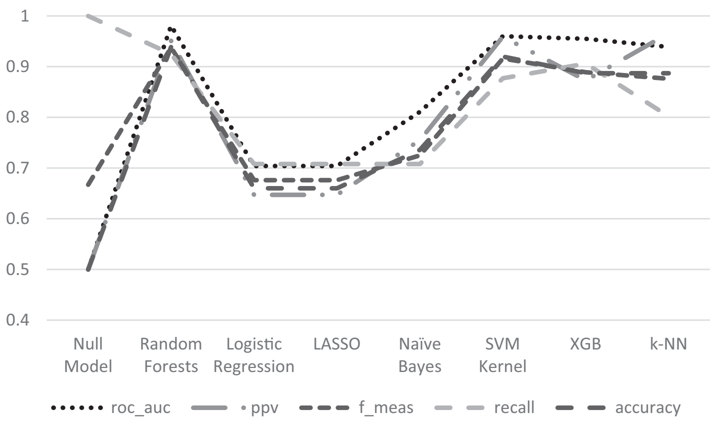

Fig. 2. Tuned classifiers performance across the criteria (GD Wave 1)

Table 7. Null model and untuned algorithms performance on testing data (GD Wave 2)

	Null model	Random forests	Logistic regression	LASSO	Naïve Bayes	SVM Kernel
ROC_AUC	0.5	0.959	0.718	0.724	0.744	0.708
PPV	0.5	0.897	0.667	0.629	0.735	0.68
F_meas	0.667	0.897	0.643	0.65	0.673	0.63
Recall	1	0.897	0.621	0.672	0.621	0.586
Accuracy	0.5	0.897	0.655	0.638	0.698	0.655

Table 8. Hyperparameter tuning summary across classifiers (GD Wave 2)

Type	Hyperparameters tuned	Tuning results
Least Absolute Shrinkage Selection Operator (LASSO)	*penalty*	0.00569
K Nearest Neighbours (k-NN)	*neighbors*	10
Support Vector Machine Kernel (SVM-K)	*cost*	32
	scale_factor	1
X Gradient Boosting (XGB)	*mtry*	1
	min_n	3
	tree_depth	11
	Learn rate (i.e., shrinkage)	0.00268
	loss_reduction	0.495
	sample_size	0.336
Random Forests	*mtry*	1
	min_n	6
Naïve Bayes	*smoothness*	0.5
	Laplace	0
Logistic Regression	*penalty*	0.0264
	mixture	0.35

See Table 3 for detailed information regarding the classifiers applied.

players' psyche into the gaming environment, that is, the facilitation of a true *"detachment from reality and the actual self"* (Šporčić & Glavak-Tkalić, 2018, p. 8).

Relatedly, the player-avatar connection/interaction is maintained by identification and idealisation, and subsequently strengthened through both the immersive qualities of the game itself, and the 'escape motives' of players (Green et al., 2021; Lemenager et al., 2020; Šporčić & Glavak-Tkalić, 2018; Stavropoulos, Gomez et al., 2020; Stavropoulos, Pontes et al., 2020; Stavropoulos, Ratan et al., 2022). Therefore, the immersion factor, expressing the experience of the avatar's needs as offline needs of the gamer, can be seen as advancing UAB understanding, while sharpening the explanatory framework for players vulnerable to GD (Stavropoulos, Ratan et al., 2022). It is perhaps unsurprising that of all the UAB aspects considered within the present study, immersion was found to be the strongest predictor of GD risk. In other words, whether a gamer resembles their avatar (i.e., identification) or wishes to be like their avatar (i.e., compensation/idealization) appears to induce lower GD risk, compared to the extent that a gamer fuses with their avatar's needs, experiencing them as theirs (Ratan et al., 2020). The latter increases more their GD likelihood and

Table 9. Tuned algorithms performance on testing data (GD Wave 2)

	Null model	Random forests	Logistic regression	LASSO	Naïve Bayes	SVM Kernel	XGB	k-NN
ROC_AUC	0.5	0.959	0.72	0.721	0.773	0.95	0.85	0.904
PPV	0.5	0.883	0.673	0.685	0.792	0.981	0.8	0.947
F_meas	0.667	0.898	0.655	0.661	0.717	0.946	0.741	0.75
Recall	1	0.914	0.638	0.638	0.655	0.914	0.69	0.621
Accuracy	0.5	0.897	0.664	0.672	0.741	0.948	0.759	0.793

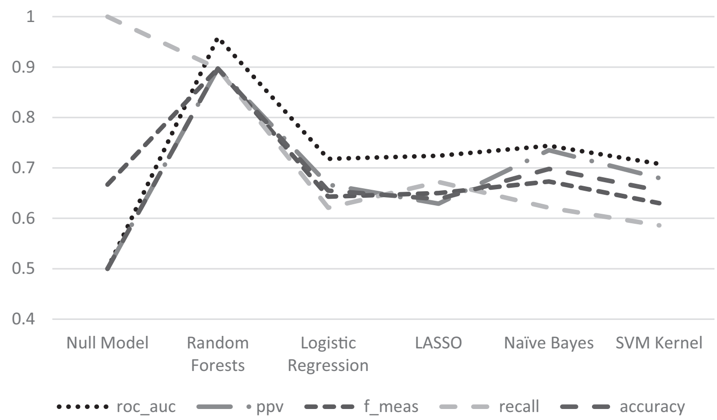

Fig. 3. Untuned classifiers performance across the criteria (GD Wave 2)

