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Examining how gamers connect with their avatars to assess their anxiety: A novel artificial intelligence approach

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ABSTRACT

Research has supported that a gamer's attachment to their avatar can offer significant insights about their mental health, including anxiety. To assess this hypothesis, longitudinal data from 565 adult and adolescent participants ($M_{age} = 29.3$ years, SD = 10.6) was analyzed at two points, six months apart. Respondents were assessed using the User-Avatar Bond (UAB) scale and the Depression Anxiety Stress Scale (DASS) to measure their connection with their avatar and their risk for anxiety. The records were processed using both untuned and tuned artificial intelligence [AI] classifiers to evaluate present and future anxiety. The findings indicated that AI models are capable of accurately and autonomously discerning cases of anxiety risk based on the gamers' self-reported UAB, age, and duration of gaming, both at present and after six months. Notably, random forest algorithms surpassed other AI models in effectiveness, with avatar compensation emerging as the most significant factor in model training for prospective anxiety. The implications for assessment, prevention, and clinical practice are discussed.

1. Introduction

The rising trend in video game popularity has surged globally in recent years and is enjoyed by an estimated 70 % of Australians (Deloitte, 2023; Digital Australia, 2022; Stavropoulos et al., 2023). Primarily engaged as a social and leisure activity, video games are playable across a broad range of devices, including smartphones, consoles, and computers (Infanti et al., 2023). Given this, empirical data is continuously generated to reflect and examine various aspects of the player's experience (Stavropoulos et al., 2023). Among such aspects, the virtual persona, which represents a player in-game – their avatar – presents to be significant (Stavropoulos et al., 2020; Szolin et al., 2022), providing avenues for interaction and self-expression while in the virtual environment (Szolin et al., 2022; Yee, 2014). Interestingly, there has been growing recognition of the avatar's role in likely influencing behaviors (Stavropoulos et al., 2020, 2023). Additionally, there has been an increasing focus on the notion of the digital phenotype (DP), wherein the analysis of digital behaviors may translate into information regarding an individual's physical and mental health (Brown et al., 2024; Stavropoulos et al., 2022). Thus, how avatar-related information can be integrated into a DP framework to provide a more comprehensive understanding of users' well-being is of academic interest (Brown et al., 2024; Stavropoulos et al., 2022). Such knowledge has the potential to pave the way for novel, avatar-mediated, clinical assessment avenues, more suitable for those who may experience discomfort in directly addressing self-report scales and clinical intreviews (Brown et al., 2024; Stavropoulos et al., 2022).

1.1. Cyber-phenotyping: gaming behaviors and anxiety

The extended phenotype concept connects an individual's genetic makeup and environmental factors/experiences (i.e. who they are) to their visible/observable (i.e. how they behave) characteristics and behaviors (Zarate et al., 2022). As such, a person's actions can be seen as reflections/footprints of their genetic predispositions combined with their past experiences (Dawkins, 1982; Loi, 2019). This implies that how an individual behaves may provide insights and traces into their overall health – including their mental health and well-being (Rozgonjuk et al., 2023; Zarate et al., 2022). For instance, patterns of poor or interrupted sleep, which can be considered as a behavioral sign/phenotype

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component, have been associated with commonly experienced mental health symptoms, such as anxiety (Harvey, 2011; Peterson & Benca, 2006). Such phenotyping hypotheses, traditionally used to understand in-depth offline behaviors, have recently been applied to online behaviors to gauge potential psychopathological risks (e.g. disordered gaming, depression, Brown et al., 2024; Stavropoulos et al., 2023; Zarate et al., 2022). Along that line, new digital methodologies (e.g. mobile monitoring) have enabled the exploration of the diagnostic magnitude of digital data and cyber-behaviors to identify mental health indicators (Insel, 2018; Schivinski et al., 2020; Zarate et al., 2022).

To date, digital footprints have been analyzed by evaluating internet usage trends, device preferences, and wearable device data (Kożybska et al., 2022; Zarate et al., 2022). These have in turn revealed promising insights into the potential for diagnosis of a range of mental health conditions using digital information (e.g. anxious and depressive behaviors; Kozybska et al., 2022; Zarate et al., 2022). The methodologies employed to transform this digital data into health insights are communicated as digital phenotype (DP) processes (Loi, 2019). Generally, these processes involve the use of digital devices to gather passive/objective data without emphasizing the specific technology or data type (Loi, 2019). However, differentiation of data across collection devices has been recommended to address ecological validity concerns (Zarate et al., 2022). Recognizing this, the current research defines DP as an overarching notion, embracing all uses of digital tools, such as smartwatches or mobile apps, and objective, non-intrusive online behavior information to evaluate/reflect an individual's physical and mental health (Zarate et al., 2022).

Further, within the DP umbrella, distinct methodological frameworks exist to serve different purposes (Zarate et al., 2022). For instance, digital biomarking methodologies measuring speech data have been used to assist in tracking cognitive decline in Alzheimer's patients (Petti et al., 2023). Notably, cyber-phenotyping methodologies focus on the continuous observation and interpretation of psychological well-being information extracted from an individual's online behavior. This aims to understand psychological, behavioral, and emotional dimensions solely through the user's engagement in their online activities (Zarate et al., 2022). Therefore, to enrich the current body of literature, this research uses the cyber-phenotyping framework to explore mental health indicators via the digital cues found within virtual game environments (Zarate et al., 2022).

1.2. Mental health insights from the user-avatar relationship

Visually representing the video game player, avatars are central to the gaming experience and facilitate navigation and engagement within the game world, while concurrently being a conduit for self-expression and virtual identity formation (Brown et al., 2024; Ratan et al., 2020; Stavropoulos et al., 2020). Avatars can provide insight into, and through the choices and decisions that players virtually engage in, such as with customizable aspects like appearance/attire, as well as with interactions with other players/broader digital communities (Badrinarayanan et al., 2014; Ratan et al., 2020; Stavropoulos et al., 2022). Indeed, research demonstrates that players with social anxiety may prefer online socialization (Bodi et al., 2021; Kiraly et al., 2023). In that line, a portion of those who are more comfortable expressing themselves online, experience fewer real-life relationships and amplified virtual relationships (Lee & Leeson, 2015). As players customize their avatars and use them to interact virtually, the psychological bond between player and avatar develops over time (Bessière et al., 2007; Ratan et al., 2020). This dual role has been advocated to offer researchers valuable data insights into how the bond between some players and their avatars may reflect or influence their real-world behaviors, thus acting like their cyber-phenotype (Szolin et al., 2022).

The user-avatar bond (UAB) is an established theory encompassing three primary dimensions: *Immersion,* or the degree to which a user perceives their avatar's in-game needs as parallel to their offline needs; *Identification,* or how similar a player feels to their avatar; and *Compensation,* or how closely a user's avatar mirrors the person they aspire to be offline (Stavropoulos et al., 2021). The stronger the connection between a player's avatar and their desired self-expression, the deeper the bond (Ratan et al., 2020). Consequently, in what is known as the "undifferentiated avatar" phenomenon, players form connections not just *with* their avatars but also *through* them, likely entering a fusion state (Coulson et al., 2017). Accordingly, when users engage in virtual environments, their avatars can mirror valuable knowledge about their actions, inclinations, and life trajectories including their anxious feelings (e.g. users may craft idealized avatars to escape anxiety; Biocca, 1997; Brown et al., 2024; Ratan et al., 2020; Stavropoulos et al., 2020, 2021, 2022; Yee, 2014; Zarate et al., 2022). Therefore, delving into exploring such potential could be particularly significant, especially for those avatar-users who may be less likely to express/verbalise their anxious feelings in person, but rather escape them through an idealized avatar (Stavropoulos et al., 2020, 2022; Yee, 2014; Zarate et al., 2022).

Aside of the way the user customizes and uses the avatar, the notion of Proteus Effect (PE) serves as a framework for defining how an individual's online avatar could also shape their behaviors and self-perceptions in both virtual and real-world contexts (Brown et al., 2024; Stavropoulos et al., 2020). In other words, PE emphasizes the transformative impact of *the avatar* on human behavior and self-concept (Lemenager et al., 2020; Ratan et al., 2020; Stavropoulos et al., 2020; Yee, 2014). The longer an individual engages with a particular avatar, the more their offline behavior and self-view may mirror that avatar's characteristics, thus strengthening purported PE (Ratan et al., 2020; Stavropoulos et al., 2020, 2021). Such types of connection(s) can firstly lead users to endow their avatars with desired traits that mirror their idealized selves, which may later increase their self-perception (Stavropoulos et al., 2022; Yee, 2014). For instance, players can avoid anxiety caused by self/body dissatisfaction through the embodiment of their ideal avatar, ending up feeling more self-confident (Bessière et al., 2007; Kiraly et al., 2023).

Nevertheless, the UAB could also pose risks (Brown et al., 2024). As users continue to identify with their avatars, they may notice disparities between their real selves and their idealized digital representations, which can emphasize the divide between their current and aspirational identities, deepening feelings of anxiety (Higgins, 1987). Some individuals even create idealized avatars as a strategy to manage anxious emotions, further distancing themselves from their true selves (Szolin et al., 2022). Consequently, video games can become a safe space for some individuals with poor self-concept (i.e., users can continuously align themselves as closely as possible to their ideal identities via the avatar to address perceived inadequacies; Szolin et al., 2022). Yet, this ongoing idealization, driven by a desire to bridge self-perceived gaps, may intensify or perpetuate well-being issues (Sioni et al., 2017; Szolin et al., 2022). Importantly, research has linked the UAB not only to emotion-related concerns like anxiety (Sioni et al., 2017), but also to disordered gaming, as a way to manage it (Green et al., 2021; Stavropoulos et al., 2020). These underscore the complex interplay between the UAB and anxiety, as well as the UAB potential to convey information about the user, and in particular the levels of anxiety they may experience.

1.3. Study aims

This research aims to investigate the user-avatar bond within the framework of the DP hypothesis, focusing on the UAB's potential link to anxiety. Specifically, the study seeks to explore the associations of distinct dimensions of the UAB—namely, identification, immersion, and compensation—with current and future (i.e., post 6 months) anxiety experiences. The player's age and the length of their avatar engagement are also evaluated, as they have been supported to vary the intensity of the UAB (i.e. younger gamers with longer connection with their avatars tend to experience stronger UAB; Brown et al., 2024). Employing AI-based machine learning (ML) techniques, this research aims to enable the automatic and accurate translation of UAB dimensions into markers for anxiety risk, continuing recent work regarding depression and gaming disorder risk (Brown et al., 2024; Stavropoulos et al., 2023). As such, this approach leverages past research findings supporting the feasibility of translating one type of data (e.g., the UAB) into another (e.g., anxiety risk; Brown et al., 2024; Stavropoulos et al., 2023), being concurrently a novel attempt to translate the UAB into a measurable anxiety risk.

Viewing the UAB as a source of information, the current research utilizes sophisticated procedures, including ML algorithms, aspiring to convert digital information into valuable implications for efficient anxiety diagnosis and treatment. In particular, building upon the theoretical background previously discussed, this study seeks to enrich the existing body of knowledge by addressing the following research questions (RQs):

RQ1. Could a gamer's connection with their in-game avatar serve as a phenotype indicative of their current anxiety risk? If so, can ML algorithms be trained to assess this risk based on reported dimensions of the UAB, age, and time spent gaming?