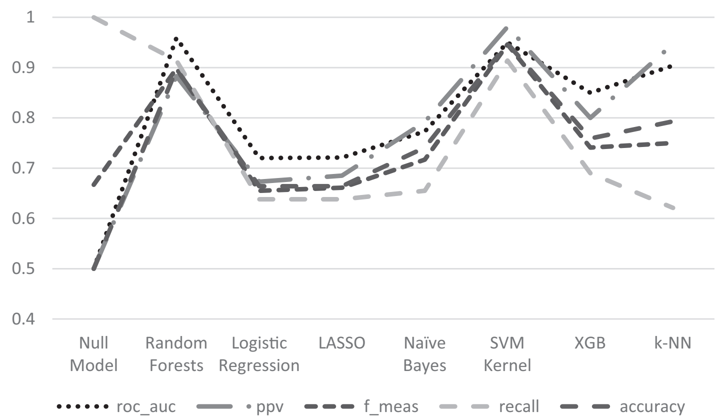

Fig. 4. Tuned classifiers performance across the criteria (GD Wave 2)

presents an opportunity for AI to better learn to detect those at risk of GD.

Furthermore, the methods employed in the present study expand and advocate for the ML/AI translation of the UAB into GD risk, while considering the age of the gamer and the number of years they have spent gaming. Findings suggest that the UAB could operate as a diagnostic indicator of GD risk both at present and prospectively (six months later), when addressed using trained ML/AI procedures. This aligns with past literature recommending the careful decoding/interpretation of the health/mental health information likely embedded in the UAB (Stavropoulos et al., 2021). Indeed, the avatar's customization by the gamer, allows conscious and less conscious projections of the gamer's wishes and characteristics into the avatar, such that avatars and the way the gamers bond with them may prove to be a valuable source of information (Stavropoulos, Ratan et al., 2022).

These interpretations reinforce (and align with) the proposed notion of 'digital phenotype', suggesting that an individual's cyber-behaviour and choices, such as their user-avatar customization and bond, may operate as a unique 'footprint' of what they are experiencing offline, if/when appropriately translated (Loi, 2019; Stavropoulos et al., 2021; Zarate et al., 2022). This possibility is additionally strengthened by the work of Lemenager et al. (2020), who reported: (i) a consistent association between disordered gaming and bonding with the avatar, and; (ii) enhanced activation of brain regions during times an individual is consumed by thoughts regarding their avatar. Interestingly, the notion of game transfer phenomena, described as the tendency of gamers to experience altered/involuntary cognitions/thoughts, behaviours and perceptions outside of their gaming sessions, has also been associated with suffering from a medical condition and/or drug abuse, indirectly advocating for the health phenotyping/footprint potential of gaming behaviours including UAB (Ortiz de Gortari & Griffiths, 2015).

IMPLICATIONS, LIMITATIONS, AND FURTHER RESEARCH

The automation of the decoding of such information using trained AI/ML procedures demonstrated here, likely revolutionizes the potential use of the UAB as a cyber-phenotype, meaning a source of information about the health/mental health of the user outside the game. More specifically, findings of the present study may: (i) pave the way for large-scale, avatar-mediated (and therefore, more gamer-friendly), low-cost, ML/AI-facilitated GD risk diagnostic procedures; (ii) help in the development of more effective GD prevention strategies, through the targeting of AI-detected GD risk gamer groups based on the way they bond with their avatars and; (iii) encourage the implementation of AIs for evaluation of user information potentially embedded within the UAB. In particular, from a conceptual perspective, and in relation to the notion of digital phenotype, the use of ML/AI to show the GD diagnostic potential of the UAB, expands past studies in the field, suggesting the need for exploration of further health and mental information likely embedded within the UAB, independent of GD risk (e.g. depression, anxiety; Lemenager et al., 2020; Loi, 2019; Ortiz de Gortari & Griffiths, 2015).

Overall, the present study suggests that GD risk can be predicted using ML/AI algorithms, that are capable of combining different variables on a large scale with reduced rates of misdiagnosis, providing more accurate diagnostic and/or risk indicators. In turn, these techniques may provide clinically relevant insights into assessment and save significant time for clinicians. Furthermore, from a GD treatment perspective, the present findings argue in favour of the utilization of the user-avatar bond when addressing GD symptoms. As Tisseron (2009) suggested, the UAB can provide the map for more accurate case formulation that can in turn drive more effective GD treatment plans, when and where avatars are involved. For instance, by observing avatar characteristics, possessions, and needs/commitments in the virtual world (e.g. using the empty chair technique to invite the 'avatar' to talk in a disordered gamer's session), clinicians may be able to work collaboratively with the treatment seeker/receiver to understand what they could be missing in their offline lives and plan how to pursue it to reduce their game-dependency (Tisseron, 2009). However, the findings of the present study should be interpreted taking into account the limitations of the present study, which utilised a rather small, community-sourced sample and relied exclusively on self-reported data, that might invite potential biases and confounding variables effects.

CONCLUSION

Despite such limitations, the present study innovatively aimed to unlock the mental health diagnostic potential, likely embedded within the UAB, through the pioneering use of a sequence of different ML classifiers and emphasizing an individual's disordered gaming risk. It did so while abiding with open science principles (i.e., accessible code and findings), such that research teams in the field can employ ML/AI to other already collected datasets related to the UAB to corroborate or negate the present findings. Furthermore, and in the context of the present study, ML/AI is converted from a game mechanic employed by industry to increase game engagement, and thus likely GD risk (Millington, 2009) into a GD protective factor.

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SUPPLEMENTARY MATERIAL

Supplementary data to this article can be found online at https://doi.org/10.1556/2006.2023.00062.

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