RQ2. Does the UAB function as a phenotype for future (i.e., post 6 months) anxiety risk? If yes, could ML procedures be trained to predict this future risk based on the same UAB dimensions, age, and time spent gaming?

It is noted that the concept of phenotype is used here as a "translatable phenomenology", meaning that the avatar bond can be examined via the use of AI/ML techniques to extract information considering the anxiety gamers may be experiencing (Loi, 2019; Zarate et al., 2022).

2. Methods

2.1. Participants

A longitudinal study was conducted to assess gaming patterns and demographics within an online community over a 6-month period. Data was collected from 627 respondents at two distinct time points. After excluding preview-only responses ($n = 7$), spam ($n = 19$), bots ($n = 1$), those without consent ($n = 12$), failed validity responses ($n = 8$), and insufficient responses ($n = 15$), the final sample comprised 565 adolescents and adults ($M_{age} = 29.3$ years, $SD = 10.6$; 50 % male, 45 % female, 4 % other gender). This cohort underwent longitudinal assessment twice separated by 6 months. Overall gaming patterns and demographics at the first time point are displayed in Tables 1 and 2. Data is available online (see Stavropoulos, 2023) and has been used to address different research questions in two past published studies (see Brown et al., 2024; Stavropoulos et al., 2023).

Based on Hill's (1998) recommendations, the 95 % confidence interval for this sample size ($n = 595$, $z = 1.96$) yields a maximum random sampling error of ±4.12 %. At the first time point, the range of missing data for the variables studied was between 0.5 % (3 cases for age) and 2.83 % (16 cases for the 9th item of the User-Avatar Bond Questionnaire), which appeared to be randomly distributed throughout the dataset (MCAR test = 38.4, $p = .14$, based on 9 missing patterns; Little, 1988). In terms of participant dropout, there was a 48.8 % attrition rate with 276 (48.8 %) participants leaving between the study waves. Consequently, the research was calibrated to identify retention/attrition effects, which ranged from low to moderate in size for basic demographics and internet use information including gender, sexual orientation, ancestry, romantic relationship involvement, education, employment, length of gaming engagement, average daily gaming time during the week and the weekend, length of social-media usage, average daily social media use time during the week/weekend and chronological age (see Stavropoulos et al., 2023).

2.2. Measures

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

The UAB-Q examined the level of distinct player-avatar bond dimensions. This 12-item measure employs 5-point Likert scale responses varying from 1 (strongly disagree) to 5 (strongly agree) and comprises three UAB dimensions, hence identification, immersion, and compensation. The identification factor was assessed with four items, such as "I share the same skills and abilities as my character." The immersion factor comprises five items, including "I focus on my character itself rather than on the game situations." The compensation factor consists of three items, like "Being similar to my character would be beneficial in certain real-life situations." As shown in Table 3, the UAB-Q demonstrated adequate internal consistency reliability across both waves of this longitudinal study.

2.2.2. The Depression Anxiety Stress Scales (DASS-21; Lovibond & Lovibond, 1995)

The 21-item DASS-21 assessed symptoms of depression, anxiety, and stress. This self-report questionnaire contains three 7-item subscales. The depression subscale includes statements like " I felt down-hearted and blue". The anxiety subscale presents items such as " I felt scared without any good reason". The stress subscale comprises items like " I found it difficult to relax". Respondents rate how much they experienced each behavior/item on a 4-point severity scale from 0 (did not apply at all) to 3 (applied very much/most of the time). Scores for each subscale are produced by adding the allocated scale items. Higher scores indicate greater symptoms. A dichotomous classification was further used to categorize individuals as either at risk for anxiety (coded 1) or not at risk (coded 0). The recommended threshold for Australian populations on the DASS-21 anxiety subscale was utilized, with scores above 9 indicating risk (Brumby et al., 2011). As shown in Table 3, the DASS-21 demonstrated adequate internal consistency reliability across both waves.

2.3. Procedure

This study received ethical approval from [*details omitted for blind review*]. Sample were recruited from several sources, including tertiary education [*details omitted*], various public and private schools [*details omitted*], gaming communities [*details omitted*], gaming venues [*details omitted*], online forums [*details omitted*], and YouTube advertising videos [*details omitted*].

Adolescents between 12 and 18 years old and adults were eligible to

Table 1
Participant's age, game playing/social media usage years and daily week and weekend consumed time at time point one.

	Age	Gaming years	Mean daily gaming time in the week	Mean daily gaming time in the weekend	Social media years	Mean daily social media usage time in the week	Mean daily social media usage time in 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 usage information at Time point one.

		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 to 12)	101	489	0.207	< 0.001
	Secondary school (Years 7 to 10)	9	489	0.018	< 0.001
	Other	12	489	0.025	< 0.001
Living arrangement	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
	Defacto	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
Social Media Users	Yes	550	565	0.973	< 0.001
	No	15	565	0.027	< 0.001
Meta 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	Yes	472	564	0.837	< 0.001

(continued on next page)

Table 2 (*continued*)

		N	Total N	Proportion	p
family members					
	No	92	564	0.163	< 0.001

Note. H_a is proportion $\neq$ 0.5.

Table 3
Internal consistency reliability of the included measures across the waves.

Measure	Wave 1		Wave 2	
	Cronbach's α	McDonald's ω	Cronbach's α	McDonald's ω
User-Avatar-Bond Questionnaire (UAB-Q)	0.804	0.812	0.849	0.867
UAB-Q Identification subscale	0.701	0.729	0.77	0.789
UAB-Q Immersion subscale	0.717	0.727	0.764	0.775
UAB-Q Compensation subscale	0.604	0.656	0.66	0.709
Depression Anxiety Stress Scales (DASS-21)	0.952	0.935	0.939	0.94
DASS-21 Depression subscale	0.915	0.915	0.906	0.907
DASS-21 Anxiety subscale	0.853	0.862	0.786	0.787
DASS-21 Stress subscale	0.894	0.892	0.885	0.885

Note. All measures displayed sufficient internal consistency across the waves.

take part in the study. All individuals interested in joining were invited to voluntarily participate in the anonymous study. Each was presented with a plain information statement detailing the study's goals, likely risks involved, and their rights, including the option to withdraw at any time without any consequences. In the case of adolescents, the information statement was initially reviewed and apporved by their parent or guardian, and then the adolescent provided assent. Adults aged 18 years and older directly provided their consent. Thus, all participants took part on a voluntary basis with full disclosure of the study details.

The data collection process comprised three distinct yet linked streams, each participant was assigned a unique code to allow de-identified data matching. First, participants completed comprehensive online questionnaires covering demographics, technology/gaming/social media usage, psychometric scales, and informed consent provisions. Second, for a period of 7 days, participants wore an actigraphy tracker device (Fitbit) to passively monitor physical activity and sleep parameters such as step count and sleep duration. Fitbit data was automatically gathered through the company's portal system using the unique participant codes. For those without access to a Fitbit device, one was provided by the research team for the 7-day monitoring period. Third, participants enabled a 7-day mobile application called Aware Light (Van Berkel et al., 2023) on their smartphones to record screen on/off time, number and duration of phone calls, and length of text messages (i.e., number of characters used). The Aware Light app data was matched to the other data streams using the unique participant codes. This three-stream data collection procedure will be repeated every 6 months for a total of 4 assessment waves, with the current study analyzing data from the first 2 completed waves. At the initiation of the online survey section, informed consent was secured from all participants. It is emphasized that the dataset analyzed in the current study was collected as part of a broader research project reported in two prior publications with different research aims and findings (Brown et al., 2024; Stavropoulos et al., 2023).

2.4. Analyses

To address the first research question on identifying current anxiety risk based on factors such as a player's age, amount of time spent gaming in years, and avatar bond dimensions, the present study implemented a series of machine learning (ML) techniques using the Tidymodels package for R language and environment for statistical computing and graphics (Horton & Kleinman, 2015; Kuhn & Wickham, 2020). The workflow for both timepoint 1 and timepoint 2 can be found in Appendix 1 and 2, respectively.

The initial step involved equalizing the dataset across the different anxiety risk categories (Yes/No) by applying synthetic minority oversampling techniques (SMOTE) through the DMwR package (Torgo et al., 2013). This process included the creation of new synthetic samples for the lesser-represented group, drawing from a selected number (k) of closest neighbors to a minority sample, determined by Euclidean distance measurements.[1] Equalizing these groups aids in enhancing the predictive accuracy of the ML models.

Subsequently, the dataset was partitioned, allocating 80 % for training and 20 % for testing purposes, with the split being stratified to ensure similar distributions of anxiety risk categories in both subsets. This stratification allows for more robust validation by testing model efficacy on new, unseen data. A conservative Bayesian prior distribution was adopted at this stage.[2] To optimize model parameters, a ten-fold cross-validation was performed on the training set, along with the creation of bootstrapped training subsets.

The ML models' recipe was then specified, using binary anxiety risk status from the first time point as the outcome and the variables age, gaming experience, and avatar identification, immersion, compensation as predictors. The model was set up to ensure at least 50 % representation of anxiety risk cases in both the training and testing data. All predictor variables were evaluated for their relevance and impact on the model (ensuring no high correlation, skewness, or zero-variance issues)[3] and were standardized and centered.

Furthermore, a range of supervised classification ML models, including both tuned and untuned variants and a baseline null model, were tested (Kuhn & Wickham, 2020). These models followed the analyses of Brown et al. (2024) and encompassed techniques such as LASSO, k-Nearest Neighbors (k−NN), Support Vector Machine Kernel (SVM—K), X Gradient Boosting (XGB), Random Forests, Naive Bayes, and Logistic Regression. The models were trained on the training data, fine-tuned on bootstrapped and cross-validation subsets of this training data, and finally applied to the test set, which was reserved from the start. Model performance was assessed based on results from the testing set.

For the second research question, focusing on prospective anxiety risk at a 6-month follow-up, the same ML approach was replicated, with

[1] *Note 3.* The k-NN algorithm identifies the k number of cases closest to a new data point and assigns the most common class among those nearest neighbors *point* (i.e., Yes/No anxiety risk; Chawla et al., 2002). This effectively bases predictions on small neighborhoods of the most similar past examples.

[2] *Note 4.* From a Bayesian standpoint, defining a prior distribution and variability range is required for all model parameters before analyzing the data. Following recommendations, a cautious t-shaped Cauchy distribution was specified with 7 degrees of freedom to convey initial uncertainty around the parameter values (Muth et al., 2018). This conservative approach avoids over-restricting the parameters before fitting the models.

[3] *Note 5.* Steps c to e did not effectively exclude any predictor.

the outcome variable being the anxiety risk status at the second time point. Model effectiveness was gauged using confusion matrices and metrics like accuracy, precision, AUC, recall, and F-measures derived from these matrices (yardstick package; Kuhn & Wickham, 2020). Tables 4, 6, and 8 provide definitions and guidelines for interpreting these metrics, as per Brown et al., 2024 and Stavropoulos et al., 2023 work. This approach thoroughly evaluated the models' ability to predict future anxiety risk based on initial baseline predictors.

3. Results

Before the main analysis, participants were divided into two groups at the first time point: those with No Anxiety Risk ($n = 488$, representing 95 % of the sample) and those with Yes Anxiety Risk ($n = 25$, 5 %). For RQ1, to facilitate machine learning (ML) analysis, the Yes Anxiety Risk group, being the smaller group, was amplified through k-NN SMOTE techniques (Chawla et al., 2002; Torgo et al., 2013) with the same process followed for the majority group, achieving a balanced dataset (Yes $n = 731$; 50 %). The dataset was subsequently divided, with 80 % for training and 20 % for testing. Analysis showed that the proportions of anxiety risk were evenly distributed between the training and testing sets (X2 = 0, df = 1, $p = 1$; Cramer's V $\geq$ 0.00; 50 % Yes Anxiety Risk in both sets). Predictive models were then set up, with scaling of predictor variables and generation of descriptive statistics for training, testing, and the complete dataset. Both ten-fold cross-validation and bootstrapped training sets were utilized, as illustrated in Appendix 1. The study then initiated baseline modeling and workflows for various algorithms including Null, LASSO, SVM-Kernel, Random Forests, Naïve Bayes, and Logistic Regression in their default settings (untuned). These models were trained on the training data and evaluated using separate testing data (details on their performance can be found in Appendix 5). In addition, the variable importance plots (VIP) R package was employed to identify the predictors/variables that most improved the (ML) learning potential (Greenwell et al., 2020).

To enhance the models' precision, refined versions of classifiers such as LASSO, Random Forests, XGB, Naive Bayes, Logistic Regression, and k-NN were introduced. The hyperparameter tuning process for each model is detailed in Table 4, as per Brown et al. (2024) and Stavropoulos et al. (2023). These adjusted models underwent training on the training set and subsequent assessment on the test data set aside. The final hyperparameters selected for each model are listed in Table 5. Considering model performance (see Table 6), it was noted that all models were better than the null model (0.763 < accuracy with LASSO being the lowest), with Random Forests showing particularly strong results across all evaluation metrics, as depicted in Fig. 1. The VIP package analysis indicated when considering the avatar bond, immersion was significant predictor for concurrent anxiety (>20) (see Appendix 1).

The same optimization and evaluation process was applied to the data from wave 2 (RQ2; see Appendix 2). In line with the wave 1 outcomes, Random Forests outperformed other models in both pre-and post-hyperparameter tuning stages (see Appendix 5 for details). The final tuned hyperparameters for the wave 2 models are presented in Table 7, and the performance of these tuned models is summarized in Table 8. Fig. 2 graphically represents the performance of all models (0.623 < accuracy with tuned Logistic Regression being the lowest), highlighting the dominance of Random Forests (see Appendix 6 for further details). The replication of Random Forests as the leading model reinforces its appropriateness for this specific research question. Furthermore, the comprehensive tuning and comparative analysis solidly establish that Random Forest modeling is exceptionally well-suited for predicting anxiety risk based on the studied variables. The VIP package analysis indicated when considering the avatar bond, compensation was the most significant predictor for prospective anxiety (>10) (see html appendix provided).

Table 4
ML models trained, tuned, and tested.

Type	Operation	Hyperparameters tuned	R-Package/ engine employed
Least Absolute Shrinkage Selection Operator (LASSO)	LASSO is a regression-based supervised machine learning classifier that uses variable selection and regularization to improve prediction accuracy. It does this by reducing noise and selecting certain features to regularize the model. Mathematically, LASSO considers the magnitude of coefficients as a penalty added to the loss function. So the loss function is modified to reduce model complexity by constraining the sum of the coefficients' magnitudes [Loss function = OLS loss + A (penalty) x sum (magnitude of coefficients)].	*penalty* = To perform regularization (L1 regularization), LASSO adds a penalty proportional to the size of the regression coefficients (predictor effects). The goal is to minimize the coefficients. The optimal penalty value is determined through hyperparameter tuning.	*glmnet*
K Nearest Neighbors (k-NN)	The k-NN algorithm is a supervised, nonparametric classification method that estimates proximity between a case and its k nearest neighbors based on their Euclidean distance. In other words, k-NN classifies a case by considering the categories of its most similar neighboring cases.	*neighbors* = The number of neighboring points (k) to consider is optimized through hyperparameter tuning to achieve the best learning and prediction performance of the k-NN algorithm.	*knn*
Support Vector Machine Kernel (SVM-K)	Kernel machine learning involves pattern analysis, with support vector machines (SVMs) being a well-known example. This study used the radial basis function as the kernel function. Kernel functions are mathematical transformations that allow SVMs to perform nonlinear classification by projecting lower-dimensional data into a higher dimension. A kernelized SVM then applies linear computations on the transformed data to solve nonlinear classification problems.	*cost* = In SVM, cost represents the logistic loss function as a piecewise linear function. In practice, the cost hyperparameter controls the optimization by setting the amount of misclassification allowed on the training data. Higher cost values lead to tighter margins and vice versa.*degree* = The degree hyperparameter determines the flexibility of the predictions, with higher values allowing more flexible decision boundaries. *scale_factor* = The scaling hyperparameter for categorical kernels indicates the optimal normalization (kernel	*Kernlab*

(*continued on next page*)

Table 4 (*continued*)

Type	Operation	Hyperparameters tuned	R-Package/ engine employed
		width) needed to avoid distorting the data.	
X Gradient Boosting (XGB)	XGBoost is well-suited for structured, tabular data. It uses gradient boosted decision trees to optimize prediction accuracy. Specifically, XGBoost performs parallel tree boosting, which combines multiple weak learner decision trees. Unlike random forest's bagging approach, XGBoost builds trees sequentially, with each new tree influenced by the previous tree's outcome.	*mtry* = The number of predictor variables randomly sampled at each tree split. *min_n* = The minimum number of data points required in a node (tree branch) to enable further splitting. *tree_depth* = The maximum tree depth (number of splits) allowed to optimize prediction. *Learn rate* (i.e., *shrinkage)* = The stepping rate for adapting the boosting over successive iterations. *loss_reduction* = The decrease in the loss function needed to continue with tree splits. *sample_size* = The fraction of data used for fitting the model at each iteration.	*xgboost*
Random Forests	Random forest is a widely used, flexible supervised ensemble machine learning model. It combines the results from multiple decision trees (bagging) that are trained to perform a prediction or classification task. In practice, random forests make a meta-estimation by averaging the outcomes of multiple decision tree classifiers trained on different subsamples of the data. This improves accuracy and prevents overfitting.	*mtry* = The number of predictor variables randomly sampled at each decision tree split. *min_n* = The minimum number of data points required in a node (tree branch) to enable further splitting.	*ranger*
Naïve Bayes	Naive Bayes is a probabilistic, supervised machine learning classifier that works generatively. This means it tries to model the distribution of the data classes, while assuming conditional independence between the features. It then uses this to predict how a particular class would generate the input data. The "naive" assumption is that the data characteristics are independent.	*smoothness* = The kernel smoothness parameter defines the density value needed for the algorithm to faster converge to the true density of numeric predictors. *Laplace* = Laplace smoothing refers to a technique that addresses the risk of zero probability values in Naive Bayes. It works by adding a small pseudo count to all the probability estimates, which prevents zeros and smoothes the model. This enables Naive Bayes to make	*naivebayes*

Table 4 (*continued*)

Type	Operation	Hyperparameters tuned	R-Package/ engine employed
		reasonable predictions even with sparse data.	
Logistic Regression	Logistic regression is a supervised machine learning classifier that uses a logistic function to model and predict binary or dichotomous target variables. It is called regression because it predicts the probability of an outcome, even though the target variable is categorical.	*penalty* = In logistic regression, the regularization penalty hyperparameter helps address overfitting by preferring simpler models. It reduces generalization error, like in LASSO. *mixture* = A regularization parameter between 0 and 1 that balances between LASSO (1) and ridge regression (0). It allows an elastic net model that combines LASSO and ridge penalties for improved accuracy.	*glm*

Note. Glmnet is derived from Friedman et al. (2010); Ranger is derived from Wright et al. (2017); Kernlab is derived from Karatzoglou et al., (2004); Xgboost is derived from Chen et al. (2019); and all other engines ae derived from Kuhn and Silge (2022).

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

Type	Hyperparameters tuned	Tuning results
Least Absolute Shrinkage Selection Operator (LASSO)	penalty	0.0000000001
K Nearest Neighbors (k-NN)	neighbors	10
X Gradient Boosting (XGB)	mtry	6
	min_n	15
	tree_depth	11
	Learn rate (i.e., shrinkage)	0.0425
	loss_reduction	0.171
	sample_size	0.455
Random Forests	mtry	1
	min_n	6
Naïve Bayes	smoothness	0.5
	Laplace	0
Logistic Regression	penalty	0.0886
	mixture	0.75

Note. See Table 3 for detailed information regarding the classifiers applied.

4. Discussion

In this longitudinal research, a significant, representative sample of gamers was used to establish AI-based ML techniques for evaluating both immediate and future anxiety risk, particularly over a six-month period. The assessment of risk was derived on how the users connected to their avatars and basic demographics, specifically considering factors such as age, total gaming time in years, and levels of avatar identification, immersion, and compensation. To determine the most efficient predictive models, a range of widely-used AI models were explored in their standard and finely-tuned forms (comprising five untuned and seven tuned models) following past literature (Brown et al., 2024; Stavropoulos et al., 2023). The dataset was partitioned into training and testing subsets, with a predictive framework designed to test the models' effectiveness in forecasting anxiety risk both presently and at the six-month mark. According to the findings, all the AI models evaluated performed above random chance, with Random Forests showing the highest potential for accurate prediction. The consistent

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

	Null Model	Random Forests	Logistic Regression	LASSO	Naïve Bayes	XGB	k-NN
ROC_AUC	0.5	0.996	0.843	0.843	0.893	0.975	0.993
PPV	0.502	0.98	0.757	0.757	0.825	0.919	1
F_meas	0.668	0.98	0.767	0.767	0.811	0.919	0.931
Recall	1	0.98	0.777	0.777	0.797	0.919	0.872
Accuracy	0.502	0.98	0.763	0.763	0.814	0.919	0.936

Accuracy reflects the ratio of correctly predicted cases across the total number of cases. It is produced via the accumulation of the true positive and the true negative cases divided to 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 (Allright, 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 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). 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).

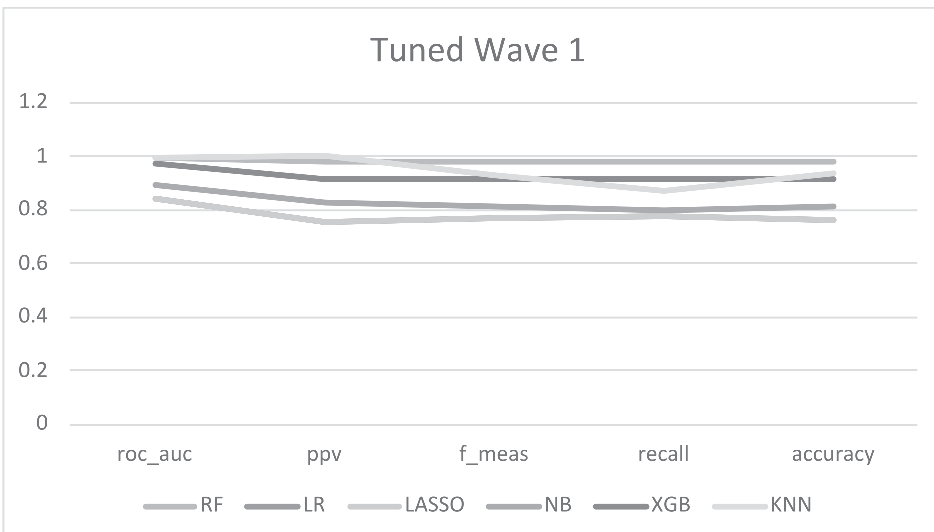

Fig. 1. Tuned classifiers performance across the criteria (Wave 1).

Table 7
Hyperparameter tuning summary across classifiers (Wave 2).

Type	Hyperparameters tuned	Tuning results
Least Absolute Shrinkage Selection Operator (LASSO)	*penalty*	0.0373
K Nearest Neighbors (k-NN)	*neighbors*	10
X Gradient Boosting (XGB)	*mtry*	6
	min_n	15
	tree_depth	11
	Learn rate (i.e. *shrinkage)*	0.0425
	loss_reduction	0.171
	sample_size	0.455
Random Forests	*mtry*	1
	min_n	6
Naïve Bayes	*smoothness*	0.658
	Laplace	0
Logistic Regression	*penalty*	0.298
	mixture	0.05

See Table 4 for detailed information regarding the classifiers applied.

performance of Random Forests at both time points suggests that its effectiveness was not a mere coincidence. Furthermore, the study highlighted that among avatar information, the dimensions of immersion and compensation were the most critical in predicting anxiety concurrently and prospectively respectively.

4.1. Anxiety & the user-avatar bond

The current results indicate that compensation is the most influential avatar factor in predicting future anxiety risk, emphasizing a potentially vital connection between aspects of the UAB and mental well-being. Interestingly, the compensation dimension could be conceptualized as how much a player compensates for inadequacies in themselves through the creation of an idealized avatar (Stavropoulos et al., 2022, 2020). Prior studies have shown that some individuals tend to create idealized avatars as a way to escape or manage psychological discomfort, which may lead to notable discrepancies between their avatar and their actual self, likely adversely affecting their mental health (Bessière et al., 2007; Burleigh et al., 2018; Higgins, 1987; Ratan et al., 2020).

The relationship between the way a gamer may idealize and compensate through their avatar with anxiety is nuanced. Not every player who customizes their avatar to surpass their actual selves exhibits

Table 8
Tuned algorithms performance on testing data (Wave 2).

	Null Model	Random Forests	Logistic Regression	LASSO	Naïve Bayes	XGB	k-NN
ROC_AUC	0.5	0.997	0.647	0.638	0.159	0.959	0.978
PPV	0.5	0.935	0.642	0.625	0.771	0.872	0.95
F_meas	0.667	0.966	0.619	0.625	0.761	0.907	0.864
Recall	1	1	0.597	0.625	0.75	0.944	0.792
Accuracy	0.5	0.965	0.623	0.625	0.764	0.903	0.875

Accuracy reflects the ratio of correctly predicted cases across the total number of cases. It is produced via the accumulation of the true positive and the true negative cases divided to 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 (Allright, 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). 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).

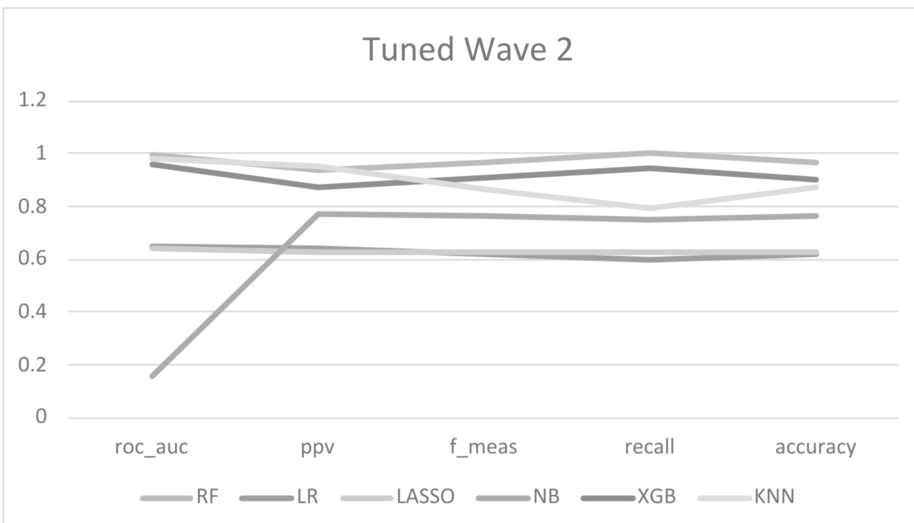

Fig. 2. Tuned classifiers performance across the criteria (Wave 2).

maladaptive behaviors, including anxiety (Mancini & Sibilla, 2017). However, certain tendencies, such as significantly improving avatar attributes, may indicate dysfunctional compensation and anxiety proneness (Stavropoulos et al., 2022; You et al., 2017). It is vital to highlight that there are various areas in which an individual may feel the need to compensate, and this is not limited to appearance (Lemenager et al., 2020; Stavropoulos et al., 2022; Yee, 2014). Players with anxiety often grapple with self-concept issues, using an idealized avatar as a conduit to express aspects they may fear revealing in their offline life, potentially representing a truer self, that is unrestricted by societal expectations and social rules (Szolin et al., 2022). However, this emotional release through their avatar can reinforce a reluctance to change their offline behaviors and/or identity, ultimately either diminishing well-being or exacerbating anxiety (i.e. becoming a short-term solution and a longer-term exacerbator of their initial problem; Szolin et al., 2022).

Immersion was also found to be crucial for the present ML model (i.e., random forests). Avatar immersion has been linked with poor self-esteem, lower social skills (You et al., 2017), and social phobia (Pang et al., 2019). Given these variables' association with anxiety, past research supports the idea that immersing oneself in their virtual avatar could be linked to anxiety risk (Sowislo & Orth, 2013). Anxious gamers often create avatars closer to an idealized version of themselves, and consequently immerse more with their avatar than their actual selves (Szolin et al., 2022). This immersion could in some cases exacerbate self-discrepancies and increase distress, including feelings of anxiety (Bessière et al., 2007; Higgins, 1987). This could create a feedback loop where anxious feelings can lead to maladaptive immersion, which can increase anxiety. Therefore, there is theoretical support for compensation and immersion in the UAB, as reliable AI classifiers' predictors of present and future anxiety.

4.2. The user-avatar bond and cyber-phenotyping

The ability to foresee anxiety using UAB dimensions, combined with factors like age and gaming duration, illustrates the significance of viewing this unique virtual interaction as a cyber-phenotype source. Situated within digital environments, the UAB can serve as a DP pathway, involving patterns such as avatar customization which are indicative of a person's inherent tendencies and psychological state, including anxiety (Loi, 2019; Szolin et al., 2022). This research builds upon the prior groundwork establishing the DP framework, while reinforcing its applicability in gaming contexts by expanding the cyber-phenotype model within the DP approach (Loi, 2019; Zarate et al., 2022). Specifically, this expansion could encompass the multidimensional data that can be extracted from the UAB. Indeed, it may be possible to significantly enhance the derivation of meaningful, yet often hard to collect well-being data, especially for more anxious and likely challenging to approach and assess in person, anxious gamers, from their avatars and gaming activities (Brown et al., 2024; Stavropoulos et al., 2023). Hence, this research strengthens the idea that avatars can be a tool for exploring our relationship with our offline selves, offering phenotypic and diagnostic value (Stavropoulos et al., 2022).

4.3. Further research, implications, and limitations

Despite its value, the current study has limitations. Since the UAB data relies on self-reported assessments, it may be less accurate than behavioral metrics related to an avatar, such as the amount of time spent playing games with a customized avatar. Moreover, the specific proportions of age, gender, and cultural heritage/ancestry within our sample limit the generalizability of our findings to potentially more diverse populations (Na et al., 2017). Another limitation of the study was the participant attrition between timepoint 1 and timepoint 2 was quite high (48.8 %). Although assessed and shown to have only low to moderate effects in relation to age and gender, it invites further longitudinal research. It is additionally important to note that only 21 participants were identified as having a high anxiety risk. Although robust analytical remedies including K-NN SMOTE were employed, this relatively small, high-anxiety proportion posed the need for cautiousness to be exercised in interpreting the current findings.

Overall, the present study advances the UAB as a potential cyber-phenotype source by demonstrating that anxiety risk, like depression and gaming disorder risk, can also be predicted through examination of the UAB factors of identification, immersion, and compensation, incorporating age and gaming duration (Brown et al., 2024; Stavropoulos et al., 2023). Given the novelty of ML, further validation of these associations is necessary. However, the incorporation of avatar metrics (e.g., UAB) into digital screening tools has the potential to facilitate the early, indirect/mediated, identification of mental health issues, including anxiety, among gamers.

As knowledge about the UAB expands, opportunities for avatars to have a positive impact increase. For example, promoting authentic avatar design may encourage healthy identity development, thereby improving self-concept clarity (Green et al., 2021). Another approach proposed has been creating avatars that embody anxiety as a way to separate one's mental illness from one's identity (Pimentel & Kalyanaraman, 2020). Overall, the UAB continues to prove itself as a useful component, and as research progresses, the implementation of the UAB into clinical assessments or interventions appears inviting.

Future research should consider utilizing behavioral metrics (e.g., number of avatars, time spent customizing avatars) rather than relying solely on self-reported data. This shift would enable an exploration of whether objective data enhances the accuracy of risk assessments. Additionally, it is crucial to investigate potential variations in the UAB across different game genres. Given the observed differences in personality traits, gaming immersion/engagement and self-control among various game genres (Kim et al., 2022; Na et al., 2017), exploring UAB differences becomes pertinent. If such distinctions exist, concurrently gathering game genre information could enhance the accuracy of ML models.

Furthermore, researchers should aim to expand the characteristics that contribute to the cyber-phenotype. This expansion might encompass reasons for gaming, such as socializing, achievement hunting, or escapism. As mentioned earlier, a well-informed cyber-phenotype has the potential to offer an accurate representation of an individual beyond the virtual world, providing insights into their well-being (Loi, 2019).

Lastly, further research with more populous and more heterogeneous high-anxiety samples would help validate and extend the conclusions drawn here regarding the relationship between the way gamers relate to their avatars and anxiety.

4.4. Conclusive summary

The current research employed AI analyses to examine self-reported dimensions of the UAB, demonstrating their capacity to reliably categorize more anxious gamers. The findings strengthen the evidence for treating the way one relates to their avatar as a credible cyber-phenotype source, indicating its usefulness in gleaning health-related insights from an individual's behavior in virtual settings. With the growing importance of virtual spaces where avatars are prevalent, it becomes increasingly vital to explore how avatars affect and reflect individuals.

Compliance with ethical standards

Informed consent was obtained from all participants included in the study.

All procedures in studies involving human participants were performed in accordance with the ethical standards of RMIT 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].

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Ethical standards – animal rights

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. This article does not contain any studies with animals performed by any of the authors.

Confirmation statement

Authors confirm that this paper has not been either previously published or submitted simultaneously for publication elsewhere.

CRediT authorship contribution statement

Kaiden Hein: Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Connor Conkey-Morrison:** Writing – review & editing, Writing – original draft, Conceptualization. **Tyrone L. Burleigh:** Writing – review & editing, Writing – original draft. **Dylan Poulus:** Writing – review & editing. **Vasileios Stavropoulos:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors of the present study do not report any conflict of interest.

Data availability

All data and syntax supporting the findings of this study are available with the article and its supplementary materials.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.actpsy.2024.104298.

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